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Underwhelming Pleasures: Toward a Self-Regulatory Account of Hedonic Compensation and Overconsumption

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Hedonic overconsumption (e.g., overconsumption of gratifying behaviors, e.g., eating, gaming) is common in daily life and often problematic, pointing to the need for adequate behavioral models. In this article, we develop a self-regulatory framework proposing that when an actual consumption experience falls short of hedonic expectations—such as when being distracted—people will want to consume more to compensate for the shortfall. In a preliminary meta-analysis, a small-scale field experiment on distraction during lunch and subsequent afternoon snacking (Study 1), and a preregistered experience sampling study (Study 2) involving more than 6,000 consumption episodes in everyday life across multiple consumption domains, we investigated the predictions from our hedonic compensation model. There was clear and consistent evidence across studies and analyses for the prediction that distraction during consumption compromises the actual enjoyment of a given consumption experience. Both empirical studies yielded consistent evidence for a positive association between actual enjoyment and consumption satisfaction but inconsistent and weaker evidence for the expected role of actual-expected enjoyment discrepancies for this part of the model. There was also consistent evidence for the expected negative association between consumption satisfaction and the need for further gratification. Finally, there was moderate and inconsistent support linking the need for further gratification to subsequent consumption across Study 1 (amount and frequency of snacking in the afternoon) and Study 2 (shorter duration to subsequent consumption). Taken together, the present framework provides initial support for the proposed link among compromising consumption contexts, consumption enjoyment, and subsequent hedonic compensation.

Keywords: hedonic compensation, distraction, consumption, self-regulation

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All procedures in this study were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. Consent to participate: Informed consent was obtained from all participants prior to study involvement.

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Hedonic consumption, which refers to consumption experiences "primarily characterized by an affective and sensory experience of aesthetic or sensual pleasure, fantasy, and fun" (Dhar & Wertenbroch, 2000, p. 61), is a critical aspect of everyday life. On any given day, a person may take great pleasure from eating tasty food, reading an interesting novel, watching a riveting television series, or playing an edge-of-the-seat online game. Yet, people often consume more hedonic goods than they want or than is good for them (Ferriter & Ray, 2011; Granow et al., 2018; Kukk & Akkermann, 2017). They may eat so much food that there is conflict with their health goals or read so long late at night that their sleep quality becomes compromised. Considering these and other consequences (e.g., overweight; Abarca-Gómez et al., 2017), much research has investigated why people overconsume hedonic goods (Hetherington, 2018). For instance, an elevated consumption of food, media, alcohol, and so forth is argued to often result because people may have insufficient self-control due to a variety of reasons, such as a tempting environment, a strong short-term desire, a lack of motivation and effort investment, a lack of control capacity or a lack of situational constraints on action, or ill-chosen strategies, to name just a few (for overviews, see Hofmann & Van Dillen, 2012; Kotabe & Hofmann, 2015; Werner & Ford, 2023).

In the present research, we propose that increased hedonic consumption may often happen for reasons outside of the scope of a self-control failure. We argue that overconsumption may also result from the way in which people regulate "hedonic shortfalls," that is, constellations in which an initial consumption experience turns out to be less enjoyable than expected. More specifically, the basis of this proposal is that (a) people are generally motivated to attenuate or extinguish discrepancies between actual and hoped-for hedonic experiences and that (b) increased hedonic consumption—whether that be consuming more goods in the same consumption episode or consuming again more quickly after consumption has finished—is often a convenient means by which people can attenuate or extinguish recognized hedonic shortfall.

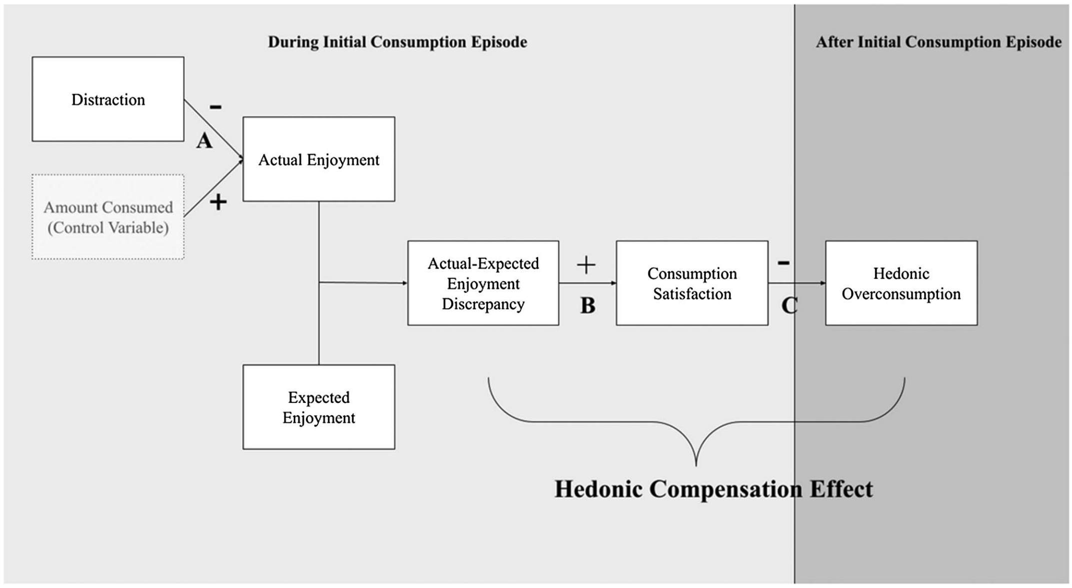
The main aim of this contribution is to present and test our hedonic compensation model (HCM), with a focus on distraction as a driver of hedonic shortfall. Our secondary aim is to show that this tendency to compensate for a hedonic shortfall helps explain a widely reported effect in extant literature—the effect whereby distraction during food consumption promotes increased food consumption (Gonçalves et al., 2019; Higgs & Spetter, 2018; S. Marsh et al., 2013; Ogden et al., 2013; Robinson et al., 2013; van Meer, Murphy, et al., 2023). Much effort has been invested to better understand why distraction promotes increased food consumption (Higgs & Spetter, 2018; Tapper, 2017; van der Wal & van Dillen, 2013; van Dillen & van Steenbergen, 2018). For instance, this link has been proposed to exist because being distracted renders people forgetful of personal health goals (e.g., to eat healthily; Tapper, 2017), less aware of satiation signals (Tapper, 2017), and less able to remember what (and how much) was eaten during a previous consumption episode (Higgs & Spetter, 2018). While the distracted eating research documented thus far has been valuable, distracted (over)eating has not yet been mechanistically connected to hedonic compensation (though for preliminary evidence, see van der Wal & van Dillen, 2013; van Meer, Murphy, et al., 2023). The distracted eating literature also overlooks the possibility that the distraction-consumption link is part of a larger story that involves all consumption domains (e.g., food, drink, gaming). In the present article, we make this broader claim—that a key reason distraction promotes increased food consumption is because of people's tendency to compensate for hedonic shortfall and because distraction promotes hedonic shortfall via its negative influence on consumption enjoyment (e.g., Green et al., 2004). We then test this idea, with the aim of showing this effect exists not just in the food domain but generally across consumption domains. In the following sections, we elaborate on the three hypotheses that make up our HCM (see Figure 1)—that distraction reduces actual consumption enjoyment (Path A), that actual-expected enjoyment discrepancy (i.e., consumption enjoyment falling short of expectations) reduces consumption satisfaction (Path B), and that lower consumption satisfaction promotes increased hedonic consumption (Path C). Support for these hypotheses will help demonstrate that distraction during consumption triggers increased hedonic consumption, and hedonic shortfall during consumption (via recognition of that shortfall) triggers a hedonic compensation effect.

Distraction and Actual Consumption Enjoyment

Distraction is typical during ongoing activities in everyday life (Kane et al., 2007). Even during hedonic consumption (e.g., watching television, eating a meal)—activities with inherent affective appeal—people's minds wander or get captured by notable aspects of their surroundings (Daunfeldt et al., 2019). For instance, during a movie, a person may find themselves thinking about a planned morning meeting or checking their emails or Twitter feed for updates. While reading a novel, a person's mind may wander until they unexpectedly find themselves many lines ahead of where they last remembered. A predilection toward distraction exists because our evolutionary ancestors had a survival advantage when keeping abreast of their surroundings to recognize danger and opportunities (Haladjian & Montemayor, 2015). Also, many spheres of modern life appear organized around an "attention economy" (Franck, 2019) that ensures environmental aspects possess considerable hedonic relevance to grab our attention (e.g., social media, advertising; Smith & Fischer, 2021).

Given its everyday prevalence, the phenomenon of distraction has attracted the attention (pun intended) of many researchers (Dean, 2021; Horberry et al., 2006; S. Marsh et al., 2013; McGreevy et al., 2015; Ogden et al., 2017; Robinson et al., 2013). However, what remains empirically untested is whether distraction during hedonic consumption reduces consumption enjoyment. In our HCM, we propose that distraction during consumption triggers downstream hedonic compensation by rendering consumption less enjoyable (Figure 1, Path A). Thus, we fill the empirical gap by testing this effect. A large body of research (for review, see van Dillen & Hofmann, 2023) suggests this effect because distraction dampens people's feelings through the capacity limits it poses on their mental resources, which prevents processing and integration of affective information. We also have a strong sense that hedonic consumption generally delivers less pleasure with less attention paid to it. When people devote less of their attention to consumption, it seems clear that they often notice and extract fewer positive experiential aspects. For instance, when people are distracted during a movie or novel, they likely experience less enjoyment because distraction will typically inhibit narrative immersion and the connection with characters that is so important for maximizing enjoyment (Green et al., 2004). For similar reasons, distraction likely hinders online game enjoyment. This realization has led some to advise that game

Figure 1
The Hedonic Compensation Model



Note. The proposed hedonic compensation model (HCM). Distraction during consumption (upon controlling for the amount consumed during the episode) is hypothesized to reduce consumption enjoyment relative to expectations via its direct effect on (actual) enjoyment (Path A). Experiencing less enjoyment during consumption relative to expectations is hypothesized to reduce consumption satisfaction (Path B), which is hypothesized to promote increased hedonic consumption (Path C). The "+" and "−" signs represent a proposed positive and negative causal effect, respectively.

developers should strive to retain gamer concentration during play to maximize gamer gratification (Sweetser & Wyeth, 2005). Strong arguments have recently been made for a negative relationship between distraction and enjoyment in the food and drink domains (Bryant & Veroff, 2017; Garbinsky & Klesse, 2021), arguments strengthened by experimental evidence (although this effect is not always found, e.g., Liguori et al., 2020). Participants that paid mindful attention during food consumption (i.e., chocolate and raisins), for instance, reported greater consumption enjoyment than participants that tackled a puzzle during consumption (Arch et al., 2016). Similarly, participants heavily distracted with a cognitive task during consumption of sweet and sour drinks and salty butter reported reduced sweetness, sourness, and saltiness, respectively, compared to undistracted participants (van der Wal & van Dillen, 2013). These and other (e.g., Garbinsky & Klesse, 2021; van Meer, van Steenbergen, & van Dillen, 2023) findings suggest that, when distracted, people generally do not fully process stimuli tied to a substance's hedonic content, so that enjoyment will likely be hindered.

Actual-Expected Enjoyment Discrepancy and Consumption Satisfaction

Next to actual enjoyment, people's expectations about consumption are an essential building block of our conceptual model (see Figure 1). The guiding assumption is that people, over time, form consummatory expectations that help them anticipate how enjoyable a given consumption experience will be (Alba & Williams, 2013; Hayes-Roth & Hayes-Roth, 1979). This tendency is at the core of what enables choice among available consumption options (e.g., which movie to watch, which menu option to order).

Assuming the presence of hedonic expectations, anything that reduces consumption enjoyment, such as distraction during consumption (but also other factors that are not the focus of the present research), should give rise to a hedonic shortfall—that is, a (negative) actual-expected enjoyment discrepancy, whereby actual enjoyment reduces relative to the enjoyment expected. As an example, consumption in conflict with other personal goals would often cause hedonic shortfall because amid fixed hedonic expectations, self-conscious emotions like guilt and regret often spoil pleasure (Hofmann et al., 2013). This effect is logical for hedonic expectations for consumption exist but remain unchanged when actual enjoyment is hindered by factors like distraction. Therefore, when actual enjoyment is reduced, a state of hedonic shortfall is either created or accentuated, resulting in an actual-expected enjoyment discrepancy (Carver & Scheier, 1982; Dehaene, 2018; Overmeyer et al., 2021). We argue this will then often promote a sense of dissatisfaction with consumption (Figure 1, Path B) because hedonic shortfall will frequently not go without notice. This is consistent with two prominent psychological theories, the first being control theory (Carver & Scheier, 1982), which argues that people continuously monitor ongoing experiences to ensure they remain in line with personal goals and often recognize discrepancies when they occur. The other, expectancy-disconfirmation theory (Oliver, 1980), claims consumption dissatisfaction primarily results when consumption is appraised to have fallen short of expectations. Both theories have much empirical support (Botvinick et al., 2001; Oliver & Linda, 1981; Phillips & Baumgartner, 2002; Yeung et al., 2004), thus strengthening the proposed actual-expected enjoyment discrepancy and Consumption Satisfaction link.

Consumption Satisfaction and Hedonic Overconsumption

According to control theory (Carver & Scheier, 1982), when people identify a discrepancy between their ongoing behaviors/experiences and their goals, in the following period they are more likely to engage in behaviors that reduce or eliminate that discrepancy. For instance, a person who recognizes that their recent eating behavior conflicts with their goal to be healthy would, according to control theory, often be expected in a subsequent instance to engage in behaviors such as exercise or healthy eating to reduce or eliminate the conflict. Considered in the present context, it seems highly plausible that registered hedonic shortfall from consumption will give rise to increased hedonic consumption. People will likely become imbued with motivation to compensate for the hedonic shortfall to address the discrepancy, which will (after the episode) frequently manifest behaviorally as excess consumption (Figure 1, Path C). Interestingly, control theory does not make explicit that self-regulatory processes take place with respect to hedonic aims; rather, affect within control theory was regarded as a signal of how well an identified goal-outcome gap was being reduced (e.g., people feel positive affect when a goal-outcome gap is being reduced at a faster rate than expected; Carver, 2006). It is also important to note that, over a longer timescale, hedonic shortfall from consumption may generally orient individuals toward alternative consumption options (Knowlton & Castel, 2022; Schultz, 2022).

Because hedonic goals may be satisfied via various means (principle of equifinality, see Kruglanski et al., 2011) and are consistent with the idea that the brain integrates various hedonic experiences under a "common currency" (Levy & Glimcher, 2012), our exploratory working hypothesis is that increased hedonic consumption manifests within and across domains rather than exclusively within domain. But assuming this suggests that the effect will be challenging to identify with typical, static measurement approaches. If many compensatory options exist, any singular behavioral manifestation (e.g., consuming for a longer period in the next episode) may represent an effect too small to uncover with anything less than a considerable amount of data. In the present research, we thus test whether recognizing hedonic shortfall predicts a plausible psychological proxy of increased hedonic consumption (i.e., how much a person desires further gratification after consumption has ended), a proximal "steppingstone" (and cause) of elevated consumption able to exhibit an effect large enough to be identified. Yet, given temporal dynamics and the idea of cross-domain regulation remain of high interest, we also investigate whether an increased postconsumption need for further gratification predicts (a) how much and frequently individuals snack afterward (Study 1) and (b) how long it takes a person to consume again after consumption has finished (Study 2; this can reflect planned consumption advanced forward and engagement in additional unplanned consumption).

Evidence for analogous compensatory regulatory mechanisms exists in achievement motivation and other domains (Cornil & Chandon, 2016; Fletcher & Sarkar, 2012; Kinnafick et al., 2014; Mummery et al., 2004; Murphy & Taylor, 2019; Sarkar & Fletcher, 2014). However, research has yet to investigate whether registering a hedonic deficit during consumption results in increased hedonic consumption, and while anecdotal evidence indicates reduced consumption satisfaction can spur increased hedonic consumption, this represents but an existence proof—it provides no indication that recognized hedonic deficit generally prompts increased hedonic consumption. In sum, further research is needed to support our proposal that hedonic deficit recognition promotes increased hedonic consumption.

Quantitative Review of the Prior Literature

To quantitatively assess the prior literature for causal evidence of the effects of distraction on our model components, we conducted a meta-analysis of studies involving experimental manipulations of distraction and relevant outcome measures for our model. Here, we summarize only the key aspects of this analysis (see the Supplemental Materials for specific methodological details and our Open Science Framework [OSF] page, which contains data and code at https://osf.io/cuzvt/). We included laboratory or field studies that had manipulated distraction and collected relevant outcome variables, that is, actual enjoyment, consumption satisfaction, and need for further gratification. After screening the titles and abstracts, applying eligibility criteria during article coding (for details, see Supplemental Materials), and transforming all available information to Cohen's d, what emerged was a small number of 16 eligible studies with a total of 45 effect sizes for the three dependent outcomes nested within these studies.[1] It should be noted that this sample was quite thematically and theoretically heterogeneous: None of the studies located specifically designed the research to test the hedonic compensation hypothesis. All were designed to test different aspects of interest (such as whether distraction hampers aesthetic judgments of stimuli), often using somewhat artificial stimulus materials. Most important, the sample also included four studies investigating the effects of distraction on exercising, an area where "consumption" enjoyment (i.e., walking the treadmill) was theorized in these studies to benefit from distracting elements such as music by diverting people's "attention away from the unpleasant somatic sensations associated with strenuous exercise" (e.g., Bird et al., 2019, p. 1163). In light of our research question dealing with distraction's presumed effects in areas where the default consumption experience is assumed to be positive rather than negative or painful, we decided to exclude these four studies and their associated effect sizes from further analyses. Therefore, the final meta-analytic sample included 12 studies comprising 31 effect sizes. Because multiple effect sizes were nested within studies, we submitted the data to three random-effects multilevel meta-analyses for actual enjoyment, consumption satisfaction, and need for further gratification using the R package metafor (Viechtbauer, 2010). This analysis

[1] Even though our initial search also included studies involving mindfulness manipulations, the respective studies were only retained for final analysis insofar as they also contained a distraction manipulation against a control condition (n = 2 studies). We decided to not include the remaining four studies with mindfulness manipulations for the present meta-analysis because coding mindfulness as the "opposite" of distraction (i.e., enhanced attention) would constitute an oversimplification. Both distraction and mindfulness have been related to reduced hedonic processing, albeit via very different processes. Whereas distraction mostly has quantitative effects on attention, mindfulness has more qualitative effects by adopting a certain perspective on one's experiences (such as through acceptance or self-distancing; van Dillen & Papies, 2015).

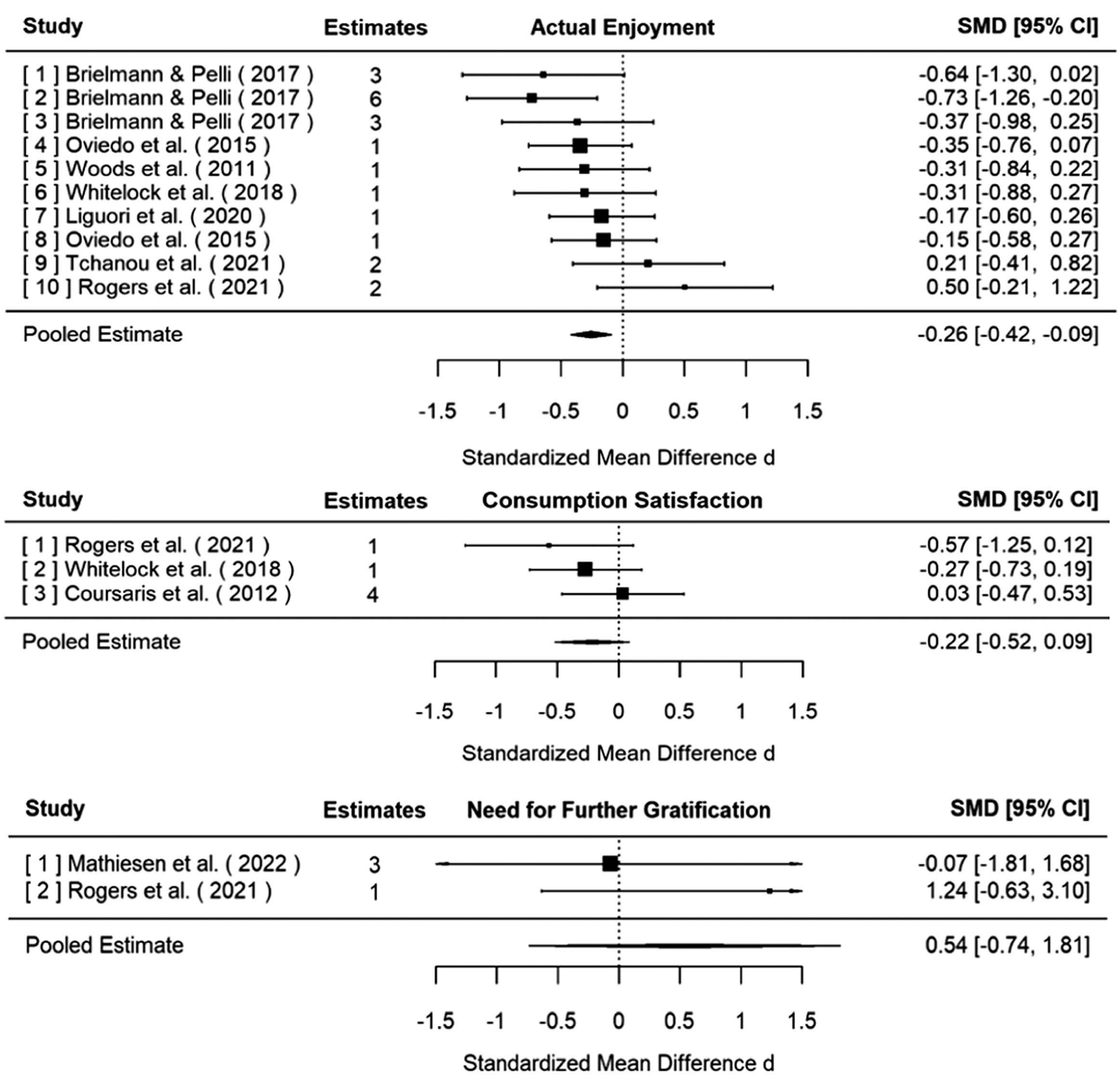
resulted in a small significant average effect of $d = -0.26$ for actual enjoyment ($SE = 0.08$, $p = .003$; 95% CI [−0.42, −0.09]) across 10 studies contributing 21 estimates (see the first forest plot in Figure 2). This average effect indicates that, consistent with our framework, distraction reduced actual enjoyment compared to no-distraction control conditions across studies.

For the analysis of consumption satisfaction, only a small number of three studies contributed a total of six estimates. Due to the low number of data points, this analysis should be interpreted cautiously. The average meta-analytic effect size was $d = -0.22$ (see the second forest plot in Figure 2). This effect was not significant ($SE = 0.15$, $p = .16$; 95% CI [−0.52, 0.09]). At a descriptive level, however, it pointed into the expected direction of a negative relationship between distraction and consumption satisfaction proposed by our framework.

Finally, the analysis of the need for gratification also suffered from a low number of data points (two studies, four estimates). The average meta-analytic effect was $d = 0.54$ ($SE = 0.65$, $p = .41$; 95% CI [−0.74, 1.81]). As can be seen from the forest plot in Figure 2, the associated confidence interval was very large, urging caution not to overinterpret this preliminary estimate, which again was, at the descriptive level, in line with our framework (see Supplemental Materials for key methodological details of included studies). In summary, there was relatively consistent evidence for a negative effect of distraction on actual enjoyment based on our meta-analysis of the prior literature. However, due to a lack of available data, there

Figure 2

Meta-Analyses of Distraction Effects on Actual Enjoyment, Consumption Satisfaction, and Need for Further Gratification



Note. Forest plots of three random effects meta-analyses on actual enjoyment (upper panel), consumption satisfaction (middle panel), and need for further gratification (lower panel). The figure displays the aggregated estimates, but the actual analysis was conducted based on the individual estimates using a multilevel model. Graphical depictions of confidence intervals exceeding the *x*-axis were truncated with an arrow symbol. SMD = standardized mean difference; CI = confidence interval.

was not enough evidential value to confirm or disconfirm the expected negative effect of distraction on consumption satisfaction as well as the expected positive association between distraction and the need for further gratification. If nothing else, this quantitative summary of the preexisting literature establishes that more empirical research is clearly needed to test the predictions from our model, especially regarding distraction's potential indirect effects on hedonic compensation.

In our review and analysis of the existing literature, we have highlighted the plausibility of each HCM path (i.e., Paths A, B, and C of Figure 1). Thus, we have supported the plausibility of our opening claims—that elevated hedonic consumption is frequently caused by consumption experiences falling short of hedonic expectations and that distraction during hedonic consumption (via its negative effect on actual consumption enjoyment) generally causes elevated downstream consumption. With a small-scale field study (Study 1) and a large experience sampling (ESM) project (Study 2), we empirically investigate these claims. In these studies, hedonic (over-)consumption following reduced consumption satisfaction was operationalized in two ways: First, via a postconsumption self-reported need for further gratification. The need for further gratification taps into the motivation for increased hedonic consumption and thus represents an ideal conceptual bridge between consumption satisfaction and subsequent consumption behavior. Second, subsequent consumption was operationalized and analyzed in study-specific ways, as described.

Study 1

Study 1 formally tests our HCM with field experiment data. In this study, participants reported (in an online questionnaire completed just prior to lunch) how much they expected to enjoy their lunch. They then ate their lunch of their own choosing and in their preferred environment under three different conditions: (a) without distraction, (b) while being moderately distracted (i.e., watching an online video), or (c) while being highly distracted (i.e., playing Tetris online). After lunch, participants reported their lunch enjoyment and satisfaction, the amount consumed, and to what extent further gratification was desired after lunch. Hours later, participants reported the amount and frequency of snacking since lunch.

We test our HCM by testing the three key hypotheses that underpin it—that distraction during consumption predicts lower actual consumption enjoyment (Hypothesis 1), that actual-expected enjoyment discrepancy predicts consumption satisfaction (i.e., that lower consumption enjoyment relative to expectations predicts reduced consumption satisfaction; Hypothesis 2), and that lower consumption satisfaction predicts increased hedonic consumption (Hypothesis 3). We also investigated a negative link between consumption satisfaction and a postconsumption need for further gratification. This variable tapping into the motivation for increased hedonic consumption represents an ideal conceptual bridge between consumption satisfaction and subsequent consumption behavior.

Method

Transparency and Openness

All materials and data from the present research are publicly available via our OSF page (https://osf.io/cuzvt/). Various additional measures were completed by participants that are not fully specified in this study. Full details of these measures and procedures are available on our OSF page (https://osf.io/cuzvt/). Please note that although Study 1 data were collected to test a hedonic compensation effect, they were not collected to specifically test the HCM. Thus, although Study 1 was formally preregistered (https://osf.io/ku5vg), various deviations from the original preregistration were required to facilitate a suitable test of the HCM. Given the many researcher degrees of freedom this leaves available to us, we test our HCM in various ways (e.g., with different data exclusion criteria; using actual enjoyment instead of actual-expected enjoyment discrepancy)—like a sensitivity or mini multiverse analysis (Steegen et al., 2016)—and consider the results in their entirety.

Participants

A total of 122 participants (80% female; 16.40% male), the majority (i.e., 74.60%) aged between 18 and 24 years (15.60% and 9.80% were aged between 25 and 44 years and 45 and 64 years, respectively), were recruited to this study. Of them, 52.50% of participants were educated to the secondary school level, 21.30% had some college education, 24.60% had a bachelor's or master's degree, and 1.60% had no formal education. Eligibility criteria for participation were to be aged 18 years or older, to understand English, and to have access to a computer. Participants were recruited through social media and the university participant recruitment tool. For completing the study, participants received student credits or a chance to win a 20-euro gift voucher. This study was approved by the Ethics Committee of the Institute of Psychology, Leiden University (No. V1-3773). Data collection took place between March and June 2022.

Procedure

Interested individuals followed a link to the Study Qualtrics page, which provided full study information and instructions. They were informed the study required 90 min of their time and that they should begin (which involved providing informed consent and clicking to the next page) before lunch. After providing informed consent, participants answered various questions, many of which were not pertinent to the present study. The full question list can be found at the study OSF page (https://osf.io/cuzvt/). Pertinent to the present study, participants reported their age, gender, formal education status, and how much they expected to enjoy their lunch ("How much do you expect to enjoy your lunch?") on a Likert scale ranging from 1 (*not at all*) to 5 (*a great deal*).

Then, participants were randomly allocated to one of three conditions. Participants were informed they should consume a lunch of their own choosing and where they liked, (a) without distraction ("No Distraction condition"; $n = 42$), (b) while watching an online video ("Moderate Distraction condition"; $n = 39$), or (c) while playing Tetris online (van der Wal & van Dillen, 2013; "High Distraction condition"; $n = 41$). All participants were instructed that their lunch should last for a minimum and maximum of 15 min and 35 min, respectively. After lunch, participants reported how much they consumed ("How much of your lunch did you finish?") on a Likert scale ranging from 1 to 6 (1 = *none of it*; 2 = *about a quarter*; 3 = *about half*; 4 = *almost everything*; 5 = *everything*; 6 = *If you ate more than your lunch, specify how much below*); if they consumed more than their intended amount, they specified the amount in an open text box. Participants then reported how much they enjoyed lunch (“How much did you enjoy your lunch?”) on a Likert scale ranging from 1 (*not at all*) to 5 (*a great deal*), how distracted they were during lunch (three items: “During lunch I was distracted by things unrelated to eating.”; “During lunch I had things on my mind that were unrelated to eating.”; “I was paying attention to my food while eating lunch”) on a Likert scale ranging from 1 (*strongly disagree*) through 4 (*neither agree nor disagree*) to 7 (*strongly agree*), how satisfied they were after lunch (“How satisfying was your lunch?”) on a Likert scale ranging from 1 (*not satisfying at all*) to 5 (*very satisfying*), how much they desired further gratification (“To what extent do you desire further gratification?”) on a Likert scale ranging from 1 (*no desire for further gratification*) to 7 (*high desire for further gratification*), and how long it took them to finish/stop consuming their lunch (“How long did you take to finish your lunch?”).

Participants were also presented with two items to confirm they were paying attention to the questionnaire content (“How many days are there in a year?”; “What color is the sky usually?”). Following, participants were instructed to leave the questionnaire and return to it before their dinner. Upon returning to the questionnaire, participants reported since their lunch the number of consumed snacks (“How many pieces/portions did you consume in total between lunch and dinner?”) on a Likert scale from 1 (*none*) through 5 (“4”) and 6 (“5”) to 12 (*more than 10*) and snacking frequency (“How many times did you consume food between lunch and dinner?”) on a Likert scale ranging from 1 (*I didn’t eat anything after lunch*) through 3 (*I ate two times*) and 4 (*I ate three times*) to 6 (*I ate more than four times*). Participants were then debriefed and compensated for their involvement.

Conditions

No Distraction. Participants in this condition were instructed to eat their lunch without distraction. To investigate participant instruction adherence, they were asked to reveal whether they were distracted during lunch (“We asked you to do nothing else while eating your lunch. We would like you to indicate here whether you complied with these instructions. Please answer honestly. This will have no effect on your compensation. What did you do during your lunch?”), with the response categories: “I didn’t do anything other than eat my lunch,” “Watching television,” “Interact with smartphone,” “Interact with computer,” “Reading,” “Listening to music,” “Talking to others,” “Something else.”

Moderate Distraction. Participants in this condition were provided with a link to a 35 min YouTube video titled “Astronaut Chris Hadfield Reviews Space Movies, from ‘Gravity’ to ‘Interstellar’” and were instructed to watch it all. Participants were informed they must answer questions about the video afterward. After watching the video, participants responded to three attention check questions: “What was the first movie the astronaut reviewed?” with the response categories: “Interstellar,” “Gravity,” and “Passengers”; “When reviewing the movie ‘Passengers’,” the astronaut explains a way of creating the sensation of gravity in space. “How can this be done?” with the response categories: “By spinning the spaceship,” “By tying the passengers down,” “By creating airtight environments”; “What does the astronaut think of the movie ‘Armageddon’?” with the response categories: “He thinks it is really bad, because there is so much wrong in this movie.” “He thinks it is very inspiring, because the movie paints an accurate picture of space.” “He thinks it is very entertaining, because the movie is humorous.”

High Distraction. Participants in this condition were provided with a website link where they were instructed to play Tetris while eating lunch (see van der Wal & van Dillen, 2013). They were asked to press the keys with one hand while eating with the other.

Analytic Procedures and Strategy

All hypotheses were tested via path modeling using the “sem” function from the “lavaan” package in R. Maximum likelihood estimation was used to estimate regression coefficients. The first part of the path model estimated the effects of our experimental manipulations on self-reported (i.e., experienced) distraction. Distraction was modeled to predict actual-expected enjoyment discrepancy directly rather than indirectly, as per our HCM. This was done for analytic convenience. However, as described below, an alternative path model in which distraction predicts actual enjoyment directly was also explored. The amount consumed during the initial consumption episode was also controlled to dispel concerns that this factor may explain the link between distraction and actual-expected enjoyment discrepancy. The next variables in the model were consumption satisfaction and the postconsumption need for further gratification. Finally, the need for further gratification was modeled as predictor of snacking amount and frequency in the period (i.e., afternoon) following the initial consumption at lunch. Supplemental Figure S2 illustrates the initial and revised path model.

To test our HCM, expected consumption enjoyment was subtracted from actual consumption enjoyment to create the item actual-expected enjoyment discrepancy, whereby higher values reflect consumption being more enjoyable than expected. Also, self-reported distraction was included in our HCM; therefore, the three distraction items were combined (the “attention” item was reversed beforehand) to form a composite distraction item ($\alpha = .61$). To investigate the effect of our distraction conditions in our path model, condition was dummy-coded, with the control condition serving as baseline.

Iterative Analyses. Given the absence of a preregistration specifying how our model would be tested, we adopted a minimultiverse/sensitivity analysis approach to our analytic strategy. This involved analyzing our data using increasingly stringent data exclusion criteria (details to follow) and concluding theoretical support only after a nuanced consideration of all iteration results. Accordingly, our model was tested by applying six successive exclusion criteria regarding participant compliance, resulting in increasingly restrictive (but also less strongly powered) data sets. The Iteration 1 was conducted on all available participants that were assigned to a condition and returned to the questionnaire so that data on all variables could be analyzed (n = 110), accepting all further possible sources of error and bias in the data. The Iteration 2 (n = 106) excluded participants who did not pass the attention check. The Iteration 3 (n = 93) additionally excluded noncompliant participants from the no-distraction condition who reported getting distracted (e.g., listening to music, watching television, talking to someone). The Iteration 4 (n = 80) additionally excluded participants who started the questionnaire before 09:00 hr or after 17:00 hr. The Iteration 5 (n = 73) additionally excluded participants who either started the questionnaire before 11:00 hr or finished the questionnaire before 12:00 hr already, and the Iteration 6 (n = 64) additionally excluded participants who took less than 2 hr overall to complete the study.

Results

Descriptive Findings

Supplemental Table S2 presents a descriptive summary and correlation analysis of the main study variables for Iterations 1 through 6. The mean questionnaire duration (including the gap whereby participants were not actively completing the questionnaire) for this sample was 5.30 hr ($SD = 1.70$ hr), with participants taking a mean of 16.48 min ($SD = 6.53$ min) to consume their lunch.

Initial Model

The initial path model closely followed our theoretical framework, as specified in Figure 1. The path-analytic results from all analytic iterations of this model (Path Model 1) are displayed in the upper half of Table 1 and are summarized graphically in Supplemental Figure S2. The first part of the model contained the effects of the experimental condition (dummy-coded) on distraction, controlling for consumption amount (see Supplemental Figure S2, upper panel, for an illustration of the model). Distraction, in turn, was modeled as a predictor of the discrepancy between actual and expected enjoyment, which was modeled as a predictor of consumption satisfaction. Consumption satisfaction, in turn, was modeled as a predictor of the need for further gratification, with snack amount and frequency as the final outcomes of the path model.

Effect of Condition on Distraction. Both the high and moderate distraction conditions had a significant effect on self-reported distraction across all six iterations (see Table 1). As expected, the high distraction condition (playing Tetris) had a stronger effect than the moderate distraction condition (watching a video). In descriptive terms, the average distraction means in the high, moderate, and no-distraction conditions averaged across all iterations were 5.31, 4.86, and 4.19, respectively (see Supplemental Table S3 for the condition means).

Distraction and Enjoyment. Across all iterations, distraction did not reliably predict the discrepancy between actual and expected consumption enjoyment, even though, descriptively, results were in the expected direction of an increasingly negative discrepancy for increasing levels of distraction (see Table 1). Exploratory analyses revealed that replacing the actual-expected difference score with actual enjoyment, the presumed entry point of distraction according to our model (see Figure 1), improved the model considerably, such that the effect of distraction on actual enjoyment was reliable in all six iterations (see Table 1, lower part). Henceforth, we also present results for this revised version (Path Model 2) and revisit this model distinction in Study 2.

Enjoyment and Consumption Satisfaction. In both path models, the respective enjoyment measure reliably predicted consumption satisfaction across all iterations. However, as can be seen from Table 1, the effect was less pronounced when regressing consumption satisfaction on the actual-expected enjoyment difference score (Path Model 1), as compared to when regressing consumption satisfaction on actual enjoyment (Path Model 2).

Consumption Satisfaction and Hedonic Overconsumption. As both estimated path models share identical structure in their last part, results are identical for the connects between consumption satisfaction, the need for further gratification, and snacking behavior (amount and frequency). Consumption satisfaction significantly predicted the need for gratification across all iterations, such that lower satisfaction was associated with an increased need for further gratification. Need for gratification, as reported after lunch, reliably predicted the reported amount of snacking in the immediate hours following lunch in four out of six iterations and the frequency of snacking in three out of six iterations.[2]

Discussion

The analyses for Study 1 generally supported the majority of the hypothesized HCM paths, but with varying strengths of evidence. First, there was clear support for our manipulations to induce varying levels of distraction in participants, as intended, with the highest levels of distraction found in the high distraction condition (i.e., playing Tetris). Distracted participants enjoyed lunch significantly less relative to participants instructed to eat their lunch without distraction, thus supporting prior research (e.g., Garbinsky & Klesse, 2021). However, this effect was only found when modeling a direct effect of distraction on actual enjoyment and not when modeling the difference between actual and expected enjoyment. One possible explanation is methodological, in that modeling a difference score results in lower reliability and precision. A second explanation is that participants may have had difficulty forming an accurate judgment of their hedonic expectations for consumption experiences. Reduced consumption enjoyment (either as a difference score or as actual enjoyment) in turn predicted lower consumption satisfaction, with stronger effects regarding actual enjoyment. Finally, results converged such that consumption satisfaction was negatively related to a greater need for further gratification postconsumption, which itself predicted, albeit less robustly, an increased amount and frequency of snacking.

Despite these identified effects and general support for our model, a dose of caution is needed when interpreting these findings. First, the quality of many participants' data was highly questionable: Several participants in the no-distraction condition admitted being somewhat distracted during lunch, and some participants completed the questionnaire much faster than they should have, suggesting imperfect compliance. However, it was somewhat reassuring to see that, as analyses progressed from optimal power (Iteration 1) to the most rigid data set of exclusion criteria (Iteration 6), results/regression weights did not change very much, suggesting some consistency. Nonetheless, we should be careful not to overinterpret our results, and more data are clearly needed to test the hypothesized effects with a high level of statistical power.

Study 2

Like Study 1, Study 2 tests the three key hypotheses that make up our HCM.[3] However, unlike Study 1, Study 2 takes an observational approach that tests our HCM with much more data (6,965 usable data points) across all major consumption domains (e.g., food, drink, media/audio, leisure reading), with greater ecological validity (participants were not directed toward a standardized distraction

[2] We also analyzed this effect using zero-inflated Poisson regression, as snack amount and frequency data were positively skewed due to an abundance of zero values. Statistical conclusions were identical for 11 out of 12 analyses, the only exception being that the effect of need for gratification on snacking amount was not significant in Iteration 4, $p = .068$.

[3] Please note that Studies 1 and 2 were conducted concurrently alongside one another, so the findings of one study did not inform the methodology of the other.

Table 1

Path Analysis Findings as Standardized Regression Coefficient for Study 1

Model path: Predictor	Model path: Outcome	Iteration 1 (n = 110)	Iteration 2 (n = 106)	Iteration 3 (n = 93)	Iteration 4 (n = 80)	Iteration 5 (n = 73)	Iteration 6 (n = 64)
			Path Model 1				
High versus no distraction	Distraction	0.41***	0.39***	0.47***	0.39**	0.42**	0.44**
Moderate versus no distraction	Distraction	0.23*	0.23*	0.33**	0.32*	0.34*	0.33*
Consumption amount	Distraction	−0.15	−0.15	−0.20*	−0.23*	−0.20	−0.18
Distraction	Actual-expected enjoyment	−0.12	−0.12	−0.15	−0.18	−0.20	−0.17
Actual-expected enjoyment	Consumption satisfaction	0.18*	0.20*	0.28**	0.28**	0.37***	0.40***
Consumption satisfaction	Need for further gratification	−0.24**	−0.22*	−0.25*	−0.24*	−0.33**	−0.28*
Need for further gratification	Snacking amount	0.27**	0.25**	0.23*	0.20	0.23*	0.19
Need for further gratification	Snacking frequency	0.29***	0.30***	0.26**	0.17	0.21	0.21
			Path Model 2				
High versus no distraction	Distraction	0.41***	0.39***	0.47***	0.39**	0.42**	0.44**
Moderate versus no distraction	Distraction	0.23*	0.23*	0.33**	0.32*	0.34*	0.33*
Consumption amount	Distraction	−0.15	−0.15	−0.20*	−0.23*	−0.20	−0.18
Distraction	Actual enjoyment	−0.31***	−0.29***	−0.36***	−0.34***	−0.35***	−0.34**
Actual enjoyment	Consumption satisfaction	0.68***	0.68***	0.69***	0.70***	0.71***	0.75***
Consumption satisfaction	Need for further gratification	−0.24**	−0.22*	−0.25*	−0.24*	−0.33**	−0.28*
Need for further gratification	Snacking amount	0.27**	0.25**	0.23*	0.20	0.23*	0.19
Need for further gratification	Snacking frequency	0.29***	0.30***	0.26**	0.17	0.21	0.21

Note. Regression coefficients are standardized. Iterations 1 through 6 represent model runs with increasingly restrictive inclusion criteria. Path Model 1 includes the difference between actual and expected enjoyment; Path Model 2 includes actual enjoyment (see Supplementary Materials for path model illustrations).

* $p < .05$. ** $p < .01$. *** $p < .001$.

activity like Tetris. Rather, distractions arose organically in daily life), and (due to our extensive data set) with a greater capacity to remove low-quality data resulting from poor participant adherence or other factors. In sum, Study 2 has the capability to support our HCM if the true population effects are in the theorized direction.

Also, like Study 1, Study 2 tests our hedonic compensation hypothesis. However, two different models needed to be run. Model 1 tests our hedonic compensation effect via the psychological proxy marker need for further gratification. Model 2 extends the analysis via a behavioral marker of hedonic compensation. This two-step process was opted for to ensure we could test the HCM model with as many data points as possible (including a good behavioral marker of hedonic compensation/overconsumption would lead to a substantial data loss). Specifically, increased hedonic consumption in Model 2 was tested via an additional path between the need for further gratification and the duration from the end of the consumption episode to the start of the next episode. This is a riskier prediction given the expected data loss and the likely smaller population effect magnitude. However, this effect would help justify our psychological proxy of increased consumption and evidence increased hedonic consumption directly. Indeed, consuming again more quickly indicates elevated consumption within a set temporal period, and overall, if such consumption is not regulated. We aim to provide convergent evidence for this effect by examining whether need for gratification also negatively predicts the duration until the end of the subsequent consumption episode, and convergent evidence for all model effects by testing indirect effects (e.g., Does actual-expected enjoyment discrepancy indirectly predict need for further gratification?) and direct effects between distal model factors (e.g., Is the direct effect between actual-expected enjoyment discrepancy and need for further gratification negative, as theorized?).

We chose an ESM design to optimally test our HCM. ESM enables studying participants consumption experiences very close in time and context to actual consumption. Proximity is critical for properly testing our HCM, for people often have difficulty remembering the finer aspects of consumption the further in the past that consumption experience is (Gmel & Daeppen, 2007). ESM also enables a robust theoretical test, given that the data will be based upon real-world consumption experiences (Hofmann & Patel, 2015). This contrasts with laboratory approaches, which, although critical for testing causal assumptions, are often constrained to retrieve data from contrived situations that do not reflect real-world experiences or behaviors (Inbar, 2020). The ESM design also enables testing of hypotheses at the within-person level (Gabriel et al., 2019)—the (process) level appropriate to our theory. For instance, Hypothesis 1 tests whether people, when they experience elevated distraction during consumption, tend to experience less enjoyment relative to expectations. It does not test whether people who experience greater distraction on average during consumption experience less enjoyment relative to expectations—a between-person question is not of primary interest here. ESM enables within-person analyses via its multiple measurement protocol. Finally, ESM typically provides high statistical power to precisely estimate the effects of interest and enables dynamic (i.e., over time) test of effects (e.g., the link between need for more gratification and duration to subsequent consumption).

Method

Transparency and Openness

Our preregistration, materials, and data from the present research are publicly available via the OSF (https://osf.io/cuzvt/). Various additional measures were completed by participants that are not fully specified in this article. Full details of these measures and procedures are available on our OSF page (https://osf.io/cuzvt/). Also, we deviated from our preregistration plan in the following places: (1) Distraction during consumption was measured using two items rather than the preregistered one item—a change made because two items enabled us to capture the underlying construct more fully. This change caused no substantive differences in our results (see Supplemental Figures S3 and S4 for these results); (2) Contrary to our preregistration plan, we do not test our HCM within each specific consumption domain (e.g., Does the hedonic compensation effect exist in the media/audio domain?). This was difficult to do given participants often reported engaging in multiple consumption types per consumption episode (e.g., food and drink consumption), meaning a suboptimal number of data points were available for testing our HCM with a single consumption type (e.g., food consumption only). Nevertheless, we could investigate some nuance here by merging consumption categories or investigating those consumption domains that contained a large amount of data (e.g., food, drink). Please see the Exploratory Analyses section "Is the Hedonic Compensation Effect Really (Consumption) Domain-General?" for these analyses; (3) For the same reason as point (2), we do not include in this article person-level analyses of our hedonic compensation effect and body mass index changes. These analyses show no significant relationship between the average postfood consumption need for further gratification and body mass index change over a 4-month period (contrary to our hypothesis; see Supplemental Figure S5 for these results); (4) We used the amount participants consumed during the consumption episode as a model control variable instead of the extent to which consumption amount matched expectations, which is what we preregistered. We made this change because we wanted to show that increased postepisode consumption reflects excess consumption (instead of action taken to deal with a consumption experience where one consumed less)—controlling for "actual" consumption amount enabled this to be tested more simply. This deviation had no substantive impact on our results (see Supplemental Figures S6 and S7 for these results); (5) We preregistered good multilevel path model fit as a comparative fit index (CFI) of 0.90 or higher, a standardized root-mean-square residual (SRMR) of 0.05 or lower, and a root-mean-square error of approximation (RMSEA) of 0.08 or lower—conventional criteria for path models (Weston & Gore, 2006). However, we now recognize that more appropriate multilevel model fit criteria target each level of analysis separately (González-Romá & Hernández, 2017). We thus retain our preregistered fit criteria but apply them only to the within-person model (the primary study focus).

Participants

Two hundred twenty participants aged between 18 and 71 years ($M = 26.10$ years, $SD = 8.90$; 162 females, 57 males, one unknown) were recruited to this study. This sample-size was preregistered and was expected to provide sufficient Level 1 data to identify small effects (i.e., Cohen's $d = 0.1$). Most (93.18%) participants were of German nationality (one participant did not report their nationality) and were students (65.45%). Twenty-six participants were in full-time employment, 24 were in part-time employment, 10 were unemployed, two were on parental leave, six were in training, and seven reported their occupation as "other" (one participant did not report their occupation). Following data exclusions (detailed in full in the Descriptive Findings section), 211 participants remained in the final sample. 93.84% were of German nationality, 65.40% were students, 11.85% were in full-time employment, 11.37% were in part-time employment, 4.74% were unemployed, 0.95% were on parental leave, 2.84% were in training, and 2.84% reported their occupation as "other."

Participants were recruited via Ruhr University Bochum mailing lists and publicly available websites and asked to participate in research investigating everyday consumption experiences. Eligibility criteria included owning a smartphone, being older than 18 years of age, being able to engage with all study aspects, and having an email account. Participants received a €10 voucher for completing the intake survey and the ESM phase[4] and an additional €30 voucher if they completed at least 75% of the surveys received during the ESM phase. Participating students could receive course credit instead of vouchers (one credit for intake and ESM phase, four extra credits for completing 75% of the surveys). This study was approved by the Ruhr University Bochum Review Board (No. 615). Data collection took place during the COVID-19 pandemic when state/governmental restrictions were in place in Germany between July and November 2020.

Procedure

Study data were gathered via an initial online intake survey that measured participant demographics (e.g., age) and a brief online survey sent out frequently during the following 7-day ESM phase, which measured factors directly pertaining to our HCM (e.g., distraction during consumption). All study information and measures were provided to participants in the German language after being back translated from English by two researchers highly proficient in both languages (a document detailing translations is available at our OSF page at https://osf.io/cuzvt/).

Participants were informed via an online platform (i.e., https://www.Qualtrics.com) that the study purpose was to better understand everyday consumption experiences (the exact study purpose was not revealed to avoid demand characteristics; Orne, 2009). Participants were also informed of study requirements, compensation they would receive for involvement, and inclusion criteria. Study requirements were reinforced by phone before formal participant registration. During this phone call, we emphasized that participants should pay careful attention to surveys received during the ESM phase and that removal from the study could result if found responding carelessly. Participants were then registered for the study on the SurveySignal website (https://www.surveysignal.com), and immediately after received a signal (i.e., a text message) containing a link to the intake survey, which they were asked to immediately complete.

During the intake survey, participants reported their age, gender, nationality, and occupation. Participants were then provided with instructions on how to complete the ESM phase beginning the following day. Key instructions were to complete ESM surveys as soon as received, to ensure their smartphone remained charged to enable receipt of each survey, to keep their smartphone near them between the hours of 09:00 hr and 22:00 hr, to complete as many questionnaires as possible, to not complete surveys when unsafe or inappropriate to do so (and in such circumstances to wait until safe or appropriate to do so), to not artificially change their consumption behavior as a result of their involvement in this study, and to contact the lead investigator if they experienced problems.

Participants were then informed that "consumption" in our ESM survey referred to engaging in one of the following behaviors: eating, drinking (except water), smoking (including e-cigarettes, vaping), use of media/audio devices for leisure purposes (5 min minimum), recreational drug use, gambling, gaming (digital and analog), leisure reading, and sport and exercise. Participants were also provided with the following definition to help determine how many consumption episodes to report since the previous signal was received:

> A consumption episode refers to the distinct period of time wherein a consumption behavior(s) takes place. Thus, having a snack between 10:00hr and 10:05hr would represent a single consumption episode. One consumption behavior (having a snack), or many consumption behaviors (having a snack while drinking a coffee and using one's mobile phone), can take place within a single consumption episode. In situations where one consumption behavior extends beyond a prototypical consumption period (e.g., having coffee with breakfast, but then finishing the coffee a few hours after breakfast), please define the entirety of this period as one singular consumption episode. The reason for this is that the process of consumption has yet to cease. It may not always be easy to define when a consumption episode ends. For instance, eating from a bag of sweets over the course of a day may leave you with a very large consumption episode (given "consumption" may, by some people, be interpreted as continuous over this period). In these (and similar) situations it is important that you use your own judgement to appraise when you feel a distinct consumption period has ended or is still ongoing. Please also report consumption episodes that started before the previous signal received but finished before the present signal. Do not report consumption episodes that are currently ongoing.

Participants were then given three consumption-related scenarios and accompanying answers as examples of how to accurately report consumption episodes. Finally, participants completed a practice version of the ESM survey.

The following day, participants began the 7-day ESM phase. During this phase, participants received seven identical surveys per day (a hyperlink in the signal directed them to the survey in Qualtrics), thus 49 surveys over the 7 days. These signals were received by participants within the 13-hr period between 09:00 hr and 22:00 hr each day. This 13-hr period was split into seven "blocks" of 1 hr 51 min (e.g., Block 1: 09:00 hr to 10:51 hr); one signal only was sent to participants during each block, with the specific time the signal was sent being random. In instances when participants did not click on the signal hyperlink to complete the survey within 15 min of receiving it, a reminder signal was sent with an identical hyperlink. Each survey hyperlink was deactivated 30 min after the original signal was sent to participants. After completing the ESM phase, participants were thanked for their involvement and fully debriefed about the specific study aims.

[4] A technical issue with the survey distribution provider, which caused only the reminder surveys to be sent out in full, led this threshold to be reduced from 75% to 60% during the period affected.

ESM Procedure and Protocol

See Figure 3 for a flow diagram of the ESM phase survey. During each survey, participants first reported the number of consumption episodes experienced (ranging from "0" to "6 or more") since the previous signal received.[5] The defining criteria for a consumption episode (initially provided during the intake survey) were included alongside this item to facilitate accurate responding. If participants reported experiencing one consumption episode since the previous signal, they were asked to report the start and finish times of this consumption episode. If participants reported more than one consumption episode, they were informed to complete the remainder of the survey with respect to the most recent consumption episode (they were then asked about the consumption episode start and finish time). If participants reported experiencing no-consumption episodes since the previous signal, they were asked how many consumption episodes they had experienced since the signal before the last signal (i.e., two signals ago). This prevented participants from reporting "0" consumption episodes (i.e., when consumption had actually taken place) to complete a substantially shorter and less burdensome survey. If participants reported at least one consumption episode since two signals ago, the remaining survey content was the same as if they had initially reported experiencing a consumption episode since the previous signal. If participants again reported experiencing no-consumption episodes since the signal before the last signal, the survey ended.

After reporting the consumption episode start and finish times, participants reported the consumption location from a drop-down menu. The options available were as follows: "home," "another person's home," "restaurant/cafeteria," "pub," "at work," "university/college/school building," "outdoor urban," "outdoor non-urban," "sport hall/gym," "casino/gambling establishment," "public transport," "private transport," "other." If participants reported "other," they were asked to report the consumption location in a text box. Participants then reported how many consumption types they engaged in during the consumption episode (ranging from "0" to "6"). Here, eating was one type, drinking another type, smoking another type, and so forth—these "types" matched the list of behaviors defined as representing consumption (see the Procedure section for details). Participants then selected which consumption type(s) they engaged in via a drop-down menu. These selections further branched into 46 subdomains (e.g., unhealthy main meal, healthy snack). If participants reported "other" for the consumption type or subdomain, they were asked to report their consumption type in a text box. Participants who reported experiencing only one consumption type (e.g., just "eating") were then asked how much consumption conflicted with other personal goals ("To what extent was engagement in this consumption behavior in conflict with at least one of your other personal goals?") on a Likert scale ranging from 1 (*no conflict at all*) to 7 (*very high conflict*). Participants were presented with a minor variation of this and other items if they experienced more than one consumption type in their most recent consumption episode (e.g., eating and drinking); for instance, "To what extent was engagement in this consumption episode in conflict with at least one of your other personal goals?" (see the OSF page at https://osf.io/cuzvt/ for these adapted items). Participants were then asked about their expected consumption enjoyment ("How much did you expect to enjoy consumption?") and actual consumption enjoyment ("How much did you actually enjoy consumption?") on a Likert scale ranging from 1 (*not enjoyable at all*) to 7 (*highly enjoyable*) and about their expected consumption amount ("How much did you expect to consume?") and actual consumption amount ("How much did you actually consume?") on a Likert scale ranging from 1 (*much less than I typically would in this situation*) through 4 (*the same as I typically would in this situation*) to 7 (*much more than I typically would in this situation*). Participants then reported how satisfied they were with consumption ("Overall, how satisfied were you with the consumption experience?") on a Likert scale ranging from 1 (*not satisfied at all*) to 7 (*highly satisfied*) and to what extent they desired further gratification ("After consumption had finished, to what extent did you desire further gratification?") on a Likert scale ranging from 1 (*no desire for further gratification*) to 7 (*high desire for further gratification*). Finally, participants were presented with two statements regarding their level of distraction during consumption ("During the consumption episode I had things on my mind that were unrelated to consumption" and "During the consumption episode I was distracted by things unrelated to consumption") and their level of stress during consumption ("During the consumption episode I felt stressed"). Participants reported the extent to which they agreed/disagreed with these three statements using a Likert scale ranging from 1 (*I strongly disagree*), through 4 (*I neither agree nor disagree*), to 7 (*I strongly agree*).

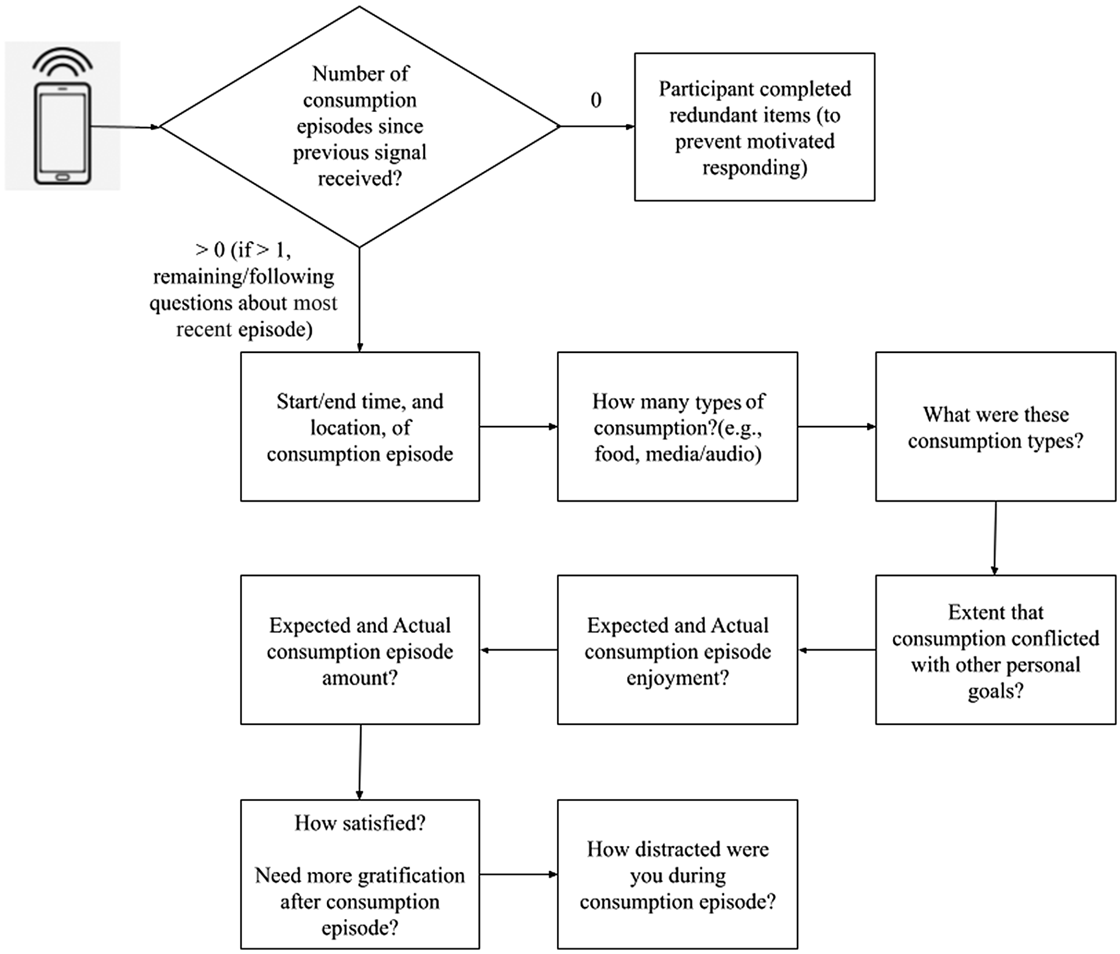
Analytic Procedures and Strategy

Data were organized and cleaned in Microsoft Excel and then R (Team, 2013). All multilevel path models were tested using the "sem" function from the "lavaan" package in R (Rosseel, 2012). Multilevel models (i.e., single-path) were tested using the "lmer" function from the "lme4" package in R (Bates et al., 2007). Maximum likelihood estimation was used for analyses, except that which tested the exploratory hypothesis that the need for further gratification would predict whether subsequent consumption type was similar to the former episode. Here, the robust estimator weighted least squares means and variance adjusted were used (Anderson et al., 2014).

Data from each completed ESM survey represented a single data point for testing each hypothesis. Distraction during consumption was calculated by taking the average of the two distraction items ($\alpha = .65$). actual-expected enjoyment discrepancy was calculated by subtracting participants expected consumption enjoyment from their actual consumption enjoyment (higher values reflect consumption being more enjoyable than expected). Duration to subsequent consumption was calculated by subtracting the reported start time of a consumption episode from the reported finish time of the previous episode. Duration to the end of the next consumption episode and to the start of the consumption episode after the next episode (see the Exploratory Analyses section for why we calculated this variable) were calculated similarly. Consumption duration (i.e., how long the consumption episode lasted—see the Exploratory Analyses section for details) was calculated by subtracting the reported start time from the reported finish time of the consumption episode. An exploratory question (see the Exploratory Analyses section for details) was whether a higher postconsumption need for further gratification

[5] For the first signal participants received during the ESM phase, they were asked to report the number of consumption episodes they had experienced within the previous 3 hr.

Figure 3
Flow Diagram Depicting Study 2 ESM Questionnaire



Note. Flow diagram depicting steps to be completed upon receiving each experience sampling (ESM) survey. The redundant items presented to participants (if they reported "0" consumption episodes since the previous signal) were identical to if >0 consumption episodes had been reported. The redundant items, however, pertained to consumption experiences since the signal before the previous signal (i.e., two signals ago) instead of the previous signal (i.e., one signal ago). Participants were presented with these redundant items to prevent participants from reporting "0" simply to complete a substantially shorter survey (data were not used in further analyses). Distraction was measured using two items (for full details about items, see the ESM Procedure and Protocol section). The "boxes" were presented in the stated order for each survey. Items within some boxes, however, were presented in a random order to participants. The flow diagram does not show items that were measured but were not utilized in the study.

rendered participants more likely, in the next episode, to engage in similar consumption types to the prior episode (e.g., eating food after food-related consumption episode). To investigate this, a binary variable was created—coded "1" if the subsequent consumption episode contained at least one behavior that was the same as in the former episode (e.g., eating in the present and the previous episode) and "0" if all consumption behavior types were different (e.g., eating in the present episode but surfing social media in the previous episode).[6] All other model variables were based upon their respective items measured without additional preprocessing.

Some models included variables calculated using data from later consumption episodes (e.g., duration to subsequent consumption was calculated using the start time of the next consumption episode). These variable data were only included in our analyses if the later focal consumption episode took place within the same day—the reason being that the gap between the last signal of 1 day and a signal of the next was at a minimum of 10 hr (this duration would likely hinder accurate recall of consumption experiences). Also, variables calculated using data from a later consumption episode (e.g., duration to subsequent consumption) were only calculated if data came from surveys not separated by an uncompleted survey, and if in the next completed survey, the participant reported only experiencing one consumption episode since the previous signal received.

[6] To ease calculation, data were excluded where more than three consumption behaviors were conducted in any one consumption episode. For instance, eating, drinking, and smoking while watching television.

ESM data are nested (observations within persons). Thus, multilevel path models were used for most analyses.[7] All model variables were person-mean-centered to test within-person effects (i.e., between-person variance was removed). The within-person component of multilevel path models was regarded as displaying good fit with the data if the CFI was 0.90 or higher, the SRMR was 0.05 or lower, and the RMSEA was 0.08 or lower (Hu & Bentler, 1999; MacCallum et al., 1996; H. W. Marsh et al., 2004). To investigate this, Level 2 (i.e., the person level) of our multilevel path models was saturated (i.e., modeled so Level 2 had perfect fit) by adding all endogenous variable variances and covariances (see https://lavaan.ugent.be/tutorial/multilevel.html for details). This ensures fit statistics can be interpreted exclusively at the nonsaturated level (here, Level 1—the "observation" level, Ryu, 2014). The Type 1 error rate increases with each additional test of effects (Lakens & Etz, 2017). Thus, the Benjamini–Hochberg Correction for Multiple Comparisons (Thissen et al., 2002) was used on confirmatory hypotheses to ensure no more than 5% of significant effects represented false positives. p values less than .05 in our path models indicate significance after Benjamini–Hochberg Correction. Two-tailed tests were used for all analyses.

Results

Descriptive Findings

Tables 2 and 3 present a descriptive summary and multilevel correlation analysis of key study variables, respectively. Of the 10,780 surveys sent to participants during the ESM phase, 8,782 (81.47%) were completed in full (14.81% were completely missing; 1.29% were partially missing; 2.43% were second or third completions/duplicates for a given measurement occasion). This equates to a mean of 39.92 fully completed surveys per participant of a maximum of 49 (SD = 8.68; range = 0–49). Only nonduplicate data from fully completed surveys were retained for further analysis. A further 1817 data points were excluded from subsequent analyses because (a) no-consumption episode was reported since the previous signal (1,006 data points), (b) the consumption episode was more than 3 hr away from the survey about that episode (232 data points), (c) the consumption episode lasted longer than 3 hr (66 data points), (d) the survey about the consumption episode was completed in less than 75 s (360 data points), (e) participants completed more than 50% of their surveys in less than 75 s (all data for four participants, i.e., 139 data points), or (f) participants completed fewer than eight surveys in total (all data for four participants, i.e., 14 data points). This left 6,965 data points available for further analyses.

Of the included data points, the mean ESM survey duration was 3.16 min (SD = 1.50 min; range = 1.77 min–10.88 min). The mean consumption episode duration was 33.09 min (SD = 11.36 min; range = 10.66 min–98.69 min). Since the previous signal that participants received, participants reported experiencing one consumption episode on 60.72% occasions, two consumption episodes on 24.64% occasions, three consumption episodes on 10.25% occasions, four consumption episodes on 2.68% occasions, five consumption episodes on 0.86% occasions, and six or more consumption episodes on 0.85% occasions. Also, participants reported conducting one consumption type (e.g., food, drink, media/audio) during 62.83% consumption episodes (where more than one consumption episode was reported, participants reported the number of consumption types with respect to the most recent episode), two consumption types during 30.50% consumption episodes, three consumption types during 5.86% consumption episodes, four consumption types during 0.73% consumption episodes, and five consumption types during 0.09% consumption episodes. No participants reported conducting six consumption types in a consumption episode. Most consumption episodes took place in the participants' homes (66.15% instances). The remaining consumption episodes took place at another person's home (7.64%), in a restaurant/cafe (3.24%), in a pub (0.24%), while at work (6.26%), within a university building (0.75%), in an outdoor urban setting (4.98%), in an outdoor nonurban setting (3.59%), in a sports building/gym (1.06%), at a casino/gambling establishment (0.01%), or on public (1.94%) or private (2.89%) transport. Participants reported "other" for this item on 1.25% of occasions.

Main Analyses

Model fit indices show Model 1, S-BX2 (5) = 142.96, $p < .001$; CFI = 0.87; SRMR = 0.05; RMSEA = 0.06 (90% CI [0.05, 0.07]), and Model 2, S-BX2 (9) = 60.86, $p < .001$; CFI = 0.88; SRMR = 0.05; RMSEA = 0.05 (90% CI [0.04, 0.06]), on the whole fit the data well. The CFI for both models was marginally below the good model fit criteria of 0.90 or above.

Distraction and Consumption Enjoyment. Distraction during hedonic consumption was theorized to render consumption less enjoyable relative to expectations while controlling for the amount consumed (Hypothesis 1). In support, distraction negatively predicted actual-expected enjoyment discrepancy (Figure 4, $\beta = -0.09$, $p < .001$, 95% CI [−0.11, −0.07]) controlling for the amount consumed ($\beta = 0.04$, $p < .001$, 95% CI [0.02, 0.06]). Decomposing this relationship from the perspective of our model further, we expected this reduction to be primarily brought about by a negative link between distraction and actual consumption enjoyment (rather than by a negative link between distraction and expected consumption enjoyment). Our secondary analyses support this hypothesis, as the effect of distraction on actual consumption enjoyment ($\beta = -0.14$, $p < .001$, 95% CI [−0.16, −0.11]) was more than 2 times greater than on expected consumption enjoyment ($\beta = -0.06$, $p < .001$, 95% CI [−0.08, −0.04]), thus supporting the theorized basis of this effect. Together, distraction and the amount consumed predicted 0.98% of the variance in actual-expected enjoyment discrepancy.

Actual-Expected Enjoyment Discrepancy and Consumption Satisfaction. We hypothesized an actual-expected enjoyment discrepancy would frequently lead people to experience less consumption satisfaction (Hypothesis 2). Our results support this idea—when consumption was less enjoyable relative to expectations, people were less satisfied with the experience (Figure 4, $\beta = 0.32$, $p < .001$, 95% CI [0.30, 0.35]). Collectively, actual-expected enjoyment discrepancy, distraction during consumption, and the amount consumed predicted 10.50% of the variance in consumption satisfaction.

[7] Lavaan did not support multilevel path analyses with a binary response variable—whether the next consumption experience is or is not similar to the previous consumption experience. Single-level (i.e., observation) path analysis was conducted instead with variables person-mean-centered to remove between-person variance. This method is viable for accurately investigating within-person effects (Costantini et al., 2019).

Table 2
Descriptive Summary of Key Study 2 Variables

Variable	*M*	*SD*	Possible range	Min	Max
Distraction	3.61	1.01	1 to 7	1.05	5.94
Consumption amount	4.14	0.34	1 to 7	2.71	5.42
Expected enjoyment	4.81	0.58	1 to 7	3.12	6.61
Actual enjoyment	4.80	0.58	1 to 7	3.12	6.55
Actual-expected enjoyment discrepancy	−0.01	0.39	−6 to 6	−0.88	1.67
Consumption satisfaction	4.93	0.59	1 to 7	3.52	6.59
Need for further gratification	2.78	1.02	1 to 7	1.00	5.26
Duration to subsequent consumption (hr)	1.31	0.47		0.42	4.83

Note. *SD* = standard deviation of participant-level mean. "Min" and "Max" refer to minimum and maximum participant-level mean, respectively. Higher values for actual-expected enjoyment discrepancy refer to more enjoyment experienced during consumption relative to expectations.

Consumption Satisfaction and Hedonic Overconsumption. As hypothesized (Hypothesis 3), reduced consumption satisfaction predicted increased hedonic consumption—in Model 1, this reflected reduced consumption satisfaction predicting greater postconsumption need for further gratification (Figure 4, $\beta = -0.10$, $p < .001$, 95% CI [−0.12, −0.07]). Consumption satisfaction, alongside preceding model variables, predicted 0.94% of the variance in need for further gratification. In Model 2, we found a greater need for further gratification to predict a shorter duration to subsequent consumption (Figure 5, upper panel, $\beta = -0.07$, $p < .001$, 95% CI [−0.11, −0.03]). Additional analyses showed that an enhanced need for further gratification predicted the duration to the end of the next consumption episode ($\beta = -0.06$, $p < .001$, 95% CI [−0.10, −0.03]), providing convergent evidence for this effect. Participants' need for further gratification, alongside the preceding model variables, predicted 0.50% of the variance in duration to subsequent consumption.

Exploratory Analyses

Is the HCM Supported When Actual Enjoyment Is Modeled Instead of Actual-Expected Enjoyment Discrepancy? Building on the results from Study 1, we investigated the consequences of modeling actual enjoyment instead of actual-expected enjoyment discrepancy as the key mediator. That is, participants may have had difficulty accurately recalling hedonic expectations for consumption experiences temporally distant from the focal questionnaire, meaning the actual-expected enjoyment discrepancy variable may have suboptimal validity and reliability. We thus tested our HCM using actual consumption enjoyment (instead of actual-expected enjoyment discrepancy), an experience arguably easier for participants to accurately recall and represents a robust proxy measure of actual-expected enjoyment discrepancy given the temporal position of distraction should not exert any meaningful influence on expected enjoyment. As can be seen from Figure 5 (lower panel), our findings support the HCM that includes actual enjoyment: Distraction negatively predicted actual enjoyment ($\beta = -0.12$, $p < .001$, 95% CI [−0.16, −0.08]), and actual enjoyment positively predicted consumption satisfaction ($\beta = 0.63$, $p < .001$, 95% CI [0.60, 0.66]). Moreover, model fit was better relative to Model 1, when actual-expected enjoyment discrepancy was included.[8] This finding replicates the conclusions emerging from Study 1, suggesting that actual enjoyment constitutes the component in the model more directly affected by distraction.

Does a Shorter Duration to Subsequent Consumption Reflect Increased Consumption? Consuming again more quickly after consumption represents increased hedonic consumption during at least a set temporal period (e.g., more hedonic consumption takes place during a 30 min period than otherwise would have had consumption been satisfactory). However, we theorized consuming again more quickly would mean increased consumption overall, in that such excesses would not be fully countered (e.g., by consuming less after the excess). We investigated this possibility by examining whether increased postconsumption need for further gratification also predicted a shorter duration to the consumption episode after the next episode. This analysis may help answer this question because if the episode after the next episode is also advanced forward, it would show people generally do not delay consumption after their indulgence (i.e., they do not self-regulate). Our exploratory findings align with our reasoning—an elevated need for further gratification also advanced the consumption episode after the next one ($\beta = -0.08$, $p = .004$, 95% CI [−0.14, −0.03]; see Supplemental Figure S8).[9]

Are People More Likely to Compensate in the Domain in Which the Shortfall Occurred? We theorized (and confirmed) hedonic compensation to be a domain-general effect—after hedonic shortfall, people often compensate with similar types of consumption (e.g., having a snack after a disappointing dinner) but also with other types of consumption (e.g., watching more television after a disappointing dinner). Nevertheless, it is valuable to know which eventuality is most likely. We investigated this using a single-level path model identical to Model 1, but where a need for further gratification predicted a binary similar-other outcome variable (see the Analytic Procedures and Strategy section for details on how this variable was calculated).[10] Our results reveal the next consumption episode was more likely to be similar to the former episode when participants had a greater desire for further gratification after the former episode ($OR = 1.05$, $p = .02$, 95% CI [1.01, 1.09]; see Supplemental Figure S9).

[8] S-BX2 (9) = 36.41, $p < .001$; CFI = 0.98; SRMR = 0.03; RMSEA = 0.03 (90% CI [0.02, 0.05]) compared to S-BX2 (9) = 60.86, $p < .001$; CFI = 0.88; SRMR = 0.03; RMSEA = 0.05 (90% CI [0.04, 0.06]).

[9] Structural fit statistics show that our model fit the data well, S-BX2 (9) = 24.49, $p = .004$; CFI = 0.92; SRMR = 0.03; RMSEA = 0.04 (90% CI [0.02, 0.06]).

[10] Structural fit statistics show that our model on the whole fit the data well, S-BX2 (9) = 39.63, $p < .001$; CFI = 0.85; SRMR = 0.01; RMSEA = 0.04 (90% CI [0.02, 0.05]).

Table 3
Multilevel Correlation Matrix of Study 2 Key Participant-Mean-Centered Variables

Variable	1	2	3	4	5	6	7	8
1. Distraction	—							
2. Consumption amount	−0.04**	—						
3. Expected enjoyment	−0.06***	0.10***	—					
4. Actual enjoyment	−0.14***	0.13***	0.59***	—				
5. Actual-expected enjoyment discrepancy	−0.09***	0.04***	−0.39***	0.51***	—			
6. Consumption satisfaction	−0.13***	0.08***	0.38***	0.64***	0.32***	—		
7. Need for further gratification	0.05***	0.03**	0.03*	−0.03*	−0.06***	−0.10***	—	
8. Duration to subsequent consumption (hr)	0.02	−0.05**	−0.02*	−0.04*	−0.03	−0.05*	−0.07***	—

Note. Correlations within-participant level variables after standard errors adjusted for participant at Level 2. Higher values for actual-expected enjoyment discrepancy refer to more enjoyment experienced during consumption relative to expectations.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Need for Further Gratification and Consuming Again More Quickly—Does Similarity Between the Initial and Next Consumption Episodes Moderate This Relationship? Exploratory analyses revealed elevated postconsumption need for further gratification predicted the next episode to be more similar to the former. This finding may help explain why an elevated need for further gratification associates with a shorter period to consumption—similar consumption types may be more readily available and thus easier to consume quickly after consumption has finished. We tested this idea by investigating whether similarity between the initial and subsequent consumption episodes moderated the link between need for further gratification and duration until subsequent consumption. We were, however, unable to find a significant effect (β = 0.01, p = .45, 95% CI [−0.02, 0.05]; see Supplemental Figure S10).

Can the Association Between Distraction and Actual-Expected Enjoyment Discrepancy Be Explained by Other Factors? Results link distraction during consumption and actual-expected enjoyment discrepancy. But it is conceivable that unmodeled factors drive this effect, for instance, the amount of stress experienced during consumption (stress often promotes distractedness, e.g., Morrison & O'Connor, 2005, and may reduce consumption enjoyment via general underlying negative affect, e.g., Bolger et al., 1989) or the extent that consumption conflicts with personal goals (pleasure from consumption can be "spoiled" the greater the conflict with personal goals; Bernecker & Becker, 2021; Hofmann et al., 2013). As such, we test our HCM and the effect of distraction while controlling for stress and goal conflict. Results show increases in goal conflict (β = −0.13, $p < .001$, 95% CI [−0.15, −0.11]) and stress (β = −0.09, $p < .001$, 95% CI [−0.12, −0.07]) negatively predict actual-expected enjoyment discrepancy (i.e., consumption enjoyment is less relative to expectations), which supports the theorized link (see Supplemental Figures S11 and S12).[11] Most importantly, however, distraction still predicts actual-expected enjoyment discrepancy when controlling for goal conflict (β = −0.09, $p < .001$, 95% CI [−0.11, −0.06]) and stress (β = −0.06, $p < .001$, 95% CI [−0.08, −0.03]), supporting distraction's contextual influence and position in the HCM.

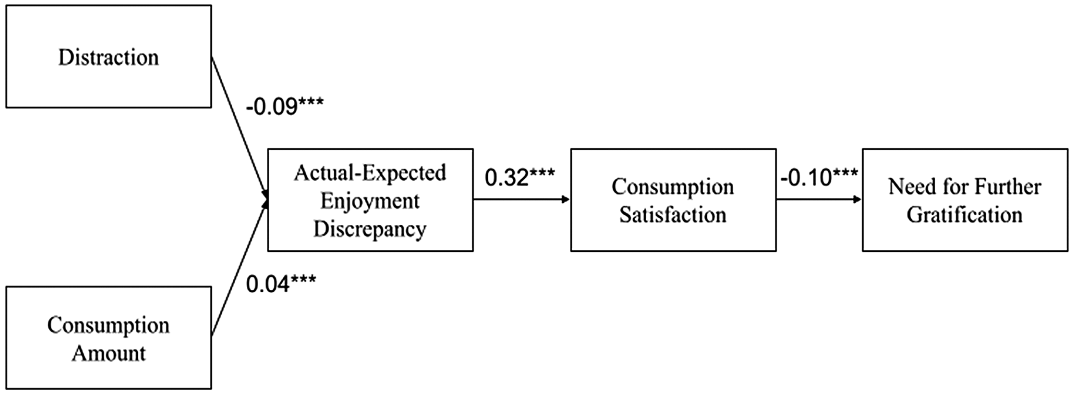
Is the Hedonic Compensation Effect Really (Consumption) Domain-General? Our primary study aim was to test a cross-consumption-domain hedonic compensation effect. Yet, it is valuable to know to what extent "consumption domain" explains variance in hedonic compensation. For instance, does hedonic shortfall from food consumption promote greater compensation relative to hedonic shortfall from drink consumption? This and similar knowledge would help better understand when overconsumption is particularly likely. This additional analysis would also provide a more robust test of our domain-general claims. Accordingly, we investigated differences in path coefficients for substance (e.g., eating, drinking, smoking) versus nonsubstance (e.g., media/audio, gambling, leisure reading) consumption and for food versus drink consumption. These consumption categories are qualitatively distinct and provide sufficient data per category to identify small differences.[12] Results show consumption type/category influences the strength of some path coefficients—the positive link between actual-expected enjoyment discrepancy and consumption satisfaction is stronger for nonsubstances relative to substances (β = 0.06, p = .02), and the negative link between consumption satisfaction and need for further gratification is stronger for food relative to drink consumption (β = 0.17, p = .02). No other significant differences were identified. Do these differences challenge the idea that hedonic compensation is a domain-general effect? We think not. Upon testing our HCM with substance-only, nonsubstance-only, food-only, and drink-only data, path coefficient directions remain identical (see Supplemental Figure S13).

Do Direct and Indirect Effects Support a Hedonic Compensation Effect? Our confirmatory findings demonstrate that the theorized model links support the HCM. However, it is possible that direct links between distal model factors may tell a different story. For instance, while our model highlights (via each direct effect in turn) that distraction indirectly promotes increased hedonic consumption after the episode, unmodeled influences may have an opposite (i.e., negative) effect on hedonic overconsumption. Moreover, it would be valuable to understand whether the indirect links between model constructs (i.e., after multiplying path coefficients together) are significant. Accordingly, we investigate these points. Multilevel correlations displayed in Table 3 capture the overall relationship between model variables and confirm that effects on the whole are in the theorized direction (e.g., distraction directly predicts lower consumption satisfaction and a higher need for further gratification). Moreover, examination of indirect effects

[11] Structural fit statistics show that model with stress, S-BX2 (7) = 461.73, $p < .001$; CFI = 0.69; SRMR = 0.06; RMSEA = 0.10 (90% CI [0.09, 0.10]), and goal conflict, S-BX2 (7) = 725.79, $p < .001$; CFI = 0.60; SRMR = 0.07; RMSEA = 0.12 (90% CI [0.11, 0.13]), poorly fit the data.

[12] There were many different consumption combinations, for example, food, drink, and leisure reading, smoking and gambling, and so forth. This limited the amount of data available in any single category.

Figure 4
Study 2: Hedonic Compensation Model 1



Note. Higher distraction during consumption predicted lower actual-expected enjoyment discrepancy (i.e., less enjoyment relative to expectations), controlling for the amount consumed. Experiencing less enjoyment relative to expectations predicted lower consumption satisfaction, which predicted an increased postconsumption need for further gratification. $N = 6{,}965$. Standardized coefficients are depicted.
*** $p < .001$.

demonstrates that distal links between model constructs are all significant: Greater distraction during consumption indirectly predicts lower consumption satisfaction ($\beta = -0.03$, $p < .001$, 95% CI [−0.04, −0.02]), a greater need for gratification ($\beta = 0.003$, $p < .001$, 95% CI [0.002, 0.004]), and a shorter duration to subsequent consumption ($\beta = -0.0001$, $p = .04$, 95% CI [−0.0003, −0.00001]), greater actual-expected enjoyment discrepancy indirectly predicts a lower need for further gratification ($\beta = -0.03$, $p < .001$, 95% CI [−0.04, −0.02]) and a longer duration to subsequent consumption ($\beta = 0.002$, $p = .02$, 95% CI [0.0002, 0.003]), and greater consumption satisfaction indirectly predicts a longer duration to subsequent consumption ($\beta = 0.005$, $p = .02$, 95% CI [0.001, 0.009]). However, there were inconsistencies with some zero-order correlations: Greater actual enjoyment and consumption satisfaction were associated with a shorter duration to subsequent consumption—overall effects in the opposite direction to that theorized (see Table 3). Furthermore, other correlations with duration to subsequent consumption were nonsignificant (e.g., distraction, actual-expected enjoyment discrepancy). In sum, whereas the indirect (mediation) effects support our predictions, the theorized pathways likely represent and explain only a part of the overall association linking actual enjoyment and consumption satisfaction while ignoring other possible influences.

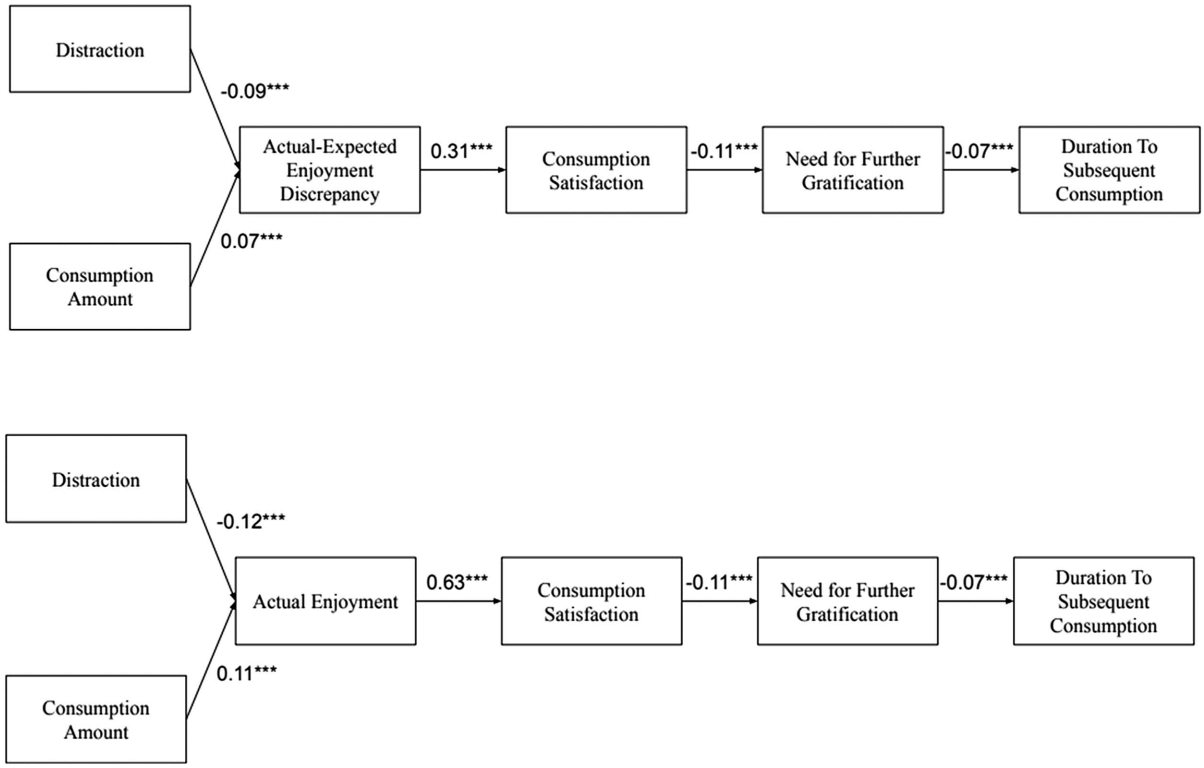
Does Need for Further Gratification Predict Other Increased Hedonic Consumption Manifestations? It is plausible that hedonic shortfall during consumption is compensated for in various ways (e.g., greater consumption amounts in the next episode, the next consumption episode being of a longer duration). Yet, we only preregistered analyses to test whether an elevated need for further gratification due to hedonic shortfall leads people to consume again more quickly afterward. Here, we test additional path models to examine whether hedonic shortfall indirectly associates with other forms of increased hedonic consumption. We found that an elevated need for further gratification did not predict the duration of (i.e., not to) the next consumption episode ($\beta = 0.001$, $p = .95$, 95% CI [−0.04, 0.04]), the amount consumed in the next episode ($\beta = 0.02$, $p = .32$, 95% CI [−0.02, 0.06]), or the expected enjoyment of the next episode ($\beta = -0.003$, $p = .87$, 95% CI [−0.04, 0.03]). However, an elevated need for further gratification did predict that the next consumption episode would be in greater conflict with other personal goals ($\beta = 0.06$, $p = .003$, 95% CI [0.02, 0.09]), suggesting that people may compensate for hedonic shortfall by engaging in those types of consumption they know may be problematic (see Supplemental Figures S14–S17).[13] Examination of indirect effects supports this notion, with distraction ($\beta = 0.0002$, $p = .02$, 95% CI [0.00002, 0.00032]), actual-expected enjoyment discrepancy ($\beta = -0.002$, $p = .009$, 95% CI [−0.003, −0.0005]), and consumption satisfaction ($\beta = -0.01$, $p = .009$, 95% CI [−0.01, −0.002]) significantly predicting goal conflict in the theoretically expected direction. Only need for further gratification directly predicts goal conflict in the next consumption episode ($\beta = 0.06$, $p = .003$), with distraction ($\beta = -0.02$, $p = .39$), actual-expected enjoyment discrepancy ($\beta = -0.01$, $p = .78$), and consumption satisfaction ($\beta = -0.0003$, $p = .99$) displaying a nonsignificant relationship.

Discussion

Our large-scale ESM study strongly supports the idea that hedonic deficit from consumption promotes hedonic compensation after the consumption episode—lower than expected consumption enjoyment predicted reduced consumption satisfaction (Hypothesis 2), which predicted increased postconsumption need for further gratification (Hypothesis 3). Moreover, increased need for further gratification predicted that the next consumption experience would conflict more with personal goals (e.g., to stay healthy), a finding that may reflect more indulgent next-episode consumption (e.g., eating a doughnut for dessert instead of fruit). However, this exploratory finding requires

[13] Structural Fit Statistics were near identical across models and show that our model fit the data well. Ranges of model indices are included where they differed across models. S-BX2 (9) = 50.76–61.57, $p < .001$; CFI = 0.89–0.91; SRMR = 0.03; RMSEA = 0.04–0.05.

Figure 5
Estimated Path Models in Study 2



Note. The upper model includes actual-expected enjoyment discrepancy (i.e., less enjoyment relative to expectations), whereas the lower model includes actual enjoyment. $N = 2{,}731$. Standardized coefficients are depicted.
*** $p < .001$.

replication. While need for further gratification predicted a shorter duration to subsequent consumption—supporting our hypothesis—overall relationships between variables call into question whether the hedonic compensation effect we traced captures the entire story linking consumption episodes with each other (i.e., actual enjoyment and consumption satisfaction correlated with a shorter duration to subsequent consumption). In sum, the present study uncovers hedonic shortfall as a reason, among many others (e.g., low self-control, negative affect, stress), for increased hedonic consumption. It also demonstrates distraction during consumption as an important contextual trigger of increased consumption by reducing consumption enjoyment (Hypothesis 1; we ruled out the possibility that stress and goal conflict can fully account for this effect). While effects overall are small and suggest hedonic shortfall exerts a minor momentary compensation effect, if such effects are not (effectively) regulated over time, their accumulation could become problematic.

General Discussion

Excessive consumption of hedonic goods or experiences (e.g., food, alcohol, media) often has undesirable effects (Ferriter & Ray, 2011; Granow et al., 2018; Kukk & Akkermann, 2017). One common account of overconsumption is in terms of self-control failure. Here, we advance and test an alternative account of hedonic overconsumption, proposing that certain context factors, such as distraction, may result in dissatisfaction with one's current hedonic consumption experience and that this dissatisfaction may, in turn, create a need for further gratification. Because consumption-related attention is critical to extracting hedonic content from consumption (Green et al., 2004), our research focused on distraction as a key context that may compromise consumption enjoyment. We tested these key propositions in a meta-analysis, a field study (Study 1), and a large-scale ESM study (Study 2), following people's everyday consumption experiences.

Theoretical Implications

Our theoretical starting point was to test whether distraction during hedonic consumption is a key contextual trigger of hedonic shortfall and thus increased consumption. We proposed the effect's presence given that people generally seem to extract more pleasure from consumption the more attention paid to it and because hedonic expectations should theoretically remain unaffected amid distractions' negative effect on (actual) consumption enjoyment (ensuring a discrepancy manifests). The present research provides strong meta-analytic, experimental, and ecologically valid support for a negative link between distraction and hedonic experience (Arch et al., 2016; van der Wal & van Dillen, 2013). Whereas there were too few studies in our meta-analysis to analyze distraction's downstream consequences, both our field experiment and the ESM study provided strong evidence that distraction predicts increased downstream consumption via hedonic shortfall. Study 2 also allowed us to rule out plausible "third" variables such as stress and goal conflict, thus supporting our theory of distraction's contextual centrality. Study 1, while chiefly exploratory and with methodological limitations, nevertheless strengthens our proposition that distraction during consumption causes hedonic shortfall and thus distally drives hedonic compensation.

Collectively, these findings reveal that something as simple as eating a sandwich while simultaneously working, mind-wandering while reading a novel, or using one's phone while watching television may be enough to stimulate elevated consumption. As such, the present findings aid our theoretical understanding of why distraction during food consumption promotes increased food intake (Robinson et al., 2013). Distraction may elicit this effect by rendering people forgetful of their health goals and desensitizing people to satiating signals. However, our research shows hedonic shortfall during consumption is likely an additional mechanism. This aligns with research showing distraction hinders the perception of sensory properties of food (van der Wal & van Dillen, 2013; van Meer et al., 2022) and the extent to which food is enjoyed (Arch et al., 2016).

How exactly may hedonic shortfall (due to distraction or other sources) lead to overcompensation? The present framework invokes control theory to better understand why people may overcompensate in contexts that compromise enjoyment. Our path-analytic findings show that people (a) feel less satisfied with their experience when their actual experiences fall short of their hedonic expectations and (b) express a higher need for more gratification, suggesting that hedonic shortfalls may promote hedonic compensation. Heightened desire for consumption is known to promote engagement in the behavior(s) so desired (Bernecker et al., 2018), particularly when consumption is highly available and socially supported and when psychological conflict is low (Hearn et al., 1998; e.g., Hofmann et al., 2012).

Consistent across both empirical studies, results involving the enjoyment component were more pronounced when modeling actual enjoyment than the difference between actual enjoyment and expected enjoyment. On the one hand, this is in line with our model in that actual enjoyment was assumed to be the main variable affected by distraction, as confirmed by additional tests. On the other hand, the fact that calibrating the effect on people's expectations did not improve the prediction of consumption satisfaction suggests that our test may have suffered from higher unreliability (due to the computation of a difference score) and/or lower validity (e.g., due to introspective limits in reporting expectations or possible adjustments), and/or that this discrepancy may matter less at a theoretical level than currently assumed. Given these varying explanations, this part of the framework may benefit most from further empirical scrutiny. Our careful conclusion at this point is that relative (i.e., uncalibrated) differences in actual enjoyment may already be a solid predictor of lower consumption satisfaction and need for further gratification.

At present, it is undertheorized and unexplored how exactly hedonic compensation may manifest. One intriguing question in this regard is whether people may primarily compensate within or across consumption domains. Exploratory analyses from Study 2 showed that the next consumption episode following a greater need for further gratification was somewhat more likely to be similar rather than different. This suggests that people may initially strive to overcompensate in the domain in which hedonic shortfall originated, which may also be due to the availability of such means of consumption. Future research may test such a two-step process more rigorously. At the same time, this effect was of a small magnitude, and therefore across-domain compensation appeared to be a frequent phenomenon, which seems consistent with a common-currency explanation of the brain's reward system (Levy & Glimcher, 2012).

Furthermore, we speculated that hedonic compensation may manifest differentially within-domains, such as excess consumption in the next episode, the next consumption episode being of a longer duration, or more frequent consumption over time. Exploratory analyses lend some support to this compensation-via-various-means argument, with need for further gratification predicting a higher snacking amount and frequency in some iterations of Study 1 and a shorter duration until subsequent consumption (and the extent to which the next consumption episode conflicted with other personal goals) in Study 2. Consuming again more quickly reflects excess consumption over a set temporal period, while engaging in consumption that is more in conflict with other personal goals suggests the interesting possibility that people willingly incur the costs associated with conflicting desires as frustration with a current consumption experience increases. However, these results from Study 2 should be cautiously interpreted, as the total direct effects were in some instances nonsignificant; for example, lower distraction and higher consumption satisfaction did not directly (and significantly) predict that the next consumption episode would be less in conflict with personal goals or were significant but in the opposite direction to the preregistered and empirically confirmed mediation pathways (e.g., increased consumption satisfaction was overall associated with a significantly shorter duration to subsequent consumption), suggesting the presence of alternative pathways not addressed in the present model. We should also make clear that an elevated need for further gratification did not significantly predict other outcomes synonymous with increased hedonic consumption, including the amount or duration consumed in the next episode, or the enjoyment participants expected from the next episode. However, this represents the absence of evidence, not evidence of absence (Aczel et al., 2018; Lakens, 2021)—with more data, theorized effects may be revealed.

Applied Implications

Knowing that increased hedonic consumption results from hedonic shortfall is valuable, for it advances understanding of what drives problematic societal behaviors, including binge eating, excessive social media use, and gambling. At the applied level, the finding that distraction predicts elevated downstream consumption uncovers potential avenues for intervention to regulate hedonic consumption, for growing research shows interventions that manipulate attention during consumption can be effective (Mason et al., 2016; Miller et al., 2014). While attentional manipulation is a recognized tool for limiting food consumption (given that much theory and evidence links distraction with overeating; Robinson et al., 2013), it is not a recognized tool to regulate other forms of consumption. Our model, however, also suggests additional possible entry points for intervention, such as practicing a cognitive reappraisal of one's actual enjoyment and satisfaction in distracting consumption contexts.

It is less clear, however, whether the effects' magnitude is large enough to be of additional concern. What our findings suggest is that excess consumption from hedonic shortfall is likely, in the moment, to be of little concern: A one-point decrease in consumption satisfaction (Study 2, Model 1) predicted only a 0.10 (standardized) increase in need for more gratification, while a one-point increase in need for gratification (Study 2, Model 2) predicted only a 2.16 min decrease in the duration to subsequent consumption. Distal model effects (e.g., lower than expected consumption enjoyment predicting an increased need for further gratification) are smaller yet. However, if the identified hedonic compensation effects are not (effectively) regulated, even small effects can accumulate and, in the long run, exert notable consequences (just as small excesses in calorie consumption lead to overweight and other health issues when unregulated, Rosenheck, 2008). This is especially relevant since in Study 2, a high prevalence (26.53%) of consumption experiences were less enjoyable than expected. Furthermore, distracted consumption is thought to be highly prevalent, as illustrated by a recent study that found that participants performed a concurrent activity during their meal 75% of the time (van Meer et al., 2022).

Limitations

A key limitation is that our samples contain predominantly students or citizens from so-called White, educated, industrialized, rich, and democratic (Henrich et al., 2010) countries, Germany and the Netherlands. This opens the door to the possibility that the identified effects in the present sample may not be generalizable to non-White, educated, industrialized, rich, and democratic samples or samples with different demographics. Another limitation is that we did not test whether hedonic shortfall during consumption associates with hedonic overconsumption in the same episode. For instance, whether a suboptimal dinner may encourage an increased intake of wine served with that dinner. This is not ideal since increased consumption within consumption episodes is a pervasive and problematic issue (e.g., Robinson et al., 2013). Study 2 tested next- rather than within-episode compensation given the increased measurement ease (participants likely find it easier to recollect their consumption experiences from the whole relative to only part of the consumption episode) and because a tendency to compensate across episodes is likely highly informative of hedonic regulation within-episodes. A final limitation is that our field experiment (Study 1), although providing tentative causal support to the ecologically designed Study 2, suffered from compliance-related issues (which we attempted to address with increasingly rigid data exclusion criteria) and did not have sufficient statistical power to find small effects. With more statistical power, it is possible that the results from both studies would have converged even more than they did.

Conclusion

In the present research, we find initial support for our hypothesis that people are likely to consume more hedonic goods to compensate for perceived hedonic deficit during consumption, underpinned by a link between hedonic shortfall during consumption and an increased postconsumption need for further gratification. We also find support for our claim that being distracted during consumption is a key driver of this hedonic compensation effect via its negative effect on consumption enjoyment. Our framework is a first step toward understanding the psychological drives behind hedonic overconsumption.

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