Does social media use show established neurocognitive signatures of addiction?

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Abstract

Social media platforms incorporate design features hypothesised to drive addiction through neurocognitive pathways. We tested three neurocognitive signatures of addiction (elevated wanting, wanting-liking dissociation, devaluation insensitivity) across two preregistered within-subjects experiments using an effort-based decision-making framework. Experiment 1 (N=95) compared motivated behaviour for TikTok and Netflix in a general population sample. Experiment 2 (N=235) compared motivated behaviour for regular and devalued TikTok rewards in individuals stratified by self-reported TikTok addiction. Across both experiments, wanting did not differ between conditions or groups. Although a wanting-liking dissociation was observed for TikTok, this was driven by reduced liking rather than elevated wanting, inverting the mechanistic prediction of the Incentive Sensitisation Theory. The dissociation was also unrelated to self-reported addiction severity. Devaluation insensitivity was not observed for individuals with self-reported addiction. The findings challenge conceptualisations of problematic social media use as neurobiologically analogous to established addictions.

Keywords*: social media, addiction, motivation, computational modelling, reward processing*

Concerns about social media addiction are widespread, reflected in headlines such as "How digital media turned us all into dopamine addicts" [1]. Moreover, design features of increasingly popular short-form video social media platforms such as TikTok are thought to drive addictive use patterns, with policy and legal consequences worldwide [3,4]. These design features include rewards (e.g. likes, comments, and notifications) presented at variable ratio schedules [5], content presented continually with few stopping cues (i.e. infinite scroll) [6], and algorithmic curation of content tailored to individuals [7,8]. These designs have become increasingly common across social media, with companies' business models intent on maximising the time individuals spend on platforms [7]. However, whether these features target the neurocognitive pathways well-established in traditional substance addictions remains unexplored. Investigating the neurocognitive similarities and differences between social media use and established addictions is fundamental to better understand social media's impacts, including whether features are "addictive", and in developing treatments for people who report feeling addicted to social media. As "addictive" social media use is becoming more widespread and has been associated with increased risk of adverse mental health outcomes, including suicidal ideation – more so even than time spent using social media – understanding this is more important than ever [9].

Social media addiction is not recognised by the major clinical diagnostic and classification systems [10,11]. Nevertheless, problematic social media use has been conceptualised predominantly through the addiction lens [12]. So-called "addictive" social media use patterns are typically assessed by adapting questionnaires of established addictions to measure similar behaviours in social media use contexts [13–15]. For example, the Bergen Social Media Addiction Scale [16] includes items targeting each proposed component of substance addiction: salience, mood modification, tolerance, withdrawal, conflict, and relapse [17]. While it is important to assess individuals' subjective experiences for any mental health condition, an explanatory approach to social media use based on symptom similarities alone risks overpathologising normative behaviours [14,18–20], while overlooking the true neurocognitive processes maintaining dysfunctional behaviours. Elucidating such neurocognitive processes would provide deeper insight into the nature of addictive social media behaviours and facilitate the development of evidence-based interventions addressing the specific mechanisms implicated.

Therefore, it is critical to understand whether the neurocognitive processes characteristic of established addictions are also present for problematic social media use [19]. The extant substance addiction literature provides well-evidenced theoretical and experimental frameworks of addiction, validated across decades of research. In this study we investigate three neurocognitive signatures underpinned by two processes considered integral to addiction development and maintenance: a) incentive salience, the pathological amplification of *wanting* for addictive rewards and their dissociation from hedonic value; and b) devaluation insensitivity, the persistence of motivational responses even when rewards become devalued. Both processes are central to contemporary theories of addiction, providing theoretically grounded and experimentally validated targets for investigating whether social media use engages the same motivational processes as established addictions.

For example, one foundational theory of addiction is Incentive Sensitisation Theory [21,22] which proposes that *wanting* and *liking* of addictive substances represent dissociable psychological and neurobiological processes. Behavioural and neurobiological evidence from animals [23–26] and humans [27–29] supports this dissociation. Whereas *liking* corresponds to hedonic pleasure derived from a reward, *wanting* reflects attribution of incentive salience to reward-associated stimuli. Repeated exposure to addictive substances or behaviours produces neuroadaptations in the brain systems mediating incentive salience, particularly dopaminergic pathways involving the ventral tegmental area and nucleus accumbens [30,31]. Neural systems mediating *wanting* become sensitised, rendering individuals progressively more responsive to drug-related cues and amplifying their motivational pull. In contrast, *liking* of the substance remains relatively stable or diminishes through tolerance. This dissociation explains a core paradox of addiction: that individuals experience powerful cravings and compulsively pursue substances despite deriving diminishing pleasure from them [20–26].

Wanting and *liking* are subserved by relatively distinct neural circuitry and neurotransmitter systems. Hedonic pleasure, i.e. *liking*, involves primarily opioid and endocannabinoid signalling within so-called hedonic hotspots in limbic structures such as the ventral pallidum and nucleus accumbens shell [32,33]. These hedonic circuits generate the experienced pleasure of consumption and remain stable or become blunted with repeated exposure. In contrast, neural systems mediating *wanting* operate through the mesolimbic dopamine system, which assigns incentive salience and motivational significance to environmental cues [22,34–36]. Dopamine transmission in the nucleus accumbens mediates the motivation to exert effort for rewards, providing the neural basis for effort-based decision-making, which is a behavioural index of *wanting* [37–39]. Consistent with this, studies depleting tonic dopamine reduce motivated behaviour, while pharmacologically enhancing dopamine signalling does the opposite [40–44]. Together, these findings establish effort-based decision-making as a sensitive behavioural measure of the dopamine-dependent *wanting* system.

Beyond incentive sensitisation, the second neurocognitive process of established addictions examined in this paper is the loss of flexible, goal-directed behavioural control: the transition from voluntary, reward-driven engagement to rigid, compulsive behaviour [45–47]. This has a well-established neural basis, as goal-directed behaviour depends on prefrontal regions operating alongside the dorsomedial striatum, whereas habitual behaviour is mediated by the dorsolateral striatum [48,49]. While goal-directed behaviour is flexible, sensitive to changes in outcome value and contingency, habitual behaviour is not. The shift from goal-directed to habitual behaviour is reflected in the diagnostic criteria for substance use disorders, which include continued use despite awareness of harm and repeated failed attempts to reduce use [10,11].

A behavioural consequence of this shift from goal-directed to habitual behaviour is *devaluation insensitivity:* compulsive engagement that persists despite negative consequences [50]. Whereas initial engagement with addictive substances is driven by their rewarding properties, continued use becomes progressively insensitive to devaluation, whether through saturation, pairing with aversive outcomes, or explicit knowledge of negative consequences. A range of experimental paradigms where addicted animals and humans fail to adjust behaviour following manipulations that reduce a substance's rewarding nature [51–53], or pair it with highly aversive experiences [54–56], provide evidence for devaluation insensitivity. This reflects the underlying dysregulation of neurocognitive systems supporting outcome evaluation and flexible motivational control. Examining how individuals respond to changes in reward value, therefore, provides a direct window into the integrity of goal-directed processes implicated in the development and maintenance of addiction.

Measuring incentive sensitisation and devaluation insensitivity in tractable human experimental paradigms is methodologically challenging. However, effort-based decision-making paradigms have emerged as a translational framework for both, formalising how individuals evaluate and integrate the costs and rewards of effortful behaviour [38,57]. Effort-based decision-making has demonstrated sensitivity to motivational states relevant to addiction in human samples and is modulated by dopaminergic manipulations consistent with the mesolimbic mechanisms outlined above [38,41,58]. Computational implementations of this framework further allow dissociation of the neurocognitive processes contributing to motivated behaviour: separating, for instance, reward sensitivity, effort sensitivity, and general motivational tendencies. The acceptance bias parameter that can be extracted from such models, in particular, captures general motivation tendencies to engage with reward that operate independently of its associated costs and benefits. This, therefore, provides a direct computational analogue of incentive salience [59]. Moreover, the framework allows for devaluation manipulations, providing a unified computational approach to test the involvement of our two target neurocognitive processes in social media behaviour.

A computational analysis of experimental effort-based decision-making tasks can therefore be used to understand whether problematic social media use exhibits three neurocognitive signatures of addiction: elevated wanting, wanting-liking dissociation, and devaluation insensitivity. These signatures are grounded in both incentive sensitisation and devaluation insensitivity processes, which have been successful in characterising traditional substance addictions. Examining these signatures could therefore reveal fundamental commonalities or differences in mechanisms implicated in addictions and problematic social media use. Moreover, they allow us to better quantify motivational shifts in social media use, going beyond self-report measures and capturing underlying decision-making processes that drive compulsive engagement.

We focus our studies on TikTok, the “most addictive” social media platform, whose design features, such as variable ratio schedules of reward presentation [5], removal of natural stopping cues [60], or algorithmic curation [7,8], have been frequently associated with addictive potential [8,61]. To isolate the neurocognitive signatures of these design features rather than entertainment more broadly, we use Netflix as a robust active control condition. The fact that TikTok has rapidly become the most-used social media platform among UK children and adolescents[62] further underscores the importance of examining whether these engagement-optimised design features produce measurable neurocognitive changes consistent with addiction.

The present pre-registered research, therefore, applies the effort-based decision-making framework across two experiments to test for three neurocognitive signatures of addiction. Specifically, we investigate whether individuals exhibit: 1) a motivational bias for social media rewards that incorporate features considered to facilitate addictive engagement; 2) a dissociation between *wanting* and *liking* of social media rewards consistent with incentive sensitisation; and 3) insensitivity to devaluation of TikTok rewards consistent with habitual, compulsive engagement. Across both experiments, we further examine whether these neurocognitive signatures correlate with dominant self-report measures of social media addiction. Together, this provides a critical test of whether problematic social media use is underpinned by the same neurocognitive mechanisms that characterise established addictions, moving the field beyond descriptive symptom-based accounts toward an evidence-based mechanistic understanding.

Results

We examined three neurocognitive signatures of addiction across two preregistered experiments (see https://osf.io/uwz5b and https://osf.io/mnk3b). In both experiments, participants repeatedly chose whether to exert effort, calibrated to the individual, to earn time on TikTok. Experiment 1 (N=95; general population) used a within-subjects design where participants completed an effort expenditure task for both TikTok and Netflix rewards across two counterbalanced in-person sessions. Experiment 2 (N_{total}=235, $N_{addiction}$=122, $N_{control}$=113) used a within-subjects design where participants completed an effort expenditure task for TikTok in a baseline (standard) condition and a devalued condition across two counterbalanced blocks within a single online session. Groups in Experiment 2 were also stratified by participants who did or did not self-report "TikTok addiction" and matched on age (BF_{10}=0.487) and gender (BF_{10}=0.031). Participant characteristics are presented in Table 1; a research design overview is presented in Fig. 1. For Bayesian analyses, effect sizes are reported as the posterior median standardised effect size (δ, analogous to Cohen's d) or correlation (ρ), or posterior mean regression coefficient (β), with evidence strength interpreted following Lee and Wagenmakers [63].

The devaluation manipulation – turning TikTok greyscale and removing sound – was selected through a within-subjects pilot study (N=49, female=33, mean age=32.449, SD=6.618) comparing three combinations of colour and sound devaluation against baseline (see Supplement 6). The combined manipulation of no colour and no sound was most effective (Cohen's d=1.747, p<0.001), demonstrating large negative effects on self-reported pleasantness relative to baseline.

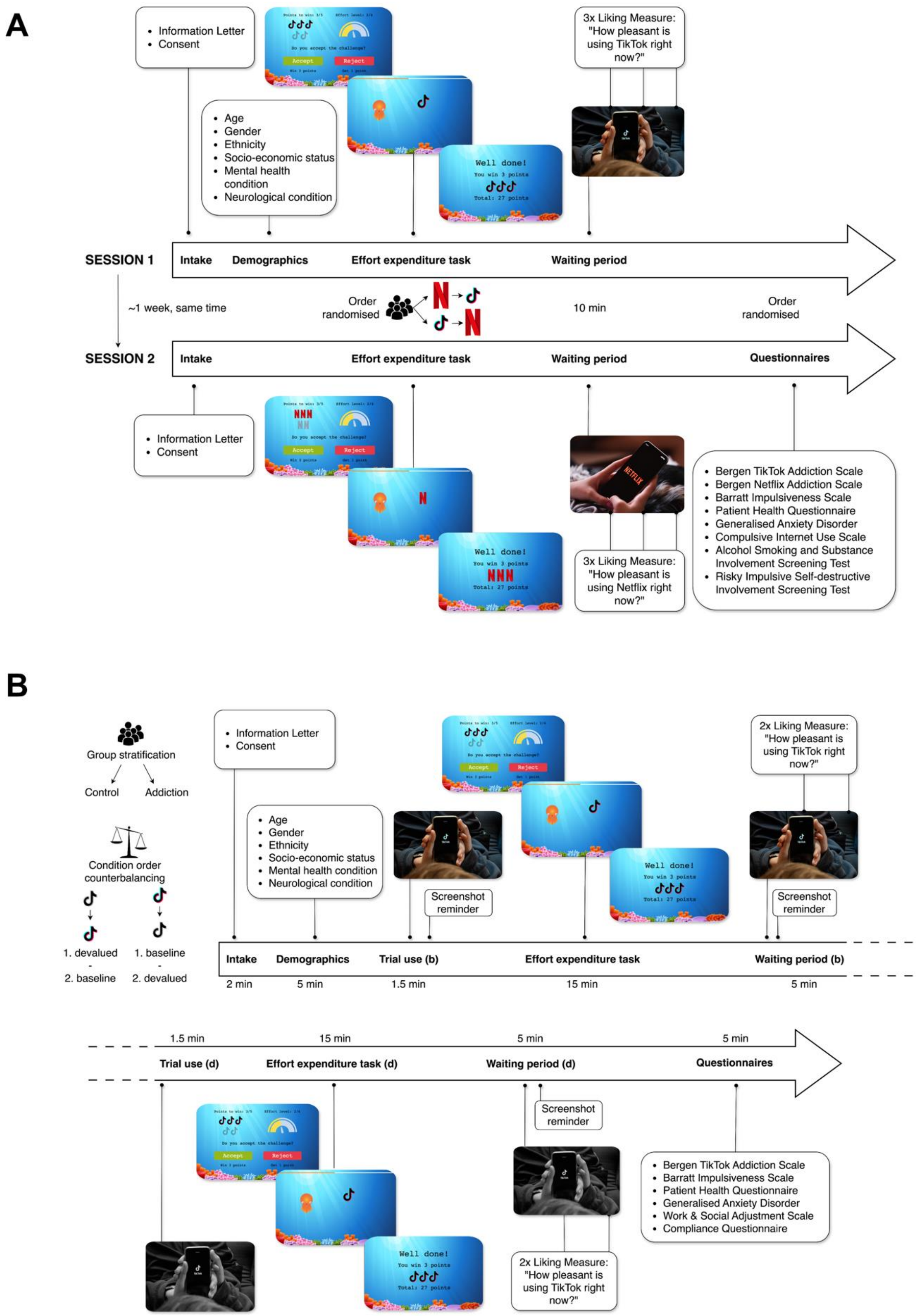

Fig. 1. Experimental procedures. The procedure is presented for **(A)** the in-person Experiment 1, which involved two sessions spaced one week apart, and **(B)** the online Experiment 2, which involved a single session with two within-subjects conditions. The devaluation condition is noted as *(d)* and the baseline condition as *(b)*.

Computational Modelling

To capture participants' effort-based decision-making, we assessed a preregistered model space of nine models differing in cost function (linear, parabolic, exponential) and free parameter inclusion (reward sensitivity and/or acceptance bias, with effort sensitivity included in all models) across both experiments (see Supplement 1). All models showed good convergence (Experiment 1: Effective Sample Size (ESS)>355; R-hats<1.011; Experiment 2: ESS>20,817; R-hats<1.001). Across both experiments and all four modelling procedures, model comparison based on out-of-sample predictive accuracy identified the winning model as implementing a parabolic cost function and all free parameters (henceforth full parabolic model). Model selection outcomes (see Supplement 2) replicated prior work using the same model space [59]. Posterior predictive checks (see Supplement 3) confirmed excellent correspondence between observed and model-predicted choice data across all four model fits (all $R^2>0.925$), and parameter recovery (see Supplement 4) showed strong correlations between simulated and recovered parameters (all $r>0.849$). Model agnostic task validity was confirmed in both experiments by significant main effects of effort, reward, and their interaction on acceptance probabilities (Experiment 1: $F(1,1422)=534.432$, 364.462, 332.351, respectively; Experiment 2: $F(1,3522)=1,586.666$, 693.544, 242.957, respectively; all $ps<0.001$). Participants successfully completed over 98.908% of accepted trials on the task in both experiments. Detailed model comparisons are presented in Supplement 2, and model agonistic task measures are presented in Supplement 5.

Neurocognitive Signature 1: Motivational Bias (Wanting)

The first neurocognitive signature we examined was *wanting,* operationalised as the computational model's acceptance bias parameter, which quantifies an individual's likelihood of expending effort to gain access to presented rewards. Specifically, we tested whether *wanting* was elevated a) for TikTok relative to Netflix rewards (Experiment 1), b) for baseline relative to devalued TikTok rewards (Experiment 2), and c) for individuals identifying as addicted to TikTok relative to a control group (Experiment 2). The results are visualised in Fig. 2A–C, respectively.

We found no difference in *wanting* for TikTok compared to Netflix rewards (Bayesian paired-samples *t*-test; $BF_{10}=0.341$; anecdotal evidence for null hypothesis), with the data approximately three times more likely under the null hypothesis (i.e. no difference in the decision to expend effort for TikTok compared to Netflix). The posterior median standardised effect size was 0.085 (95% Credible Interval (CI) [–0.101,0.277]).

We found no difference in *wanting* for devalued compared to baseline TikTok rewards (Bayesian paired-samples *t*-test; BF_{10}=0.151; δ=–0.005, 95% CI [–0.129,0.119]; moderate evidence for null hypothesis), suggesting no effect of devaluation on the decision to expend effort. Given the devaluation was highly effective in reducing *liking* (BF_{10}=4.45^{32}; δ=0.969, 95% CI [0.812,1.128]), the absence of a difference in acceptance bias was not attributable to a failure of the devaluation manipulation (see Supplement 7).

We found anecdotal evidence in favour of no difference when testing whether *wanting* for TikTok rewards differed in the addiction compared to the control group (Bayesian independent-samples *t*-test; BF_{10}=0.668; δ=–0.158, 95% CI [–0.403,0.081]).

Across both experiments, therefore, there was no evidence of a general shift in the motivation to expend effort for potent social media rewards as quantified by the acceptance bias parameter (i.e. *wanting*), diverging from predictions based on an addiction account of problematic social media use.

Neurocognitive Signature 2: Incentive Sensitisation (Wanting-Liking Dissociation)

The next neurocognitive signature we examined was the wanting-liking dissociation: the difference between acceptance bias (*wanting*) and momentary self-reported enjoyment (*liking*). This is quantified using the difference between the computational *wanting* parameter, and momentary self-reported levels of *liking.* We tested whether the wanting-liking dissociation was higher for a) TikTok relative to Netflix rewards (Experiment 1), and b) for individuals identifying as addicted to TikTok relative to a control group (Experiment 2). The results are visualised in Fig. 2D–E, respectively.

We find strong evidence that the wanting-liking dissociation is greater for TikTok compared to Netflix (Bayesian paired-samples *t*-test; BF_{10}=145.493). The data are over 140 times more likely under the alternative hypothesis that there is a difference in wanting-liking dissociation between the two platforms than under the null hypothesis. The posterior median standardised effect size was 0.373 (95% CI [0.167,0.585]).

However, we find that this dissociation is down to participants exhibiting lower *liking* for TikTok rewards (Bayesian multivariate model with condition as a predictor and random intercepts for participants; β=–0.584, 95% CI [–0.795,–0.371]) rather than higher *wanting* (β=0.154, 95% CI [–0.156,0.473]). This suggests that *liking*, rather than *wanting*, differentiates the two platforms. The condition difference remained robust when controlling for age (β=0.039, 95% CI [–0.127,0.203]) and gender (β_{male}=–0.728, 95% CI [–1.667,0.209]).

In Experiment 2, the within-subjects design enabled replication of this finding across addiction and control groups. We find moderate evidence that there is no difference in the wanting-liking dissociation for baseline TikTok rewards between addiction and control groups (Bayesian independent-samples *t*-test; BF_{10}=0.281; δ=0.017, 95% CI [–0.207,0.248]). This finding contrasts observations from Experiment 1, where the wanting-liking dissociation is more pronounced for TikTok compared to Netflix rewards. However, this effect was driven by *liking* differences and across both experiments, we observe consistent evidence indicating no difference in wanting-liking dissociation in line with incentive-sensitisation processes.

The wanting-liking dissociation was unrelated to trait impulsivity in both Experiment 1 (BIS-11 total: BF_{10}=0.269, ρ=0.049, 95% CI [–0.149,0.241]; all subscales $BF_{10}\leq$0.741) and Experiment 2 (BIS-21-R: BF_{10}=0.152; ρ<–0.000, 95% CI [–0.126,0.125]). Detailed correlations for impulsivity measures are presented in Supplement 12.

Neurocognitive Signature 3: Devaluation Insensitivity

The final neurocognitive signature we test for is devaluation insensitivity, i.e. whether *wanting* for TikTok rewards persists despite a reduction of reward value, and whether this persistence is more pronounced in participants with self-reported TikTok addiction (Experiment 2). The result is visualised in Figure 2F.

As reported in “Neurocognitive Signature 1”, we found that acceptance bias (*wanting*) did not differ between baseline and devalued TikTok conditions (BF_{10}=0.151), providing no evidence for devaluation sensitivity across the full sample. Further, we find anecdotal evidence for devaluation sensitivity differing between addiction and control groups (Bayesian independent-samples *t*-test; BF_{10}=1.137, δ=–0.203, 95% CI [–0.453,0.038]). However, this preregistered test was two-sided, while in the pre-registration our hypothesis was expressed directionally (expecting lower devaluation sensitivity in the addiction vs control group). In contrast, our data shows higher devaluation sensitivity in the addiction (mean=0.220) compared to the control group (mean=–0.250). An exploratory one-sided test in our pre-registered hypothesised direction shows moderate evidence against our initial hypothesis (BF_{10}=0.108, δ=0.038, 95% CI [0.002,0.160]). Group differences remained consistent when controlling for age (β=–0.010, 95% CI [–0.061,0.041]) and gender (β_{male}=0.070, 95% CI [–0.462,0.599]).

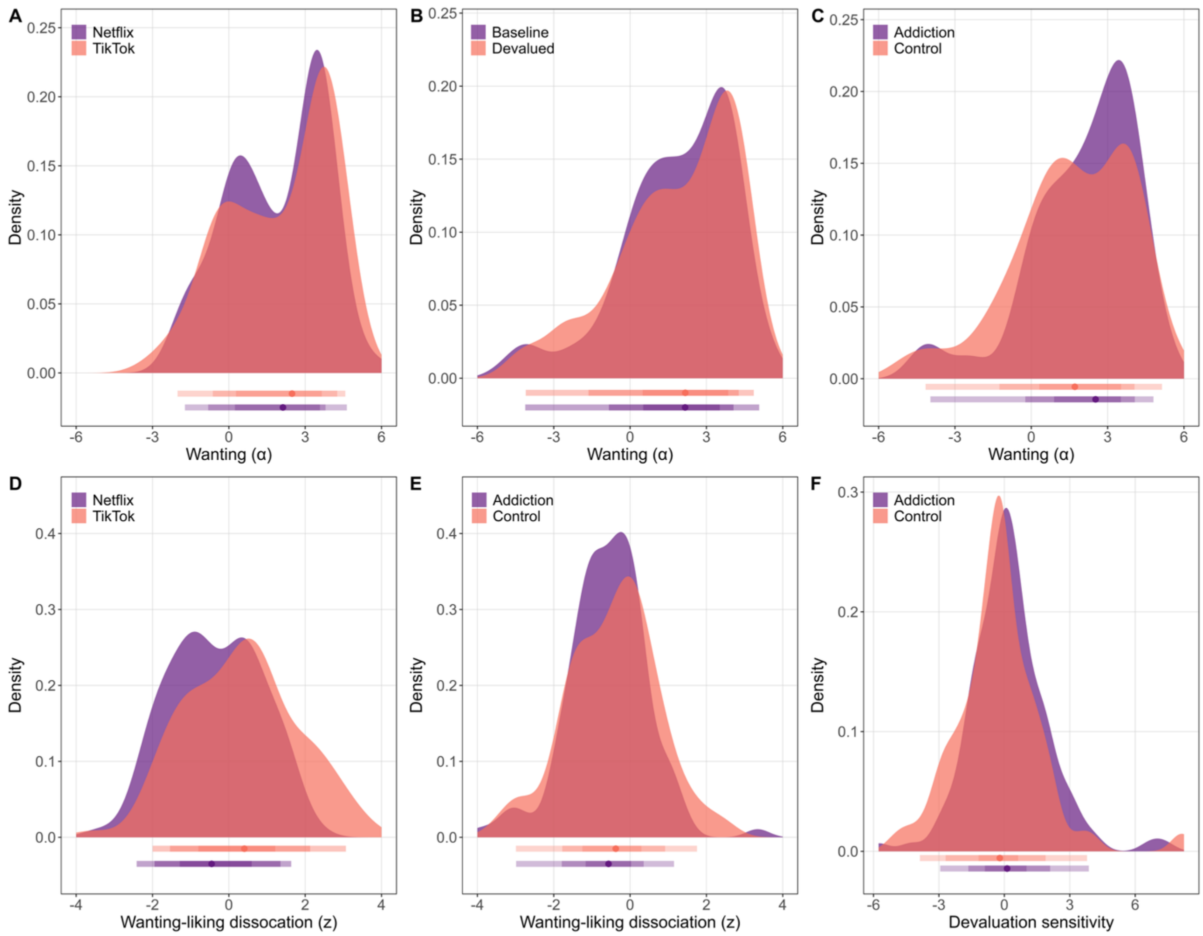

Fig 2. Distribution of devaluation sensitivity for self-reported addiction and control participants. (A) Experiment 1 difference in *wanting* between Netflix and TikTok rewards. **(B)** Experiment 2 difference in *wanting* between baseline and devalued TikTok rewards. **(C)** Experiment 2 difference in *wanting* between the addiction and control group. **(D)** Experiment 1 difference in wanting-liking dissociation for Netflix and TikTok rewards. **(E)** Experiment 2 difference in wanting-liking dissociation between the addiction and control group. **(F)** Experiment 2 difference in devaluation sensitivity between the addiction and control group.

To contextualise the observed patterns in devaluation sensitivity, we explored group differences in *liking* across baseline and devalued conditions in Experiment 2. The addiction group liked TikTok more than the control group at baseline (BF_{10}=48; δ=–0.410, 95% CI [–0.670,–0.150]), but this difference was absent under devaluation (BF_{10}=0.650; δ=0.160, 95% CI [–0.075,0.400]). The reduction in *liking* from baseline to devalued was significantly larger in the addiction group (BF_{10}=35; δ=–0.390, 95% CI [–0.660,–0.140]), suggesting that the devaluation manipulation was more effective for the addiction group. A Bayesian linear regression predicting devaluation sensitivity from group membership, age, and *liking* difference indicated a tendency for lower devaluation sensitivity in the control group (β=–

0.396, 95% CI [–0.897,0.107]), though the credible interval crossed zero. Neither age (β=–0.011, 95% CI [–0.061,0.039]) nor *liking* difference (β=0.071, 95% CI [–0.072,0.216]) were meaningfully associated with devaluation sensitivity.

Relationship to Self-reported Addiction Severity

Across both experiments, we examined whether the three neurocognitive indices related to self-reported social media addiction severity as measured by the Bergen Social Media Addiction Scale (BSMAS; Andreassen et al., 2016; Duradoni et al., 2020). In short, we observed no associations between any neurocognitive markers of addiction and self-reported TikTok addiction. The correlations between the neurocognitive markers of addiction and self-reported social media addiction are visualised in Fig. 3.

In exploratory analyses, *wanting* of TikTok rewards showed no relationship with self-reported TikTok addiction in Experiment 1 (Bayesian correlation analysis; BF_{10}=0.238, ρ=0.010, 95% CI [-0.181,0.208]), and Experiment 2 (BF_{10}=0.187, ρ=0.041, 95% CI [-0.082,0.164]).

The wanting-liking dissociation for TikTok rewards showed no relationship with self-reported TikTok addiction (quantified as BSMAS scores) for Experiment 1 (Bayesian correlation analysis; BF_{10}=0.288; ρ=–0.063, 95% CI [–0.254,0.137]) and Experiment 2 (BF_{10}=0.281; ρ=0.019, 95% CI [–0.208,0.246]). Across analyses, the observed data was over three times as likely under the null hypothesis that the wanting-liking dissociation does not relate to self-reported TikTok addiction. There was also anecdotal evidence for the wanting-liking dissociation for Netflix rewards being related to self-reported Netflix addiction (BF_{10}=1.186; ρ=–0.177, 95% CI [–0.361,0.015]).

Likewise, devaluation sensitivity in Experiment 2 showed no relationship with self-reported TikTok addiction (BF_{10}=0.177; ρ=–0.036, 95% CI [–0.160,0.092]), with the data over five times as likely under the null hypothesis.

Sensitivity analyses across a range of prior specifications and analysis decisions are reported in Supplement 9 and 10, and substantiate that there is no relationship between any neurocognitive markers and self-reported social media addiction. Correlations between self-reported addiction and other computational parameters (effort sensitivity, reward sensitivity) are presented in Supplement 11.

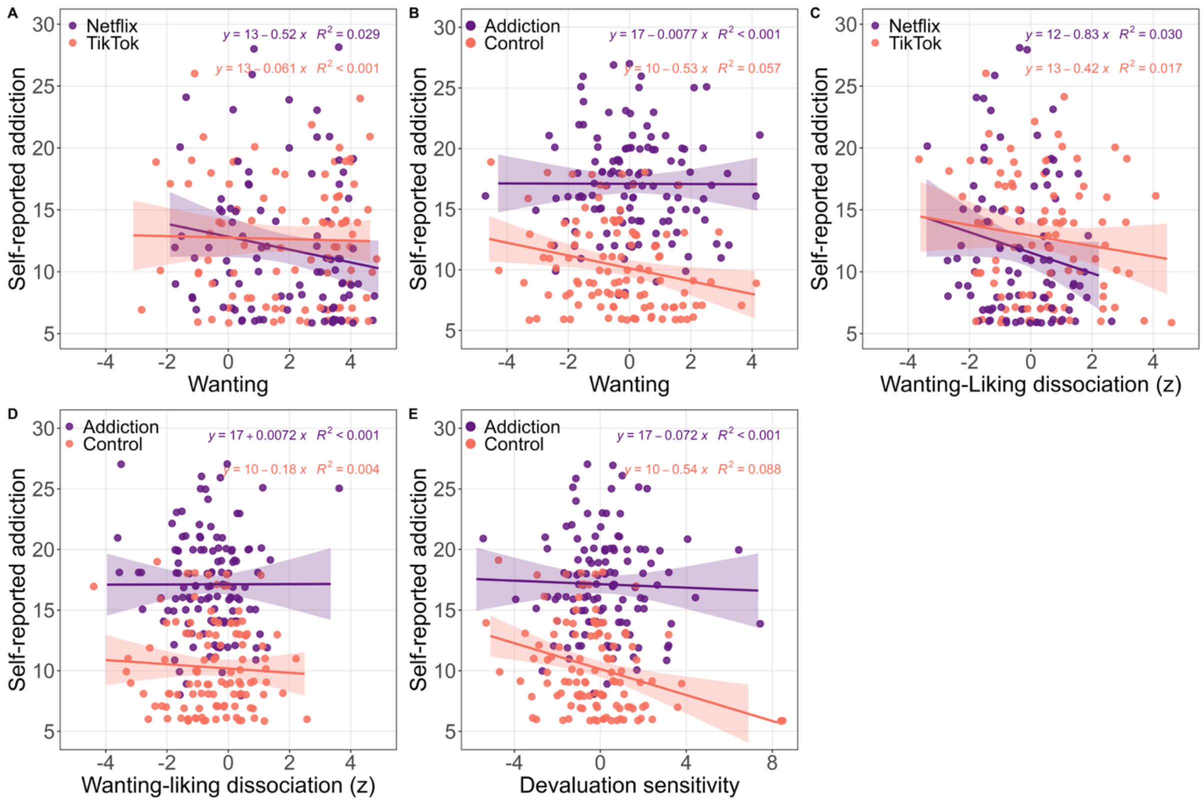

Fig. 3. Correlations Between Neurocognitive Signatures of Addiction and Self-report Measurements. The plots illustrate the correlations between self-reported social media addiction scores and **(A)** *wanting* of TikTok and Netflix rewards and their respective self-report addiction scores, **(B)** *wanting* of TikTok rewards in the addition and control group and their respective self-report addiction scores, **(C)** wanting-liking dissociation of TikTok and Netflix rewards and their respective self-report addiction scores, **(D)** wanting-liking dissociation of TikTok rewards in the addiction and control group and their respective self-report addiction scores, and **(E)** devaluation sensitivity to TikTok rewards in the addiction and control group.

Discussion

Concerns about social media addiction have intensified as platforms increasingly engineer and deploy powerful features designed to maximise user engagement [7]. While this is concerning and worthy of action and attention in and of itself, whether these design features operate through the same neurocognitive pathways as established addictions remains unexplored. Our work represents, to our knowledge, the first attempt at testing this. Combining experimental design with behavioural and computational indices, we move beyond the prevailing confirmatory and self-report approach of the extant social media addiction literature. Across two preregistered within-subjects experiments, we test for three neurocognitive signatures of established addictions: heightened *wanting* of platform-specific rewards, pronounced dissociation between *wanting* and *liking* of platform-specific rewards, and insensitivity to changes in addiction-related reward value. We find consistent evidence that users of social media platforms with purportedly addictive design features do not exhibit characteristic neurocognitive signatures of addiction, and that this is unrelated to self-reported social media addiction severity.

Central to established addictions is the observation that individuals develop heightened motivation to exert effort for the substance or behaviour, and that this motivation becomes increasingly independent of experienced reward. Indeed, elevated *wanting* has been reported in both established substance and behavioural addictions [65–68]. However, we found *wanting* did not differ between TikTok and Netflix rewards. In Experiment 2, *wanting* likewise did not differ between baseline and devalued TikTok conditions both in our full sample, nor when comparing participants who reported feeling addicted to TikTok and those who did not. *Wanting* was further unrelated to self-reported addiction severity across both experiments. Given that dopamine-mediated incentive sensitisation in the mesolimbic system is considered a hallmark of addiction[22,36], the consistent absence of differential motivated behaviour across platforms, groups, and conditions suggests that TikTok's design features do not induce this neurocognitive signature characteristic of addictive processes.

Aligned with expectations, we did observe a more pronounced dissociation between *wanting* and *liking* for TikTok relative to Netflix. However, Incentive Sensitisation Theory postulates that *wanting* and *liking* dissociate as repeated exposure produces neuroadaptations that amplify incentive salience, increasing *wanting* for the substance or behaviour, while *liking* remains stable or diminishes [21,22,32]. Our findings invert this pattern. *Wanting* is indistinguishable between TikTok and Netflix rewards, while *liking* is lower for TikTok rewards. The neurocognitive signature is therefore present in form but absent in mechanism: produced by lower hedonic engagement rather than by amplification of incentive salience. This is important because it forecloses the interpretation that TikTok engagement has induced dopaminergic neuroadaptations central to Incentive Sensitisation Theory. This interpretation is further corroborated by Experiment 2, which found no difference in wanting-liking dissociation between those with self-reported TikTok addiction versus a control group. A wanting-liking dissociation that is based on *liking* differences and unrelated to self-reported addiction is best interpreted as a reflection of TikTok's broader features that capture the attention of users, rather than evidence of neurocognitive mechanisms of addiction. Nevertheless, the finding of decreased *liking* for TikTok could be relevant in understanding the unique qualities of social media rewards, as well as the subjective experiences of social media addiction, although distinct from the incentivising features of addictive substances.

Healthy behaviour is characterised by the capacity to flexibly adjust actions in response to changing internal states (e.g. motivation) and external contingencies (e.g. reward structures). Behaviour can become problematic when this flexibility is impaired, such as when behaviour persists despite shifting motivations or accumulating negative consequences. Impairment in goal-directed control is therefore another neurocognitive signature of addiction, offering a mechanistic account of why engagement with addictive substances or behaviours is maintained despite accumulating negative psychological, physiological, or social consequences (for alternative views, see [69,70]). To index goal-directed behaviour in the social media context, we employed our computational model of effort-based decision-making in combination with a devaluation manipulation. This allowed us to estimate whether participants' behaviour was sensitive to manipulations of TikTok's reward value. While our devaluation manipulation was effective in reducing reward value, we did not observe a change in *wanting* of TikTok rewards. Further, contrary to theory, users who reported feeling addicted to TikTok did not exhibit greater insensitivity to reward devaluation than those in the control group. Likewise, devaluation sensitivity was unrelated to self-reported levels of TikTok addiction indexed by the Bergen Social Media Addiction scale.

What distinguished the TikTok addiction group from controls was not how they translated subjective reward value into behaviour, but rather their perception of reward value itself. Relative to controls, the addiction group reported greater *liking* of baseline TikTok rewards and a larger reduction in perceived reward value following devaluation. This pattern runs counter to predictions derived from Incentive Sensitisation Theory [21], further challenging the conceptualisation of problematic social media use as a conventional addiction. Rather than reflecting the blunted reward sensitivity characteristic of established addictions, our findings suggest that individuals who report feeling addicted to social media may instead experience reward hypersensitivity, as in a heightened responsiveness to both the presence and absence of social media rewards. This raises the possibility that the neurocognitive mechanisms sustaining problematic social media use are fundamentally distinct from those underlying other established substance or behavioural addictions, and may be better captured by alternative frameworks than those studied here.

In both experiments no neurocognitive signature of addiction was associated with self-reported addiction severity as indexed by the Bergen Social Media Addiction Scale [16], the most widely-used survey instrument in the social media addiction literature (3,000+ citations). This carries important implications. Whereas self-report measures of social media addiction have demonstrated utility in predicting adverse mental health outcomes above and beyond time spent on platforms [2,64,71], our findings challenge whether these instruments capture the traditional addiction construct – underpinned by corresponding neurocognitive mechanisms – they purport to measure. They may instead index subjective distress, perceived loss of control, or functional impairment; while these are all constructs with genuine clinical relevance and scientific importance, they might not correspond to the neurobiological processes that define medical addiction. Emerging neurobiological evidence appears to align with the conclusions presented here, suggesting that problematic social media use is not neurobiologically similar to substance addictions [72,73].

This does not diminish the real experiences reported by individuals who feel unable to control their social media use, nor does it imply that such experiences do not warrant support or that social media designs are harmless. The subjective sense of compulsion, interference with daily functioning, and associated distress documented in this literature warrant attention [2,13,74]. What our findings do challenge is the assumption that these experiences are best viewed through the lens of an addiction model. This also puts into question the pursuit of interventions modelled on substance addiction alone, including abstinence-based approaches. If problematic social media use is not underpinned by neurobiological mechanisms of addiction, then interventions derived from such frameworks may be theoretically misaligned and clinically ineffective. Our findings call for caution in interpreting self-report scales as indices of medical addiction, and suggest that developing appropriately-targeted support will require the further identification of specific mechanisms driving problematic social media use, which our work suggests are likely distinct from those of substance addictions [18,19].

Several limitations warrant consideration, however. First, although we examined three neurocognitive markers from two predominant theories of addiction, the addiction literature encompasses a broader set of implicated processes, including cue reactivity or inhibitory control processes, that were beyond the scope of the present research [75–78]. Cognitive and behavioural manifestations of addiction likely reflect contributions from multiple interacting neurocognitive processes, and future research should examine whether specific components of social media use resemble any of these further addiction signatures, and their development across time, before drawing strong conclusions about the absence or presence of neurobiological overlap.

A second limitation concerns the operationalisation of *wanting* and *liking.* Translating the constructs of Incentive Sensitisation Theory into human experimental paradigms has proven methodologically challenging, and the approaches taken across the literature have varied substantially, making direct comparisons difficult. Self-report measures of wanting have been criticised for their conceptual proximity to hedonic appraisal, complicating the disentangling of *wanting* and *liking* necessary to test incentive sensitisation [79]. The present research addresses this by deriving *wanting* from a computational model of observed choice behaviour under varying cost-benefit conditions, an approach robustly associated with the mesolimbic dopaminergic processes that incentive sensitisation implicates [38,41,58], and more consistent with the translational paradigms used in animal research [51–53]. Nevertheless, a fuller characterisation of the wanting-liking dissociation in the context of social media use would benefit from complementary approaches, such as pharmacological intervention or Positron Emission Tomography that can index neural and neurochemical substrates of incentive salience more directly.

Conclusion

The present study examined whether problematic social media use exhibits three neurocognitive signatures characteristic of established addictions. We did not find evidence for predictions from Incentive Sensitisation Theory that social media rewards should elicit stronger *wanting* responses in platforms such as TikTok that incorporate design features hypothesised to drive addictive engagement. There were also no differences in *wanting* for those feeling addicted to TikTok versus controls. Although we did observe the characteristic dissociation of motivated *wanting* and hedonic *liking* for platforms featuring addictive design features such as TikTok, this dissociation did not resemble purported addiction mechanisms and was likewise unrelated to self-reported addiction severity. We further found no evidence that individuals considering themselves to be addicted to TikTok showed impaired behavioural adaptation in response to devalued TikTok rewards. We therefore demonstrate consistent evidence challenging the prevailing conceptualisation of social media “addiction” as neurobiologically similar to established addictions.

This suggests that problematic use of short-form social media platforms such as TikTok are likely not underpinned by the dopamine-mediated incentive sensitisation processes that characterise addictive neuroadaptation. The widespread adoption of an addiction lens to understand problematic social media use may mischaracterise its true drivers. It could also misdirect intervention efforts. Nevertheless, increasing reports of social media addiction across the population are important to address. Understanding the true mechanisms underlying problematic use is becoming increasingly urgent. This research presents a new avenue to advance our understanding of such neurocognitive determinants of problematic social media use, introducing more theory-driven, mechanistic approaches to the study of social media “addiction”.

Methods

Participants

Experiment 1 recruited participants via the MRC Cognition and Brain Sciences Unit research participant panel and materials distributed across public locations in Cambridge. Inclusion criteria included English-speaking adults aged 18–27 years with access to a personal TikTok account. An a priori power analysis indicated a required sample size of 84 paired observations to detect a small to medium effect (Cohen's d=0.4) at 95% power for a paired t-test. A total of 99 participants completed both sessions and were reimbursed £38. Preregistered exclusion criteria included failure of multiple attention checks (n=1) and non-compliance with task instructions (n=3; e.g. failure to use TikTok during the designated period), yielding a final sample of 95 participants.

Experiment 2 recruited participants via Prolific (www.prolific.com). Inclusion criteria included English-speaking adults aged 18–35 years, based in the United Kingdom or the United States, with access to a personal TikTok account and no reported hearing impairments or colour blindness. We screened 721 prospective participants on Prolific, who were stratified into addiction and control groups based on a single screening item ("I feel addicted to TikTok"); those responding "agree" or "strongly agree" were allocated to the addiction group, and those responding "disagree" or "strongly disagree" to the control group. Participants selecting the neutral response were excluded. The groups were matched on age and gender. An a priori power analysis indicated a required sample size of 210 participants (n=105 per group) to detect a medium effect size (Cohen's d=0.5) at 95% power for an independent samples t-test. A total of 240 participants completed the session and were reimbursed £11. Preregistered exclusion criteria included failure of attention checks (n=1), non-compliance with experimental instructions determined by independent review of qualitative responses by two researchers (n=3), and incomplete data (n=1), yielding a final sample of 235 participants.

Ethics

All procedures complied with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008, and were approved by the University of Cambridge Psychology Research Ethics Committee (PRE.2024.059). All participants provided written (Experiment 1) or digital (Experiment 2) informed consent prior to participation.

Procedure

Experiment 1

The block-randomised within-subjects experiment involved two in-person testing sessions scheduled for the same time of day ($mean_{t2\text{-}t1}$=12.863 minutes, $SD_{t2\text{-}t1}$=22.000 minutes) and spaced between five and eight days apart ($mean_{d2\text{-}d1}$=6.985 days, $SD_{d2\text{-}d1}$=0.491 days). Participants were randomly allocated a starting condition (TikTok/Netflix) at their first session and completed the alternative condition at their second session. Each session followed an identical structure: participants first completed the effort expenditure task ($mean_{session1}$=28.557 minutes; $mean_{session\ 2}$=28.651 minutes), then used TikTok on their personal phone or Netflix on a provided tablet for a fixed waiting period (10 minutes). Participants were told that task performance would determine the proportion of the waiting period that would be allocated to using the platform (rather than reading magazines), with more points translating to more time on TikTok/Netflix. Unbeknownst to participants, the time allocated was the same across participants, regardless of task performance. At the transition between the task and the waiting period, participants were instructed to call for the experimenter, who would enter a code on the computer, which participants were told was based on their task performance. This was implemented to maintain the credibility of the performance-contingent framing. Participants in the Netflix condition were instructed not to switch videos and were given one minute to select content. At three evenly-spaced time points during the waiting period, participants rated their momentary enjoyment of the platform ("How pleasant do you find using TikTok/Netflix right now"). Following the second session, participants completed the self-report questionnaire battery.

Experiment 2

The block-randomised within-subject experiment involved a single online session (mean=61.664 minutes, SD=14.826) programmed in JavaScript using the jsPsych library [80] and hosted on the MRC Cognition and Brain Sciences Unit's JATOS server [81]. Each session comprised two experimental blocks corresponding to the baseline (TikTok in colour and sound) and devalued (TikTok in greyscale and without sound) conditions, counterbalanced across participants. The devaluation manipulation was selected on the basis of a pilot study (for details, see Supplement 6). Each block followed an identical structure: participants first completed a 1.5-minute familiarisation phase during which they scrolled TikTok under condition-dependent settings to familiarise themselves with the reward value. Thereafter, participants completed the effort expenditure task and finally used TikTok for a 5-minute waiting period. The familiarisation phase was included to ensure participants were acquainted with the value of the reward prior to the task. After completion of the effort expenditure task, participants proceeded to the 5-minute waiting period, during which they scrolled through their recommended feed on their personal TikTok accounts. At 2.5 and 5 minutes, a sound prompted participants to rate how much they liked using TikTok in the moment (i.e. “How pleasant is using TikTok right now?”). After their first familiarisation phase and after both waiting phases, participants were asked to take screenshots of their TikTok screen time. Although we did not ask participants to upload the images, participants were informed they would be asked to upload them at the end of the experiment to increase accountability. Following the completion of the two experimental blocks, participants completed the self-report questionnaire battery and a compliance check, with explicit assurance that responses would not affect remuneration.

Effort Expenditure Task

The effort expenditure task was adapted from Mehrhof & Nord [59] to quantify motivated behaviour for social media rewards. Each session began with a calibration phase which involved three ten-second periods during which participants were asked to click as fast as possible. The average clicking speed across the second and third calibration was used to set the reference for the maximum clicking capacity, which was used to determine the effort levels. Effort was quantified as the required mouse-clicking speed and duration required to succeed on a given trial. The four effort levels corresponded to 30% of clicking speed for 8 seconds (level 1), 50% of clicking speed for 11 seconds (level 2), 70% of clicking speed for 14 seconds (level 3), and 90% of clicking speed for 17 seconds (level 4).

Following the calibration, participants completed a practice trial without an associated reward for each effort level. Participants who failed a level were asked to repeat it, and upon repeated failure, their maximum clicking capacity was adjusted to the maximum speed reached. Finally, participants were presented with detailed instructions highlighting that the points collected throughout the task would determine the time during the fixed waiting period that would be allocated to a) reading magazines, or b) watching TikTok or Netflix. Specifically, participants were informed that more points during the task would translate to a larger proportion of the time spent on TikTok or Netflix (condition-dependent). Thereafter, participants completed a six-question quiz to ensure the effort expenditure task instructions were understood, which was repeated until they had gotten all the questions correctly.

The main task involved the repeated presentation of challenges, and participants were faced with the binary choice to accept or reject the challenge. A challenge consisted of an associated effort and reward level. Effort was quantified as the speed and duration participants needed to click. Reward was quantified as the number of (TikTok/Netflix) points that could be collected (varying between 2, 3, 4, or 5 points). The trial-by-trial presentation of effort-reward combinations was made semi-adaptively for each participant, resulting from 16 randomly interleaved staircases (see Mehrhof & Nord [59] for details). The staircasing procedure was implemented to maximise the informative value of each trial, and participants were presented with a total of 64 and 32 effort-reward combinations in Experiment 1 and Experiment 2, respectively. Upon accepting a challenge, participants had to achieve the respective effort level in order to win the points. Upon rejecting a challenge, participants waited for the duration of the effort level and received a single point.

Self-Report Measures

Across both experiments, the questionnaire batteries included the Bergen Social Media Addiction Scale (BSMAS; Andreassen et al., 2016). The BSMAS is the most widely used instrument for this purpose in the extant literature [13]. It was administered for TikTok in both experiments and additionally for Netflix in Experiment 1. Moreover, both studies included the Patient Health Questionnaire (PHQ-8; Kroenke et al., 2001) and the Generalised Anxiety Disorder scale (GAD-7; Spitzer et al., 2006), and questionnaires were presented in randomised order.

In Experiment 1, the questionnaire battery included the following additional questionnaires: the Compulsive Internet Use Scale (CIUS; Meerkerk et al., 2009), the Risky Impulsive Self-Destructive Behaviour Questionnaire (RISQ; Sadeh & Baskin-Sommers, 2017), and the Alcohol Smoking and Substance Involvement Screening Test (ASSIST; Humeniuk et al., 2010). Moreover, screentime measures for TikTok and Netflix were obtained using read-outs from the application settings and self-reports, respectively. We also asked participants to estimate their checking frequency of TikTok, with options ranging from “at least once every 15 minutes” to “not every day”.

In Experiment 2, the questionnaire battery included the following additional questionnaires: the Barratt Impulsiveness Scale Revised (BIS-21-R; Kapitány-Fövény et al., 2020) and the Work and Social Adjustment Scale adapted for TikTok (WSAS; Mundt et al., 2002).

Computational Model

Effort-based decision-making was modelled using a preregistered space of nine models that differed in their implementation of the parameters and cost function (see Fig. 4 and Supplement 1). The models were variations of the economic decision-theory model, consisting of a cost and a softmax function. The cost function (equation 1) transforms the effort and reward associated with an action into a subjective value:

$$SV = (\beta_R \cdot R) - (\beta_E \cdot E) \qquad (1)$$

with E and R for given effort and reward levels, and the free parameters effort sensitivity (β_E) and reward sensitivity (β_R). Higher values in effort and reward sensitivity mean the subjective value changes more as a function of changes in effort and reward. Likewise, lower values mean the subjective value and subsequent behaviour are less susceptible to changes in effort and rewards. The latent subjective value is transformed into an acceptance probability using a softmax function (equation 2):

$$p(accept) = \frac{1}{1 + e^{-(\alpha + SV)}} \qquad (2)$$

with *p(accept)* for the predicted probability of accepting a given offer, and α for the intercept representing acceptance bias. A higher acceptance bias parameter captures a participant's tendency to accept rather than reject offers.

The nine formulations of the above equation differed in their inclusion of the free parameter reward sensitivity (β_R) and acceptance bias (α), and the form of the cost function which used either linear (proportional discounting across all effort levels), parabolic (increase in effort are discounted more at higher effort levels), or exponential (increases in effort are discounted more at lower effort levels) function.

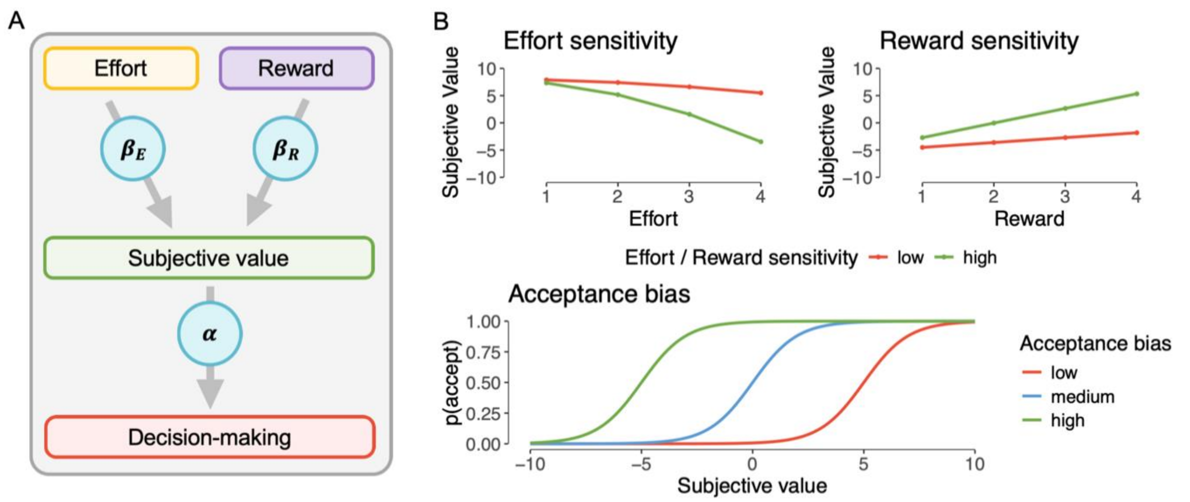

Fig 4. Bayesian hierarchical modelling approach. Figure copied from Mehrhof and Nord (2025) with permission from the authors. **(A)** Economic decision-making models posit that efforts and rewards are joined into a subjective value, weighed by individual *effort* and *reward sensitivity* parameters. The SV is then integrated with an *acceptance bias* parameter and translated to decision-making. **(B)** The model suggests that subjective value decreases as effort increases and increases as reward increases. The magnitude of this relationship depends on the individual effort and reward sensitivity parameters. The acceptance bias

parameter acts as an intercept to the softmax function, thereby changing the relationship between subjective value and acceptance probability.

We took a hierarchical Bayesian approach to model fitting, using weakly informative Gaussian priors for all free parameters [89,90]. All model-based analyses were implemented with the CmdStan R interface [91], using Markov-Chain Monte Carlo sampling with 2,000 warm-up iterations and 10,000 sampling iterations, by four chains. Model convergence and chain mixing were assessed with the Effective Sample Size (ESS) and split R-hats, as well as visual inspection of the trace plots. We standardised the effort and reward values before model fitting. Models were fit separately for the two conditions (i.e. TikTok/Netflix or baseline/devalued), and the resulting parameter estimates were used for the subsequent analyses.

Statistical Analyses

Bayesian paired samples *t*-tests were used to examine within-subjects differences in acceptance bias (Experiments 1 and 2) and the wanting-liking dissociation (Experiment 1). Bayesian independent samples *t*-tests were used to examine between-group differences in devaluation sensitivity and the wanting-liking dissociation (Experiment 2). All *t*-tests were conducted in *R* [92] using the *BayesFactor* package [93], with alternative hypotheses specified as a Cauchy distribution with the scale parameter 1/3 centred on zero. Bayesian correlation analyses used the *correlationBF* function from the *BayesFactor* package with a Cauchy prior scaled at 1/3 centred on zero. A Bayesian multivariate model with condition as a predictor and random intercepts for participants was used to decompose the wanting-liking dissociation into *wanting* and *liking* components. A Bayesian linear regression was used to examine predictors of devaluation sensitivity. Sensitivity analyses across a range of prior specifications and analysis decisions are reported in Supplements 9 and 10.

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Table 1. Participant characteristics.

	N	Age		Gender			Ethnicity			
		Mean	SD	F	M	NB	White	Black	Asian	Other
Experiment 1										
	95	22.137	2.512	67	26	2	38	5	44	8
Experiment 2										
Addiction	122	27.172	5.038	85	35	2	79	21	9	13
Control	113	27.920	4.732	73	40	0	63	29	9	12
Total	330	25.979	4.985	225	101	4	180	55	62	33

Note. The table presents the descriptive statistics for participants across the two experiments. F=female, M=male, NB=non-binary. The gender distribution is approximately representative of problematic social media use patterns [94–96].