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Identifying the psychological processes delineating non-harmful from problematic binge-watching: A machine learning analytical approach

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ABSTRACT

As on-demand streaming technology rapidly expanded, binge-watching (i.e., watching multiple episodes of TV series back-to-back) has become a widespread activity, and substantial research has been conducted to explore its potential harmfulness. There is, however, a need for differentiating non-harmful and problematic binge-watching. This is the first study using a machine learning analytical strategy to further investigate the distinct psychological predictors of these two binge-watching patterns. A total of 4275 TV series viewers completed an online survey assessing sociodemographic variables, binge-watching engagement, and relevant predictor variables (i.e., viewing motivations, impulsivity facets, and affect). In one set of analyses, we modeled intensity of non-harmful involvement in binge-watching as the dependent variable, while in a following set of analyses, we modeled intensity of problematic involvement in binge-watching as the dependent variable. Emotional enhancement motivation, followed by enrichment and social motivations, were the most important variables in modeling non-harmful involvement. Coping/escapism motivation, followed by urgency and lack of perseverance (two impulsivity traits), were found as the most important predictors of problematic involvement. These findings indicate that non-harmful involvement is characterized by positive reinforcement triggered by TV series watching, while problematic involvement is linked to negative reinforcement motives and impulsivity traits.

1. Introduction

As the worldwide adoption of Subscription-Video-on-Demand services (e.g., Netflix, Hulu, Disney+) continues to increase from year to year (Statista, 2020a), binge-watching (i.e., watching multiple episodes of TV series in one sitting) became the viewing norm

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for many (Business Wire, 2019; Rubenking and Bracken, 2021; Statista, 2020b). Such remarkable evolvement in watching habits essentially stems from the availability of the endless user-centered access to hundreds of compelling TV series, at whatever time and in whatever manner (i.e., through nearly any kinds of digital media).

With this evolution in the way TV series are consumed, there has been growing international interest in research on the antecedents and consequences of binge-watching behaviors, as witnessed by the first systematic literature reviews conducted on the topic (Flayelle et al., 2020a; Starosta and Izydorczyk, 2020). These reviews come to the same conclusion in that binge-watching reflects a two-sided phenomenon. On the one hand, binge-watching can be an inherently beneficial and fulfilling experience involving positive media effects on viewers' well-being (Granow et al., 2018; Pittman and Steiner, 2021). On the other hand, this highly immersive on-demand experience may generate loss of control on time spent watching (i.e., watching for far longer than intended; Castro et al., 2021; Riddle et al., 2017), thereby potentially triggering significant guilt and feelings of regret (Granow et al., 2018; Shim et al., 2018), or even functional impairments (e.g., sleep disturbances, decrease of work performance; Exelmans and Van den Bulck, 2017; Rubenking et al., 2018). There is, therefore, growing agreement that non-harmful involvement needs to be separated from problematic involvement in binge-watching to prevent over-pathologizing this activity. There is a lack, however, of research identifying the specific features and underlying mechanisms behind these two different watching patterns, and the specific conditions or factors that favor the shift from one to the other (Flayelle et al., 2020a; Flayelle and Lannoy, 2021; Steins-Loeber et al., 2020). The current study was designed to address this shortcoming by investigating the distinct psychological predictors of non-harmful and problematic binge-watching patterns.

2. Literature review

Such emphasis on questioning the core differences between these two behavioral patterns notably builds on the conceptual frame of the *Dualistic Model of Passion* (DMP; Vallerand, 2015; Vallerand et al., 2003), according to which any time-consuming activity that one considers as personally important and meaningful falls within the scope of either the *Harmonious* or *Obsessive* type of passion. Characterized by free will and self-control, *Harmonious Passion* is generally performed in harmony with other spheres of daily life, thus promoting a broad range of positive affective, cognitive, and behavioral outcomes which globally add to the individual's existence (Curran et al., 2015). A strong attachment to the passionate activity therefore develops naturally as a result of the various short and long-term benefits this activity may bring (Lalande et al., 2017). *Obsessive Passion*, however, manifests itself through rigid and inflexible behavior patterns characterized by self-control deficiencies, in which the activity interferes with other aspects of everyday life, thereby promoting negative outcomes at the affective, cognitive, and behavioral levels (Curran et al., 2015). Such overreliance on the passionate activity was proposed as reflecting a compensatory behavior in response to low psychological needs satisfaction in important life areas (Lalande et al., 2017). Thus clinging to their passionate activity in a compulsory way to help filling a void, individuals' involvement would in this view gradually translate into maladaptive attachment to the activity that may be of a functionally impairing nature. Previous research has indeed shown positive associations between both adaptive correlates of TV series watching (e.g., self-development, offline chatting) and *Harmonious Passion*, and maladaptive outcomes (e.g., conflict with other activities) and *Obsessive Passion* (Tóth-Király et al., 2019).

In keeping with this theoretical framework, and coherent with the recent concept of *digital emotion regulation* implying that people adjust their emotional states through the use of digital technologies (Wadley et al., 2020), the assumption that maladaptive coping or emotion-regulation strategies underlie problematic binge-watching (Boursier et al., 2021; Flayelle et al., 2019a; Sigre-Leirós et al., 2022) may reveal an important role in the genesis of such delineation between binge-watching development either from a complementary (i.e., resulting in non-harmful involvement, or *Harmonious Passion*) or compensatory (i.e., leading to problematic involvement, or *Obsessive Passion*) understanding. According to this view, positive and negative affect are at the roots of this dichotomy. Classic hedonic entertainment theories (e.g., *Mood Management Theory*; Reinecke, 2017) conceptualize media use as an effective means to enjoy gratifying experiences, thereby engendering positive affective states while lessening negative affective states in media users (Vorderer and Reinecke, 2015). While promoting positive emotions *per se* (through intensified enjoyment while viewing; Granow et al., 2018; Merrill and Rubenking, 2019) and more general positive affective outcomes (e.g., viewers' hedonic and eudaimonic well-being; Halfmann and Reinecke, 2021; Muñiz-Velázquez and Lozano Delmar, 2021), binge-watching completely falls within this framework as it has also been associated with mental health conditions which one would seek to alleviate, such as anxiety and depression (Ahmed, 2017; Tefertiller and Maxwell, 2018). Further supporting this notion is the fact that available evidence demonstrates the co-existence of hedonic motivations (i.e., entertainment, enjoyment) – best-known inducers of engagement in leisure activities – and emotion-focused avoidance coping motivations as two main motivational factors in binge-watching (Flayelle et al., 2020a), beyond other prime-order expected gratifications such as eudaemonic (e.g., personal enrichment; Flayelle et al., 2017; Merrill and Rubenking, 2019) or socialization (Granow et al., 2018; Panda and Pandey, 2017) derived benefits. Lying at the heart of classic hedonic entertainment conceptualizations, such emotionally motivated or mood-repair related media use is assumed to explain why consumption of entertainment media, initially perceived as enjoyable and fulfilling, might become dysfunctional over time when repeatedly invested as the primary option to escape from negative affective states, thereby fueling a misguided self-reinforcing loop (Reer et al., 2021). The drive to engage in appetitive behaviors to relieve negative emotional states is indeed a well-supported risk factor associated with problematic recreational involvement across various domains (e.g., video gaming, gambling, cybersex; Blasi et al., 2019; Canale et al.,

2015; Wéry and Billieux, 2016), ultimately expressing potential maladaptive compensation for insufficient satisfaction of real-life needs (e.g., Allen and Anderson, 2018). Whether these media use coping strategies become maladaptive, however, seems to strongly depend on individual differences in self-control abilities according to the DMP. Interestingly, in addition to emphasizing positive links between binge-watching and self-regulation deficiencies (Merrill and Rubenking, 2019; Hasan et al., 2018), previous research has demonstrated that only unintentional binge-watching (i.e., occurring unexpectedly) is related to impulsivity (Riddle et al., 2017). While impulsivity is a psychological factor of key importance for addictive behaviors (Jentsch et al., 2014), emotion-related impulsivity (i.e., the "urgency" component of impulsivity according to the *UPPS model of impulsivity*; Cyders and Smith, 2008; Whiteside and Lynam, 2001), which is considered a transdiagnostic factor of psychopathology (Berg et al., 2015), notably stands out because of its well-known role in predicting maladaptive behaviors aimed at alleviating negative emotional states (Anestis et al., 2007; Billieux et al., 2010; Nock et al., 2008).

According to this line of reasoning, three psychological factors (i.e., affect, viewing motivations, and impulsivity) thus emerge as a combination of prime candidates to better capture what is at the core of the differentiation between non-harmful (i.e., viewers engaging in needs-satisfying daily lives who integrate binge-watching in a complementary and healthy manner) and problematic (i.e., viewers with low day-to-day needs satisfaction who use binge-watching in a compensatory and unhealthy manner) involvement in binge-watching based on the hypothesis that emotion regulation may constitute a pivotal mechanism through which binge-watching unfolds.

2.1. The current study

At a time when research is needed to move forward in the comprehension of non-harmful versus problematic involvement in binge-watching, the main aim of this exploratory study was to investigate the distinct psychological predictors of these two watching patterns. To this end, this study is the first one capitalizing on machine learning analyses to model binge-watching intensity, both from an adaptive and maladaptive perspective, based on our model of relevant predictor variables (i.e., affect, viewing motivations, and impulsivity). Specifically, we used supervised machine learning, which implements statistical and computational methods to recognize patterns in example/training data for the purpose of improving predictions in other sets of data (Hastie et al., 2016; Kuhn and Johnson, 2013). Because of using a large set of example data to initially train a statistical model prior to application, and unlike traditional statistics which use a one-shot approach in data modeling, supervised machine learning has a record of generally outperforming traditional statistical methods (LeCun et al., 2015). As detailed below, we began with a large sample and divided it into a large training subset (i.e., 80 % of the participants) and a testing subset (i.e., 20 %) randomly to ensure comparability of the two subsets. We used the first subset to train our statistical model in modeling the dependent variables (i.e., high involvement and problematic involvement). Through training across many iterations (including small sets of example data), we aimed at finding optimal regression weights, subsequently applied to the remaining test subset (i.e., 20 %) in modeling the dependent variable. Moreover, in addition to these improved prediction advantages of training and testing in supervised machine learning, we employed specific types of machine learning algorithms (also detailed below) that overcome the usual limits of more common statistical approaches (e.g., general linear modeling) such as collinearity and predictor variable overlap, two-dimensional relationship modeling, and overfitting (discussed below in the Statistical Analysis section). By overcoming these limitations, the use of such machine learning algorithms has resulted in improved accuracy and diminished replicability issues (Orrù et al., 2020). Because of these advantages, machine learning has been increasingly used in recent psychiatry and psychology research (Dwyer et al., 2018; Shatte et al., 2019). In the absence of established diagnostic criteria for problematic binge-watching, we employed regression-based forecasting within machine learning to model adaptive versus maladaptive binge-watching intensity (i.e., non-harmful versus problematic involvement) as two distinct continuous dependent variables.

3. Method

3.1. Participants and procedure

French-speaking TV series viewers were recruited from various Facebook groups and discussion forums dedicated to TV series' enthusiasts in November and December 2016. They were invited to anonymously fill in an online questionnaire about their viewing practices. This study was approved by the Psychological Sciences Research Institute Ethics Committee of the Université catholique de Louvain (Belgium). Before taking part in the assessment, informed consent was systematically collected from the participants who obtained no compensation. Subsets of the data currently gathered were the subject of previously published work involving distinct research objectives (Flayelle et al., 2019b, 2019c), where further methodological details regarding the study setting can also be found. The data and materials underlying this article can be consulted in the *Open Science Framework* (OSF), at: https://osf.io/unjzq/?view_only=184f4ebf757d4ed1b4f988e116d9c268 (DOI:10.17605/OSF.IO/UNJZQ).

For this study, our effective sample size included 4275 participants (not differing from the original 6882 sample respondents in terms of age and gender),[1] as only data related to the measures of interest described below were considered for analysis. The average age was 24.82 years (SD = 7.54). The majority of participants were women (n = 3398, 79.5 %), and had pursued higher education

[1] These data are also available in the OSF at: https://osf.io/unjzq/?view_only=184f4ebf757d4ed1b4f988e116d9c268.

beyond high school (n = 3556, 83.2 %); a much smaller proportion of 719 participants (16.8 %) only had high school education. Just over half of the sample were single (n = 2340, 54.7 %), with 1935 (45.3 %) in a relationship. Participants reported watching TV series on average 2.41 (SD = 1.62) hours on a typical working day and 3.61 (SD = 1.70) hours on a typical day off, with a mean number of 3.67 (SD = 1.77) episodes seen during a typical viewing session (see descriptive statistics regarding participants' viewing habits in supplementary analyses at: https://osf.io/unjzq/?view_only=184f4ebf757d4ed1b4f988e116d9c268).

3.2. Instruments

After answering a short sociodemographic questionnaire (age, gender, education background, and relationship status), participants were administered the following set of self-reported measures.

3.2.1. Binge-Watching engagement and symptoms questionnaire (BWESQ)

The BWESQ (Flayelle et al., 2019b, 2020b) consists of 40 items measuring involvement in binge-watching as well as indicators of problematic binge-watching across the seven following dimensions: *engagement*, *positive emotions*, *pleasure preservation*, *desire/savoring*, *binge-watching*, *dependency*, and *loss of control*. As the current study focuses on non-harmful and problematic binge-watching, we only used the subscales *engagement* (i.e., 8 items assessing the degree of non-harmful recreational engagement in TV series watching, for example, « In my opinion, TV series are a part of my life and they contribute to my welfare. ») and *loss of control* (i.e., 7 items assessing adverse outcomes associated with problematic and uncontrolled binge-watching, for example, « My school, university or work results are suffering from the amount of time I spend watching TV series. ») to measure the two viewing patterns of interest. Items are rated on a 4-point Likert scale ranging from 1 (strongly disagree) to 4 (strongly agree), and a mean score is computed for each subscale. The current sample's internal consistency estimates were 0.80 (*engagement*) and 0.82 (*loss of control*).

3.2.2. Watching TV series motives questionnaire (WTSMQ)

The WTSMQ (Flayelle et al., 2019b, 2020b) comprises 22 items measuring TV series watching motivations along four facets: *social* (e.g., « I watch TV series because I bow to my close circle's pressure when they advise me to watch a given series. »); *emotional enhancement* (e.g., « I watch TV series to feel strong emotions like the excitement or the thrill they give me. »); *enrichment* (e.g., « I watch TV series to discover whole new worlds and to increase my knowledge on a number of subjects. »); and *coping/escapism* (e.g., « I watch TV series to get away from the daily hassles. »). Items are rated on a 4-point Likert scale ranging from 1 (not at all) to 4 (to a great extent), and a mean score is computed for each subscale. Internal consistency in the current sample ranged from 0.64 (*emotional enhancement*) to 0.80 (*coping/escapism*).

3.2.3. Short impulsive behavior scale (s-UPPS-P)

The s-UPPS-P (Billieux et al., 2012) contains 20 items assessing five impulsivity traits: *negative urgency* (e.g., « I often make matters worse because I act without thinking when I am upset. »), *positive urgency* (e.g., « When overjoyed, I feel like I can't stop myself from going overboard. »), *lack of premeditation* (e.g., « My thinking is usually careful and purposeful. »), *lack of perseverance* (e.g., « I finish what I start. »), and *sensation seeking* (e.g., « I quite enjoy taking risks. »). Items are rated on a 4-point Likert scale ranging from 1 (strongly agree) to 4 (strongly disagree), and a mean score is computed for each subscale. In view of the current high correlation ($r = 0.50$, $p < .001$) between the *negative* and *positive urgency*'s subfacets, and considering previous research showing that distinguishing between positive and negative urgency as separate psychological constructs is not necessarily tenable (Berg et al., 2015; Billieux et al., 2021), *negative* and *positive urgency*'s scores were aggregated as a unique score under the label *urgency*. Internal consistency in this sample ranged from 0.82 (*lack of premeditation*, *sensation seeking*) to 0.89 (*lack of perseverance*, *urgency*).

3.2.4. Positive and negative affect schedule (PANAS)

The PANAS (Gaudreau et al., 2006) includes two 10-item measures of *positive affect* (e.g., "Enthusiastic") and *negative affect* (e.g., "Distressed"). Participants were invited to assess how much they generally feel each individual emotion using Likert-type responses of 1 (not at all) to 5 (very much). A mean score is calculated for each subscale. Internal consistencies for the current sample were 0.73 (*positive affect*) and 0.84 (*negative affect*).

3.3. Statistical analysis

R statistical software, version 3.6.2 (R Core Team, 2020), was used with the following packages for preliminary analyses: *fmsb* (for internal consistency), *pastecs* (descriptives), and *mice* (missing data imputation). R's *caret* package was used to conduct machine learning, with the following packages for particular machine learning algorithms: *glmnet* (for "shrinkage" algorithms discussed below), *kernlab* (support vector machine), *randomForest* (random forests), and *xgboost* (extreme gradient boosting).

Of the current sample of 4275 participants, 288 (6.7 %) were missing one of the scale variables, so we estimated and imputed those missing values using the expectation maximization algorithm. All continuous predictor and dependent variables were within normal

limits for univariate normality. Pearson's correlations were computed for these variables, along with coefficient alphas.

We randomly shuffled the sample's participant rows using a fixed number seed for later consistent replication. After shuffling, we randomly selected 80 % of the sample (n = 3420) as the training sample, and the residual 20 % (n = 855) as the hold-out test sample, a common practice in supervised machine learning (Elhai and Montag, 2020). We preprocessed the data, centering and scaling the predictors and dependent variables as z-scores, after allocation to the training and test samples (Kuhn and Johnson, 2013).

Then, the machine learning analyses were performed. We first tested our model of predictor variables in modeling non-harmful involvement as the dependent variable. Next, we tested the same model of predictors in modeling problematic involvement as the dependent variable.

Six machine learning algorithms were tested. We employed three "shrinkage" or "penalty" algorithms – lasso, ridge and elastic net. Unlike traditional statistical methods, these algorithms impose a penalty on regression coefficients from substantially collinear variables, reducing coefficient sizes to reduce the adverse impact of collinearity. Ridge regression shrinks coefficients toward (but not exactly to) zero, while lasso and elastic net can shrink coefficients to precisely zero in order to conduct variable subset selection for a more parsimonious model (Zou and Hastie, 2005). Note that the forms of subset selection in machine learning result in substantially more generalizable results than the more "greedy" and traditional stepwise regression method (Peres and Fogliatto, 2018). We also employed a support vector machine algorithm with a radial basis function kernel, with the advantage of mapping relations in a three-dimensional space to improve linear separability in the dependent variable. Finally, we included two ensemble algorithms – extreme gradient boosting, and random forests – where weaker learners (subsets of predictors and participants) are iteratively tested and aggregated to form a stronger model, which results in decreased overfitting and reduced variance. The algorithms were compared with one another by relying on the following fit indices: root mean square error (RMSE), mean absolute error (MAE), and R-squared values. We compared their performance using objective statistical tests.

We trained and tested our predictor models in two ways, first through simulation, and then through hold-out sample testing. For simulation, k-folds repeated cross-validation was used (Hastie et al., 2016; Kuhn and Johnson, 2013), by splitting the training sample into 5 non-overlapping subsets (folds) of participants, training the first four subsets and simulating testing on the fifth one. Such process was conducted four more times with the training sample, so that each subset served as the simulated test sample once; then, we repeated the whole procedure across nine additional iterations, for a total of 50 simulated cross-validations (Hastie et al., 2016; Kuhn and Johnson, 2013). Finally, we took the final aggregated model and tested it with the hold-out test sample.

4. Results

Table 1 presents the bivariate (unadjusted) correlation matrix of continuous variables, along with descriptive statistics and internal consistency estimates. Further correlation analyses (involving non-harmful/problematic involvement in binge-watching and participants' viewing habits) are also available in the OSF at: https://osf.io/unjzq/?view_only=184f4ebf757d4ed1b4f988e116d9c268. These supplementary results demonstrate that self-reported viewing duration and number of episodes seen during a typical viewing session are each more strongly associated with non-harmful involvement in binge-watching. This is consistent with the results of previous studies having examined viewing patterns in non-problematic and problematic binge-watchers (e.g., Flayelle et al., 2020c), and supports the notion that quantifiable markers (such as number of episodes seen and hours spent viewing) are not necessarily a reliable indicator of problematic involvement in binge-watching (Flayelle et al., 2019c; Ort et al., 2021).

The comparison of the algorithms in modeling non-harmful involvement in binge-watching (Table 2) suggests that the shrinkage algorithms performed best. Bonferroni corrected pairwise tests show that the shrinkage algorithms were significantly better fitting than the other algorithms, but not better than one another. Tests of the hold-out sample showed similar results. The model accounted for about 26 % of the variance in the dependent variable using the shrinkage algorithms. As an illustration to demonstrate the relative importance of predictor variables, we display Fig. 1 using elastic net regression's variable importance estimates (as an example, as one of the best performing algorithms), interpreted as standardized, adjusted regression coefficients as we standardized variables using z-scores. Emotional enhancement, enrichment, and social motives conferred the highest relative importance in modeling the continuous dependent variable.[2]

Next, we present the comparison of algorithms in modeling problematic involvement in binge-watching. Table 3 indicates that the shrinkage algorithms generally outperformed the others, except for support vector machine performing best on MAE. Using Bonferroni-adjusted *p*-values for pairwise comparisons, the shrinkage algorithms outperformed most other algorithms, but did not significantly outperform each other. A similar pattern of findings emerged for comparisons with the hold-out sample. The variance accounted for was approximately 29 % among the shrinkage algorithms. We again used elastic net regression's variable importance estimates, presented in Fig. 2, indicating that coping/escapism motive, followed by urgency and lack of perseverance, had the greatest relative importance in modeling the continuous dependent variable.[3]

[2] Consistent results were obtained via traditional statistical approaches (i.e., linear regressions), whether by accounting for the whole sample or by excluding participants who usually watch only 1 episode per viewing session (3.9% of the sample), see supplementary analyses at: https://osf.io/unjzq/?view_only=184f4ebf757d4ed1b4f988e116d9c268.

[3] Again, consistent results were obtained via traditional statistical approaches (i.e., linear regressions), whether by accounting for the whole sample or by excluding participants who usually watch only 1 episode per viewing session (3.9% of the sample), see supplementary analyses at: https://osf.io/unjzq/?view_only=184f4ebf757d4ed1b4f988e116d9c268.

Table 1
Means, standard deviations, alphas (in parentheses), and correlations.

Variable	Range	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Age	18–69	24.82	7.54													
2. Non-harmful involvement in binge-watching	1–4	2.42	0.59	-0.12**												
3. Problematic involvement in binge-watching	1–4	1.94	0.64	-0.19**	**0.36****											
4. Social motive	1–4	1.75	0.55	-0.12**	**0.31****	0.21**	(0.69)									
5. Emotional enhancement motive	1–4	3.19	0.50	-0.13**	**0.40****	0.20**	0.28**	(0.64)								
6. Enrichment motive	1–4	2.92	0.57	-0.22**	**0.33****	0.10**	**0.34****	**0.37****	(0.71)							
7. Coping/Escapism motive	1–4	2.49	0.61	-0.17**	**0.32****	**0.45****	**0.32****	**0.47****	0.22**	(0.80)						
8. Urgency	1–4	2.52	0.61	-0.13**	0.14**	0.26**	0.18**	0.17**	0.03*	0.28**	(0.89)					
9. Lack of premeditation	1–4	1.94	0.59	-0.04**	0.01	0.11**	0.03*	-0.02	-0.07**	0.04**	**0.33****	(0.82)				
10. Lack of perseverance	1–4	1.90	0.65	-0.06**	0.06**	0.23**	0.06**	0.04*	0.00	0.18**	0.11**	**0.36****	(0.89)			
11. Sensation seeking	1–4	2.56	0.70	-0.15**	0.04**	0.08**	0.09**	0.06**	0.17**	0.05**	0.23**	0.11**	-0.04**	(0.82)		
12. Positive affect	1–5	3.35	0.54	0.08**	-0.05**	-0.16**	-0.01	0.05**	0.13**	-0.14**	0.01	-0.18**	**-0.40****	0.25**	(0.73)	
13. Negative affect	1–5	2.35	0.70	-0.12**	0.12**	0.28**	0.13**	0.19**	0.05**	**0.39****	**0.39****	0.05**	0.16**	0.02	-0.04**	(0.84)

Note. *p <.05; **p <.01.

Table 2
Comparison of the six machine learning-based regression algorithms in predicting non-harmful involvement in binge-watching.

	Fit indices for the Training Sample			Fit indices for the Test Sample		
	RMSE	**MAE**	**R^2**	**RMSE**	**MAE**	**R^2**
Lasso	0.8699	0.7037	0.2441	0.8605	0.7023	0.2595
Ridge	0.8699	0.7038	0.2441	0.8606	0.7027	0.2595
Elastic Net	0.8699	0.7037	0.2441	0.8605	0.7024	0.2596
Support Vector Machine	0.8839	0.7164	0.2218	0.8664	0.7043	0.2490
Extreme Gradient Boosting	0.8752	0.7095	0.2350	0.8692	0.7064	0.2444
Random Forest	0.8831	0.7180	0.2231	0.8740	0.7141	0.2385

Note. RMSE = root mean squared error; MAE = mean absolute error.

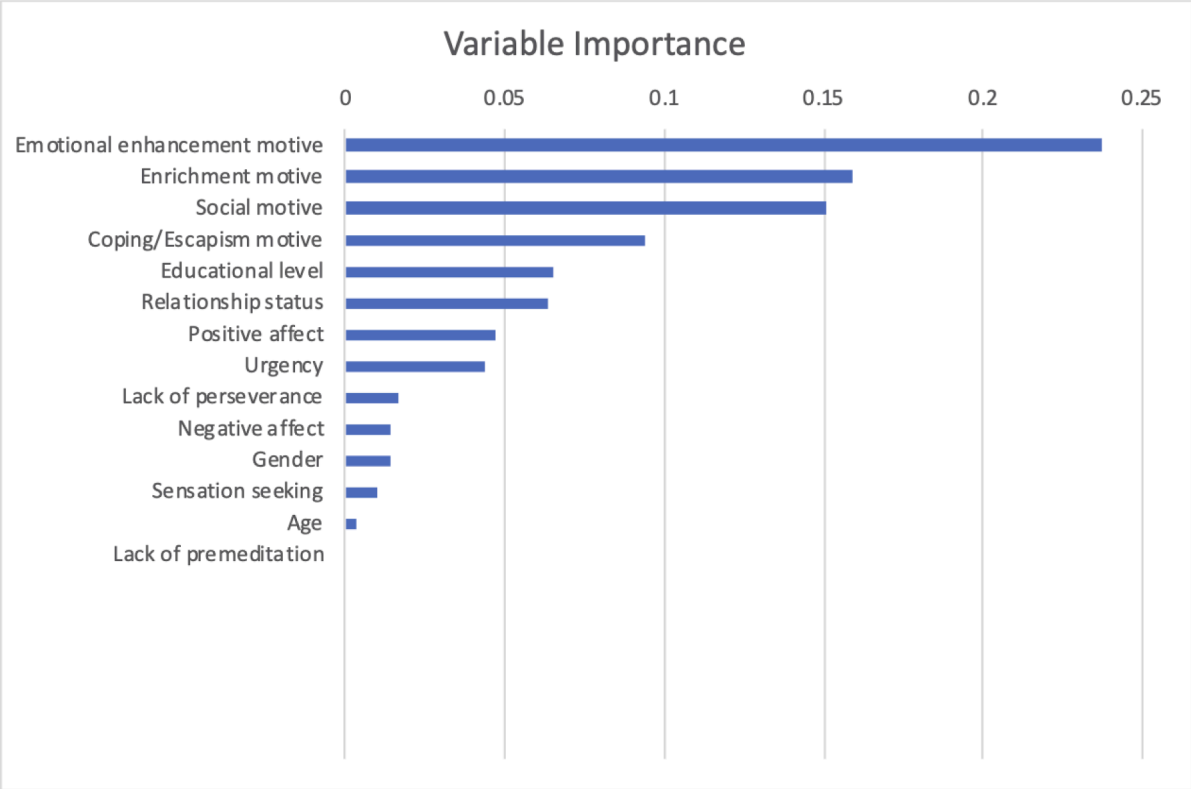

Fig. 1. Variables importance in modeling non-harmful involvement in binge-watching.

Table 3
Comparison of the six machine learning-based regression algorithms in predicting problematic involvement in binge-watching.

	Fit indices for the Training Sample			Fit indices for the Test Sample		
	RMSE	**MAE**	**R^2**	**RMSE**	**MAE**	**R^2**
Lasso	0.8615	0.6856	0.2586	0.8445	0.6861	0.2872
Ridge	0.8614	0.6861	0.2587	0.8447	0.6862	0.2876
Elastic Net	0.8614	0.6858	0.2586	0.8445	0.6861	0.2874
Support Vector Machine	0.8752	0.6848	0.2460	0.8485	0.6768	0.2853
Extreme Gradient Boosting	0.8658	0.6884	0.2514	0.8484	0.6850	0.2802
Random Forest	0.8756	0.7022	0.2369	0.8525	0.6930	0.2801

Note. RMSE = root mean squared error; MAE = mean absolute error.

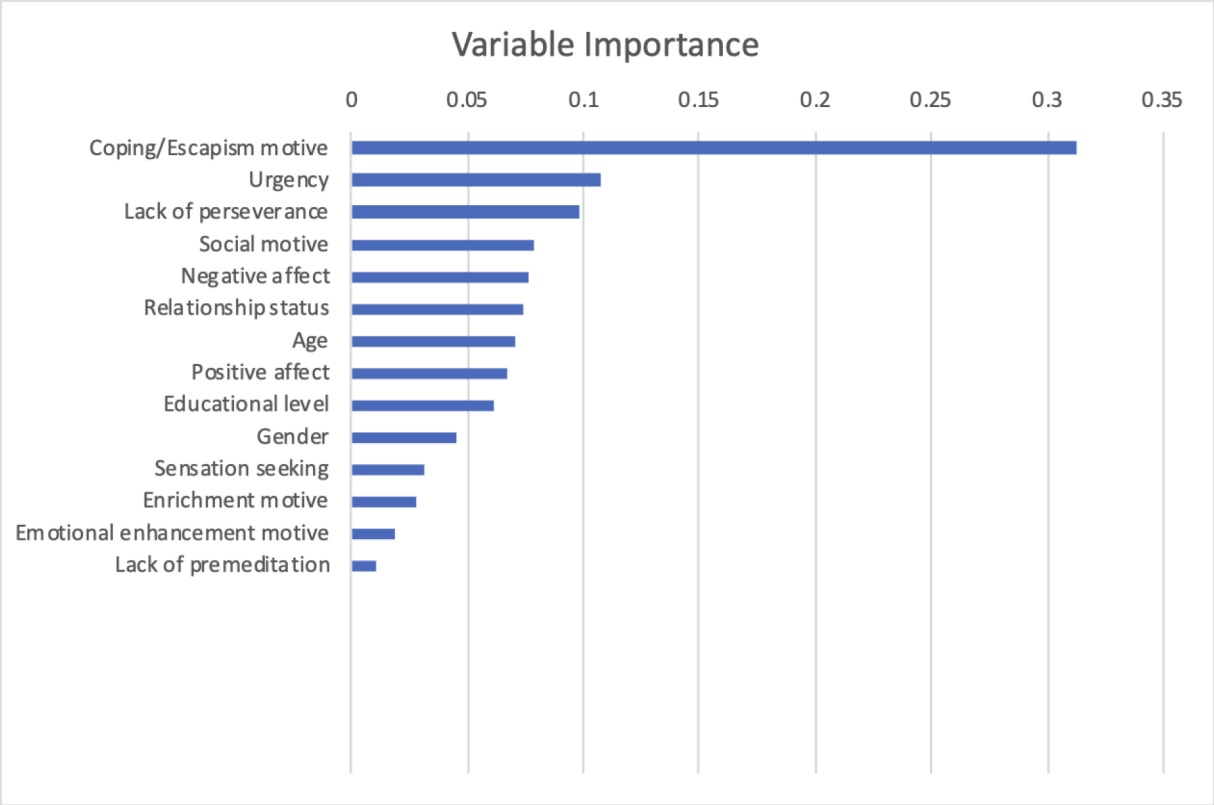

Fig. 2. Variables importance in modeling problematic involvement in binge-watching.

5. Discussion

As binge-watching research continues to make progress, there is increasing evidence that such behavior may be both beneficial or harmful to viewers, thus calling for an expanded understanding of the factors associated with non-harmful versus problematic involvement in such a popular leisure activity (Flayelle et al., 2020a; Flayelle and Lannoy, 2021; Steins-Loeber et al., 2020; Tóth-Király et al., 2017). In this respect, one emerging hypothesis is that problematic binge-watching reflects maladaptive coping or emotion-regulation strategies (Boursier et al., 2021; Flayelle et al., 2019a; Sigre-Leirós et al., 2022), which may constitute an important demarcation line between the two. Therefore, the present study was aimed at examining the respective weight of relevant psychological predictor variables (i.e., affect, viewing motivations, and impulsivity facets) associated with these distinct behavioral patterns, for the first time using machine learning approaches to model binge-watching intensity, both from adaptive and maladaptive perspectives. While expanding prior research on the topic, the present results point towards a clear delineation between non-harmful and problematic binge-watching, the interpretation of which being consistent with a complementary *vs* compensatory-derived model; the *Dualistic Model of Passion* (DMP).

The combination of emotional enhancement, enrichment, and social motivations for TV series watching proved to be best in modeling non-harmful binge-watching engagement. This is fully in line with the understanding that media entertainment use is essentially driven by satisfaction of a variety of needs, which is at the core of the *Uses & Gratifications* theoretical framework (Katz et al., 1973; Rubin, 2009). Likewise, the current variable rankings in terms of relative dominance clearly suggest the prominent role of hedonistic motivations (i.e., entertainment, enjoyment) behind binge-watching (e.g., Castro et al., 2021; Starosta et al., 2019), while lending further support to the notion that enjoyment acts as the most influential driver in prompting standard media use (Baran and Davis, 2015; Tamborini et al., 2010). As binge-watching is known to involve higher levels of enjoyment, notably through enhanced experiences of narrative transportation and emotional bonding with fictional characters (Anghelcev et al., 2021; Erickson et al., 2019; Granow et al., 2018), it can thus be argued that non-harmful engagement in this activity stems primarily from the resulting pleasure. Nevertheless, gratifying media effects are not limited solely to experiencing pleasure. Instead, media entertainment may be also experienced as particularly rewarding on other dimensions, typically those involving cognitive and social needs (Bartsch and Viehoff, 2010). The present findings fully support the latter, as enrichment and social motivations for TV series watching conferred the two subsequent largest contributions in modeling non-harmful involvement in binge-watching. Not only consistent with previous evidence attesting to the significant role of self-development (or thought-provoking) and social communication incentives in binge-watching (Anghelcev et al., 2022; Flayelle et al., 2017; Mikos, 2016; Shim and Kim, 2018), these results are also mainly in line with the widely held notion that media use is typically driven by one's search for deeper insight in life, and derived benefits in terms of

socialization (Chandler and Munday, 2011; Oliver and Raney, 2011; Ruggiero, 2000). By allowing viewers to indulge in the concurrent gratification experiences inherent in TV series watching (i.e., experiencing pleasure upon being immersed in the fictional world of a TV show, while developing critical thinking and social conversations) to a greater extent, but not at the expense of other areas of life, non-harmful binge-watching engagement appears to be driven by positive reinforcement mechanisms, thus bringing this viewing pattern closer into line with the DMP's understanding of a *Harmonious* level of *Passion* for TV series watching.

Considering problematic binge-watching, a striking feature of the current results is that coping/escapism motivation for TV series watching showed the greatest relative importance by far, in modeling such maladaptive viewing engagement. Interestingly, individual differences within two impulsivity components, headed by urgency (i.e., emotion-laden impulsivity), then accounted for the next greater amounts of variance in this respect. While in line with earlier evidence of positive relationships between binge-watching and both coping motivations (Castro et al., 2021; Starosta et al., 2019) and higher levels of impulsivity (Riddle et al., 2017; Steins-Loeber et al., 2020), the current findings point to some compensatory-like dynamics which may put viewers at risk to develop maladaptive patterns of binge-watching. Negative reinforcement motives (e.g., loneliness management, escapism from everyday worries), which act as a common and prominent process underlying problematic involvement in various online activities (e.g., cybersex, social networking, video gaming, Internet use; Bowditch et al., 2018; Hormes et al., 2014; Kardefelt-Winther, 2014; Laier and Brand, 2014), may interact with dispositional emotion-related impulsivity, generally constituting a vulnerability factor for emotion dysregulation, which is also characteristic of problematic behaviors' development and maintenance (Billieux et al., 2010; Cyders and Smith, 2008; Selby et al., 2008). Finally, although somewhat less important in its contribution to problematic involvement intensity, a lack of perseverance (i.e., having difficulty to stay focused on uninteresting and/or difficult tasks, or being easily distracted) may exert a sustaining influence on the whole process in a context where indulging in binge-watching behaviors has never been more tempting. By suggesting that an overreliance on binge-watching negatively impacting other life areas probably involves emotional regulation difficulties and, thereby, logics of compensation, the current results further support the notion that problematic involvement in binge-watching most likely operates as a maladaptive coping or emotion regulation strategy (Boursier et al., 2021; Flayelle et al., 2019a; Sigre-Leirós et al., 2022). Problematic binge-watching should, therefore, be seen as mainly driven by negative reinforcement mechanisms, and interpreted as denoting an *Obsessive* level of *Passion* for TV series watching, according to the DMP's theoretical rationale.

With the notion of problematic binge-watching as a maladaptive emotion regulation strategy becoming more popular, a promising way forward to improve our understanding of binge-watching would be to dissect the various types of (first-order) emotion regulation strategies that viewers are bringing into play through binge-watching. Information and Communication Technologies (ICTs) now make 24/7 access to media content possible, thereby also offering plenty of opportunities to instantly regulate emotional states (as endorsed in the emerging concept of *digital emotion regulation*; Wadley et al., 2020). It is thus crucial to investigate how viewers' binge-watching behaviors translate into specific strategies aimed at modulating their emotional experiences, and whether these conform to (adaptive and maladaptive) emotion regulation strategies established by previous research. In this respect, the following provides a first attempt at such linkages to give impetus, and possibly direction, to such avenue for further academic efforts at the crossroads of entertainment and psychology research.

According to one of the most important models in the field of emotion regulation, the *Gross's process model* (1998, 2015), emotion regulation strategies can be sub-divided into five main categories, depending on when they take place in the emotion-generation process. At the very first stage, individuals may intervene to shape their emotional experience by situation selection (i.e., selecting situations that could generate desired emotions while avoiding situations that could produce undesirable ones). Once facing the situation, other strategies can then be applied by acting directly on the external situation to which one is exposed to through situation modification (i.e., modifying tangible aspects of the situation) or by taking action at a more internal level via attentional deployment (i.e., shifting one's focus of attention toward or away from an emotionally relevant situation) and cognitive change (i.e., reappraising an emotion-eliciting situation to modulate its whole impact). Finally, after experiencing an emotion, individuals may employ response modulation (i.e., modifying the experiential, behavioral or physiological effects of a generated emotion). In line with others who recently postulated that media use might reflect such antecedent/response focused regulation strategies in the context of both external and media-related emotion-eliciting situations (Vandebosch and Poels, 2021), we propose in Fig. 3 a preliminary taxonomy of exemplars of such strategies with respect to binge-watching, selected on the basis of qualitative evidence (derived from focus-groups and in-depth interviews exploring specific habits and routines of binge-watchers; see the set of studies cited below). Through examples drawn from such literature, relevant strategies are thus classified according to their adaptive and maladaptive value or, following the line of reasoning described in the current study, their representativeness for binge-watchers displaying non-harmful involvement on the one hand, and problematic binge-watchers, on the other hand.

In keeping with the understanding of non-harmful binge-watching in a complementary perspective (i.e., such activity adds to one's life), some prototypical patterns of TV series consumption related-behaviors identified in qualitative studies may be understood as situation selection and modification strategies falling under a healthy, positively reinforcing drive that passionate individuals may demonstrate towards binge-watching. This includes, for example: 1) binge-watching to reward oneself after a long productive day (Devasagayam, 2014; Rubenking et al., 2018) or to fall asleep more easily (Flayelle et al., 2017; Gangadharbatla et al., 2019; Steiner and Xu, 2020); 2) implementing pleasure preservation or enhancement strategies (e.g., waiting until the whole series is out to initiate binge-watching for all the seasons, developing proactive attitudes to avoid getting spoiled as much as possible — which might resemble problem-focused coping —, planning when and how binge-watching in order to maximize the related pleasure; Flayelle et al., 2017; Steiner and Xu, 2020); 3) re-watching a whole series to relive the thrill or joy previously experienced (Flayelle et al., 2017; Rubenking et al., 2018; Steiner and Xu, 2020); and, in a more instrumental manner, 4) putting series as background music to make performing everyday chores more pleasant or efficient (Devasagayam, 2014; Flayelle et al., 2017; Steiner and Xu, 2020). Within this category of viewers, and through personal enrichment they typically derive from such activity, binge-watching may also underpin more cognitive

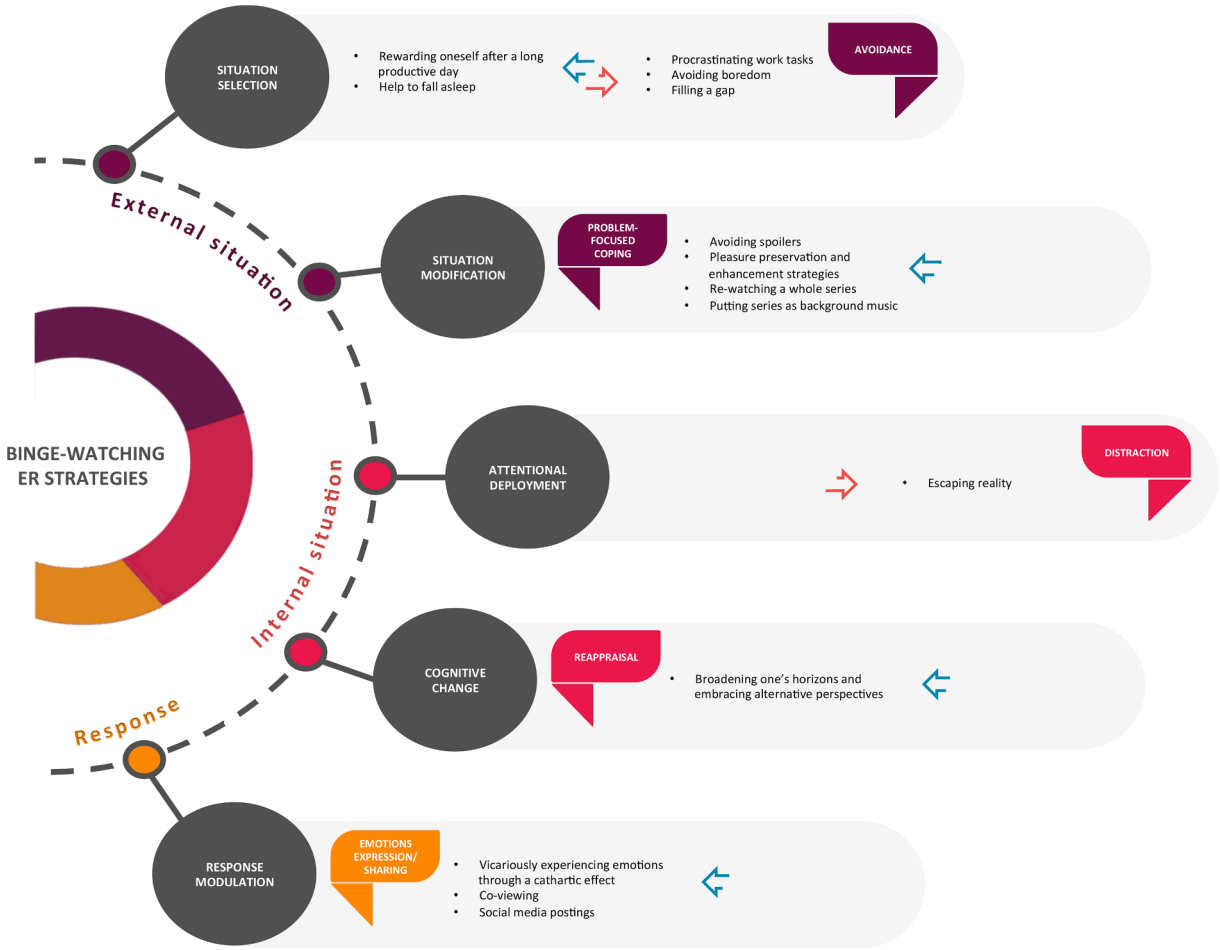

Fig. 3. Examples of typical binge-watching related behaviors potentially instantiating emotion regulation strategies according to the *Gross's process model. Note.* ER: Emotion Regulation. Binge-watching related behaviors deemed equivalent to adaptive ER tactics are indicated by the blue arrow in the left side of each strategies' family box whereas others deemed equivalent to maladaptive ER tactics are indicated by the red arrow in the right side of each strategies' family box. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

emotion regulation strategies such as cognitive reappraisal. Indeed, binge-watchers report broadening their views and embracing alternative perspectives about a number of topics by watching TV series (Flayelle et al., 2017; Irwansyah, 2020), which is likely to lead them to cognitively reappraise their own experiences. Along the same lines, a key determinant of content selection and binge-watching engagement lies in emotional connection (i.e., the extent to which the storyline is echoing one's real-life experiences and personal feelings or emotional state) with the narrative (Flayelle et al., 2017); binge-watching may likewise support emotional release through a cathartic effect. The latter suggests that media consumption may offer an avenue for recognizing and modulating one's emotions by vicariously experiencing them while viewing fiction (Vandebosch and Poels, 2021). This would make binge-watching a potential vehicle to emotion expression in terms of response modulation. Finally, the fundamentally social dimension of binge-watching, reflected by the widespread adoption of co-viewing practices (i.e., binge-watching TV series with friends, family and significant others; Flayelle et al., 2017; Mikos, 2016; Rubenking et al., 2018) and social media postings for the purpose of experience-sharing (Ahmed, 2020; Irwansyah, 2020; Steiner and Xu, 2020), also affords opportunities for emotion sharing, thus supplementing other adaptive response modulation strategies likely to be deployed by individuals driven by a healthy enthusiasm for binge-watching.

Other typically encountered patterns of behaviors such as binge-watching as a way of procrastinating work tasks (Ahmed, 2020; Gangadharbatla et al., 2019; Rubenking et al., 2018), to avoid boredom or as a gap-filling strategy (Flayelle et al., 2017), might be examples of situation selection strategies that apply to problematic binge-watching, by reflecting an avoidance coping strategy embedded at the core of its compensatory understanding (i.e., problematic binge-watchers rely on such activity in a substitutive manner). According to the latter, binge-watching as a way to escape reality (Da Costa et al., 2021; Flayelle et al., 2017; Panda and Pandey, 2017; Rubenking et al., 2018), which may be understood as an attentional deployment strategy in providing maladaptive distraction and thought suppression, would therefore constitute the hallmark of such escapist-suppressive, negatively reinforcing, mechanisms underlying a problematic pattern of binge-watching aimed at detracting from one's life.

These considerations open up new avenues towards a more fine-grained conceptualization of binge-watching as a (mal)adaptive emotion regulation strategy at a time when digital technologies themselves also offer promising research prospects to measure and continuously monitor binge-watching activity and related emotional states. The latest developments in this respect include, for example, the Binge-Watching Data Analysis Tool (BWDAT), a smartwatch app designed to record in real time (e.g., directly at home) viewers' interactions with video-on-demand (VOD) platforms and physiological indicators of emotion regulation such as heart rate variability (Cordeiro et al., 2021). Such synchronous measurement of physiological parameters and content watched may thus facilitate the naturalistic examination of varying emotion regulation strategies embodied in binge-watching, and other closely related issues (e.g., individual differences in binge-watching emotion regulation styles, identification of binge-watched contents that prove most suited for emotion regulation). This approach may also contribute to a deeper understanding of the broader area of emotion regulation through entertainment media consumption (Reinecke, 2017; Vandebosch and Poels, 2021).

Applying a process-based approach to potentially problematic online behaviors (Flayelle et al., 2019d), the current findings demonstrate that different motivations (i.e., positively reinforcing *vs* negatively reinforcing) lead to different outcomes (i.e., harmonious *vs* obsessive involvement, or non-harmful *vs* problematic involvement) of the same behavior (i.e., binge-watching), thus holding additional important theoretical and clinical implications. First and foremost, they further substantiate the recent call for a systematic differentiation between non-harmful versus problematic involvement in binge-watching (Flayelle et al., 2020a; Flayelle and Lannoy, 2021; Steins-Loeber et al., 2020), as in other online recreational activities (e.g., video gaming; Billieux et al., 2019). Second, by informing the central nature of the contributing mechanisms to a potential shift from one to the other — that follow a compensation logic rather than one of reward — these findings suggest the relevance of interventions aiming to improve emotion regulation strategies in problematic binge-watchers for whom such a recreational activity is no longer performed for its own sake.

Still, the design of the current study carries with it limitations, which should be acknowledged. First, its cross-sectional character prevents causal conclusions to be drawn (especially concerning the relationships between affect and binge-watching). Second, its reliance on self-report measures may have involved a number of biases (e.g., general influence of mood, social desirability or mere lack of recall). Third, relatively young age profile of the sample ($M = 24.82$ years old) may have impacted the generalizability of our results. Fourth, some Cronbach's alpha values for the WTSMQ subfacets were slightly below the commonly recommended threshold of 0.70 (Hunsley and Mash, 2008). More generally, another weakness is the lack of consideration of further variables that could have been of interest or relevance to the present research, such as emotion regulation parameters. Finally, although binge watching habits appear quite stable over time (Rubenking and Bracken, 2021), future studies should explore whether the results observed here remain constant with the potential evolution of this behavior.

Despite these limitations, by taking advantage of training/testing and improved algorithms, machine learning remains a particularly useful approach to build upon for future studies aimed at further examining key predictors of non-harmful and problematic patterns of engagement in binge-watching; a direction that binge-watching research should more than ever focus on.

Author Note

Outside the scope of the present paper, JDE notes that he receives royalties for several books published on posttraumatic stress disorder (PTSD); is a paid, full-time faculty member at University of Toledo; is a paid, visiting scientist at Tianjin Normal University; occasionally serves as a paid, expert witness on PTSD legal cases; and receives grant research funding from the U.S. National Institutes of Health. PM is funded by the Belgian Fund for Scientific Research (FRS-FNRS, Belgium).

Declaration of Competing Interest

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

Data availability

The data is made available in the OSF at: https://osf.io/unjzq/?view_only=184f4ebf757d4ed1b4f988e116d9c268

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