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Bibliographie Elise Ricadat

Cette bibliographie est une sélection de textes, chapitres ou autres écrits/supports que j'ai publiés dans le cadre de mes recherches depuis une petite dizaine d'années. Les textes surlignés en jaune sont préférablement à lire pour la conférence du vendredi 11 avril au soir. Ceux surlignés en bleu, pour celle du samedi matin 12 avril : sans obligation ni de tout lire, ni de respecter scrupuleusement cette répartition ! Ils témoignent tous de mon trajet de psychologue clinicienne exerçant auprès d'enfants, d'adolescents et d'adultes en pratique libérale, mais également pendant plus de 10 ans au sein de diverses institutions, essentiellement pour adolescents (psychiatrie, oncologie hospitalière ou éducatifs) ou adultes en soins somatiques avant d'entamer un parcours de recherche et d'enseignement à l'université.

I. Publications

1. Publications dans des revues indexées (ACL) : 20

1. Ricadat E., « Le développement des métiers du patient partenaire : apports de la psychodynamique du travail », **Travailler**, 2025 (soumis)

2. Virole L., Gabarro C., Ricadat É., « Social Support for the Chronically Ill during Lockdown, Qualitative Research in the COVID-19 Pandemic », **Sociology of health and illness** (accepted)

3. **Ricadat E.,** Marx E. (2022), « sexualité et cancer », éditorial numéro spécial, **Psycho-Oncologie**, 16, 3 :282-283, doi.org/10.3166/pson-2022-0208

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13. **Ricadat É**. (2020), « Recherche qualitative en psychanalyse : l'étude du cas de la théorisation ancrée », **In Analysis**, 2020/1, doi : 10.1016/j.inan.2020.01.007

14. **Ricadat É.**, Schwering K.-L., Fradkin S., Boissel N., Aujoulat I. (2019), "Adolescents and young adults with cancer: how multidisciplinary healthcare teams adapt their practices to better meet their specific needs", **Psycho-oncology,** 2019, Jul, 28(7), 1576-1582 (PubMed-Medline Elsevier) doi : 10.1002/pon.5135.

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2. Publications dans d'autres revues à comité de lecture (ACLN) : 6

1. **Ricadat É.**, Virole L. (2022), "Combining interviews and drawings: methodological considerations", **New trends in Qualitative Research**, Book of the 6th world conference on qualitative research book, vol. 11; doi : 10.36367/ntqr.11

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3. Revues autres (ASCL ou AV) :

1. **Ricadat É.**, Lefève C., Maglio M. (2023), « Revivre après le traitement d'une maladie génétique rare : le cas de la drépanocytose », **The Conversation-Santé**, publié le 7/12/2023, https://theconversation.com/revivre-apres-le-traitement-dune-maladie-genetique-rare-lexemple-de-la-drepanocytose-218968

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4. Ouvrages :

1. **Ricadat É**., Taïeb L. (2012), *Rien à me mettre ! Le vêtement, plaisir et supplice*, préfacé par P. Grimberg, Albin Michel, Paris.

2. **Ricadat É**., Taïeb L. (2009), *Après le cancer du sein, un féminin à reconstruire*, préfacé par N. Châtelet, Albin Michel, Paris.

5. Contributions à des ouvrages scientifiques (OS) :

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6. **Ricadat É.**, Aujoulat I., Boissel N., Schwering K.-L. (2023), Sexualité et vie amoureuse des adolescents et jeunes adultes atteints de cancer et leur prise en soin dans une unité dédiée », in *Grand Manuel de psycho-oncologie de l'enfant et de l'adolescent*, (sd) Vander Haegen M., Flahault C., Marioni G., Paris, Dunod, p. 141-171.

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8. Gargiulo, M., Proia-Lelouey, N., Ricadat, É. & Scelles, R. (2021). Maladies, handicap : approches psychanalytiques. Dans : Alain Ducousso-Lacaze Éd., *Ce que les psychanalystes apportent à l'universit*é Toulouse, Érès, p. 65-71.

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6. Autre (OV)

1. Intervention pour la Capsule vidéo « éthique du soin au cinéma" coordonnée par Lefève C., vidéo 10 « Accompagner celle ou celui qui va mourir – Still the water, Naomi Kawase, 2014, avec J.- M. Frodon »
https://www.youtube.com/playlist?list=PLwGJioG4MrR8kfPa224uVtQaTGJeJl69x

2. Participation à la conception et rédaction de 3 plaquettes d'information « cancer et fertilité, quels problèmes, quelles solutions ? » pour les jeunes femmes, les adolescentes et les jeunes adultes hommes pour **La Ligue contre le Cancer**, **2016**.
https://www.ligue-cancer.net/sites/default/files/brochures/cancer-fertilite-adolescentes-2016-10-.pdf

3. Participation à la conception et rédaction du référentiel « Santé sexuelle et la vie intime des adolescents et des jeunes adultes (AJA) » diffusé par l'Association Francophone de Soins Oncologiques de support **(AFSOS), 2018**.
http://www.afsos.org/fiche-referentiel/sante-sexuelle-vie-intime-adolescents-jeunes-adultes-aja/

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Bibliographie Léo DUTRIAUX

Original Article

How to change your memory of an object with a posture and a verb

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Abstract

According to grounded cognition, the format of representation of knowledge is sensorimotor. This means that long-term memory shares processing resources with the sensorimotor system. The main objective of this work is to provide new evidence in favour of two claims from the embodied cognition framework: (1) memory is grounded on the sensorimotor system, that is, memory shares processing resources with the sensorimotor system, and (2) memory serves at least in part to support action. For this purpose, the present experiment aimed to show that the action context modulates the motor simulation and, consequently, the memory of manipulable objects. Participants were presented with short phrases comprising the name of a manipulable object, and an action verb ("To take a cup") or an attentional verb ("To see a cup"). During this phase, they had to put their hands in front of them in the control condition, whereas they had to keep them behind their back in the interfering condition. A cued recall test followed after a short distractive letter-matching task, with the verbs serving as cues. Results showed that memory of the words denoting manipulable objects was impaired by the interfering posture when associated with an action verb, but not when associated with an attentional verb. This suggests that a context which does not favour action interferes with motor simulation and thus decreases the memory of manipulable objects. These results provide strong evidence for a grounded account of memory and language.

Keywords

Grounded cognition; long-term memory; action; mental model; language

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Introduction

In recent decades, the format of representation of knowledge has been one of the most debated questions in cognitive science. According to grounded cognition, memory retrieval should be seen as a sensorimotor simulation, that is, a re-enactment of the sensorimotor activity at encoding (Barsalou, 1999; Versace et al., 2014; see Matheson & Barsalou, 2017). This suggests that the format of representation of knowledge is sensorimotor and that long-term memory shares processing resources with the sensorimotor system. The activation of the concept of a manipulable object (such as a hammer) from long-term memory is claimed to involve not only the reinstatement of the visual or auditory patterns of activation related to previous experiences with the object but also the reinstatement of the motor patterns related to its use, that is, their affordances. Glenberg (1997) underlined the importance of motor system in memory, claiming that the main function of knowledge is to support action. He proposed that memory encodes the environment in terms of affordances and that the subsequent simulation of these affordances aims to support action. The affordance of an object is defined here, along with Glenberg's ideas, as the potential actions that an organism can perform on it, given the actual state of the object, the prior history of the organism's interactions with this object, and the

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organism's ability to act. Given this background, the main aim of the present work is to provide new evidence in favour of two claims from embodied cognition theories (Wilson, 2002): (1) long-term memory is grounded on the sensorimotor system, that is, memory shares processing resources with the sensorimotor system, and (2) long-term memory serves at least in part to support action.

In support of these ideas, many studies have shown via the stimulus–response compatibility paradigm that the viewing of a manipulable object potentiates motor actions associated with the use of that object (e.g., Bub, Masson, & Cree, 2008; Rueschemeyer, Pfeiffer, & Bekkering, 2010; Tucker & Ellis, 1998, 2004; van Elk, van Schie, & Bekkering, 2009). Tucker and Ellis (2004) asked their participants to indicate whether an object (depicted in a picture) was a man-made or a natural object. Half of the objects could be grasped with either a precision grip or a whole-hand grip. The response could be made either with a precision grip device or with a whole-hand grip device. Faster reaction times were found when the response and the object grip were compatible. Numerous neuroimaging experiments have shown that viewing pictures of manipulable objects activates motor regions more than non-manipulable objects or animals (see Chouinard & Goodale, 2010, for a meta-analysis; see Noppeney, 2008, for a review). Importantly, similar stimulus–response compatibility effects (Bub et al., 2008; Tucker & Ellis, 2004; but see Flumini, Barca, Borghi, & Pezzulo, 2015) and motor activations (e.g., Carota, Moseley, & Pulvermüller, 2012; Rueschemeyer, Pfeiffer, et al., 2010; Rueschemeyer, van Rooij, Lindemann, Willems, & Bekkering, 2010) have been observed when words denoting manipulable objects were presented instead of pictures. This suggests that the motor simulation arises not only from the visual properties of the object but also from the activation of the concept from memory. Nevertheless, the main limitation of these paradigms is that the motor activations could be the mere consequences of an activation cascade, without any role in concept representation (Mahon & Caramazza, 2008).

To assess more directly the role of motor simulation in the representation of manipulable objects, several studies have instead addressed the effect of motor interference on the processing of manipulable objects, as suggested by Mahon and Caramazza (2008). First, it seems that a motor impairment following a stroke (Buxbaum & Saffran, 2002; Myung et al., 2010) or a transcranial magnetic stimulation protocol (Pobric, Jefferies, & Lambon Ralph, 2010) provokes a deficit in knowledge or processing of manipulable objects. However, it is important to note that other studies have not demonstrated such effects (Garcea, Dombovy, & Mahon, 2013; Kemmerer, Miller, Macpherson, Huber, & Tranel, 2013; Negri et al., 2007; Reilly et al., 2014). A few studies have investigated the effect of interfering movements on the conceptual processing of manipulable objects (e.g., Bub, Masson, & Lin, 2013; Witt, Kemmerer, Linkenauger, & Culham, 2010; Yee, Chrysikou, Hoffman, & Thompson-Schill, 2013). For instance, Witt et al. (2010) found that squeezing a ball in one hand made it more difficult for healthy participants to name tools whose handles faced the squeezing hand. These studies show that the retrieval of manipulable object knowledge from long-term memory involves the retrieval of motor information, which is impaired by a motor interference and leads to a decrease in observed performances. Nonetheless, Matheson, White, and McMullen (2014) found the same interference with manipulable objects as well as with non-manipulable objects, suggesting that this effect might not be specific to action-related objects. Concerning the effect of motor interference on short-term memory, results are again controversial (see Zeelenberg & Pecher, 2016, for review). On one hand, several studies by Guérard and colleagues (Downing-Doucet & Guérard, 2014; Guérard, Guerrette, & Rowe, 2015; Lagacé & Guérard, 2015) have shown that the recall of manipulable objects decreases when learned while performing an incongruent interfering motor task. On the other hand, Pecher and colleagues failed to find such effects (Pecher, 2013; Pecher et al., 2013; Quak, Pecher, & Zeelenberg, 2014). This inconsistency could be explained by the fact that the motor system may not be necessary to maintain visuospatial information in short-term memory. Concerning the effect of motor interference on long-term memory, only very few attempts have been made up to now (Dutriaux & Gyselinck, 2016; van Dam, Rueschemeyer, Bekkering, & Lindemann, 2013). Dutriaux and Gyselinck (2016) searched for a way to modulate the motor simulation at encoding and see whether it affects the motor simulation at retrieval. As stated earlier, Glenberg (1997) proposed that the world is encoded in terms of affordances, which are dependent on the organism's ability to act. Thus, if the simulation of affordance is involved in the representation of manipulable objects, a constraining posture should interfere with the affordance and thus decrease the memory of manipulable objects. Based on this reasoning, Dutriaux and Gyselinck (2016) used two different postures. The control posture, in which the participants' hands were free in front of them, was chosen to favour free-hand actions and thus motor simulation. The interfering posture requires the participants to keep their hands behind their back to interfere with action possibilities and thus with the supposed motor simulation of affordance. This posture has been chosen because it has been found to have a negative effect on motor simulation (e.g., Ambrosini & Costantini, 2017; Sirigu & Duhamel, 2001). Dutriaux and Gyselinck (2016) showed that keeping one's hands behind one's back interferes with the long-term memory of pictures as well as words denoting manipulable objects, but did not interfere with the memory of non-manipulable objects. This specific interfering effect of posture on action material, referred to as the *Postural Interference effect* (PI effect), clearly shows that conceptual memory and the motor system share processing resources and that long-term memory serves at least in part to support action.

This experiment might be taken as evidence that motor simulation depends on whether the context (i.e., the posture) is more or less conducive to action. Several other studies are consistent with this idea. For instance, previous experiments have suggested that an interfering posture (e.g., Sirigu & Duhamel, 2001) can reduce motor simulation. In the same vein, when an object is presented in the non-reachable space, the motor simulation is reduced (Cardellicchio, Sinigaglia, & Costantini, 2011; Costantini, Ambrosini, Scorolli, & Borghi, 2011). Given that motor simulation has been shown with pictural as well as with verbal materials (e.g., Dutriaux & Gyselinck, 2016; Tucker & Ellis, 2004), providing a non-action linguistic context might be able to modulate the motor simulation of affordance in a similar way. The objective of the present study was to explore this idea by modulating the action context with both posture and language. A number of researchers have proposed that the comprehension of a sentence requires a sensorimotor simulation of its meaning as a whole (e.g., Barsalou, 1999; Glenberg & Robertson, 1999), which could be seen as a sensorimotor situation model (see "Discussion" section). It follows that the sensorimotor simulation of a concept is flexible in that its simulation should depend on the linguistic context of the sentence. That is, the motor simulation should vary, depending on to what extent the linguistic context emphasises action or not (Masson, Bub, & Warren, 2008; Moody & Gennari, 2010; van Dam, Brazil, Bekkering, & Rueschemeyer, 2014). In support of this hypothesis, a functional neuroimaging study by van Dam et al. (2014) showed that the motor activity related to the reading of a word denoting a manipulable object depends on whether the typical use of the object is emphasised by the linguistic context. Masson et al. (2008) presented their participants with sentences containing a manipulable object and a verb. The verb was either an "attentional verb," that is, without any direct physical interaction ("looking at the calculator"), or a non-manual action verb ("kicking the calculator"). Attentional sentences were found to facilitate only the actions related to the function of the object, whereas action sentences were found to prime also the actions related to grasping it (see also Ambrosini, Scorolli, Borghi, & Costantini, 2012; Borghi & Riggio, 2009). Thus, it seems that the verb associated with the object in the sentence modulates the simulation. It follows from these various studies that when a word denoting a manipulable object is presented in an action context, the associated motor simulation is favoured. We should therefore evidence a greater motor interference when the context highlights action than when it does not. To validate this hypothesis, the present experiment aimed to show that the PI effect on manipulable objects observed by Dutriaux and Gyselinck (2016) will be modulated by an action context. A PI effect related to the verb was tested with the names of manipulable objects inserted in phrases with action verbs ("To take a cup") or with attentional verbs ("To see a cup"). The participants had to learn the phrases presented one by one. As in Dutriaux and Gyselinck (2016), they had to put their hands in front of them during the learning phase in the control condition, whereas they had to keep them behind their back in the interfering condition. After a distractive letter-matching task, the participants had to perform a cued recall task. The verbs were presented one by one, and the participants had to recall the object associated with each verb during the learning phase. Previous studies (e.g., Masson et al., 2008) have shown that the simulation of affordance depends on the verb associated with the object, suggesting a sensorimotor simulation of the whole sentence and not of each word individually. The motor simulation related to the object should consequently be less pronounced with attention than with action verbs. Furthermore, if long-term memory is for action, one would expect a worse memory when the context does not favour action. Thus, if a constraining posture that prevents action interferes with motor simulation during encoding, we should expect a PI effect related to the verb, that is, a greater interference effect of the constraining posture on the memory of manipulable objects associated with an action verb than with an observation verb.

Method

Participants

In total, 36 undergraduates studying psychology at Paris Descartes University took part in the experiment for course credits. All participants gave their informed consent to the experimental procedure.

Materials

In total, 40 names of manipulable objects (i.e., tools, for example, "pen," "hammer") and 20 verbs were used (see Supplemental Files at the Open Science Framework website: https://osf.io/kewpu/). The 40 names of manipulable objects were divided into four lists of 10 objects. Among the verbs, 10 were action verbs (e.g., "to grasp") and 10 were attentional verbs (e.g., "to observe"), matched in terms of objective frequency ($U=47$, $p=.85$) and word length ($U=29.5$, $p=.12$). Objective frequency means were computed with the database "lexique" (New, Pallier, Ferrand, & Matos, 2001).

Procedure and design

Participants were tested individually in a quiet room with the experimenter present. For each list, participants were exposed to a learning phase, then to a distractive task, and

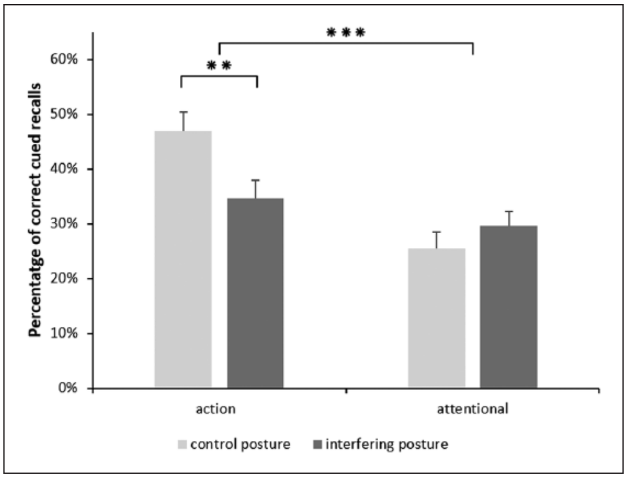

Figure 1. Means for the percentage of items recalled as a function of verb type and posture.
Error bars represent standard errors of the mean (**p<.01; ***p<.001).

finally to an oral free recall. During the learning phase, half of the names of manipulable objects were randomly associated either with an action verb (e.g., "to grasp a hammer") or with an attentional verb (e.g., "to observe a hammer"). Each phrase of each list was presented one by one as a whole on a computer screen during 3,500 ms, with an interstimulus interval of 1,000 ms. In each list, five of the names of manipulable objects were associated with an action verb, and five were associated with an attentional verb. Given that there are 40 objects for 20 verbs, each verb was used twice, but never in the same list. For each participant, lists were presented randomly, and, within each list, verbal expressions were also presented randomly. Participants were instructed to learn the sentences while adopting different postures. They were said that the verbs will be used as a cue and that they will have to recall the corresponding object. They were warned that they would have to recall the name of the object corresponding to the verb cues. In the control condition, they were instructed to put their hands on the desk in front of them, at rest. They were allowed to move their hands if necessary (e.g., to scratch their head), but not to cross their arms. In the interfering condition, they had to keep their hands behind their back, while holding one of their wrists with the other hand. Each participant was presented with three lists in the control condition and three lists in the interfering condition. The order of the two blocks of three lists was counterbalanced across participants. At the beginning of the 2-min distractive task, participants in the interfering condition had to put their hands back on the desk. Pairs of letters were presented. For each pair, one letter was in upper case, whereas the other was in lower case, and participants had to say orally whether the letters were the same (e.g., "A," "a") or different (e.g., "A," "b"). Finally, still with their hands in front of them, participants had to perform a cued recall task. Each verb was presented one by one as a cue, and the participants had to recall orally which objects were associated with the verbs during the learning phase.

Results

Figure 1 shows the mean percentages of objects correctly recalled. These percentages were computed by considering that only exact answers (and not synonyms) were correctly recalled. The data were analysed using a 2 × 2 repeated measure analysis of variance (ANOVA), with verb type and posture as within-subject variables. First, the results showed a main effect of verb type, $F(1, 35) = 21.81$, $p < .001$, $\eta_p^2 = .38$, that is, objects associated with an action verb during the learning phase were better recalled than objects associated with an attentional verb. In line with preceding results (Dutriaux & Gyselinck, 2016), the main effect of posture was nearly significant, $F(1, 35) = 3.9$, $p = .06$, $\eta_p^2 = .10$, with a decrease in the memory of manipulable objects learned with the interfering posture. Crucially, the expected interaction corresponding to the PI effect was found, $F(1, 35) = 9.94$, $p = .003$, $\eta_p^2 = .22$. To assess whether the effect of posture is specific to objects associated with action verbs, two planned comparisons were run, contrasting both postures for each verb type. As predicted, the planned comparisons showed that the interfering posture decreased the memory of objects associated with action verbs, $t(35) = 3.35$, $p = .002$, $\eta_p^2 = .25$, but not of objects associated with attentional verbs, $t(35) = 1.43$, $p = .16$, $\eta_p^2 = .06$.

Discussion

The objective of this experiment was to show that the action context produced by the linguistic context and the posture modulates motor simulation of affordance and, consequently, the memory of words denoting manipulable objects. Participants were presented with lists of phrases that were composed of an action or an attentional verb associated with a manipulable object. Participants had to learn the phrases while adopting a control posture (i.e., their hands free in front of them) or an interfering posture (i.e., hands behind their back). After a distractive task, participants had to recall the objects' names, with the verb presented as a cue. The results showed first that the recall of the manipulable objects associated with an action verb was better than those associated with an attentional verb. More importantly, the expected PI effect was observed, that is, the postural interference affected the memory of the objects associated with the action verbs, but not the memory of the objects associated with an attentional verb.

This result is first consistent with the idea that memory and motor systems share processing resources. Previous studies have shown that motor simulation of object-related actions is less intense when the object name is presented with an attentional verb than with an action verb (e.g., Masson et al., 2008). It seems here that the posture with hands behind the back interfered with the motor simulation allowed by the action verbs (and not the attentional verbs), and that this interference decreased the memory of manipulable objects. As suggested by previous work (Matheson et al., 2014), this interference might not be specific to the memory of manipulable objects. A control condition combining verbs and non-manipulable objects would be needed to make sure that this interference is specific to manipulable objects. Given that Dutriaux and Gyselinck (2016) found no effect of posture on single words referring to non-manipulable objects, it is likely that the same would hold with non-manipulable objects associated with verbs, but it would require further investigations. Even though the mechanism behind the postural interference has still to be clarified (see Dutriaux and Gyselinck, 2016), these results are consistent with other studies showing that keeping one's hands behind the back affects motor simulation (e.g., Ambrosini & Costantini, 2017; Sirigu & Duhamel, 2001). Altogether, those elements suggest that motor simulation has indeed a role in memory. This is in line with other studies showing motor interference on manipulable objects (e.g., Lagacé & Guérard, 2015; Myung et al., 2010; Pobric et al., 2010; Witt et al., 2010; Yee et al., 2013), but, as emphasised in the "Introduction" section, contradicts others (e.g., Garcea et al., 2013; Matheson et al., 2014; Zeelenberg & Pecher, 2016). Further investigations are thus needed to support this hypothesis.

Second, this experiment showed that in the conditions that did not favour action—that is, with hands behind the back and with the action verb—the recall of manipulable objects decreased. Even though these results are consistent with the view that memory is for guiding action, this interpretation might be questioned. First, the main effect of verb might be explained by a difference in terms of imageability or concreteness between the two kinds of verbs. It is indeed likely that action phrases are more concrete and imageable than attention sentences, and thus easier to learn, which is a shortcoming for the interpretation of these results. However, it is difficult to explain how concreteness could account for the specific effect of posture on action sentences. One might also argue that it is not possible to say whether the effect of posture arises from the motor or proprioceptive information about the position of the arms, about holding their wrist, or from the visual absence of the hands. That question would be an interesting avenue for future research. However, all of these different explanations involve the fact that the hands are less available for actions, and are thus consistent with the idea that long-term memory and action share processing resources and that memory encodes information in part for guiding action.

This study also has implications for language comprehension. The mental model theory (Johnson-Laird, 1983) claims that language comprehension results from the construction of a situation model. According to this theory, a situation model is an amodal representation that is structurally analogous to the described situation. Thus, a situation model could be seen as an amodal simulation of language. Embodied cognition, however, suggests that situation models are sensorimotor simulations (Barsalou, 1999; Glenberg & Robertson, 1999). Consistent with this idea, some studies have shown that the motor simulation related to the name of a manipulable object depends on whether the context highlights action (e.g., Masson et al., 2008; van Dam et al., 2014). This kind of conceptual flexibility is in line with the idea that language comprehension relies on the sensorimotor simulation of the meaning of the whole sentence, that is, a sensorimotor situation model. However, these motor activations could be the mere consequences of an activation cascade, without any role in comprehension (Mahon & Caramazza, 2008). The present experiment demonstrated a PI effect, that is, a motor interference in the processing of concepts of manipulable objects only when the linguistic context highlighted action. This study is thus the first one, to our knowledge, to show that the modulation of motor simulation has a role in the flexibility of manipulable object concepts, that is, in the construction of situation models. Furthermore, this experiment suggests that the processing of a sentence is modulated by posture, which means that situation models are constructed in the context of our action possibilities. Thus, it can be argued that an embodied situation model does not represent the elements of the described environment necessarily to the same extent, but it represents them in such a way as to guide action.

To sum up, this research newly shows that motor interference, that is, hands behind the back posture, decreases the memory of words denoting manipulable objects when associated with an action verb, but not when associated with an attentional verb. It suggests that motor simulation has a role in long-term memory and language processing. Furthermore, the recalls decreased when the context did not highlight action. Thus, this work shows quite clearly (1) that long-term memory and motor systems share processing resources, and (2) that memory is at least in part for guiding action.

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Open Practices

The data and materials from the present experiment are publicly available at the Open Science Framework website: https://osf.io/kewpu/.

Supplementary material

The Open Practices disclosure form is available at journals.sagepub.com/doi/suppl/10.1177/1747021818785096.

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Incidental exposure to hedonic and healthy food features affects food preferences one day later

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Abstract

Memories acquired incidentally from exposure to food information in the environment may often become active to later affect food preferences. Because conscious use of these memories is not requested or required, these incidental learning effects constitute a form of indirect memory. In an experiment using a novel food preference paradigm ($n = 617$), we found that brief incidental exposure to hedonic versus healthy food features indirectly affected food preferences a day later, explaining approximately 10% of the variance in preferences for tasty versus healthy foods. It follows that brief incidental exposure to food information can affect food preferences indirectly for at least a day. When hedonic and health exposure were each compared to a no-exposure baseline, a general effect of hedonic exposure emerged across individuals, whereas health exposure only affected food preferences for high-BMI individuals. This pattern suggests that focusing attention on hedonic food features engages common affective processes across the general population, whereas focusing attention on healthy food features engages eating restraint goals associated with high BMI. Additionally, incidental exposure to food features primarily changed preferences for infrequently consumed foods, having less impact on habitually consumed foods. These findings offer insight into how hedonic information in the obesogenic food environment contributes to unhealthy eating behavior that leads to overweight and obesity. These findings further motivate the development of interventions that counteract the effects of exposure to hedonic food information and that broaden the effects of exposure to healthy food information.

Keywords: Eating, Food preference, Food exposure, Habits, Incidental learning, Indirect memory

Significance

We demonstrate that incidentally acquired memories of hedonic and healthy food features influence eating preferences. We further demonstrate that even brief exposure to food information can have lasting effects for at least a day. Finally, we demonstrate that exposure to hedonic information generally affects most individuals, whereas exposure to healthy information primarily affects individuals high in BMI. These findings have significant implications for understanding eating cognition and behavior. They also have significance for developing interventions that discourage unhealthy eating and promote healthy eating. To establish these findings, we developed a novel experimental paradigm informed by basic research in cognitive psychology. Specifically, we examined how the classic memory processes of incidental learning and indirect memory combine to influence food preferences. We further demonstrated how individual differences can be integrated into this paradigm (BMI, healthy eating habits), along with differences in foods (tasty foods vs. healthy foods; habitually consumed foods vs. occasionally consumed foods). Finally, we developed an approach to mixed-effect modeling that focuses on establishing effect sizes and on assessing the generalizability of effects across participants and foods.

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People are constantly exposed to diverse sources of food information that highlight various outcomes of food consumption, such as immediate hedonic pleasure, long-term health, and physical attractiveness. On the one hand, the food industry uses images and language to promote how tasty, filling, satisfying, and enjoyable consuming a food will be. On the other, health experts recommend reducing the consumption of foods high in fat, salt, and sugar, while increasing the consumption of foods that lead to health and longevity.

Previous research has established that exposure to food information in advertising, store placement, brand endorsements, and digital games can have considerable impact on consumer behavior. Norman et al. (2016), for example, reviewed effects of exposure to hedonic food information in children and found it to have a causal, dose–response effect on preferences, choices, and consumption of unhealthy foods. Vukmirovic (2015) reviewed effects of exposure to both hedonic and healthy information in adults and found that both types of information affected food preference, choice, and consumption.

Exposure to hedonic food information is likely to play a central role in the obesogenic food environment, amplifying the widespread consumption of unhealthy energy-dense foods that are palatable, socially acceptable, and inexpensive (Marteau et al. 2012). Although sources of health information encourage healthy eating, their influence may often fail to counteract the overwhelming effects of their unhealthy counterparts. In this context, overweight and obesity have become challenging public health issues worldwide, with high prevalence in both children and adults (Hales et al., 2017), accompanied by serious health consequences (GBD Obesity Collaborators, 2017). Additionally, most overweight and obese individuals cannot achieve and maintain significant weight loss (Knowler et al., 2009).

To better understand how exposure to food information affects eating behavior, it is important to establish the cognitive and affective processes that underlie food preference, choice, and consumption (cf. Sheeran et al., 2017). By establishing these processes, we can better understand the effects of exposure to hedonic and healthy food information in the environment, along with whom it affects most. We can also develop precision interventions that offset the effects of unhealthy food information and that enhance the effects of healthy food information. Here, we develop an experimental approach for examining these issues, motivated by memory research in cognitive psychology.

Incidental acquisition of food information

Some food information may be learned intentionally and remembered deliberately, as when people learn and practice dieting. The acquisition and use of most food information, however, may often occur in a much more incidental and unintentional manner (e.g., Marteau et al., 2012; Papies, 2016a, b, 2017). When people encounter food information in the environment, it is unlikely that they intentionally try to establish memories of it. Although people may actively engage with this information as they process and evaluate it, they may not attempt to learn anything from it intentionally. Nevertheless, information from these processing episodes may become established in memory incidentally, especially when processed deeply (as well-designed food information is typically meant to be).

Classic memory research indeed demonstrates that extensive learning occurs incidentally as a byproduct of deep processing (e.g., Craik & Lockhart, 1972; Craik & Tulving, 1975; Hyde & Jenkins, 1973; Jacoby, 1983). As long as participants process a stimulus deeply for its meaning or self-relevance, they remember it well on later memory assessments, even though they had no idea that memory would be tested (e.g., Hamilton et al., 1980; Nairne et al., 2007; Roediger, 1990; Rogers et al., 1977). People often remember incidentally acquired information as well or better than information acquired intentionally. The implication is that a tremendous amount of information becomes established incidentally in memory. No doubt, much useful information is acquired in this manner, although detrimental information can be acquired as well (e.g., prejudice and stereotypes; Greenwald & Banaji, 1995, 2017). To the extent that food information is processed deeply, it is likely to leave long-term effects on memory, even though no intention existed to acquire it.

Indirect activation and use of food information

Once food information has been acquired incidentally, it may become active unintentionally on later occasions when encountering related foods and deciding whether to purchase or consume them. Although no intention exists to retrieve and use this information, it becomes active involuntarily when encountering a relevant food and influences decision-making, especially when little explicit thought goes into the decision. Following a classic distinction in the memory literature, we assume that unintentionally activating previously acquired food information constitutes a form of *indirect memory*: Whereas direct memory occurs during a conscious deliberate attempt to remember something, indirect memory occurs when memories become active involuntarily in the absence of a conscious intention to remember (Johnson & Hasher, 1987; Richardson-Klavehn & Bjork, 1988).

Importantly, the distinction between direct and indirect memory tasks makes no assumptions about *underlying memory processes*. Potentially, both explicit memories and implicit memories can become active during each kind of task (where explicit memories are typically assumed to be conscious and effortful, and implicit memories are typically assumed to be unconscious and effortless; Johnson & Hasher, 1987; Richardson-Klavehn & Bjork, 1988). Although direct memory tasks primarily engage explicit memory processes, they may also engage implicit memory processes to a lesser extent. Although indirect memory tasks primarily engage implicit memory processes, they may also engage explicit memory processes occasionally. Thus, the indirect activation of food information when making food choices potentially includes both implicit and explicit memories. The paradigm developed here was not designed to establish which types of memory become active indirectly, nor does this issue bear on the claims we make. Instead, our primary claim is simply that foods activate memories indirectly, in turn affecting food preferences.

It is important to note that the indirect activation of incidentally acquired food information differs from classic priming effects that result from immediate contextual cues. Of interest in the experiment reported here is how *a food itself*—in the absence of contextual primes—indirectly activates incidentally learned information that affects its processing. We return to the distinction between incidental learning and health priming in eating research later.

Much memory research demonstrates that information in memory becomes active indirectly as people perform a broad spectrum of cognitive tasks (e.g., Corkin, 1968; Jacoby, 1983; Jacoby et al., 1989; Milner et al., 1968; Reber, 2013; Roediger, 1990; Roediger & McDermott, 1993; Schacter et al., 1993; Squire et al., 1993). Because this information is not required for task performance, it is not activated intentionally but instead becomes active involuntarily. Although some indirectly activated information may be experienced consciously, much of it often remains unconscious. Nevertheless, these indirect activations often have considerable impact, speeding the processing of perceptual stimuli, facilitating the execution of motor responses, and activating relevant semantic information.

Processing food information in the environment offers a paradigm case of the continual interaction between incidental learning and indirect memory. For example, after encountering food information that highlights hedonic features of cheeseburgers (e.g., tasty, savory, filling), later encountering a cheeseburger may indirectly activate memories of these incidentally established features, producing a hedonic simulation of enjoying the cheeseburger that motivates its consumption (Papies & Barsalou, 2015). Alternatively, after encountering food information that highlights a cheeseburger's unhealthy features (e.g., high in fat, salt, and additives), later encountering a cheeseburger may indirectly activate memories of these features, producing simulations of unhealthy long-term consequences that inhibit consumption.

Paradigm

In a novel well-controlled experimental paradigm, we assessed whether incidentally acquired memories of hedonic versus healthy food features affected food preferences indirectly a day later. We next provide an overview of this paradigm and our measure of food preference.

Assessing indirect effects of incidentally acquired food information

During an initial incidental learning procedure, one group of randomly assigned participants was exposed to hedonic features of 24 tasty foods and 24 healthy foods (the hedonic exposure group). A second group of participants was exposed to healthy features of the same 48 foods (the health exposure group). Figure 1A and B illustrate examples of the tasty and healthy foods. Figure 1C presents the hedonic features that the hedonic exposure group received, and Fig. 1D presents the healthy features that the health exposure group received. In what was presented as a consumer feedback task, the hedonic exposure group endorsed the hedonic features that they perceived in each food, and the health exposure group endorsed the healthy features that they perceived in each food. Participants in both groups were led to believe that they were simply evaluating the features of foods in a consumer survey, with nothing said about learning or a later memory assessment. Thus, the endorsement task created an incidental learning manipulation between groups, with the hedonic group exposed to hedonic features, and the health group exposed to healthy features.

Similar to how food information in the environment is often presented to consumers, the endorsement task made food features salient and actively engaged participants in processing them deeply. As people encounter food information, they may evaluate it, discuss it with others, and make decisions about purchasing or consuming specific foods. Establishing the features that a food does or does not have is an important part of this process, captured by the endorsement task in our exposure manipulation.

One day later—after processing associated with incidental learning had subsided—participants performed a food preference task (Fig. 1E). On each trial, participants were asked how much they would want to eat each food for a particular meal (e.g., How much would you want to eat FISH AND CHIPS for DINNER?). Of interest was whether information acquired incidentally the day before during exposure became active indirectly to affect food preferences.

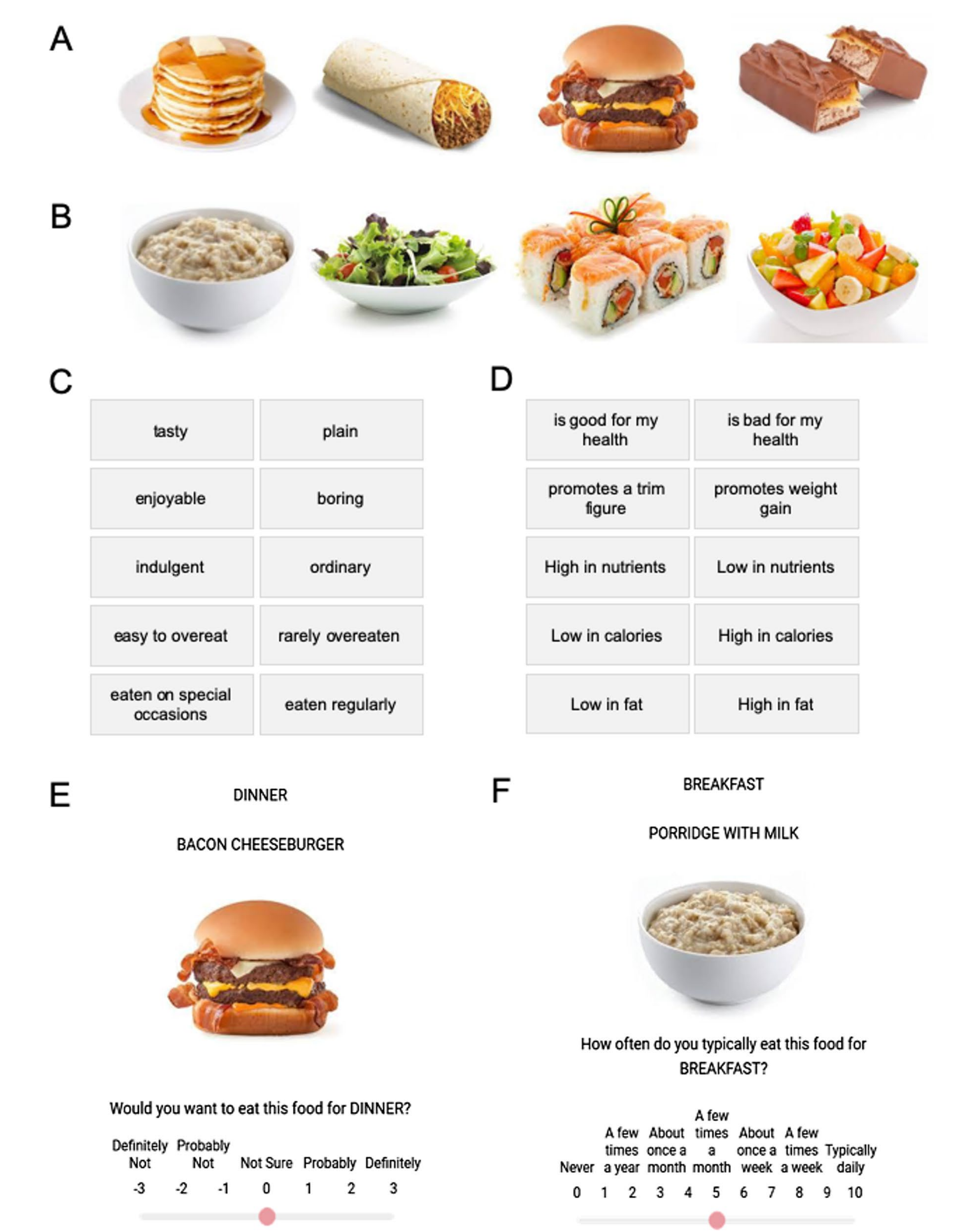

Fig. 1 Examples of the tasty foods (**A**) and healthy foods (**B**) used in the experiment (see Additional file 1: Figures SM-1 and SM-2 for the complete food sets). Hedonic features (**C**) and healthy features (**D**) that participants could endorse for foods during the training phase. An example of a food preference trial (**E**). An example of a frequency trial for habitual food consumption (**F**)

To assess whether either hedonic exposure, health exposure, or both types of exposure affected food preference relative to a baseline, a third group of participants performed the preference task with no previous exposure (the no-exposure baseline group). The three different types of exposure were implemented between groups to minimize demand and repetition effects that would have complicated interpretations of a repeated measures design. A no-exposure baseline was used because it offers the most naturalistic approach to assessing whether exposure to hedonic and healthy food information affects food preferences.[1] Of interest in the real world is how exposure to new food information changes food preferences relative to the steady state of current food knowledge (for discussion of other possible baselines, please see footnote 1).

To further minimize demand while participants made food preference judgments, a comprehensive cover story obscured the relation between the incidental learning and food preference tasks. As a consequence, participants had no reason to intentionally learn or deliberately remember information from the exposure phase. Instead, if information from the exposure phase affected food preferences later, it is likely to have done so indirectly.

We assessed exposure effects relative to people's eating habits. One possibility is that exposure to hedonic and healthy features affects preferences for all foods, regardless of whether they are consumed frequently or infrequently. Another possibility is that exposure has relatively little impact on frequently consumed foods. Because eating habits have much more strength in memory than information acquired incidentally via brief exposure, eating habits could dominate preference. If so, then exposure effects should primarily occur for foods consumed infrequently, given the greater potential for influencing their preferences. Much related work demonstrates the powerful ability of habits to override other sources of influence in cognition and behavior (Mazar & Wood, 2018; Orbell & Verplanken, 2018; Ouellette & Wood, 1998; Webb & Sheeran, 2006). To assess these possibilities, our paradigm collected data on how frequently participants consumed the 48 foods (in an additional consumer survey that followed the food preference task; Fig. 1F).

Finally, we assessed whether exposure effects interact with individual differences. Much research reports that individual differences interact with interventions to change eating habits (e.g., Buckland et al., 2018). We therefore included measures of healthy eating habits, dietary restraint, and body mass index (BMI)[2] to assess whether these individual differences moderated any observed exposure effects. It is important to note that even though BMI is not a perfect indicator of health, it nevertheless remains strongly associated with unhealthy eating behavior, body fat, and poor health outcomes in eating research (please see footnote 2 for further details).

Assessing food preference

As just described, our experiment assessed the impact of exposure to hedonic versus healthy features on food preferences for tasty versus healthy foods. We could have measured these preferences in the preference phase by simply asking participants to indicate their overall preference for tasty foods and their overall preference for healthy foods (as often done in the literature; e.g., Hearty et al., 2007). Much work shows, however, that general decontextualized assessments often fail to predict behavior well. Instead, *focused assessments in specific situations* are more accurate (e.g., Ajzen & Fishbein, 1977, 2005; Glasman & Albarracín, 2006; Siegel et al., 2014).

For this reason, we focused the assessment of food preference in two ways. First, instead of assessing each participant's overall preference for tasty and healthy foods, we assessed their preference for each of 24 specific foods within each food type. Additionally, instead of assessing a participant's general preference for a specific food, we asked them how much they would want to eat the food for a specific meal (e.g., how much would you want to eat

[1] We considered a variety of active baselines as well, but each was associated with a bias towards hedonic or healthy foods (e.g., simple exposure to food pictures without the endorsement task is likely to induce hedonic processing; Papies et al., 2012; Papies et al., 2015). Furthermore, by contrasting hedonic exposure with health exposure, we compared two conditions that contained the same amount of stimulus presentation and processing across two days. If neither type of exposure had an effect (or if they both simply produced an overall fluency effect relative to the no-exposure baseline), then there should have been no differences between them. To the contrary, we observed substantial differences between the two exposure conditions across experiments, each producing a unique pattern of results. Thus, when one exposure group was treated as an active control for the other, large predicted differences occurred, demonstrating that both exposures have unique effects. Additionally, the absence of an overall exposure effect rules out the possibility that the exposure conditions produced a simple fluency effect relative to the no-exposure baseline. Various results suggest instead that food features processed during the endorsement task were responsible for the specific exposure effects observed. Later, Hypothesis 1 captures this contrast between two equally matched exposure conditions, with each exposure condition serving as an active control for the other. Additionally, Hypothesis 2 captures the contrast of a single exposure condition to a passive no-exposure baseline, as described in the text. Thus, both active and passive baseline were addressed and captured in the results reported.

[2] We assess BMI here because it remains a widely used and accepted measure in current eating research. Nevertheless, it is important to note that BMI is limited in various ways. For example, high BMI does not always indicate poor health (e.g., body builders), nor consumption of unhealthy food (e.g., people who eat too much healthy food). Additionally, BMI can inadvertently promote fat-shaming and negative stereotypes towards populations associated with greater body weight (e.g., low SES, various racial and ethnic groups). Notwithstanding such limitations, BMI nevertheless remains strongly associated with unhealthy eating behavior, body fat, and poor health outcomes in eating research. Consistent with these widespread results, we found that BMI strongly predicted preferences for tasty and healthy foods (Fig. 3, Table 2). We also found that BMI predicted effects of health exposure (Figs. 6 and 7, Table 5), as found widely in the literature. Throughout our experiment, BMI behaved as expected, providing a valid statistical measure of unhealthy eating behavior.

PIZZA for DINNER?). By specifying both specific foods and specific meals, we focused participant's judgments on specific eating situations.

Measures of food preference typically correlate with consumption (e.g., Boswell et al., 2018; Hollands & Marteau, 2016; Van Dessel et al., 2018; also see Norman et al., 2016; Vukmirovic, 2015). As authoritative reviews by Subar et al. (2015) and Thompson and Subar (2017) describe, self-report measures often provide accurate estimates of consumption, especially when the goal is not to estimate energy intake precisely in terms of calories, but is instead to assess the foods consumed. Indeed, these reviews document the importance of self-report eating instruments in health and nutrition science. To establish the validity of our food preference measure, we demonstrate later that it tracks predicted differences in BMI and healthy eating habits. We also discuss the importance of assessing food preferences and eating intentions during the preliminary phases of eating prior to consumption (also see Sobal et al., 2014).

Experiments performed

Using the paradigm just described, we performed three experiments that assessed the indirect effects of incidental exposure to food information. The first was a small pilot experiment that offered a preliminary assessment of hedonic and health exposure effects and their interaction with eating habits without the no-exposure baseline ($n = 39$). As predicted, the pilot experiment found that: (1) manipulating hedonic versus health exposure affected food preference, and (2) exposure interacted with eating habits. We do not report the pilot experiment's results here but provide a document on OSF that provides a complete account of its methods and results (https://osf.io/y2zpk/).

Based on the pilot experiment, we subsequently ran two identical pre-registered experiments with larger samples that attempted to replicate the pilot experiment's critical findings ($n = 302$, $n = 315$). Besides replicating the basic design of the pilot experiment, these second and third experiments added the no-exposure baseline and assessed individual difference measures for BMI, healthy eating habits, and eating restraint.

The pre-registration for the second experiment formalized the informal predictions in the pilot experiment and added new predictions for the exposure baseline and individual difference measures (https://osf.io/re5mw/). The second experiment's results replicated the pilot experiment's key findings and partially confirmed the new predictions for the no-exposure baseline and individual difference measures. Because these new predictions were only partially confirmed, we wanted to replicate the pattern of results obtained.

We therefore used the second experiment's results to make pre-registered predictions for the third experiment (https://osf.io/aes79/). Because the second and third experiments were identical, our intention at that time was to eventually combine them. Thus, the second pre-registration predicted, first, that the third experiment would replicate the second experiment's results, and second, that when we combined these two experiments, the combined results would demonstrate the second experiment's results with greater power (https://osf.io/aes79/).

As predicted, the second and third experiments produced the same general pattern of predicted results. To simplify presentation, we only present results from the combined experiment here and only address its pre-registered predictions. For interested readers who would like to compare results across the two parts of the combined experiment, the individual results can be found in Additional file 1, the Supplemental Material (SM), referred to there as Parts A and B.

To further streamline presentation, only the primary hypotheses in the combined experiment's pre-registration are addressed here.[3] All hypotheses not addressed

[3] Here, we list preregistered hypotheses for the combined experiment that are not addressed in the main text. Most often, these hypotheses were pre-registered for the combined experiment only because they were significant in Part A, or seemed like they would become significant with the increased power that resulted from combining Parts A and B. Otherwise, these hypotheses were typically not of interest. All details can be found on OSF in a Preregistrations Summary document (https://osf.io/y2zpk/).

(a) We predicted an exposure × frequency × food type interaction on food preference. As Table 4 in the main text shows, this interaction did indeed occur, significant for Model 2. We only preregistered this hypothesis because it was significant in Part A, not because it was of interest. Indeed, we're not sure how to interpret it.

(b) We originally predicted a four-way interaction between exposure × food type × BMI × healthy eating habits because it appeared significant in Part A. When, however, the lmer package that produced it was updated at one point, this interaction was no longer significant. By then, however, we had pre-registered the interaction for Part B and the combined experiment, where it was also not significant. Again, we only pre-registered it for the combined experiment it because it initially appeared present in Part A.

(c) We originally predicted a food type × exposure × healthy eating habits interaction, first, when hedonic exposure was contrasted with no-exposure, and second, when health exposure was contrasted with no-exposure. Because these interactions appeared present in Part A to varying extents, we thought that they would likely emerge with the greater power of the combined experiment. They did not. Again, we only preregistered this hypothesis because this interaction appeared present in Part A, not because it was of interest or easily interpretable.

(d) When comparing hedonic exposure to no-exposure, we originally predicted that hedonic exposure would interact significantly with BMI. This interaction did not reach significance in Part A. Because, however, a hint of it appeared in Part A, we preregistered it for the combined experiment. Contrary to our speculation, this interaction was again not significant in either Part B nor in the combined experiment. Because it didn't actually reach significance in Part A, we probably should not have preregistered it in the first place.

(e) Because we had performed successful mediation analyses for Part A, we preregistered the same mediation analyses for Part B and the combined experiment. Following these preregistrations, we decided that our designs did not meet the assumptions for mediation analysis, and so removed these results from the current article. We note, however, that all mediation analyses supported all preregistered hypotheses related to them (complete analyses can be found the Preregistrations Summary document at https://osf.io/y2zpk/). We further note that other results that we do report in the main article capture the critical components of the mediation analyses.

were secondary (a complete list of these hypotheses and their results can be found in footnote 3). A document that presents all pre-registered hypotheses for Part A, Part B, and the combined experiment can be found on the project's OSF site, together with the specific results that bear on each (https://osf.io/y2zpk/).

Hypotheses

The hypotheses presented next were the central ones preregistered on OSF for the combined experiment. For readers interested in the underlying theoretical motivation for these hypotheses, detailed explanations for specific predictions can be found in an additional document on OSF (https://osf.io/y2zpk/; for a general account, see Papies & Barsalou, 2015).

Hypothesis 1: Effects of hedonic versus health exposure on food preference

Incidental exposure to hedonic versus healthy food features will indirectly influence preferences for tasty versus healthy foods a day later. Although tasty foods will be preferred more than healthy foods in *both* the hedonic and health exposure groups (a main effect), tasty foods will become even more preferred relative to healthy foods following hedonic exposure than following health exposure (an exposure × food type interaction on food preference).

Should this predicted interaction occur, it follows that incidental learning affects food preferences indirectly a day later. If incidental learning has no effect, the two exposure conditions should not differ. Furthermore, because the two exposure conditions are well-matched for content and tasks during training (day 1), any observed difference between them rules out the possibility that effects on food preference (day 2) only reflect simple fluency (Jacoby, 1983; Jacoby et al., 1989). If only fluency were operating, the two exposure conditions would not show different patterns for food preference. Instead, differential exposure effects most likely result from differential processing of food features during the endorsement task (please see footnote 1 for further discussion).

Hypothesis 2: Effects of hedonic versus health exposure relative to the no-exposure baseline

Relative to the no-exposure baseline, only hedonic exposure will produce a group-level effect on food preferences. Although tasty foods will be preferred more than healthy foods for *both* the hedonic and no-exposure groups (a main effect), tasty foods will be even more preferred relative to healthy foods following hedonic exposure than following no exposure (an exposure × food type interaction on food preference). Because hedonic exposure activates common affective processes associated with pleasure and reward across individuals, it will generally influence individuals regardless of their BMI and healthy eating habits.

In contrast, health exposure will not exhibit a group-level effect of on food preferences. Because health exposure is most likely to only influence food preferences for individuals concerned about their body weight (e.g., individuals with high BMI), health exposure will not produce a group-level effect (for related results, see Buckland et al., 2018; Papies, 2016a, 2016b). As predicted in Hypothesis 5, however, health exposure will influence food choices for high-BMI individuals (i.e., an individual-level effect).

Hypothesis 3: Effects of hedonic and healthy endorsements on food preference

As just predicted, we only expected hedonic exposure to have an overall effect on food preferences—not health exposure. An explanation of this potential effect is that only making hedonic endorsements during the exposure phase affected food preferences later—making healthy endorsements did not.

Specifically, we reasoned that as more hedonic features become active and endorsed during hedonic exposure, more pleasure will be anticipated from consuming the food being evaluated (Papies & Barsalou, 2015). In the process of simulating these pleasure experiences, robust memories will be established incidentally. When participants perform the food preference task the next day, these robust memories will be highly available and become active indirectly to affect task performance. As the number of hedonic features in an activated memory for a food increases, preference for consuming the food will become stronger, reflecting greater anticipated pleasure.

In contrast, we expected that health exposure would produce relatively "cold" cognitive appraisals of foods that lack the "hot" affective elements associated with hedonic pleasure and reward (Metcalfe & Mischel, 1999; Strack & Deutsch, 2004). As a consequence, memories established incidentally during health exposure will not be as robust and accessible as memories established during hedonic exposure. As a further consequence, these memories will be less likely to become active and affect food preferences.

To establish whether only hedonic endorsements affected food preferences, we predicted the presence of an exposure × endorsements interaction (Hypothesis 3). Specifically, we predicted that preferences for foods would only increase as more hedonic features were endorsed for them, not as more healthy features were endorsed.

Hypothesis 4: Effects of consumption frequency on food preference

As foods are consumed more frequently, preferences for them will increase substantially across all exposure conditions (a main effect of consumption frequency). In other words, eating habits will produce a large frequency effect on current food preferences.

Additionally, because eating habits have much more strength in memory than information acquired incidentally during brief exposure, eating habits will dominate preference relative to endorsement. As a consequence, the endorsement effect predicted for Hypothesis 3 will become minimal at high levels of consumption frequency (a frequency × endorsement interaction on food preference)—increasing consumption frequency will attenuate the effect of increasing endorsement.

Finally, because we only predict an endorsement effect for hedonic exposure (Hypothesis 3), the attenuating effect of consumption frequency on endorsement will primarily occur for hedonic exposure (an exposure × frequency × endorsement interaction on food preference).

Hypothesis 5: BMI modulates the effect of health exposure

As described for Hypothesis 2, we did not expect health exposure would have a general effect on food preferences across individuals (relative to the no-exposure baseline). Instead, we hypothesized that health exposure would only influence food preferences for individuals who are likely to be concerned about their body weight (e.g., individuals high in BMI; for related results, see Buckland et al., 2018; Papies, 2016a, b). Rather than predicting a group-level effect of health exposure, we predicted an individual-level effect. Specifically, health exposure will only affect individuals high in BMI (relative to the no-exposure baseline), decreasing their overall preference for all foods, regardless of whether foods are tasty or healthy (a health exposure × BMI interaction on food preference).

We reasoned that during health exposure, healthy features of food will become salient and important for many high-BMI individuals. As a consequence, robust memories of food healthiness will become established in memory incidentally for them. When these individuals perform the food preference task the next day, these robust memories will be highly available and become active to affect preferences indirectly. Specifically, these individuals will adopt a restrained perspective on food consumption that reduces their overall preference for both food types. Consistent with reducing overall calorie intake, these individuals will temper their interest in all foods, both tasty and healthy.

Methods

The Ethics Committee of the College of Science and Engineering at the University of Glasgow approved this research. All experimental materials are available in the SM and on OSF (https://osf.io/ys4q2/).

Design

To avoid demand and repetition effects, exposure was manipulated between three exposure groups (not as repeated measures): hedonic exposure, health exposure, and no exposure. During the exposure phase on day 1, participants in the hedonic and health exposure groups endorsed each of the same 48 foods (24 tasty, 24 healthy) for either its hedonic features (hedonic exposure) or for its healthy features (health exposure). One day later, participants in all three exposure groups performed a test session on the 48 foods from day 1 (identical across groups). The test session included: (1) a food preference task; (2) a consumption frequency task; (3) collection of individual difference measures (BMI, healthy eating habits, dietary restraint); (4) assessment of experimental demand.

Overall, the experimental design included one independent variable manipulated at the group level (exposure), another manipulated within participants (food type), and five continuous predictors (endorsements, consumption frequency, BMI, eating habits, restraint). Food preference served as the primary dependent variable. Foods and participants were included as random effects.

Participants and sample size

Following the pilot experiment, we performed a power analysis to establish suitable power for Part A of the combined experiment (described in the SM). Based on this analysis, Part A included 302 participants assigned randomly to hedonic exposure ($n=102$), health exposure ($n=100$), and no-exposure ($n=100$). Part B provided a replication of Part A that included 315 participants assigned randomly to hedonic exposure ($n=103$), health exposure ($n=105$), and no-exposure ($n=107$). When Parts A and B were combined, the hedonic, health, and no-exposure groups contained 205, 205, and 207 participants, respectively, (617 total). All participants in Parts A and B were recruited from the Prolific online platform, which had a panel of over 50,000 individuals at the time (paid £6/h). Requirements for participation included age (18–30), minimum number of previous Prolific studies (10), minimum Prolific approval rate (95%), language fluency (English), and residence (a current UK resident). Because the pilot experiment developed a sample of foods relevant for UK participants aged 18–30, both later experiments sampled the same age group as well.

No participant who completed both sessions in any of the three experiments was excluded. In the pilot experiment, all participants completed both sessions. In Parts A and B, 3 and 8 participants, respectively, did not complete both sessions and were not included in the sample sizes just reported.

Materials

For each of 4 eating situations (breakfast, lunch, dinner, snack), 6 tasty and 6 healthy foods were sampled from previously established food norms (Werner et al., 2021). In these norms, the 24 tasty foods were highly rated for tastiness and fillingness but not for healthiness, whereas the 24 healthy foods exhibited the opposite pattern. Later results verify our pre-registered prediction that hedonic and healthy endorsements would confirm the assignments of foods to the tasty and health food groups.

To support the experimental cover story, 6 hedonic and 6 healthy birthday gifts were also included (e.g., cocktail making master class, fitness tracker wristband). The SM provides a complete set of the food and gift stimuli presented across experiments.

Day 1 procedure

After being recruited on the Prolific platform, participants were directed to the Qualtrics platform, where they performed the first session online. Participants were informed that their data would be completely anonymous and that we would have no access to their personal data. Participants were then told that they would perform a series of consumer surveys across two sessions on two consecutive days and provided consent. At multiple points, the instructions conveyed that there were no correct answers to any of the questions that participants would be asked and that instead we wanted to know how *they* perceive the qualities and desirability of consumer products. We further asked them to answer intuitively with whatever came to mind naturally without a lot of thought. Once participants read the instructions, they were asked to work in a quiet place where there were no distractions. They were also asked to not take any breaks.

To prevent demand, participants were led to believe that the individual surveys in the two sessions were unrelated. Specifically, participants were told that we were surveying products from multiple consumer categories, including cars, clothing, electronics, foods, and gifts, and that, across a series of surveys, products from these categories would be assessed for a variety of their qualities and desirability. Participants were then told that they had been selected to evaluate products from the categories of gifts and foods. To introduce participants to the first survey, they received an example of a gift (juicer) with 10 features arranged in 2 columns below. Participants in the hedonic exposure group received 5 pairs of hedonic/nonhedonic properties; participants in the health exposure group received 5 pairs of healthy/unhealthy properties. The 10 endorsement features in each exposure condition were constant across gifts. Nothing was said to participants about whether the features they assessed were hedonic or healthy, and they knew nothing of the other exposure group. They simply received the 10 features below each gift and were asked to tick off as many or as few of the features that they believed applied to it. Specifically, they were asked, "From the list below, please select all the qualities that you think apply to this gift."

Participants then received an example of a food (Victoria sponge cake), with analogous instructions to tick off as many or as few of the features that they believed applied to the product. Figure 1C presents the 10 features that the hedonic exposure group assessed; Fig. 1D presents the 10 features that the health exposure group assessed (constant across foods). Again, nothing was said to participants about whether the features they assessed were hedonic or healthy. Participants again had no idea that another group of participants was assessing different features for the foods.

Similar to the presentation of much food information in the environment, the endorsement task made food features salient and actively engaged participants in processing them. This task also had several useful properties for implementing incidental learning: (1) It ensured deep processing of the foods, similar to orienting tasks often used to implement depth-of-processing manipulations in the memory literature. (2) It made hedonic or healthy food features salient. (3) It provided a cover story that blocked intentional learning. (4) It allowed us to establish that the 24 tasty foods were indeed high in hedonic features and low in healthy features, and conversely, that the 24 healthy foods were high in healthy features and low in hedonic features.

Participants then performed these two surveys. During the first, they received 12 gifts from the category of birthday gifts (with the category mentioned explicitly). Although these trials served as practice, participants were not aware of this, but instead believed that we were collecting consumer evaluations of gifts. The 12 gifts were randomized differently for each participant.

Participants then received the 48 foods, which were similarly presented in blocks of 12 for breakfast foods, lunch foods, dinner foods, and snack foods. These blocks were presented in a fixed order to reflect the temporal order in which meals normally occur over the course of a day (snacks were presented last, given that they could occur any time). The relevant eating situation was labeled explicitly prior to each block, with its 12 foods randomized for each participant.

Once participants finished evaluating the 48 foods, they were immediately asked to repeat the two surveys just performed (i.e., thereby doubling the amount of exposure received). To justify these repeated tasks to participants, we told them that performing the surveys again would increase the accuracy of our product assessments. Specifically, participants were told that, "Previous research has found that people's evaluation of consumer products improves with practice. For this reason, we would like you to evaluate the products again one more time. This will help us establish the perceived qualities of these products as best as possible." Participants then evaluated the same 12 gifts and 48 foods as before, with the products in each block shown in a new random order.

Once participants completed these last two blocks, they were told that further consumer surveys would follow the next day. Participants had no reason to believe that they needed to learn information during the exposure phase, such that any information acquired was learned incidentally (not intentionally). The day 1 session took approximately 20 min. All participants performed this session on the same day, within a few hours of recruitment messages being distributed.

Endorsement scores

We computed an endorsement score for a participant's assessment of each food. For hedonic exposure, the number of non-hedonic features endorsed (Fig. 1C, right) was subtracted from the number of hedonic features endorsed (Fig. 1C, left) to create an endorsement score for each food from -5 to + 5 (non-hedonic to highly hedonic). For health exposure, the number of unhealthy features endorsed (Fig. 1D, right) was analogously subtracted from the number of healthy features endorsed (Fig. 1D, left), to create an endorsement score for each food from − 5 to + 5 (highly unhealthy to highly healthy). A participant's overall endorsement of a food was calculated as the average of the endorsement scores from its two presentations.

Day 2 procedure

Twenty-four hours after the day 1 session, all participants in the hedonic exposure and health exposure groups received a second anonymous link via Prolific that redirected them to the Qualtrics platform for the day 2 session. Concurrently, additional participants were recruited from Prolific for the no-exposure group, who met the same inclusion criteria as the participants recruited into the exposure groups. Participants in all groups were required to perform the day 2 session by midnight.

Participants were informed that they would perform a series of consumer surveys. Again, they were told that we were interested in how people perceive products in various consumer categories (cars, clothes, electronics, foods, gifts), and that they had been chosen to evaluate gifts and foods. Nothing indicated to the exposure groups that session 2 was related to session 1 in any way. Instead, the day 2 session was simply described as further consumer surveys. To the extent that any information learned incidentally became active during session 2, it became active indirectly. Rather than being asked to deliberately remember information, participants were simply asked to provide food preferences and frequency estimates. Thus, any information from session 1 that became active was indirect in the sense of not being requested explicitly or necessary for performing the current tasks.

Participants first performed a preference task on the 12 birthday gifts from the day 1 exposure session, randomly ordered for each participant. For each gift, they were asked, "Would you want to give this as a BIRTHDAY GIFT?" Participants responded on a -3 to + 3 continuous slider with the labels: *definitely not, probably not, not sure, probably, definitely* (positioned initially at 0). Participants then performed a preference task on the 48 foods from the day 1 exposure session in explicitly labeled blocks for breakfast, lunch, dinner, and snack (in this fixed order, with the 12 foods in each block randomly ordered for each participant). For both preference tasks, participants were told that we were interested in the desirability of products from the two consumer categories. Prior to the gift block, participants practiced on 1 gift and 1 food.

For the food preference task, participants were asked, "Would you want to eat this food for [MEAL]?", where [MEAL] could be BREAKFAST, LUNCH, DINNER, or SNACK (Fig. 1E). We selected this wording because it is sufficiently ambiguous to motivate preferences based on either hedonic or healthy features. Participants could want to eat a food because it would be pleasurable or because it would be healthy. Indeed, phrasing the task as "Would you want to eat this food…" implies wanting something because of its incentive value, which can take many different forms, including hedonic pleasure and healthy outcomes (Berridge, 1996; Berridge et al., 2009).

To make each food preference judgment, participants clicked the point on the slider scale that best represented how much they would want to eat the food for a particular eating situation. The more likely they were to eat a food, the more they should click a point on the scale toward + 3. The less likely they were to eat the food, the more they should click a point toward − 3. The more unsure they were about whether or not to eat the food, the more they should click a point near 0. The preference slider was always positioned at 0 initially.

After completing the gift and food preference trials, participants were told that a final consumer survey would ask them to estimate how often they give each gift as a birthday present, and how often they eat each food for a meal. Participants received the 12 gifts in a random order and rated each on a 0 to 10 continuous slider scale for "How often do you give this as a BIRTHDAY GIFT?" with scale labels ranging from "Never" to "Every time." They then received the 48 foods and rated each on a 0 to 10 continuous slider scale for "How often do you typically eat this food for [MEAL]?" with scale labels from "Never" to "Typically daily." Figure 1F presents the screen format and slider scale for the assessment of food consumption frequency, with the slider always positioned initially at 5. Again, foods were blocked by meals in a fixed order (breakfast, lunch, dinner, snack), with the 12 foods randomized within each block for each participant.

Following the frequency assessments, demand was assessed with a series of four quantitative items: (1) To what extent did your responses to the survey questions reflect your personal assessments of the products you viewed? (2) To what extent did you try and respond in a way that you thought the survey researchers wanted to hear? (3) To what extent did you respond intuitively and naturally to the survey questions without a lot of deliberate thought? (4) To what extent do you believe that there are correct answers to the survey questions? Participants responded to all four questions using a 0 to 6 continuous slider scale with the labels: Not at all, Moderately, Completely.

Individual difference measures were then collected. To establish BMI, we asked participants for their height and weight (without mentioning that BMI was being assessed). To assess healthy eating habits, we asked participants to complete the Adolescent Food Habit Checklist (Johnson et al., 2002). To assess eating restraint, we asked participants to complete the restraint scale of the Three Factor Eating Questionnaire (TFEQ-R18; Anglé et al., 2009).

Finally, participants were debriefed, thanked, and redirected back to the Prolific platform for payment. Qualtrics screens for the survey can be found on OSF (https://osf.io/ys4q2/).

Regression analysis procedure

The primary goals of our analysis procedure were to: (1) identify likely effects, (2) establish their effect sizes, and (3) assess their generalizability across participants and foods. To do so, we first *z*-transformed the dependent variable and its predictors to specify each predictor's effect in standard deviation units. As a consequence, each estimated regression coefficient indicates the standard-deviation-unit change in the dependent variable associated with each standard-deviation-unit change in the respective predictor. The sign of these standardized coefficients indicates the direction of the relationship. If, for example, a standardized coefficient for the relation between consumption frequency and food preference happened to be 0.50, this meant that food preference increased positively by 0.50 of a standard deviation for each standard deviation increase in consumption frequency. The larger a coefficient, the larger its effect size.

In each regression analysis, we implemented a sequence of three multilevel mixed-effect models (using the lme4 package in R; Bates et al., 2015). We will refer these models as *Model 1*, *Model 2*, and *Model 3*. These models were *multilevel* because they predicted a dependent variable such as food preference using both food-level predictors (endorsements, consumption frequency) and individual-level predictors (BMI, healthy eating habits). These models were *mixed effect* because they simultaneously assessed both fixed effects (exposure, food type) and random effects (random intercepts for participants and foods; random slopes that captured variability in the fixed effects across participants and foods). Assessing random effects is essential for generalizing results beyond participants and foods in the current samples (Barr et al., 2013). Mixed-effect modeling offers a powerful approach for establishing the generalizability of effects across participants and foods simultaneously.

In the first stage of our analysis procedure, Model 1 identified predictors (main effects and interactions) likely to have meaningful effects on the dependent variable. Model 1 included main effects for all predictors of interest at the participant and food levels, all interactions of these predictors up through three-way, and random intercepts for participants and foods. This relatively liberal model served to identify potentially important predictors that were subsequently examined more closely and conservatively in Models 2 and 3. For a main effect or interaction to pass this initial screening, the t for its estimated regression coefficient had to be greater than $|1.96|$ (associated with a p value ≤ 0.05). We assumed that any effect that failed this relatively liberal initial screening would be unlikely to have a meaningful impact on the dependent variable.

For each potentially important effect identified in Model 1, we then assessed it more conservatively in a unique Model 2 that tested it *maximally* (Barr et al., 2013). Specifically, maximal testing established whether an effect in Model 1 generalized across participant-level and food-level variability in the current sample, and also whether it is likely to generalize across future samples of participants and foods. Imagine, for example, that a 0.50 estimated regression coefficient for consumption frequency survived initial screening in Model 1. If large individual differences in participants and habits were associated with this effect, then it might not generalize to the broader populations of participants and foods. To test an observed effect in Model 1 maximally, Model 2 added one empirically determined random slope for each participant that modeled the effect for that participant. Additionally, Model 2 added one empirically determined random slope for each food that modeled the effect for that food. Of interest was whether the t for the effect in Model 2 remained greater than $|1.96|$ once the variances of all random effects for participants and foods were accounted for simultaneously (i.e., both intercepts and slopes). If the effect passed this maximal testing, we concluded that it generalizes both in and beyond the participants and foods sampled here. If the effect failed maximal testing, we assumed that it does not.

Including appropriate random slopes simultaneously in Model 2 for each and every predictor that survives initial screening in Model 1 is typically not possible, as the sheer complexity of the model disrupts optimization and convergence. To circumvent this problem, Barr et al. (2013, p. 276) suggested maximally testing each effect of interest one at a time (i.e., including appropriate random slopes for foods and participants associated with the effect of interest, while not including random slopes for any remaining effects). Thus, when maximally testing the effect of (say) consumption frequency, a unique Model 2 was constructed by adding random slopes for consumption frequency to Model 1 but not adding random slopes for any other effect. In this manner, a unique Model 2 was constructed for each effect that passed Model 1 screening. Importantly, whenever a higher-order *interaction* passed Model 1 screening, random slopes were also included for all lower-order interactions and main effect terms nested within it (see Barr et al., 2013).

If an effect passed maximal testing in Model 2, it was evaluated one more time in a unique Model 3 that established how much unique variance it explained in Model 2. In each Model 3, we dropped the main effect or interaction being tested from its Model 2, along with any interactions containing it and any associated random slopes, while keeping everything else the same as in Model 2. We then subtracted the total variance for the effect's Model 3 from the total variance for its Model 2. The difference in R^2 (ΔR^2 expressed as a percentage) established how much unique variance the effect captured when included *as a fixed effect together with associated interactions and random effects* in Model 2.

Using this analysis procedure, we established effects that generalized across the current samples of participants and foods, and that are also likely to generalize across future samples. For each effect established as generalizable in Model 2, we obtained two measures of its effect size: (1) its standardized regression coefficient in Model 2, and (2) its ΔR^2 derived from Model 3.

Results

Only results from the combined experiment are reported here. As described earlier, individual results for Parts A and B can be found in the SM, and results for the pilot experiment can be found on OSF (https://osf.io/y2zpk). The data and R analysis scripts for the combined experiment can also be found on OSF, along with those for Part A, Part B, and the pilot (https://osf.io/s5u3p). For interested readers, the SM also provides the average non-standardized measures for endorsement, preference, and consumption frequency in the combined experiment, for each of the 48 foods, in each exposure condition.

Preliminary analyses

We first present the results of two preliminary analyses. The first provided a manipulation check of food type, demonstrating that the tasty and healthy foods varied in hedonic and healthy features as predicted. The second assessed the validity of our food preference measure, demonstrating that it reflected predicted differences in BMI and healthy eating habits. Each of these two analyses assessed (and verified) pre-registered predictions for the combined experiment.

Validation of the tasty versus healthy foods manipulation

The endorsement scores collected during the day 1 session offered a manipulation check of the tasty versus healthy food assignments. We predicted that the tasty foods would be endorsed as having many hedonic features and few healthy features. Conversely, we predicted that the healthy foods would be endorsed as having many healthy features and few hedonic features.

As described earlier, a single endorsement score resulted from how many hedonic or healthy features a participant endorsed for a food on each trial of the exposure phase, with the scores for the two presentations of the same food averaged across exposure blocks. In the hedonic exposure condition, increasing endorsement scores indicated that a food was perceived as increasingly hedonic. In the health exposure condition, increasing endorsement scores indicated that a food was perceived as increasingly healthy.

To assess the validity of our tasty and healthy food assignments, endorsement scores were regressed onto exposure condition and food type. Figure 2 plots the results, and Table 1 presents the statistical analysis. As predicted, tasty foods received high hedonic endorsement scores from participants in the hedonic exposure condition, while receiving low healthy endorsement scores from participants in the health exposure condition.

Conversely, healthy foods received low hedonic endorsement scores from participants in the hedonic exposure condition, while receiving high healthy endorsement scores from participants in the health exposure condition. As the interaction in Fig. 2 further illustrates, tasty and healthy foods differed much more in how healthy they were perceived than in how hedonic they were perceived (i.e., the slope for healthy endorsements was much steeper than the slope for hedonic endorsements). Participants clearly distinguished the relative healthiness of the tasty versus healthy foods.

As Table 1 illustrates, the exposure × food type interaction in Fig. 2 passed maximal testing in Model 2, exhibiting a robust estimated regression coefficient ($t > |1.96|$). As a consequence, this predicted interaction generalizes across foods and participants here, and is likely to generalize across future foods and participants. Additionally, this interaction explained 61% unique variance associated with endorsement scores in Model 3, indicating that tasty and healthy foods differed substantially as expected.

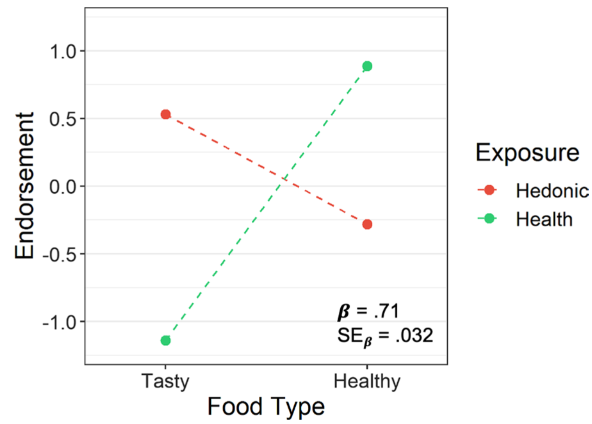

Fig. 2 Evidence for the validity of the food type manipulation between tasty and healthy foods. Whereas tasty foods were high on hedonic endorsements and low on healthy endorsements, healthy foods were low on hedonic endorsements and high on healthy endorsements. Hedonic endorsements were produced in the hedonic exposure condition, and healthy endorsements were produced in the health exposure condition. A modeled interaction from regression is shown, with the endorsement scale plotted in standardized units. From Table 1, the standardized estimated regression coefficient for the interaction is shown (β), together with its standard error to provide a measure of expected variability (SE_β)

Validation of the food preference measure

If the food preference measure is valid, it should respond in expected ways to individual differences in healthy eating habits and BMI. Consistent with this prediction, the food preference measure was strongly related to these individual difference measures. As participants' eating habits became increasingly healthy, preferences for healthy foods increased, whereas preferences for tasty foods decreased (Fig. 3A). Conversely, as participants' BMI increased, preferences for healthy foods decreased, whereas preferences for tasty foods increased (Fig. 3B). These two interactions indicate that the food preference measure tracked predicted differences in healthy eating habits and BMI, demonstrating its validity.

Table 2 presents the supporting statistical results from regressing food preference onto food type, healthy eating habits, and BMI. As predicted, both the healthy eating habits × food type interaction and the BMI × food type interaction survived maximal testing in Model 2, exhibiting robust estimated regression coefficients ($t > |1.96|$). As a consequence, both interactions generalized across participants and foods here, and are likely to generalize across future participants and foods.

The results for Model 3 in Table 2 further indicate that each interaction explained large amounts of unique variance in food preference. Specifically, the healthy eating habits × food type interaction explained 11% unique variance in food preference, and the BMI × food type interaction explained an additional 7%. These large predicted interactions demonstrate that the food preference measure closely tracked important individual differences in eating.

Further validation of the food preference measure comes from the predicted food type × eating habits × BMI interaction in Fig. 3C, D. As just described,

Table 1 Mixed-effect regressions of endorsement on food type and exposure

DV: endorsement	Model 1			Model 2					Model 3	
Predictor	Estimate	SE	t	Estimate	SE	t	R^2	AIC	ΔR^2	AIC
Food type	− .30	.028	− 10.78	− .30	.030	− 10.05	73	32,045	− 5	34,454
Exposure	.13	.010	12.70	.13	.031	4.01	73	31,779	− 4	34,531
Food type × exposure	.71	.004	176.94	.71	.032	22.29	78	28,847	− 61	53,007

Regressions were performed on standardized measures. Thus, an estimate is the estimate of a standardized regression coefficient in the respective model, with SE and t being the standard error and t value of the estimate. R^2 is the total variance explained by Model 2, and ΔR^2 is the amount of variance explained by the main effect or interaction dropped in Model 3 (both in percentages. AIC is the value of the Akaike Information Criterion for Models 2 and 3. For Food Type, tasty foods were coded + 1, and healthy foods were coded − 1. For Exposure, hedonic exposure was coded + 1, and health exposure was coded − 1

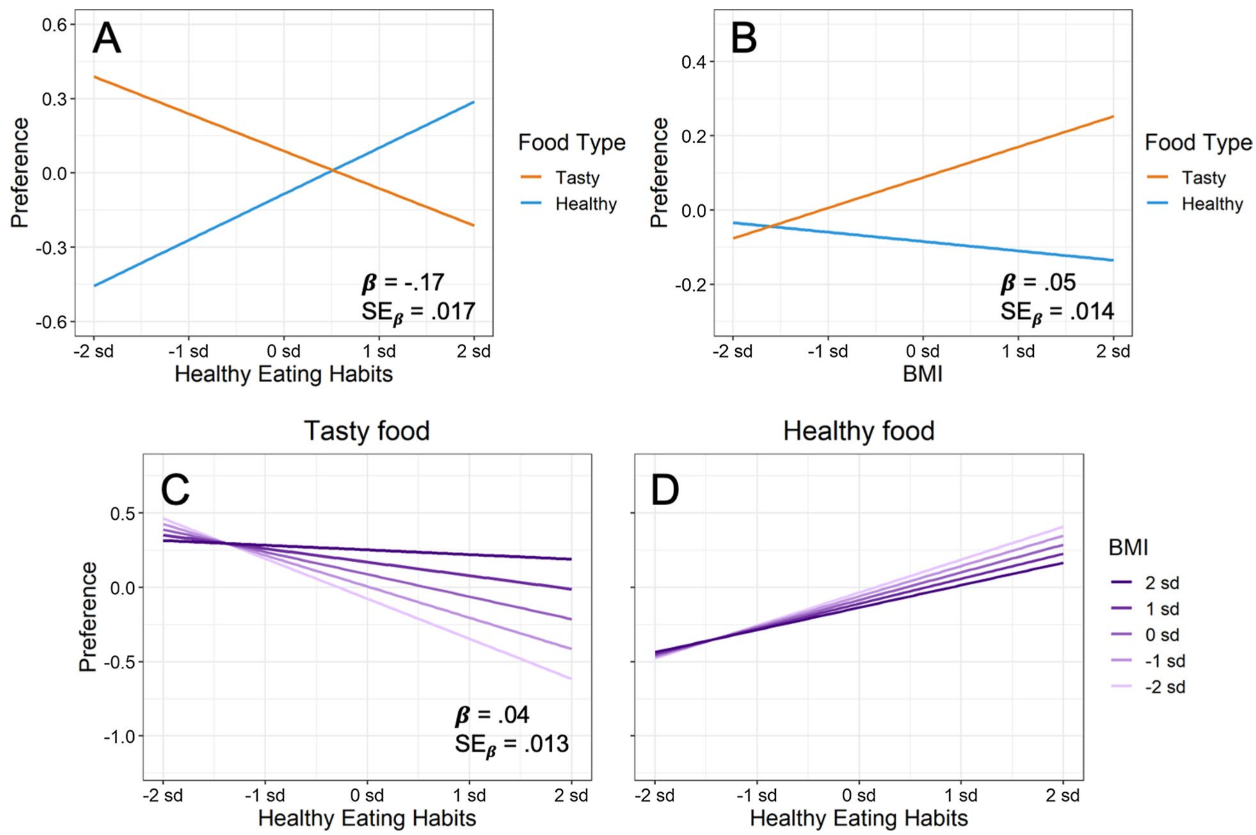

Fig. 3 Evidence for the validity of the food preference measure. **A** As participants' eating habits become increasingly healthy, preferences for healthy foods increased, whereas preferences for tasty foods decreased. **B** Conversely, as participants' BMI increased, preferences for healthy foods decreased, whereas preferences for tasty foods increased. (C and D) The food type × eating habits × BMI interaction further shows that BMI modulated the food type × eating habits interaction in Panel A. In each panel, a modeled interaction from regression is shown, with all scales plotted in standardized units. From Table 2, the standardized estimated regression coefficient for each interaction is shown (β), together with its standard error to provide a measure of expected variability (SE_β)

Fig. 3A demonstrated that healthy eating habits were associated with decreasing consumption of tasty food and increasing consumption of healthy food. Importantly, however, BMI significantly moderated this interaction. As Fig. 3C illustrates, increasing BMI largely eliminated the decreased preference for tasty foods associated with healthy eating habits. Conversely, Fig. 3D illustrates that increasing BMI diminished the increased preference for healthy foods associated with healthy eating habits, although to a much lesser extent.

As Model 3 in Table 2 illustrates, an additional 8% unique variance in food preference was explained by the food type × eating habits × BMI interaction. Together the three interactions between food type, eating habits, and BMI explained a substantial 26% unique variance in food preference. These strong predicted interactions demonstrate the validity of the food preference measure, showing that it tracks important individual differences related to food consumption that originate outside the laboratory.

Hypothesis 1: **Effects of hedonic versus health exposure on food preference**

Our central prediction was that incidentally acquired memories of hedonic versus healthy food features would indirectly influence preferences for tasty versus healthy foods a day later. As Fig. 4 illustrates, tasty foods were preferred over healthy foods in both the hedonic and health exposure groups. Notably, however, this preference was much larger following hedonic exposure than following health exposure.

The top section of Table 3 (Hedonic vs. Health Exposure) presents the supporting statistical evidence. As predicted, there was a main effect of food type, with both exposure groups preferring tasty food over healthy food. Most importantly, the predicted food type × exposure interaction survived maximal testing in Model 2,

Table 2 Mixed-effect regression of food preference on food type (Food), healthy eating habits (Habits), and body mass index (BMI)

DV: food preference	Model 1			Model 2					Model 3	
Predictor	Estimate	SE	*t*	Estimate	SE	*t*	R^2	AIC	ΔR^2	AIC
Food type	.09	.038	2.26	.09	.040	2.18	28	76,731	− 7	78,345
Healthy eating habits	.02	.014	1.26							
BMI	.03	.015	1.90							
Food × Habits	− .17	.005	− 32.53	− .17	.017	− 9.96	29	76,532	− 11	79,380
Food × BMI	.05	.005	9.90	.05	.014	3.83	29	76,687	− 7	78,438
Food × Habits × BMI	.04	.006	6.99	.04	.013	3.00	29	76,502	− 8	78,389

Exposure was not included as a factor because the interactions of interest above remained constant across the three exposure conditions (i.e., the regression was performed on all 617 participants). All regressions were performed on standardized measures

indicating that the preference for tasty foods over healthy foods was stronger following hedonic exposure than following health exposure. Because this interaction survived maximal testing, it generalized across participants and foods here, and is likely to generalize across future participants and foods.

The results for Model 3 in Table 3 further indicate that the food type × exposure interaction explained a large amount of unique variance in food preference (11%). When hedonic versus health exposure was manipulated between groups of participants, it produced a substantial change in the relative preference of tasty over healthy foods. This result supports our central hypothesis that incidental learning influences food preferences indirectly a day later. Relatively small amounts of exposure to hedonic versus health information can impact food preferences considerably.

Hypothesis 2: Effects of hedonic versus health exposure relative to the no-exposure baseline

We further predicted that, relative to the no-exposure baseline, only hedonic exposure would produce a group-level effect on food preferences—health exposure would not. Whereas hedonic exposure would increase preferences for tasty foods over healthy foods, health exposure would not decrease this preference (relative to the preference for tasty foods over healthy foods in the no-exposure group). As Fig. 4 illustrates, the difference between hedonic exposure and no-exposure was indeed relatively large, but the difference between health exposure and no-exposure was not.

The second and third sections of Table 3 confirm these observations. For the Hedonic versus No-Exposure contrast, the food type × exposure interaction survived maximal testing in Model 2. For the Health versus No-Exposure contrast, however, the food type × exposure interaction failed maximal testing, reflecting the presence of large individual differences. When random slopes were added for health exposure, food type, and their interaction in Model 2, the exposure × food type interaction became much weaker, indicating that it does not generalize across participants and foods (i.e., $t = -1.11 < |1.96|$). This finding foreshadows the importance of individual differences later when we turn to BMI and healthy eating habits.

As Table 3 further illustrates for the Hedonic versus No-Exposure contrast, the food type × exposure interaction explained a large amount of unique variance in food preference (10%). Relative to the no-exposure baseline, hedonic exposure produced a large increase in the preference of tasty over healthy foods. A relatively small amount of exposure to hedonic information increased the relative preference for tasty foods across foods and participants a day later.

Hypothesis 3: Effects of hedonic and healthy endorsements on food preference

The endorsement data offer potential insight into the finding for Hypothesis 2 that only hedonic exposure influenced food preferences relative to the no-exposure baseline. Building on that finding, Hypothesis 3 further predicted that preferences for foods would only increase as more hedonic features were endorsed for them—not as more healthy features were endorsed (an exposure × endorsements interaction on food preference). On the one hand, endorsing hedonic features during hedonic exposure should incidentally establish highly accessible affective memories that influence food preferences indirectly a day later. On the other, endorsing healthy features during health exposure should produce less accessible memories that do not influence food preferences generally across participants. As a consequence, food preferences would only be related to the number of hedonic features endorsed, not to the number of healthy features endorsed.

The results in Fig. 5A confirm these predictions. Food preferences increased with the number of hedonic features endorsed during hedonic exposure but did not increase with the number of healthy features endorsed during health exposure. Although participants clearly discriminated the relative healthiness of tasty versus healthy foods (Fig. 2), their perceptions of healthiness

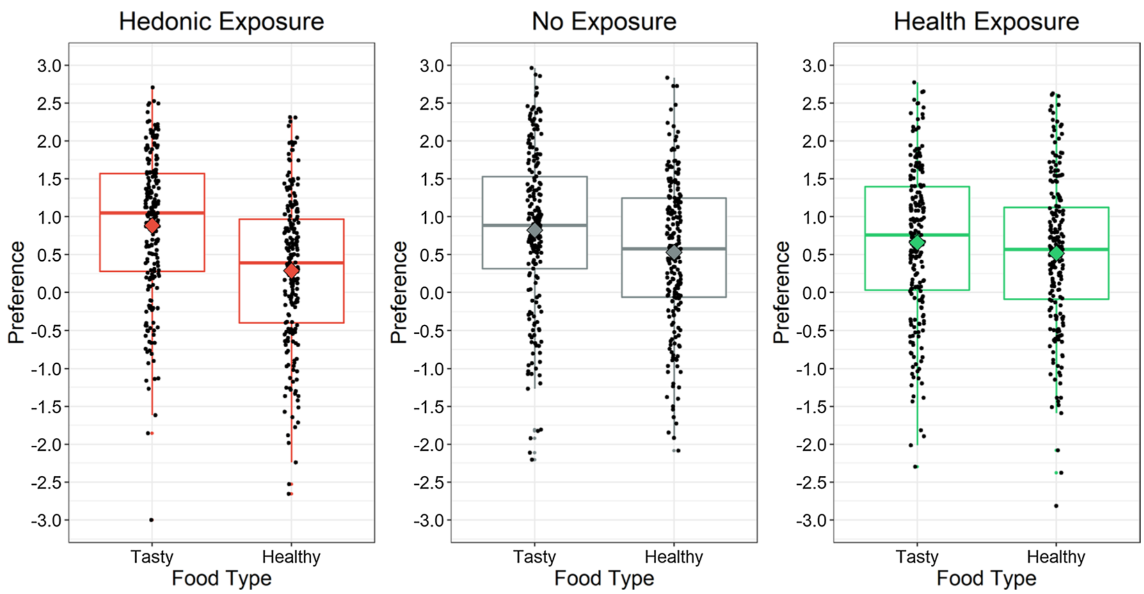

Fig. 4 Results for the food preference task. The vertical axis represents responses on the original − 3 to + 3 preference scale. For each exposure group, a diamond represents the mean; a box and whisker plot represents the median and inter-quartile range. Each point represents a participant's average judgment for either the 24 tasty foods or for the 24 healthy foods

Table 3 Mixed-effect regressions of food preference on food type and exposure

DV: food preference	Model 1			Model 2					Model 3	
Contrast/Predictor	Estimate	SE	*t*	Estimate	SE	*t*	R^2	AIC	ΔR^2	AIC
Hedonic vs. Health Exposure										
Food Type	.09	.040	2.26	.09	.043	2.09	29	51,312	− 11	53,146
Exposure	− .00	.017	− 0.07							
Food Type × Exposure	.06	.006	8.58	.06	.018	3.16	29	51,308	− 11	53,215
Hedonic vs. No Exposure										
Food Type	.11	.038	2.83	.11	.041	2.62	28	51,171	− 10	52,883
Exposure	− .02	.017	− 1.32							
Food Type × Exposure	.04	.006	5.72	.04	.017	2.13	28	51,167	− 10	52,909
Health vs. No Exposure										
Food Type	.05	.038	1.38							
Exposure	− .02	.018	− 1.20							
Food Type × Exposure	− .02	.006	− 2.81	− .02	.016	− 1.11	28	51,508		

Regressions were performed on standardized measures. For Food Type, tasty foods were coded + 1, and healthy foods were coded − 1. In the Hedonic vs. Health Exposure regression, hedonic exposure was coded + 1, and health exposure was coded − 1. In the Hedonic vs. No Exposure regression, hedonic exposure was coded + 1, and no exposure was coded − 1. In the Health vs. No Exposure regression, health exposure was coded + 1, and no exposure was coded − 1

were unrelated to their food preferences (Fig. 5A). Table 4 presents the supporting statistical results, showing that the endorsement × exposure interaction survived maximal testing in Model 2 and explained 4% unique variance in Model 3. Consistent with the results for Hypothesis 2, only hedonic endorsements on day 1 were related to food preferences on day 2.

Hypotheses 4: Effects of consumption frequency on food preference

We predicted that eating habits—as reflected in a participant's reported consumption frequency for each food—would heavily influence their food preferences. As a participant consumed a food more often, their preference for it would increase.

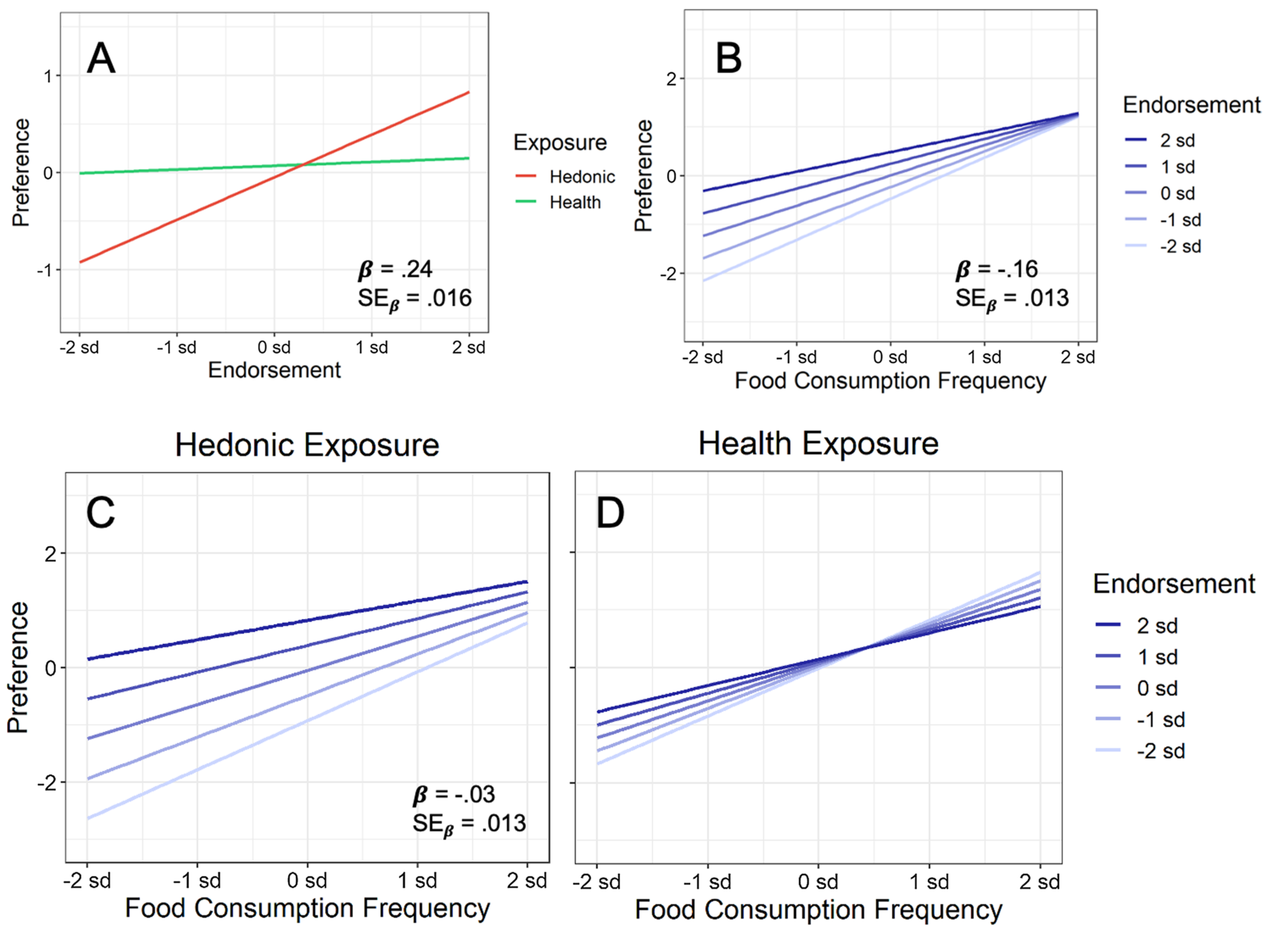

Fig. 5 **A** Interaction between exposure condition and endorsement on food preference (for increasing hedonic endorsements in the hedonic exposure condition and for increasing healthy endorsements in the health exposure condition). **B** Consumption frequency × endorsement interaction on food preference. **C**, **D** Endorsement × frequency × exposure interaction on food preference for the hedonic and health exposure conditions individually. In each panel, a modeled interaction from regression is shown, with all scales plotted in standardized units. From Table 4, the standardized estimated regression coefficient for each interaction is shown (β), together with its standard error to provide a measure of expected variability (SE_β)

Figure 5B plots the results, and Table 4 presents the statistical analysis. As Fig. 5B illustrates, food preference increased substantially as consumption frequency increased. As Table 4 documents, consumption frequency explained more unique variance in food preference than any other predictor in the experiment (17%), with a standardized regression coefficient of 0.62. As hypothesized, eating habits strongly predicted food preferences.

Because eating habits have much more strength in memory than information acquired via brief exposure, Hypothesis 4 further predicted that eating habits should dominate food preferences relative to endorsements. As a consequence, the endorsement effect just reported in Fig. 5A for Hypothesis 3 was predicted to become minimal at high levels of consumption frequency (a frequency × endorsements interaction on food preference). As Fig. 5B and Table 4 illustrate, consumption frequency did indeed interact with endorsements, explaining 9% of the variance in food preference. Consistent with our prediction, the effect of endorsements was weakest at the highest levels of consumption frequency. Whereas endorsements had large effects on food preferences for foods consumed occasionally, they had relatively little effect for foods consumed frequently. Together, frequency, endorsements, and their interaction explained a total 30% unique variance in food preference.

Table 4 Mixed-effect regressions of food preference on predictors that included frequency (Freq) and endorsement (Endorse), along with food type (Food) and exposure (Expo)

DV: food preference	Model 1			Model 2					Model 3	
Predictor	Estimate	SE	t	Estimate	SE	t	R^2	AIC	ΔR^2	AIC
Frequency	.62	.010	61.80	.63	.024	26.82	64	39,816	− 17	44,712
Endorsement	.24	.009	25.83	.27	.016	16.27	61	40,424	− 4	41,885
Food Type	.07	.026	2.52	.08	.028	2.95	59	40,450	− 2	41,236
Exposure	− .06	.018	− 3.30	− .06	.020	− 2.85	59	41,135	− 1	41,241
Frequency × Endorsement	− .11	.009	− 12.36	− .16	.013	− 12.26	67	38,838	− 9	41,382
Frequency × Exposure	− .02	.010	− 2.41	− .02	.015	− 1.28	65	39,686		
Endorsement × Exposure	.20	.009	21.52	.24	.016	14.85	61	40,372	− 4	41,688
Food × Exposure	− .07	.010	− 7.19	− .09	.017	− 5.55	60	40,343	− 2	41,282
Freq × Endorse × Food	− .02	.009	− 2.49	− .04	.012	− 2.83	68	38,528	− 10	41,236
Freq × Endorse × Expo	− .02	.009	− 1.96	− .03	.011	− 2.74	67	38,777	− 9	41,234
Freq × Food × Expo	.07	.010	6.84	.08	.012	6.68	67	38,927	− 9	41,277
Endorse × Food × Expo	− .03	.010	− 3.23	− .03	.013	− 2.33	62	40,098	− 4	41,241

Regressions were performed on standardized measures. For Food Type, tasty foods were coded + 1, and healthy foods were coded − 1. For Exposure, hedonic exposure was coded + 1, and health exposure was coded − 1

As we also saw in Fig. 5A for Hypothesis 3, the endorsement effect only occurred for hedonic exposure. It follows that the attenuating effect of consumption frequency on endorsements should therefore occur primarily for hedonic exposure and not for health exposure (an exposure × frequency × endorsements interaction on food preference). As Fig. 5C, D illustrate, frequency and endorsements did indeed interact with exposure. In Table 4, the exposure × frequency × endorsements interaction survived maximal testing in Model 2 and explained an additional 9% unique variance in Model 3. Whereas increasing endorsements and increasing consumption frequency both increased food preference following hedonic exposure, only increasing consumption frequency increased food preference following health exposure. Again, increasing healthy endorsements had no overall effect on food preference (illustrated previously in Fig. 5A).

Nevertheless, the frequency × endorsements interaction exhibited a common property across both the hedonic and health exposure conditions: As hedonic and healthy endorsements increased, they each attenuated the effect of consumption frequency on food preference (Figs. 5C, D). In both cases, increasing endorsements "flattened out" the strong effect of consumption frequency.

Importantly, however, hedonic endorsements attenuated the frequency effect much more than did healthy endorsements (i.e., the frequency effect became much flatter with increasing hedonic endorsements in Fig. 5C than with increasing healthy endorsements in Fig. 5D). Additionally, food preference increased for each increasing level of hedonic endorsements in Fig. 5C, but not with each increasing level of healthy endorsements in Fig. 5D. This latter effect essentially reflects the endorsements × exposure interaction presented earlier in Fig. 5A, where food preference only increased with hedonic endorsements but not with healthy endorsements.

Finally, increasing hedonic endorsements were associated with higher food preferences across all levels of consumption frequency, from low to high, with the increase becoming smaller as frequency increased. Increasing healthy endorsements, however, behaved differently. At low levels of frequency, increasing healthy endorsements increased food preferences, but at high levels, increasing healthy endorsements decreased food preferences. The latter effect could reflect the fact that foods high in healthy features are also low in hedonic features, leading to lower preferences.

Hypothesis 5: BMI modulates the effect of health exposure.

As reported for Hypothesis 2, we found that health exposure did not have a general effect across participants relative to the no-exposure baseline (Fig. 4, Table 3). We only expected that health exposure would influence food preferences for individuals who are likely to be concerned with their body weight. To assess this possibility, we assessed relations between health exposure and individual difference measures for BMI, healthy eating habits, and dietary restraint. We only report analyses for BMI and healthy eating habits because: (a) BMI and healthy eating habits were relatively unrelated ($r = -0.09$), (b) restraint correlated with healthy eating habits ($r = 0.52$), and (c) restraint behaved much like healthy eating habits

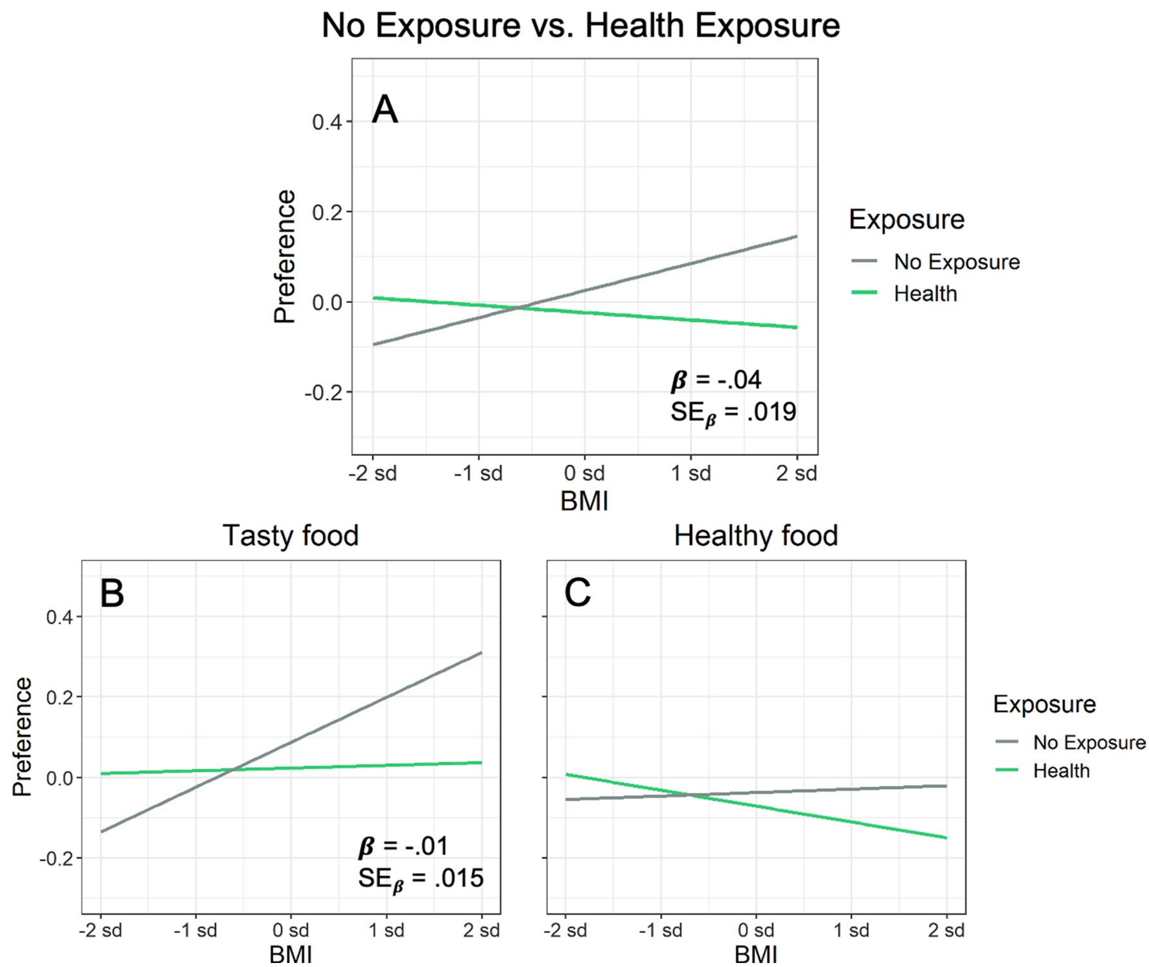

Fig. 6 **A** Exposure × BMI interaction on food preference. **B**, **C** Interaction individually for tasty and healthy foods, respectively (illustrating the *lack* of an exposure × BMI × food type interaction). In each panel, a modeled interaction from regression is shown, with all scales plotted in standardized units. From Table 5, the standardized estimated regression coefficient for each interaction is shown (β), together with its standard error to provide a measure of expected variability (SE_{β})

in the analyses to follow but showed weaker effects. Similar to healthy eating habits, restraint also correlated -0.09 with BMI.

To assess whether BMI and eating habits modulated the effect of health exposure relative to the no-exposure baseline, we assessed these individual difference measures in an analysis that contrasted health exposure with no-exposure. Figure 6 plots the relevant results, and the top half of Table 5 presents the statistical analysis. As Fig. 6A illustrates, BMI modulated the effect of health exposure. For the no-exposure condition in Fig. 6A, overall food preference increased with BMI, as normally expected. Following health exposure, however, this tendency disappeared and even reversed, such that overall food preference actually decreased slightly with BMI.

Although the Exposure × BMI interaction survived maximal testing in Model 2 (Table 5), the food type × exposure × BMI interaction did not, indicating that the decrease in food preference with BMI occurred for *both* tasty and healthy foods. Figure 6B, C illustrate this common predicted decrease across the two food types. This pattern indicates that health exposure diminished food preference across both tasty and healthy foods, suggesting that dieting goals became engaged and tempered overall interest in food.

Figure 7 presents a non-preregistered interaction between BMI and health exposure established in discovery mode (the top half of Table 5 provides the statistical details). In the no-exposure group, BMI interacted with healthy eating habits for preferences of tasty and healthy foods combined (Fig. 7A). Specifically, at low BMI, overall food preference decreased as healthy eating habits increased. Conversely, at high BMI, overall preference increased as eating habits became healthier.

Table 5 Mixed-effect regressions of food preference on predictors that included healthy eating habits (Habits) and BMI, along with food type (Food) and exposure (Expo)

DV: food preference	**Model 1**			**Model 2**					**Model 3**	
Predictor	**Estimate**	**SE**	***t***	**Estimate**	**SE**	***t***	***R*²**	**AIC**	**Δ*R*²**	**AIC**
Health Exposure vs. No Exposure										
Food Type	.06	.038	1.45							
Expo sure	− .03	.018	− 1.38							
Healthy eating habits	.01	.018	0.74							
BMI	.02	.019	1.15							
Food × Habits	− .18	.006	− 27.81	− .18	.018	− 9.94	29	51,259	− 10	53,000
Food × BMI	.04	.007	5.51	.04	.016	2.33	28	51,335	− 6	52,272
Exposure × Habits	− .04	.018	− 2.06	− .04	.018	− 2.03	23	52,163	− 1	52,246
Exposure × BMI	− .04	.019	− 2.01	− .04	.019	− 2.01	22	52,234	− 1	52,245
Food × Expo × BMI	− .01	.007	− 2.10	− .01	.015	− 0.98	28	51,341		
Food × Habits × BMI	.04	.007	6.19	.04	.015	2.74	29	51,242	− 7	52,280
Expo × Habits × BMI	− .04	.019	− 2.21	− .04	.019	− 2.20	23	52,157	− 1	52,246
Food × Expo × Hab × BMI	− .01	.007	− 2.09	− .01	.014	− 0.96	29	51,249		
Hedonic Exposure vs. No Exposure										
Food Type	.11	.038	2.96	.11	.040	2.80	28	51,030	− 6	52,032
Exposure	− .02	.017	− 1.35							
Healthy eating habits	.04	.017	2.46	.04	.022	1.91	23	51,885		
BMI	.04	.018	2.38	.04	.020	2.24	22	52,010	0	52,030
Food × Exposure	.05	.006	7.28	.05	.015	3.14	28	51,025	− 7	52,077
Food × Habits	− .16	.006	− 25.64	− .16	.020	− 8.27	29	50,867	− 10	52,671
Food × BMI	.08	.007	11.07	.08	.017	4.57	29	51,007	− 7	52,146
Habits × BMI	.04	.019	2.27	.04	.020	2.23	23	51,859	− 1	52,029
Food × Expo × Habits	.02	.006	2.82	.02	.014	1.26	29	50,862		
Food × Expo × BMI	.03	.007	3.76	.03	.015	1.69	29	51,011		
Food × Habits × BMI	.05	.007	6.52	.05	.016	2.92	30	50,852	− 8	52,067

Regressions were performed on standardized measures. For Food Type, tasty foods were coded + 1, and healthy foods were coded − 1. In the Hedonic vs. No Exposure regression, hedonic exposure was coded + 1, and no exposure was coded − 1. In the Health vs. No Exposure regression, health exposure was coded + 1, and no exposure was coded − 1

This interaction in the no-exposure group illustrates that high BMI counteracted the benefits of healthy eating habits on overall food preference. As Fig. 7B illustrates, however, health exposure completely eliminated this effect of BMI. Health exposure reversed the relation of BMI to overall preference, such that the lowest overall preference levels occurred for individuals high in both BMI and healthy eating habits.

Finally, the lower half of Table 5 further confirms the generalizability of the hedonic exposure effect reported earlier for Hypothesis 2. As found earlier, the effect of hedonic exposure relative to the no-exposure baseline survived maximal testing in Model 2, demonstrating that it generalizes across foods and participants (Fig. 4, Table 3). The lower half of Table 5 further illustrates that the hedonic exposure effect generalizes across individual differences in BMI and healthy eating habits. Specifically, in the contrast between hedonic exposure and no-exposure, no interaction of hedonic exposure with either BMI or healthy eating habits survived maximal testing in Model 2. In other words, individual differences in BMI and healthy eating habits did not modulate the effect of hedonic exposure. Again, hedonic exposure appears to have a robust effect that generalizes broadly.

Assessing demand

On the questions that assessed experimenter demand, no evidence of demand was observed. When participants were asked whether their responses reflected personal assessments, their median response was 6 (all responses were made on 0 to 6 slider scales). When asked whether they responded naturally and intuitively without a lot of deliberate thought, their median response was 5.7. Conversely, when participants were asked whether they responded in a way that the experimenters wanted to

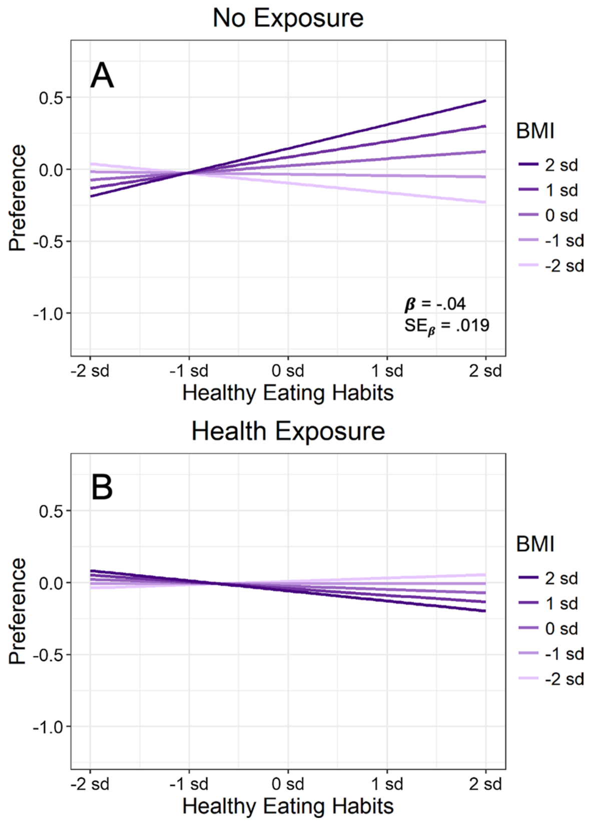

Fig. 7 **A**, **B** Exposure × healthy eating habits × BMI interaction on food preference for the no-exposure and health exposure groups, respectively (combined across tasty and healthy foods). In each panel, a modeled interaction from regression is shown, with all scales plotted in standardized units. From Table 5, the standardized estimated regression coefficient for the interaction is shown (β), together with its standard error to provide a measure of expected variability (SE_{β})

hear, their median response was 0. When asked whether they thought there were correct answers to the survey questions, their median response was 0.

Most importantly, responses to these four questions did not differ between the two exposure conditions and the no-exposure condition. If demand had been operating in the exposure conditions, we should have seen lower responses for both conditions on the first two questions above relative to the no-exposure condition, and higher responses on the last two questions above. In other words, the initial exposure session should have created demand that was not observed in the no-exposure condition. In linear regressions that contrasted each type of exposure with no-exposure, no hint of an exposure effect appeared, thus providing no evidence of demand (median estimated regression coefficient $= -0.02$, median $t = -0.49$).

Discussion

Summary of results

We introduced a novel paradigm for assessing two classic memory processes in exposure to food information: incidental learning and indirect memory. To minimize demand during the food preference phase, we used a comprehensive cover story to obscure the relation between the incidental learning of food information initially and food preference judgments later. As a consequence, participants had no reason to intentionally learn or deliberately remember hedonic or health information from the exposure phase, such that any effects of this information during the preference phase occurred indirectly.

Hedonic versus health exposure

Incidental exposure to hedonic versus healthy food features affected food preferences one day later. Just two exposures to food features changed relative preferences for tasty versus healthy foods, with the interaction between exposure and food type explaining 11% unique variance in food preferences. Assuming that this manipulation falls on the early part of a dose–response curve, many more exposures could have still larger effects. It further follows that brief exposure to food information can be expected to affect food preferences for at least one day.

Assessing hedonic and health exposure against a no-exposure baseline

When hedonic and health exposure were each compared to a no-exposure baseline, only a strong group-level effect of hedonic exposure emerged. Following exposure to hedonic food features, overall food preference increased for tasty foods, relative to the no-exposure baseline. Because the effect of hedonic exposure survived maximal testing in our analysis procedure, it not only generalizes across participants and foods here but is also likely to generalize across future participants and foods. Further evidence for the generalizability of hedonic exposure comes from its lack of interaction with BMI and healthy eating habits. Hedonic exposure affected individuals across a broad range of individual differences associated with eating.

We speculate that the general effect of hedonic exposure reflects basic affective mechanisms associated with pleasure and reward that operate outside conscious awareness and self-regulation (e.g., Rolls, 2015). As participants endorsed hedonic features during hedonic exposure, they may have simulated the experience of "liking" foods, perhaps followed by "wanting" them (Berridge, 1996; Berridge et al., 2009). As neuroimaging research shows, focusing attention on the hedonic qualities of foods activates brain areas associated with hedonic enjoyment and reward (e.g., Chen et al., 2016a, 2016b; Pelchat et al., 2004; Siep et al., 2012). Imagining the pleasure of eating may occur naturally across most individuals, leaving behind robust memories that later become active indirectly to influence food preferences.

Individual differences in the effect of health exposure

Unlike hedonic exposure, health exposure did not produce a general effect across individuals in food preferences. Although participants in the health exposure condition clearly perceived a large difference in the healthiness of tasty versus healthy foods during exposure, these perceptions did not affect group-level preferences.

Importantly, however, health exposure *did* affect food preferences for individuals high in BMI, causing them to lower their overall food preferences for *both* tasty and healthy foods. During health exposure, healthy features of food may have become salient and important for high-BMI individuals, establishing robust memories of food healthiness incidentally. When these individuals performed the food preference task the next day, these robust memories were highly available and became active to affect their preferences. As a consequence, high-BMI participants adopted a restrained perspective on food consumption that reduced their overall preferences for both tasty and healthy foods (consistent with reducing overall calorie intake).

Impact of eating habits

The prior frequency of consuming foods explained more variance in food preference than any other factor, demonstrating the powerful effect of habits on behavior (Marteau et al., 2012; Ouellette & Wood, 1998; Verplanken, 2018). People have a strong tendency to choose foods for a meal that they typically eat for it.

As further predicted, exposure to hedonic and healthy food information interacted with consumption frequency. In general, exposure to food information attenuated the effect of frequency, weakening its relation to food preference. As both hedonic and healthy endorsements increased, they weakened the frequency effect. Importantly, however, hedonic endorsements attenuated the frequency effect much more than did healthy endorsements. Healthy endorsements had relatively little impact on the consumption frequency effect, further illustrating the relatively weak effects of health exposure.

Relations to previous research

To our knowledge, the research presented here is the first to assess whether incidentally acquired memories of hedonic versus healthy food features affect food preferences indirectly. Related experimental work in two other areas, however, complements our work.

Cognitive training

One prominent line of research implements cognitive training on eating and other health behaviors, and then assesses the impact of this training on behavior change (for reviews, see Cristea et al., 2016; Jones et al., 2018; Kakoschke et al., 2017; Stice et al., 2016). Most typically, these paradigms implement the training of *attention* (attending to healthy stimuli and avoiding unhealthy stimuli), *inhibition* (inhibiting responses to unhealthy stimuli), and *approach-avoidance responses* (approaching healthy stimuli and avoiding unhealthy stimuli). In all cases, the focus is on training some form of action, ranging from attention to motoric movements.

An emerging theme in this literature is the importance of making health consequences salient. Research on inhibition and approach-avoidance training increasingly concludes, for example, that the active ingredient in such training is not action related to food per se (e.g., inhibition, approach, avoidance), but the inferred *consequences* of performing these actions, such as good versus poor health outcomes (Chen et al., 2016a, b; Eder & Hommel, 2013; Stice et al., 2016; Van Dessel et al., 2018).

Whereas cognitive training changes actions related to eating, our paradigm establishes incidentally acquired food memories that become active indirectly to affect food preferences. A commonality across both approaches is a focus on the consequences of eating. Similar to cognitive training, our incidental learning procedure establishes the hedonic or healthy consequences of consuming specific foods. An important difference, however, is that our paradigm induces the incidental processing of hedonic and health consequences *in the absence of explicitly training action*. Simply strengthening the consequences of eating in memory affected food preferences, even when actions were not trained.

Health priming

A second prominent line of research places cues in an individual's immediate environment to prime healthy eating goals, which in turn aim to induce healthy eating. Field studies, for example, have used a wide variety of environmental cues to effectively influence eating goals, where these cues include posters, slogans, menus, recipes, and screensavers (Berger & Fitzsimons, 2008; Brunner & Siegrist, 2012; Papies & Hamstra, 2010; Papies & Veling, 2013; Papies et al., 2014; Stöckli et al., 2016). As these studies show, using environmental cues to prime health goals can induce healthier eating preferences, choices, and consumption.

Importantly, health priming is most successful in individuals who have established healthy eating goals during their previous eating behavior (Buckland et al., 2018; Papies, 2016a, b). When individuals have not previously established such goals, health primes typically have little if any effect on food preferences. Consistent with our finding that health exposure only influenced food preferences in high-BMI individuals, having a healthy eating goal already in place is important for a health priming intervention to work. Health primes only have an effect when a well-established healthy eating goal is available to prime.

Well-controlled laboratory experiments similarly find that explicitly priming healthy versus hedonic eating goals can have immediate effects on food preference (e.g., Boswell et al., 2018; Hollands & Marteau, 2016; Hollands et al., 2011; Young & Fazio, 2013). Effective priming procedures in the laboratory include asking participants to evaluate foods for their healthiness versus tastiness, or asking participants to associate foods with images of healthy versus unhealthy eating outcomes. Similar to environmental cues in field studies, these laboratory procedures prime eating goals that influence subsequent food preferences. Also similar to field studies, individual differences in BMI and healthy eating habits moderate these priming effects.

Our paradigm differs from health prime paradigms because *it does not include any cues in the immediate environment that induce priming*. In our experiment, participants simply evaluated individual foods with no health primes present. Additionally, our key manipulation occurred one day earlier during the exposure phase, when participants acquired either healthy or hedonic food memories of foods incidentally. Of interest was whether these memories became active indirectly as the foods were encountered again a day later. Rather than assessing health priming, our paradigm assessed indirect activation of incidentally acquired information. In our paradigm, no cues were present when food preferences were evaluated that could differentially prime healthy or hedonic eating goals.

An important implication of health priming research is that priming a health goal can have considerable impact. When a health prime is present in an individual's immediate environment, it can activate healthy eating goals that induce healthy eating behavior. When a health prime is not present, however, the indirect activation of incidentally acquired food information is likely to dominate food preferences instead. Our findings provide insight into what happens under these conditions: Hedonic memories are more likely to influence food preferences than healthy memories, except for high-BMI individuals. Although the priming of health goals offers an important mechanism for influencing immediate food preferences, it is a different mechanism than the indirect activation of incidental memories.

Assessing exposure effects on consumption

Eating is *not* a simple one-act event of consumption, but is a "multifaceted, contextual, dynamic, multilevel, integrated, and diverse" activity that unfolds across time, space, and culture (Sobal et al., 2014, p. 6). From this perspective, it is important to understand the preliminary processes associated with consumption—not just consumption itself—including the eating preferences and intentions that arise during meal planning and shopping. Interventions can target not only final acts of food consumption, but also preliminary processes that play central roles in producing these acts. In Chile, for example, increasing research demonstrates that Chilean food labeling policies affect preliminary processes that precede food purchases, long before the consumption that eventually follows (e.g., Durán Agúero et al., 2020; Taillie et al., 2020). Our work similarly demonstrates that exposure to food information affects preliminary processes associated with food consumption. Exposure to hedonic and healthy food features changed preferences one day later for consuming tasty versus healthy foods at specific meals.

Our approach further lends itself to assessing the effects of hedonic and health exposure on consumption itself. Instead of assessing food preferences one day following exposure, one could assess eating behavior. Does hedonic and/or health exposure affect the relative amounts of tasty and healthy food consumed? Because of problems associated with measuring consumption in the laboratory (e.g., Best et al., 2018; Robinson et al., 2018), our preference would be to assess consumption in people's normal everyday eating situations, using interview techniques shown to be highly effective (e.g., the Automated Multiple-Pass Method; Subar et al., 2015; Thompson & Subar, 2017), or using emerging mobile technologies.

Much remains to be learned about the pathway from exposure to preference to intention to consumption, with this pathway likely differing for hedonic versus health exposure. Process models are needed that combine current eating habits with information acquired through exposure to produce preferences and intentions on specific occasions. These accounts must further combine preferences and intentions with other contextual factors that determine consumption in immediate eating situations. Our work sheds light on one part of this overall pathway.

Developing effective interventions

A sobering finding from our experiments is that exposure to hedonic food features increased the preference for tasty foods over healthy foods across broad individual differences in BMI and healthy eating habits. Another sobering finding is that exposure to healthy food features had little impact on making food preferences healthier, except for high-BMI individuals. These findings offer insight into the problems of overweight and obesity in the obesogenic food environment (e.g., Marteau et al., 2012; Norman et al., 2016; Papies, 2016a, 2017). The effectiveness of exposing people to hedonic food features, coupled with the relative ineffectiveness of exposing them to healthy features, offers one reason why maintaining a healthy body weight can be so difficult.

Given the strong hedonic orientation that people take to eating—as evidenced by the robust effects of hedonic exposure here—one approach to increasing the consumption of healthy foods is to make the experience of consuming these foods more hedonic. Increasing work does indeed demonstrate that bringing out the hedonic qualities of healthy foods can increase their consumption (e.g., Papies et al., 2020; Robinson et al., 2012; Turnwald & Crum, 2019).

A contrasting approach is to minimize contributions of hedonic processing and instead draw attention to the importance of long-term health consequences. As we just saw, priming health consequences increases the immediate likelihood of healthy behavior. As also noted, however, when health primes are not present, incidental memories of hedonic experiences are likely to dominate preference, leading to unhealthy behavior. If so, then a key issue becomes how to best activate healthy eating goals in situations where people may instead be more naturally inclined to adopt hedonic ones.

One possibility is designing shopping and eating environments to prime healthy eating behavior (e.g., Hollands et al., 2017; Papies, 2017; Pechey et al., 2020; Rosenblatt et al., 2018). To change eating behavior, change the eating environment (Marteau et al., 2012). By manipulating the availability, positioning, and properties of foods in food choice situations, social policy can shift food preferences away from unhealthy foods towards healthy foods. Certainly, it is also important to continue pursuing internal forms of behavior change, but evidence increasingly implicates the critical importance of externally encouraging healthy preferences while discouraging unhealthy ones (Cadario & Chandon, 2019).

Conclusion

We have shown that brief exposure to food information establishes memories incidentally that become active indirectly a day later to influence preferences for tasty vs. healthy foods. Relative to a no-exposure baseline, exposure to hedonic food information increased the preference for tasty foods over healthy foods, an effect that generalized across foods, participants, BMI, and healthy eating habits. In contrast, exposure to healthy food information did not have a robust effect, only influencing food preferences in high-BMI individuals. In the absence of environmental cues that prime health goals, incidentally acquired memories of food information are likely to influence eating preferences indirectly.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s41235-021-00338-6.

Additional file 1. Supplementary Material (SM).

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Authors' contributions

LB, JF, and EP developed the original Pilot experiment as JF's honors thesis at the University of Glasgow under LB's supervision. All authors extended the paradigm to subsequently implement Parts A and B of the experiment reported here. LB developed the initial analysis procedure. LD enhanced it significantly and implemented all final analyses for all experiments. JF collected the data in the Pilot; LD and LB collected the data in Parts A and B of the main experiment. LB and LD drafted the manuscript, and all authors contributed to its revision. All authors approved the final manuscript.

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Availability of data and materials

All data files, analysis scripts, and materials for all experiments can be found at the Open Science Foundation's online repository. The materials for all experiments can be found here, https://osf.io/ys4q2/. All data files and analysis scripts for the pilot experiment, the combined experiment, and Parts A and B of the combined experiment can be found here, https://osf.io/s5u3p/. A supplementary document that describes the methods and results of the pilot experiment can be found here, https://osf.io/y2zpk/, along with another supplementary document that presents the theoretical framework motivating the research.

Declarations

Ethics approval and consent to participate

The Ethics Committee for the College of Science and Engineering at the University of Glasgow granted ethics approval for this project on 13 October 2017 (Application 300170032).

Consent for publication

Not applicable. No personal data were collected, and all data were collected with complete anonymity.

Preregistrations

Preregistration for the Combined Experiment reported here, along with preregistrations for Parts A and B of it, can be found at the Open Science Foundation's online repository. The preregistration for the combined experiment reported in this article can be found here, https://osf.io/aes79/. The preregistration for Part A of the combined experiment can be found here, https://osf.

io/re5mw/. The preregistration for Part B of the combined experiment can be found here, https://osf.io/aes79/. Finally, a summary document that integrates the three preregistrations for all studies, together with the results that bear on each prediction, can be found here, https://osf.io/y2zpk/.

Competing interests
The authors declare that they have no competing interests.

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Publisher's Note

Original Research Article

Developing and Evaluating a Situated Assessment Instrument for Trichotillomania: The SAM^2 TAI

Assessment
1–21

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Abstract

Measuring trichotillomania is essential for understanding and treating it effectively. Using the Situated Assessment Method (SAM^2), we developed a psychometric instrument to assess hair pulling in situations where it occurs. In two studies, pullers evaluated their pulling in relevant situations, along with how much they experience factors that potentially influence it (e.g., external triggers, reduction in negative emotion, negative self-thoughts). Individual measures of pulling, averaged across situations, exhibited high test reliability, construct validity, and content validity. Large differences between situations in pulling were observed, along with large individual-situation interactions (with limited evidence distinguishing focused versus automatic pulling subtypes). In linear regressions for individual participants, factors that influence pulling tended to correlate with pulling as predicted, explaining a median 74%–83% of its variance. By identifying factors that predict pulling for each individual across situations, the SAM^2 Trichotillomania Assessment Instrument (TAI) offers a rich understanding of an individual's pulling experience, potentially supporting individualized pulling interventions.

Keywords

trichotillomania, individual differences, psychometrics, situated assessment method

Trichotillomania, or hair pulling disorder, is characterized by the recurrent pulling of one's own hair, leading to hair loss and marked functional impairment (American Psychiatric Association, 2013). Trichotillomania is a highly heterogenous disorder, varying in pulling situations (e.g., watching TV, looking in the mirror), in pulling sites (e.g., head, arm, eyebrows), and in pulling duration (Barber et al., 2024). Hair pulling further varies in whether it is focused or automatic (Flessner, Woods, Franklin, Keuthen, et al., 2008). Focused pulling occurs when an individual pulls their hair intentionally, with awareness of the pulling and an associated urge to do so. Automatic pulling occurs when an individual pulls their hair with little or no awareness that they are doing so. There is debate as to the existence of these subtypes and the potential number, with some researchers suggesting as many as four (Flessner, Conelea, et al., 2008) and others three (Grant et al., 2021). Recent research has also suggested that focused and automatic subtypes are not valid or useful, with individuals often enacting both types within and across pulling episodes (Grant & Chamberlain, 2021a).

Significant distress can be associated with trichotillomania, impacting a person's quality of life (Barber et al., 2024; Grant et al., 2020). Despite the potentially serious consequences of trichotillomania, relatively limited research has addressed it, compared to other psychopathologies, making the design of effective treatments all the more difficult. To develop appropriate well-motivated treatments, it is first important to measure and characterize trichotillomania accurately. Our primary aim here is to contribute a novel psychometric tool for doing so.

Methods for Measuring Trichotillomania

Current approaches for assessing trichotillomania take an unsituated approach, using decontextualized items that ask an individual to abstract over situations and establish general impressions of how much they agree

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with statements about pulling. For example, a widely used self-report psychometric instrument, the Massachusetts General Hospital Hair Pulling Scale (the MGH-HPS; Keuthen et al., 1995), asks individuals to answer seven statements, such as “On an average day, how often did you feel the urge to pull your hair?” To answer such assessment items, an individual must abstract over life situations (e.g., watching TV, sitting in a meeting) to provide a general impression of their urges. Individuals need not consult their experience of pulling in specific situations but can simply access or construct general impressions of their overall pulling experience, using whatever information comes to mind. Other examples of unsituated measures used currently to assess trichotillomania include self-report measures such as the Trichotillomania Scale for Children (TSC; Tolin et al., 2008), the Milwaukee Inventory for Styles of Trichotillomania—Adult and Children Versions (MIST-A, MIST-C; Flessner et al., 2007; Flessner, Woods, Franklin, Cashin, et al., 2008), and the Trichotillomania Dimensional Scale (TTM-D; LeBeau et al., 2013). Additional unsituated measures include interview scales such as the NIMH Trichotillomania Impact Scale/Trichotillomania Severity Scale (TIS/TIM; Swedo et al., 1989), the Yale-Brown Obsessive-Compulsive Scale-Trichotillomania (Y-BOCS-TM; Stanley et al., 1993), and the Psychiatric Institute Trichotillomania Scale (PITS; Winchel et al., 1992).

Using these unsituated measures for trichotillomania could lead to inaccurate responses when it is difficult for individuals to abstract an accurate judgment across relevant situations. Instead, individuals may rely on intuitive theories and/or the availability heuristic to do so (Ajzen, 1977; Gelman & Legare, 2011; Tversky & Kahneman, 1973).

A second issue is that unsituated measures ignore situational variability (Bandura, 1978; Cervone, 2005; Cervone et al., 2001; Fleeson & Jayawickreme, 2021; Mischel & Shoda, 1995). Decades of research demonstrate that individuals do not exhibit constant levels of a construct or behavior across situations. Consider hair pulling. An individual may pull their hair regularly when alone watching TV but may pull rarely when at work. In addition, different individuals may respond differently to the same situations, such that an individual-situation interaction results. While one puller might pull mostly in stressful situations, another might pull mostly in boring situations. Thus, when assessing a construct, it is important to go beyond simply establishing a single trait-level measure for each individual. It is also essential to capture how the construct varies for each individual uniquely across situations. Dutriaux et al. (2023) provide further discussion about the implications of situation effects for assessment instruments. Indeed it has been noted that assessing trichotillomania is particularly challenging due to the heterogeneous nature of the condition both between and within individuals (Barber et al., 2023). Unsituated measures may therefore struggle to capture the rich individual differences documented in the trichotillomania literature (Barber et al., 2023; Woods & Houghton, 2014).

An Alternative Approach to Measuring Trichotillomania—The Situated Assessment Method

The Situated Assessment Method (SAM^2) is a general assessment framework that measures diverse behaviors in a situated manner, thereby addressing the limitations of unsituated assessment measures just described (for a detailed treatment, see Dutriaux et al., 2023). When constructing a SAM^2 assessment instrument to assess a construct, one first identifies relevant situations where the construct does and does not occur (to ensure unrestricted variance) and then subsequently identifies processes that influence the construct in these situations. Thus, to establish a SAM^2 Trichotillomania Assessment Instrument (the SAM^2 TAI), we first identified a set of situations where pulling typically does and does not occur. We then identified processes established in the scientific and clinical literatures known to influence trichotillomania, presumably in these kinds of situations. The following sections describe how we integrated these two dimensions of situatedness to build the SAM^2 TAI.

Establishing Situations Where Pulling Does and Does Not Occur

Often experience sampling is used to measure a construct in situations where it occurs. Experience sampling exhibits two important limitations that can make it difficult to assess individual differences efficiently and accurately (Dutriaux et al., 2023). First, because experience sampling is typically performed over many days, collecting situational data is expensive and effortful, making it a relatively inefficient assessment procedure. Second, because the situations sampled are not controlled, they can vary widely between individuals. As a result, well-controlled measures across individuals do not result, creating challenges to assessing individual differences accurately.

The SAM^2 approach offers solutions to both problems. First, a SAM^2 assessment can be performed in a single session, making it efficient (Dutriaux et al., 2023, further suggest a variety of approaches for creating brief SAM^2 instruments that are even more efficient). Second, SAM^2 assesses all individuals in a comparable manner by assessing them in the same set of situations (rather than in different sets).

To establish situations for the SAM^2 TAI here, we first conducted a norming study that collected 435 unique pulling and non-pulling situations (fully described in SM-1). From these 435 situations, we sampled a representative set of 52 situations to evaluate in the SAM^2 TAI (31 pulling situations, 21 non-pulling situations). Tables 1 and 2 present these situations. As Dutriaux et al. (2023) describe, presenting these situations to participants is likely to activate specific situational memories from their life that they then evaluate when responding to survey items.

Establishing Processes in Situations That Influence Pulling

To establish processes likely to influence pulling for individuals with trichotillomania, we turned to the current literature. Of particular interest were three models of hair pulling: the Comprehensive Behavioral (ComB) Model, the Model of Cognitions and Beliefs, and the Emotion Regulation Model. The ComB Model was included because it offers a well-established explanation of hair pulling behavior, developed to capture and address important aspects of the hair pulling experience. The ComB Model also motivated the first treatment developed for trichotillomania, a treatment that has received significant support in the literature (Bottesi et al., 2020; Carlson et al., 2021; Falkenstein et al., 2016). The Emotion Regulation Model was also included here because it offers a widely accepted and established account of hair pulling (Bottesi et al., 2016; Crowe et al., 2024). Finally, the Model of Cognitions and Beliefs was included to establish potentially important cognitions in hair pulling, given that dominant models in the literature have tended to focus on behavior and emotion regulation (Rehm et al., 2016). We address each model next in turn, describing processes that each suggests are likely to influence pulling and urges. Finally, we summarize the processes extracted from these models for use in the SAM^2 TAI.

The Comprehensive Behavioral Model. The ComB model is rooted in behavioral theory, following principles of classical and operant conditioning, thereby focusing on conditioned cues, discriminative stimuli, conditioned behaviors, and their consequences (Mansueto et al., 1997). Mansueto et al. propose that encountering a conditioned cue for pulling increases the urge to pull. Cues can be external (e.g., settings, pulling implements) and/or internal (e.g., affective, sensory, and cognitive states). Mansueto et al. posit that external and internal cues become classically conditioned to hair pulling, such that they become triggers for pulling urges and pulling behaviors.

In addition to the proposed processes that trigger urges and pulling, ComB further proposes that instrumental processes can facilitate or inhibit pulling. Similar to cues that initiate pulling, cues that modulate pulling can be external or internal. Once the cycle of pulling begins, accompanying behaviors can occur ritualistically before pulling, during pulling, or after pulling. These behaviors can lead to consequences that are reinforcing, including emotional consequences (e.g., pleasure) and relief from unwanted emotions. Aversive consequences can also occur, such as undesired emotional states that appear when pulling terminates. If these aversive consequences also function as cues for the individual, the pulling cycle may continue.

Model of Cognitions and Beliefs. Rehm et al. (2015) identified six superordinate themes related to cognitions and beliefs that are often central to the pulling cycle: (a) *negative self-beliefs*, with subthemes for worthless self and viewing oneself as abnormal; (b) *control beliefs*, with subthemes for loss of control and importance of control; (c) *coping beliefs*, with subthemes for low coping efficacy and experiential avoidance; (d) *negative emotional beliefs* that deem emotions as "good" or "bad," with subthemes for tolerability and acceptability; (e) *permission giving beliefs*, with subthemes for justification, all-or-nothing, and reward; (f) *perfectionism* related to judgments about hair quality and pulling quality, with subthemes for "just right" standards and mastery through perfection. These beliefs and cognitions play different roles at different points in the pulling cycle, sometimes being antecedent and sometimes supporting maintenance.

Emotion Regulation Model. Emotion regulation refers to how a person experiences and expresses emotion, along with how they influence its presence and timing (Roberts et al., 2013). The Emotion Regulation Model for hair pulling focuses on negative reinforcement, where the function of pulling is to alleviate negative emotion, with relief subsequently reinforcing and perpetuating pulling behavior. When an uncomfortable emotional experience occurs, it triggers a pulling episode that results in relief, which in turn rewards pulling.

Processes That Influence Pulling Included in the SAM^2 TAI. To measure processes that influence pulling behavior in pulling situations, the SAM^2 TAI initially included 13 processes extracted from the three models just reviewed (later reduced in Study 2 based on the results of Study

Table 1. The 31 Pulling Situations Assessed by all Participants in Studies 1 and 2.

Item	Domain	Situation description	Pulling situations				Non-pulling situations			
			Generated frequency	Frequency	Arousal	Valence	Generated frequency	Frequency	Arousal	Valence
Pulling situations										
28	LeisHome	Watching TV	41	4.63	0.44	1.97	1	3.00	1.00	1.00
22	LeisHome	Reading a book	36	3.87	0.38	1.81	1	3.00	0.00	0.00
12	NonLeis	Paying bills	13	3.38	1.57	−2.00	1	3.00	0.00	0.00
16	LeisOut	Watching a film at the cinema	13	2.85	1.00	2.31	10	2.43	0.29	2.00
23	LeisHome	Lying in bed	13	4.64	0.67	1.55	1	4.00	0.00	2.00
20	FamRel	Using social media (e.g. Facebook, Twitter, Instagram)	12	4.82	0.50	1.55				
26	FamRel	Talking on the phone	12	4.00	1.00	0.91	1	3.00	0.00	0.00
8	UniWork	Writing assignments	9	4.22	0.83	0.11	2	3.50	0.00	−0.50
13	Travel	Flying on a plane	9	1.88	0.89	0.13	6	1.40	0.00	0.00
21	LeisHome	Playing video games	8	4.38	0.14	2.29	4	4.67	1.00	3.00
5	NonLeis	Folding/putting away laundry	7	3.71	1.29	−1.00				
6	UniWork	Using the computer	7	5.00	0.50	−0.33	4	4.50	0.00	0.50
10	Travel	Being stuck in traffic	7	4.33	2.00	−1.00				
14	Health	Plucking body and facial hair	7	4.33	0.40	2.17				
19	Health	Resting when ill	6	1.83	0.33	−1.50				
11	UniWork	Worrying/stressing about work	5	3.60	0.60	0.40				
2	UniWork	Being bored at school/university/work	4	3.33	0.25	0.33				
24	LeisOut	Shopping for groceries	4	3.75	2.25	0.75	2	4.00	2.50	0.50
27	FamRel	Having an argument with a partner/spouse	4	1.67	1.00	−0.67				
9	Travel	Driving long distances	3	1.67	0.33	−1.50				
15	Health	Looking in the mirror	3	4.00	3.00	−1.00				
25	Health	Having trouble sleeping	3	4.00	0.00	−1.00				
29	Travel	Waiting at the airport	3	1.67	1.00	−1.00				
1	UniWork	Sitting in a meeting	2	4.50	1.00	−1.00				
4	UniWork	Being tired from work	2	5.00	0.00	1.00				
18	Travel	Planning vacations	2	2.00	0.00	0.00				
30	NonLeis	Worrying about money	2	4.00	2.50	−1.00				
31	UniWork	Daydreaming	2	3.00	0.50	1.00				
3	Health	Sitting on the toilet	1	5.00		0.00				
7	NonLies	Cooking in a quiet place	1	3.00	0.00	2.00				
17	Health	Worrying about health	1	3.00	0.00	−1.00				

Note. The situations above were established in a separate norming study. Each situation is presented with its domain, its generated frequency, and its average judgment for frequency, arousal, and valence across the participants who produced it. See the text and SM-1 for further details. For both Tables 1 and 2, the domains are as follows: UniWork-activities related to university or work; FamRel-activities related to families or relationships,; Travel-travel related activities; Health-health related activities; LeisHom-leisure activities at home; LeisOut-leisure activities outside of the home; NonLeis-non-leisure activities at home. Generated frequency refers to how commonly a situation was generated by participants for either pulling or non-pulling situations. Frequency was assessed by participants on a scale from 0 (*never*) to 5 (*once or more a day*) for how often the situation occurred. Arousal was assessed by participants on a scale from 0 (*no bodily arousal*) to 4 (*intense bodily arousal*) for how much bodily arousal they felt during the situation regardless of pulling. Valence was assessed by participants on a scale from −3 (*highly unpleasant*) to 3 (*highly pleasant*) for how pleasant they found the situation regardless of pulling.

Table 2. The 21 Non-Pulling Situations Assessed by All Participants in Studies 1 and 2.

			Pulling situations				Non-pulling situations			
Item	Domain	Situation description	Generated frequency	Frequency	Arousal	Valence	Generated frequency	Frequency	Arousal	Valence
Non-pulling situations										
44	LeisOut	Shopping with friends					1	3.00	0.00	3.00
48	FamRel	Family outings					1	3.00	1.00	3.00
36	LeisHome	Gardening in garden					2	2.00	3.00	2.50
40	Travel	Going on a family vacation					2	1.00	0.00	3.00
52	NonLeis	Doing the ironing					2	0.00		
42	LeisHome	Playing with a dog					3	4.67	2.00	2.00
47	Health	Having a haircut					3	2.33	1.00	2.00
39	Travel	Walking to somewhere					4	4.50	1.25	1.25
43	LeisHome	Listening to music					4	5.00	1.00	2.50
45	LeisHome	Petting a cat					4	5.00	1.00	2.33
33	UniWork	Socializing with peers/co-workers					5	3.80	0.60	1.20
37	LeisOut	Eating with friends					5	3.25	0.25	3.00
46	Health	Brushing your teeth	2	5.00	0.50	0.00	6	5.00	0.00	0.40
50	Health	Washing hair					6	4.17	0.67	1.00
49	LeisOut	Swimming in a pool					8	2.71	1.50	2.33
32	UniWork	Working with other people					9	4.00	0.63	−0.13
34	FamRel	Having sex					16	3.40	3.14	2.86
38	LeisOut	Exercising at the gym	1	4.00	0.00	−2.00	16	3.33	1.87	1.00
35	NonLeis	Washing the dishes	2	4.50	0.00	0.00	19	4.12	0.31	−1.44
41	Health	Having a shower					21	4.21	1.06	1.20
51	NonLeis	Cleaning the house	10	4.00	1.00	−0.22	23	3.60	0.68	−0.53

1). Table 3 presents these processes, together with the scales used to measure them. Consistent with the ComB Model, we included processes for triggers (external cues and internal cues), behavior (automatic vs. focused pulling, ritualized behavior), and reward (reduction in negative emotion, how good pulling feels, long-term consequences). Consistent with the Cognitions and Beliefs Model, we included processes for negative self-beliefs (internal triggers, self-valence), negative emotion (self-valence, arousal), control beliefs (external control, internal control), poor coping (experiential avoidance), justifying outcomes (reduction in negative emotion, how good pulling feels, long-term consequences), and perfectionism (perfectionistic standards, ritualized behavior). Consistent with the Emotion Regulation Model, we included processes for emotional states (self-valence, arousal), emotion regulation (internal control), and pulling as emotion regulation (reduction in negative emotion).

Because the processes important for each of the three models overlap, most of the included processes were not specific to one model. Instead, our aim was to capture all relevant processes across models to establish a comprehensive set that could potentially predict an individual's pulling behavior at a high level across pulling and non-pulling situations.

Overview and Hypotheses

The primary aim of the following two studies was to assess the SAM^2 TAI's psychometric properties related to individual differences, test reliability, situation effects, construct validity, and content validity. Another primary aim was to see what we could learn about trichotillomania from using the SAM^2 TAI to assess it. A secondary aim was to compare the SAM^2 TAI with a traditional unsituated psychometric instrument for assessing trichotillomania (the MGH-HPS). A final aim was to investigate how both measures of trichotillomania are related to personality traits, self-control, and automatic versus focused pulling.

After performing Study 1, we developed two additional aims for Study 2. First, we aimed to replicate the basic pattern of results observed in Study 1. Second, we wanted to improve on the set of predictors in the SAM^2 TAI. Study 1 used 13 predictors that, in some cases, were highly correlated, leading to potential problems with collinearity. In addition, participants had to evaluate 52 situations for 13 predictors, thereby requiring much time to complete the assessment. Study 2 therefore distilled the initial 13 predictors into 8 critical predictors, making them less redundant and less work for participants to evaluate. As we will see, reducing the number of predictors did not diminish their overall ability to explain variance in pulling—indeed, the 8 predictors actually explained more variance than the 13 predictors.

Because Studies 1 and 2 were exploratory, we did not pre-register hypotheses. Nevertheless, we did have tentative hypotheses about results that we expected to see, especially after performing Study 1. We were also interested in performing several exploratory analyses.

Hypothesis 1: Large Reliable Individual Differences in Trichotillomania

Specifically, we expected that mean individual scores for pulling frequency and urge strength across situations on the SAM^2 TAI would range across at least half the scale from 2.5 to 7.5.

Hypothesis 2a: Substantial Situation Effects

Specifically, we expected that a given participant would pull frequently in some situations but not pull at all in others, such that their judgments would typically range across the entire scale from 0 to 10.

Hypothesis 2b: Substantial Situation by Individual Interactions

Specifically, we expected that participants would differ considerably in how they pull across the same situations, such that the intraclass correlation for agreement between would not be high (i.e., $< .50$).

Hypothesis 3: High Construct and Content Validity for SAM^2 Measures of Trichotillomania

Specifically, for construct validity, we predicted that the SAM^2 TAI measures for frequency and urge would tend to be moderately to highly correlated with many, if not most, of the influential processes ($>|.30|$ to $|.60|$). For content validity, we predicted that the influential processes would explain high amounts of variance in individual regressions (>60%), demonstrating that these processes explain pulling comprehensively.

Hypothesis 4: Low Correlations Between Situated and Unsituated Measures of Pulling

Specifically, we predicted that the SAM^2 TAI measures for frequency and urge would correlate $< .30$ with the MGH-HPS. Because the SAM^2 TAI assesses pulling in a specific set of relevant situations, its trait-level measure of pulling should differ significantly from the trait-level measure in an unsituated instrument, where a much

Table 3. Scale, Interrater Agreement, and Test Reliability for the 13 Measures Assessed in Study 1 and for the 8 Distilled Processes in Study 2.

Measure	Rating question	Scale	Agreement (ICC2)	Test reliability (ICC3k)
Frequency (Study 1/2)	How frequently do you pull in this situation?	0–10 (never, half the time, all the time)	.41/.43	.94/.94
Urge (Study 1/2)	How strong is the urge to pull in this situation (independent of actual pulling)?	0–10 (not strong at all, moderately strong, very strong)	.42/.41	.94/.94
Triggers				
Study 1				
External cue	How much do specific things and people in this situation trigger the urge to pull?	0–10 (not at all, somewhat, completely)	.23	.95
Internal cue	How much do specific thoughts and feelings experienced in the situation trigger the urge to pull?	0–10 (not at all, somewhat, completely)	.33	.96
Study 2	In this situation, how much does the external situation and internal states you experience in it trigger pulling?	0–10 (not at all, somewhat, completely)	.30	.96
Valence				
Study 1				
Self-valence	How negatively vs. positively do you feel about yourself in this situation?	−5 to 5 (very negatively, neutral, very positive)	.25	.93
Experiential avoidance	How willing are you to experience and be there with what you are feeling in the situation?	0–10 (not at all willing, somewhat willing, very willing)	.19	.90
Study 2	How negatively vs. positively do you feel about yourself in this situation?	−5 to 5 (very negative, neutral, very positive)	.29	.94
Arousal (Study 2/3)	How much bodily arousal do you experience in this situation?	0–10 (none, moderate, intense)	.15/.13	.96/.96
Control				
Study 1				
Situational control	How much changes are you able to effectively make in this situation?	0–10 (not at all able, somewhat able, very able)	.25	.95
Internal control	How much can you control any emotional response that you have in this situation?	0–10 (no control, moderate control, complete control)	.22	.95
Study 2	How much can you effectively control the situation and your emotional response in it?	0–10 (no control, moderate control, complete control)	.24	.95
Hair-pulling subtype				
Study 1				
Hair-pulling subtype	How automatic vs. focused is your pulling in this situation?	−5 to 5 (completely automatic, both, completely focused)	.05	.96
Perfectionistic standards	How much of a perfectionist are you about any pulling that you perform in this situation?	0–10 (not at all a perfectionist, somewhat of a perfectionist, complete perfectionist)	.07	.98
Study 2	How automatic vs. focused does your pulling in this situation tend to be?	−5 to 5 (completely automatic, both, completely focused)	.05	.96
Ritualized behavior (Study 1/2)	How much do you perform ritualized behaviors before and/or after pulling in this situation?	0–10 (never, sometimes, always)	.07/.15	.99/.98
Reduction				
Study 1				
Reduction in negative emotion	How much does pulling in this situation reduce any negative emotion that you are feeling?	0–10 (not at all, somewhat, completely)	.05	.99
How good pulling feels	How good does it feel physically to carry out the act of pulling in this situation?	−5 to 5 (extremely bad, neutral, extremely good)	.09	.98
Study 2	How good does it physically feel to pull in this situation, and how much does pulling reduce negative emotion?	0–10 (none at all, some, a lot)	.20	.97
Long-term consequences (Study 1/2)	How likely is it that any pulling in this situation produces long-term consequences that you will regret later?	0–10 (not at all, somewhat, completely)	.05/.08	.99/.99

Note. Intraclass correlations were computed using the ICC function in the R Psych package. The values on the left that assessed interrater agreement for a measure across situations used the ICC2 measure for random effects, such that these values are likely to generalize across samples of participants from the same population. Test reliability, estimated by ICC3k, for each measure is shown on the far right (i.e., Cronbach's alpha). The first two measures are the dependent variables (frequency, urge). The following eight measures correspond to the eight distilled measures in Study 2. For the processes that were distilled in Study 2, the measures from Study 1 that they were distilled from are shown as well. For instance, triggers in Study 2 were distilled from external cue and internal cue in Study 1 because of their high correlation.

smaller set of situations may be evaluated, a different set, or perhaps none at all.

Discovery. In a first discovery analysis, we assessed how consistently pullers exhibited automatic versus focused pulling across situations. In a second discovery analysis, we explored correlations of the SAM^2 TAI measures for pulling frequency and urge strength with unsituated measures for the Big Five personality traits, self-control, and automatic versus focused pulling but had no specific predictions. In a final discovery analysis, we assessed whether participants exhibited awareness of the influential processes that are most important in their pulling. To explore this issue, we assessed the correlation of (a) a participant's explicit judgments of how much the different processes influence their pulling with (b) the SAM^2 TAI's implicit assessments of how strongly the processes were actually associated with the individual's pulling across situations.

Methods

Because the methods and analyses used for Studies 1 and 2 were essentially the same, except for the influential processes assessed, the methods for both studies have been combined into a single methods section. Similarly, the results for both studies have later been combined into a single results section.

Participants

Study 1 recruited 124 participants from social media support groups for trichotillomania and from the TLC Foundation for Body-Focused Repetitive Behaviors (www.bfrb.org). Study 2 recruited 99 participants from social media support groups. For both studies, available funds for paying participants determined the number of participants sampled. Participants were required to be aged 18 years or older, be fluent English speakers, and self-report having trichotillomania.

Several diagnostic checks were conducted before running the main analyses to identify participants who either responded mechanically (giving a constant response) or randomly. Seven participants were excluded from Study 1 as a result of these checks, leaving a total of 117 participants ($F = 105$, $M = 7$, other = 5, mean age = 29. 38, $SD = 8.77$). No participants were excluded from Study 2 ($n = 99$, $F = 90$, $M = 8$, other = 1, mean age = 28.59, $SD = 8.33$). For both studies, participants were paid £7 in Amazon vouchers (or the equivalent in USD, CAD, or EUR).

Design

Studies 1 and 2 both used a multilevel design, with all participants at the individual level evaluating the same 52 situations at the situation level (Tables 1 and 2). Both studies assessed the same two dependent variables across situations (pulling frequency and urge strength), together with processes known to influence them (13 processes in Study 2, 8 processes in Study 3; Table 3). In addition, all participants completed four unsituated individual difference measures at the individual level.

Materials

SAM^2 Trichotillomania Assessment Instrument. The SAM^2 TAI used the 52 situations in Tables 1 and 2, together with 15 judgment scales (Study 1) or 10 judgment scales (Study 2) in Table 3. The situations were sampled from a norming study presented in SM-1. As described in the introduction, the judgment scales were motivated by models of pulling.

In Study 2, we wanted to reduce the number of influential processes assessed in Study 1 for two reasons. First, some of these processes were highly correlated in Study 1, thereby potentially introducing problems of collinearity. Second, participants needed a lot of time to evaluate the 13 processes, and we wanted to reduce the time needed to evaluate them significantly. We therefore assessed the 13 influential processes carefully, first examining the empirical correlations between them in Study 1, and second examining how related they are conceptually and/or theoretically. Based on these analyses, we reduced the 13 influential processes in Study 1 to 8 processes in Study 2 as described next.

Because external and internal cues were highly correlated ($r = .66$) and are closely related conceptually/theoretically, we distilled them into a single process that combined both types of cues. Because (negative) self-valence and experiential avoidance were highly correlated ($r = .66$) and are related conceptually/theoretically, we distilled them into a single process that captured negative valence. Because situational control and internal control were highly correlated ($r = .69$) and are closely related conceptually/theoretically, we distilled them into a single process that combined both types of control. Because hair pulling subtype and perfectionist standards were modestly correlated ($r = .37$) and because perfectionism is often associated with more focused pulling (Grant et al., 2021), we distilled them into a single process that focused on pulling subtype. Because reduction in negative emotion and how good pulling feels were moderately correlated ($r = .49$) and are closely related conceptually/theoretically, we distilled them into a single process that combined both.

Again, we wanted to distill the influential processes as much as possible to reduce the time required to perform the SAM^2 TAI. As will become clear later, reducing the number of predictors from 13 to 8 did not diminish the SAM^2 TAI's performance—if anything performance improved. To see how scales for the influential processes evolved from Study 1 to Study 2, please see the specific forms they took in Table 3.

Unsituated Individual Difference Measures. The following psychometric instruments were used to assess personality, self-control, hair pulling severity, and hair pulling subtype: The Big Five Inventory (BFI, John & Srivastava, 1999); Brief Self-Control Scale (BSCS; Tangney et al., 2004); The MGH-HPS (Keuthen et al., 1995); and The Milwaukee Inventory for Subtypes of Trichotillomania–Adult version (MIST-A, Flessner, Woods, Franklin, Cashin, et al., 2008).

Awareness of Influential Processes. To assess participants' awareness of how strongly the influential processes in each study were related to their pulling, they were asked to estimate, "To what extent does [influential process] in a situation influence the amount of pulling you perform?" SM-3 presents all the specific questions asked in Studies 1 and 2. For each process, the estimated influence was measured on a slider scale from 0 to 100, with the labels, "no influence at all," "moderate influence," and "very strong influence." Results, presented in SM-3, indicate that participants exhibited some awareness of the processes that influence their pulling, accompanied by many incorrect beliefs.

Procedure

All participants performed the study online using the Qualtrics platform, after being referred there by a link on social media or a website. Participants first received an information sheet about the study and then provided informed consent. Ethics approval was granted by the College of Science and Engineering Ethics Committee at the University of Glasgow (application 300180053).

Participants first evaluated the 52 situations for the two dependent variables, urge and frequency, and then evaluated the 13 processes in Study 1 or for the 8 distilled processes in Study 2 (Tables 1 and 2). For Study 1, the 15 measures were presented in six blocks that combined two or three measures in a block as follows: Block 1 assessed urge strength and pulling frequency; Block 2 assessed external and internal cues; Block 3 assessed valence, arousal, and experiential avoidance; Block 4 assessed situational and internal control; Block 5 assessed subtype, perfectionistic standards, and ritualized behavior; Block 6 assessed how pulling feels, reduction in negative emotion, and long-term consequences. In each of the six blocks, the 52 situations were presented in a random order. As each situation appeared, participants evaluated it sequentially on the two or three measures assessed in the respective block. For all participants, the six blocks were presented in the order described above. Similarly, the measures within each block were collected for each situation in the order just described. Instructions at the start of each block provided a detailed description of the measures to be evaluated in it.

For Study 2, the two dependent variables were presented initially in two separate blocks ordered randomly for each participant, followed by the eight blocks for the distilled processes in Table 3, also ordered randomly. While 15 measures were combined in 6 blocks for Study 1, 10 measures were collected individually in 10 blocks for Study 2. As for Study 1, the 52 situations were randomized within each block uniquely for each participant, and instructions for each measure were presented at the start of the respective block.

For both studies, the collection of demographic information for nationality, gender, age, and education level followed the SAM^2 blocks. Then, to assess explicit awareness of the processes that influence pulling, participants estimated how much they believed each of the 13/8 processes influence their pulling. Finally, the four unsituated individual difference measures followed: the BFI, the BSCS, the MGH HPS, and the Milwaukee Inventory of Subtypes of Trichotillomania (adult version).

At the conclusion of each study, participants were debriefed, thanked for their participation, and paid. Including breaks, participants took approximately 100 minutes to complete Study 1 and approximately 55 minutes to complete Study 2.

Results

All data and analysis scripts are publicly available online at OSF (https://osf.io/sqhzu/).

Hypothesis 1: Large Reliable Individual Differences in Trichotillomania

We predicted that individuals would exhibit considerable variability in trait levels of pulling frequency and urge strength (when averaged across situations). Figure 1 shows each participant's mean judgment across the 52 situations for each dependent variable (pulling frequency, urge strength), together with their mean evaluation for each of the 13 influential processes in Study 1 and for each of the 8 influential processes in Study 2.

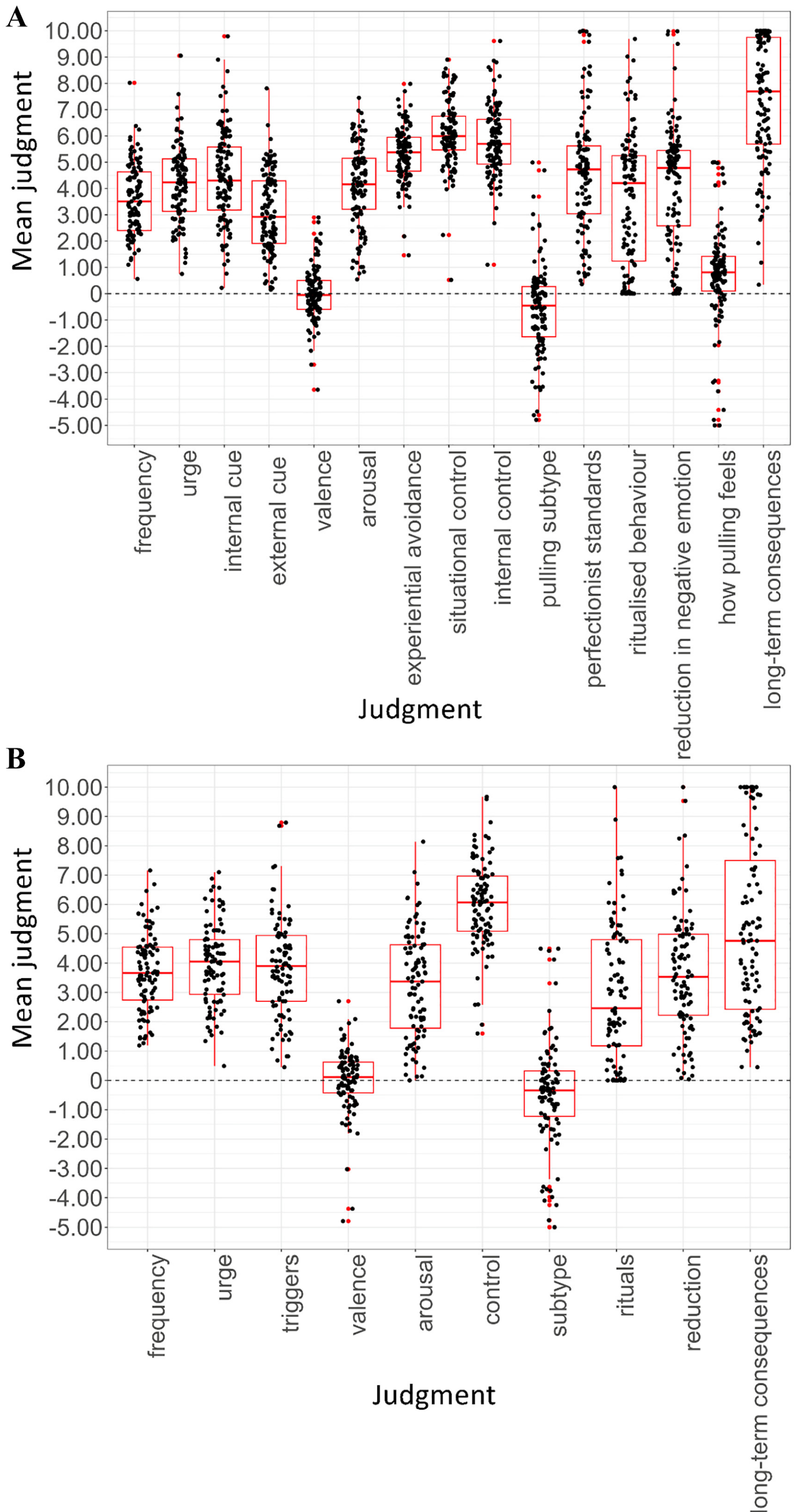

Figure 1. Box and Whisker Plots for Average Pulling Frequency, Urge Strength, and the Influential Processes in Study 1 (Panel A) and Study 2 (Panel B).

Note. Each point in a distribution represents the average judgment for a single participant across the 52 situations in Tables 1 and 2. Each box and whisker plot shows the median for a measure and its interquartile range.

Each plot shows the distribution of trait-level values for a measure across the individuals sampled. In both studies, median levels of about 3.5 for pulling frequency and of about 4 for urge strength indicate that many individuals typically experienced low to moderate levels of pulling and urges across these situations. As we will see shortly, however, each individual tended to vary widely in their pulling and urges across situations, typically exhibiting high levels in some situations.

The median levels of pulling frequency and urge strength in Figure 1 were accompanied by substantial individual differences, as predicted. In both studies, trait-level values of pulling frequency ranged from about 0.5 to 8, and trait-level values of urge strength ranged from about 0.5 to 9, both covering nearly the entire scale. Across the same 52 situations, some individuals exhibited very low overall levels of pulling frequency and urge strength, whereas others exhibited very high levels.

Interestingly, as Figure 1 illustrates further, roughly half the individuals in each study tended to be focused pullers across situations (with a mean value for subtype greater than 0), whereas the other half tended to be automatic pullers (with a mean value less than 0). Although a few individuals in each study exhibited extreme levels of focused pulling (approaching $+5$) or automatic pulling (approaching -5), most participants exhibited values near 0, exhibiting a mixture of both focused and automatic pulling (as seen in more detail later).

As we just saw in Figure 1, the SAM^2 TAI establishes large individual differences for trait-level measures of pulling frequency and urge strength. It also establishes reliable measures, as established by Cronbach's alpha (specifically ICC3k; Shrout & Fleiss, 1979). Table 3 presents these results on the far right. As can be seen, satisfactory alphas were observed well above the acceptable range of 0.70–0.80, averaging around 0.95. Similar levels also occurred for the influential processes in both studies, demonstrating that the SAM^2 TAI exhibits excellent test reliability for all its measures. Because we were only interested in the reliability of overall measures, coefficient alpha was sufficient for this purpose. Because it is not necessary that the situations in the SAM^2 TAI exhibit internal consistency (Dutriaux et al., 2023), it was not appropriate to assess coefficient omega (Flora, 2020).

Hypothesis 2a and 2b: Substantial Situation Effects and Individual-Situation Interactions

We predicted that specific situations would have a substantial impact on an individual's pulling frequency and urge strength, with their levels varying situation by situation. Rather than exhibiting constant trait levels of pulling as situations varied, we expected to observe substantial variability in each individual's pulling across situations. Indeed, we expected that a participant's judgments for pulling frequency and urge strength would typically cover the entire range of these scales across situations (also see Fleeson & Jayawickreme, 2021). We further predicted that there would be a large individual-situation interaction for each measure, as the levels of pulling and urges would depend not only on the situation but also on the individual.

Figures 2A and 2B present strong support for these hypotheses. In each visualization, a row represents a participant's judgments of pulling frequency in Study 1 or Study 2. Each column represents the judgments for 1 of the 52 situations. Each cell represents a participant's judgment of pulling frequency in the respective situation. The redder a cell, the higher the pulling frequency; the bluer the cell, the lower the pulling frequency. Highly similar results were obtained for urge strength, but because the two dependent variables correlated .85 and .88 in Studies 1 and 2, respectively, we only present the results for pulling frequency here.

As Figure 2 illustrates, substantial situation effects are present. For most participants, their individual judgments covered nearly the entire scale across situations. Across participants, some situations exhibited a consistently high (red) pulling frequency, whereas other situations exhibited a consistently low (blue) frequency. Figure 2 also visualizes the trait levels of pulling for individuals shown earlier in Figure 1, reflected here in the overall redness/blueness of a participant's row.

Finally, Figures 2A and 2B demonstrate substantial individual-situation interactions. Specifically, individuals varied widely in the pattern of pulling frequency they exhibited across the same 52 situations (further reflected in the different clusters of individuals shown on the left). Across situations, different participants (and clusters of participants) exhibited different patterns of pulling. The intraclass correlations for agreement in Table 3 quantify the magnitude of these interactions, establishing the average correlation between participants. Specifically, the average correlation between participants (rows) in their judgments of pulling frequency across situations (columns) was only .41 in Study 1 and .43 in Study 2. As these values for agreement indicate, participants interacted with situations considerably by showing different patterns of pulling across the same 52 situations. Again, the SAM^2 TAI captured these large individual differences.

In an exploratory analysis, we further assessed situation effects for the pulling subtype measure. Of interest was how consistent individuals were across situations in focused versus automatic pulling, and also how much individual patterns differed across situations. Figures 3A and 3B visualize the hair-pulling subtype

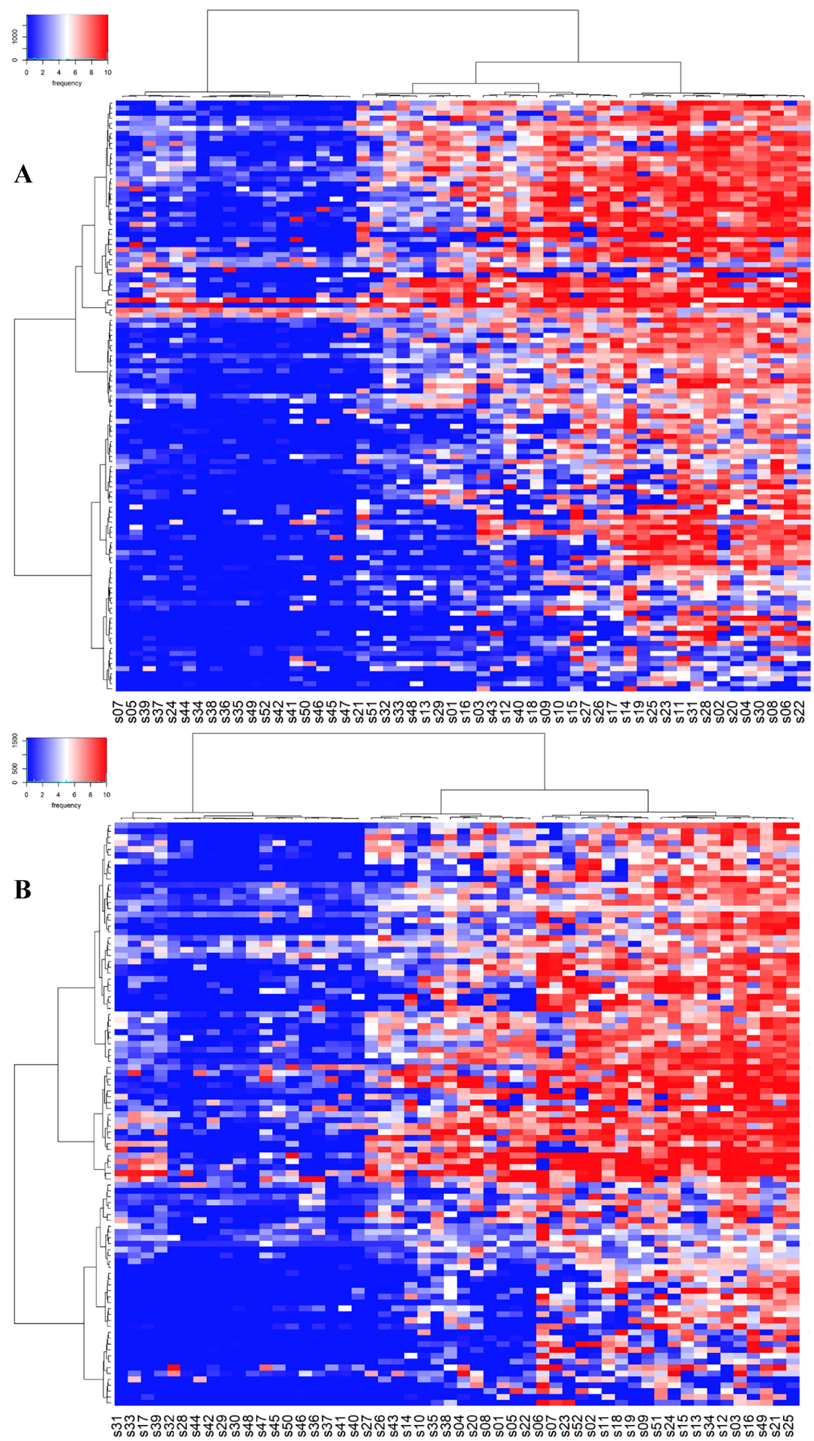

Figure 2. Visualizations of the Pulling Frequency Judgments for the 117 Participants in Study 1 (Panel A) and the 99 Participants in Study 2 (Panel B) Across the 52 Situations.

Note. The 52 frequency judgments for each participant are presented in a single row. The number below each column corresponds to the number of the corresponding situation in Tables 1 and 2. As a cell becomes increasingly red, the frequency judgment increasingly approached 10 (on a scale of 0–10; Table 3). As a cell becomes increasingly blue, the frequency judgment increasingly approached 0. As a cell becomes increasingly white, the frequency judgment increasingly approached 5. Dendrograms from hierarchical clustering using the Ward D measure established groups of participants having similar vectors of values across situations (left) and groups of situations having similar vectors of values across participants (top).

judgments in Study 1 and Study 2 for each participant (rows) in each situation (columns). As values become redder, individuals pulled in a more focused manner; as values become bluer, they pulled in a more automatic manner.

As Figure 3 illustrates, only a small minority of individuals solely performed a single type of pulling across the 52 situations. Instead, most individuals performed both types of pulling in different situations, with the specific situations where each type of pulling occurred varying considerably between individuals. As a result, very large individual-situation interactions occurred in both studies, as reflected in agreement (ICC2) of only .05 in Table 3 for pulling subtype measure. As Figure 3 further illustrates, three clusters of individuals emerged for the subtype. A top cluster in both panels exhibited mixed pulling (both automatic and focused). A smaller middle cluster predominantly exhibited focused pulling (but not always) and a cluster toward the bottom predominantly exhibited automatic pulling (again not always). These patterns not only demonstrate there are no clear automatic and focused pullers but also show how much situations affect the type of pulling an individual performs, and also how these situational effects differ across individuals.

Hypothesis 3: High Construct and Content Validity for SAM² TAI Measures of Trichotillomania

We next assessed construct validity at the individual level. For each individual, we first computed a composite measure of pulling frequency and urge strength (i.e., for each situation, the average of an individual's frequency and urge judgments). Because these two measures correlated very highly (r = .85 in Study 2; r = .88 in Study 3), they captured highly similar information. Combining them simplified later analyses and created a robust dependent variable that reflected both measures.

For each individual, we then correlated their composite measure of pulling across the 52 situations with each of their judgments for the 13 influential processes across situations in Study 1, or with each of their judgments for the 8 influential processes across situations in Study 2. The resulting vector of 13/8 correlations constituted a prediction profile for each individual. If the SAM² TAI exhibits construct validity, correlations within these prediction profiles should be high. The composite measure of pulling should correlate highly with processes known to influence pulling.

Figures 4A and 4B visualize the individual prediction profiles obtained in this analysis. Each row in Figure 4A represents the vector of 13 correlations for one individual in Study 1; each row in Figure 4B represents the vector of 8 correlations for one individual in Study 2. Each column represents the correlations for a single influential process across individuals. Each cell in a row visualizes the magnitude of a correlation for an individual between the composite measure of pulling and a specific influential process. As a cell becomes redder, the correlation approaches + 1; as a cell becomes bluer, the correlation approaches −1; as a cell becomes whiter, its correlation approaches 0. The correlations are summarized at the bottom of each figure, presenting the median and interquartile range of the correlations for each influential process across participants.

General patterns across individuals emerge in Figures 4A and 4B. Consistently, across both studies, internal and external cues (just *triggers* in Study 2) predicted pulling the strongest (median r = .62, .79, .79). Reduction in negative emotion also predicted pulling strongly in both studies (median r = .55 and .77). In Study 1, internal control (−0.53) predicted pulling well, followed by situational control (−0.38), ritualistic behaviors (0.37), perfectionist standards (0.36), valence (−0.35), how pulling feels (0.30), experiential avoidance (−0.29), and long-term consequences (0.18). In Study 2, rituals (0.70), control (−0.64), and long-term consequences (0.63) all predicted pulling well, followed by valence (−0.39) and arousal (0.22). Pulling subtype tended not to predict pulling well in either study (0.13, 0.02). Similar to what we saw earlier in Figures 3A and 3B, individuals varied widely in how subtype related to their pulling. For about one-third of the individuals, pulling increased as focused pulling increased (red cells); for another third, pulling increased as focused pulling decreased and automatic pulling increased (blue cells); and for the final third, little relation emerged between pulling and pulling subtype.

These results establish strong construct validity for the SAM² composite measure of pulling. Processes established in the literature that influence pulling predicted pulling well in the SAM² TAI at the individual level (except for pulling subtype, which showed substantial individual differences).

Finally, we assessed the content validity of the SAM² TAI. We hypothesized that the influential processes would explain a relatively large amount of variance in the composite measure of pulling, demonstrating comprehensive coverage. To assess content validity at the group level for the composite measure, we established the amount of variance that a multilevel mixed-effect model explained in it. For each study, the influential processes were modeled as fixed effects. Due to the moderate-to-high correlations between five pairs of processes in Study 1 (described earlier in the methods), a single component was constructed for each pair using principal component analysis. Three original processes were left unchanged, resulting in a total of eight fixed

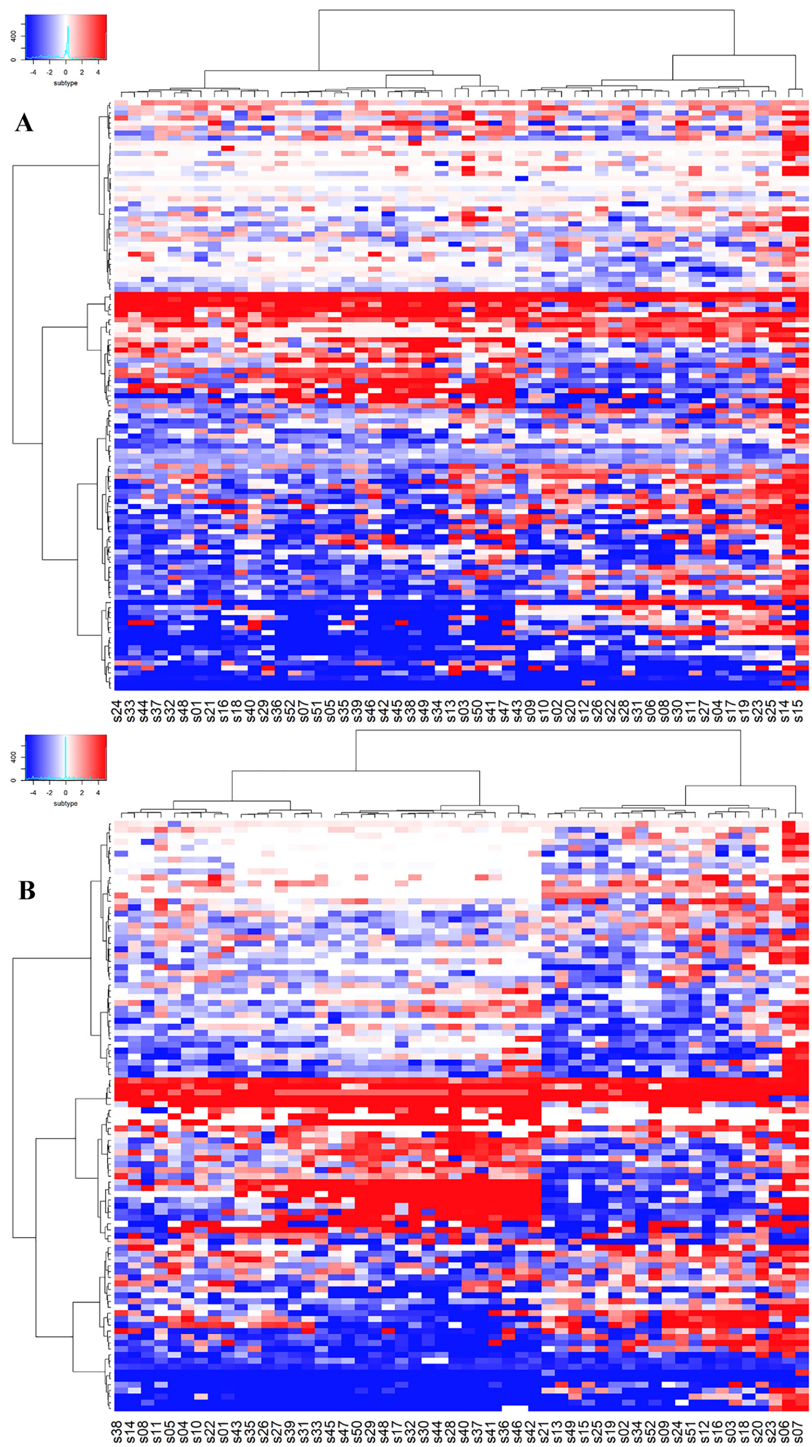

Figure 3. Visualizations of the Hair-pulling Subtype Judgments for the 117 Participants in Study 1 (Panel A) and the 99 Participants in Study 2 (Panel B) Across the 52 Situations.

Note. The 52 subtype judgments for each participant are presented in a single row. The number below each column corresponds to the number of the corresponding situation in Tables 1 and 2. As a cell becomes increasingly red, the subtype judgment increasingly approached 5 (focused pulling, on a scale of −5 to 5; Table 3). As a cell becomes increasingly blue, the subtype judgment increasingly approached −5 (automatic pulling). As a cell becomes increasingly white, the subtype judgment increasingly approached 0 (mixed pulling). Dendrograms from hierarchical clustering using the Ward D measure established groups of participants having similar vectors of values across situations (left) and groups of situations having similar vectors of values across participants (top).

factors included to predict the composite measure of pulling. For Study 2, all eight of the original processes were included as fixed factors, given that no problems emerged with collinearity. For both studies, random intercepts and slopes were included for participants and situations. Across models, the variance explained at the group level was around 65% in Study 1 and 70% in Study 2. These results indicate that the SAM^2 TAI exhibits high content validity at the group level, with the influential processes comprehensively explaining variance in the composite measure of pulling.

At the individual level, the variance explained was even higher, indicating that explained variance at the group level was attenuated by individual differences. For each individual, their composite measure was regressed onto their judgments for the 13/8 influential processes across situations (using simple linear regression). The median individual variance explained across these individual regressions was 74% for Study 1 and 83% for Study 2. These high levels of explained variance at the individual level again indicate that the influential processes comprehensively explained the composite measure of pulling in the SAM^2 TAI.

Hypothesis 4: Low Correlations Between Situated and Unsituated Measures of Trichotillomania

We predicted that there would be low correlations of the SAM^2 measures for pulling frequency and urge strength with the unsituated MGH-HPS (Keuthen et al., 1995). Indeed, the correlation between the SAM^2 measures and the MGH-HPS was relatively low, but nevertheless significant in both studies (Study 1 frequency $r = .33$, $p < .001$, Study 1 urge $r = .31$, $p < .001$, Study 2 frequency $r = .23$, $p = .020$, and Study 2 urge $r = .24$, $p = .019$). These correlations are noticeably lower than the correlations between the SAM^2 measures for pulling frequency and urge strength with each other ($r = .85$ in Study 1, $p < .0001$; $r = .88$ in Study 2, $p < .0001$).

Discovery: Correlations Between SAM^2 TAI Measures and Individual Difference Measures

In a final discovery analysis, we explored correlations of the SAM^2 measures for pulling frequency and urge strength with measures for the Big 5 personality traits, self-control, and focused versus automatic pulling but had no specific predictions. For Study 1, only the SAM^2 measure for urge strength correlated significantly with neuroticism ($r = .32$, $p = .0005$); no other correlations were significant. For Study 2, both SAM^2 measures for frequency and urge correlated significantly with neuroticism ($r = .38$, $p = .0001$; $r = .36$, $p = .0002$) and focused pulling ($r = .44$, $p < .0001$; $r = .39$, $p < .0001$). Interestingly, all these correlations were higher for the SAM^2 measures than for the MGH-HPS measure (and also for Study 2 relative to Study 1; SM-2 presents the full tables of correlations).

Discussion

Using the Situated Assessment Method (SAM^2; Dutriaux et al., 2023), we developed a situated approach to assessing trichotillomania. Rather than assessing hair pulling with unsituated test items—as in typical psychometric instruments—we assessed it in specific situations where hair pulling does and does not tend to occur. In addition, we assessed processes known to influence pulling frequency and urge strength in these situations from well-established models of pulling in the literature. Using this approach, we established a rich descriptive profile of pulling for each individual across pulling and non-pulling situations.

Summary of Results

Individual Differences. Using the SAM^2 TAI, we established trait levels of pulling frequency and urge strength for each individual (i.e., their mean judgment for each construct across the 52 pulling and non-pulling situations). The median trait-level value for both pulling frequency and urge strength was around 3.5 to 4 in both studies (on a scale of 0–10), indicating moderate levels in our samples (Figure 1). More important was how much these trait judgments varied across individuals, indicating substantial individual differences. Some individuals exhibited very low levels of pulling frequency and urge strength, whereas others experienced very high levels across the same situations. When Cronbach's alpha was used to assess test reliability, these trait-level measures exhibited excellent levels around .95.

Situation Effects and Situation by Individual Interactions. Not only did the SAM^2 TAI establish large individual differences, it also established large differences between situations (Figures 2A and 2B). As expected, some situations exhibited relatively high levels of pulling frequency and urge strength, whereas others exhibited relatively low levels. More importantly, large situation by individual interactions emerged for both pulling frequency and urge strength, indicating that individuals experienced the same 52 situations quite differently with respect to pulling and urges. On average, across the two studies, pulling frequency for one individual across situations only correlated around .42 with pulling frequency for another individual on average. A similar level of .42 emerged for urge strength (Table 3).

All these results indicate that both situation effects and situation-individual interactions are important when assessing individual levels of pulling frequency and urge strength. Only focusing on a single trait-level measure masks considerable individual-specific variability at the situation level. Establishing the unique pattern of situational variability for an individual is central to understanding their pulling (Dutriaux et al., 2023; Fleeson & Jayawickreme, 2021). The SAM^2 TAI captures these patterns. Because different individuals experience different patterns of pulling and urges across the same situations, the situation alone is not the sole cause of their pulling experience. Instead, each individual's unique cognitive-affective system also plays a major role, reflecting the kinds of processes proposed in the three models of trichotillomania addressed earlier (Bandura, 1978; Cervone, 2005; Cervone et al., 2001; Dutriaux et al., 2023; Fleeson & Jayawickreme, 2021; Mischel & Shoda, 1995).

Construct Validity. The SAM^2 TAI exhibited high levels of construct validity. Specifically, the SAM^2 composite measure of pulling correlated well with processes known to influence pulling in the literature (Figure 4). Some of these processes correlated quite highly with pulling, including external cues, internal cues, and reduction in negative emotion. Other processes correlated moderately to weakly with pulling, including self-valence, the abilities to control situations and emotions, ritualized pulling behavior, perfectionist standards, long-term consequences, and arousal. In general, the SAM^2 composite measure of pulling captured diverse sources of influence known to affect pulling, thereby establishing its construct validity.

Perhaps one finding that deserves some explanation is the positive correlation between the long-term consequences of pulling and the SAM^2 composite measure. It might seem surprising that pulling increases as the negative long-term consequences of pulling increase as well. Instead, it might seem that people would pull less as the long-term consequences of pulling become increasingly severe. What this relationship might indicate instead is that the more people pull, the worse the long-term consequences become. Rather than long-term consequences causing pulling to decrease, increased pulling causes long-term consequences to increase. Because our correlational data do not justify causal conclusions, these possibilities constitute a potential topic for future research.

Content Validity. The SAM^2 TAI also exhibited high levels of content validity. Specifically, the influential processes that the SAM^2 TAI assessed explained high levels of variance in the composite measure of pulling (i.e., the average of pulling frequency and urge strength). At the group level, the influential processes explained around 65%–70% of the variance. At the individual level, the influential processes explained an even higher 74%–83%. Higher explanation at the individual level most likely resulted from large individual differences attenuating prediction at the group level. These results indicate that the influential processes in the SAM^2 TAI explain the construct of hair pulling comprehensively.

Relations to Unsituated Individual Difference Measures. The SAM^2 TAI correlated significantly with the unsituated MGH-HPS but only at low to moderate levels (r = .24–.33), indicating that the situated and unsituated measurements captured related but different information. Because the SAM^2 TAI assesses pulling in a specific set of relevant situations, its trait-level measure of pulling differed significantly from the trait-level measure in an unsituated instrument, where a much smaller set of situations may have been evaluated, a different set, or perhaps none at all.

Of further interest was the relationship between the SAM^2 TAI and other unsituated individual difference measures. For both studies, urge strength correlated positively with neuroticism (emotionality); for Study 2, pulling frequency correlated positively with neuroticism as well. This is perhaps not surprising, given that neuroticism has correlated with trichotillomania consistently (Grant & Chamberlain, 2021b; Hagh-Shenas et al., 2015; Keuthen et al., 2015, 2016).

Implications for Models of Hair Pulling

When examining the correlational results for each individual (Figure 4), evidence for current models of air pulling emerged. Support for the ComB emerged most strongly (Mansueto et al., 1997), as reflected in the strong positive correlations for triggering cues for almost every participant. Furthermore, for many participants, but not all, ritualistic behavior also demonstrated strong positive correlations with frequency and urges. Consistent with the reward component of the ComB model, reduction in negative emotion and how good pulling feels exhibited strong positive correlations for the majority of participants.

In support for the Model of Cognitions and Beliefs (Rehm et al., 2015), the importance of negative self-beliefs and negative appraisal of negative emotions was captured by influential processes here for internal cues and self-valence (negative self-beliefs). In Figure 4, self-valence often correlated negatively with pulling, and internal cues often correlated positively. Also central to

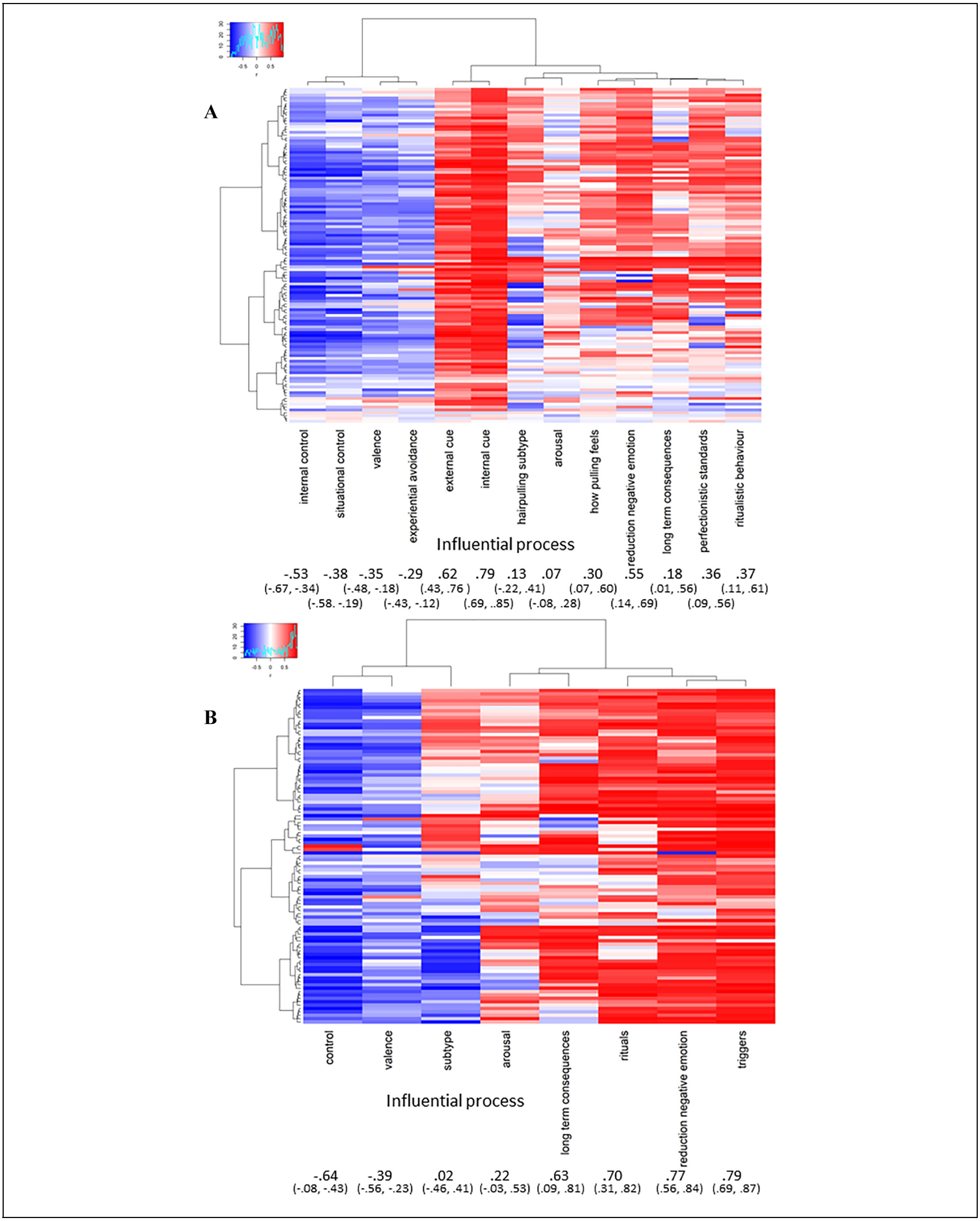

Figure 4. Individual Prediction Profiles of Pulling in Study 1 (Panel A) and Study 2 (Panel B).

Note. Visualizations of the correlations between the the composite measure of pulling and the 13 influential process in Study 1 and the 8 distilled processes in Study 2. The 13/8 correlations for each participant appear in a single row. As a cell becomes increasingly red, the correlation was increasingly positive. As a cell becomes increasingly blue, the correlation was increasingly negative. As a cell becomes increasingly white, the correlation increasingly approached 0. Dendrograms from hierarchical clustering using the Ward D measure established groups of participants having similar vectors of values across situations (left) and groups of situations having similar vectors of values across participants (top).

the model by Rehm et al. is the role of experiential avoidance in pulling. Consistent with this account, Study 1 exhibited a negative relationship between experiential avoidance and pulling for many individuals (Figure 4A). As individuals became less willing to experience negative emotion, they pulled more (although a minority of individuals exhibited the opposite relation). Control in the hair-pulling cycle also plays a central role in this model. Again, in our results we can see that, for many individuals, low levels of control, particularly internal control, were associated with increased pulling. Similar to the ComB model, the positive correlations of pulling with reduction in negative emotion and how good pulling feels also support the cognitions and beliefs model. For both models, pulling is related to the outcomes of pulling. Finally, this model also discusses the importance of perfectionistic standards in the hair-pulling cycle. Figure 4 offers mixed support for this factor, with it being quite important for some individuals but not important for others, in particular, more automatic pullers.

Finally, our results also support the Emotion Regulation Model of hair pulling. Perhaps the strongest evidence comes from the importance of internal cues (which could be one's emotional state), internal control (evidence of emotion regulation—or lack of), and reduction in negative emotion. Although these influential processes have a strong relationship with pulling and offer support for the emotion-regulation model, one could also argue that this model ignores a lot of other important processes in the pulling cycle. Indeed, all three models receive support here, but no one alone accounts for all the influential processes in pulling observed.

Perhaps the Situated Action Cycle can be used to integrate the important insights across all three models (Barsalou, 2020; Dutriaux et al., 2023). In the Situated Action Cycle, perceived entities and events in the environment typically initiate the cycle, such as external cues for pulling. Once these cues are perceived, their self-relevance is assessed in relation to the individual's goals, values, social norms, and identity. For hair pulling, self-relevance takes the form of internal cues, how good pulling feels, reduction in negative emotion, and self-valence. These states of self-relevance then induce affect that can take the form of emotions or motivations, including the urge to pull, self-valence, arousal, internal control, and experiential avoidance. If motivation to pull is sufficiently strong, it can induce actions such as actual hair pulling (frequency of pulling), situational control, subtype behavior (automatic vs. focused), perfectionistic standards, and ritualized behavior. Finally, actions lead to outcomes, including how good pulling feels, reduction in negative emotion, and long-term consequences. As this brief summary illustrates, the Situated Action Cycle offers a natural way to integrate processes across the three models of hair pulling.

Hair Pulling Subtypes

As the distribution of trait-level values for subtype in Figure 1 illustrates, the SAM^2 TAI captured individual differences in focused versus automatic pulling. Whereas some individuals exhibited high levels of focused pulling across situations (high positive values), other individuals exhibited high levels of automatic pulling (low negative values).

When looking at the correlations between subtype and the composite measure of pulling in Figure 4, similar differences emerged. For some individuals, the more focused their pulling, the more they pulled. For other individuals, the more automatic their pulling, the more they pulled.

Figure 3, however, suggests a striking heterogeneity within pulling types, with most individuals exhibiting various mixtures of automatic and focused pulling across situations. From examining these visualizations, it is difficult to conclude that there are two distinct types of pullers, or even three. Instead, it appears that most individuals pull in both ways, with some individuals pulling more often in an automatic manner, with others pulling more often in a focused manner, and with still others pulling in an evenly mixed manner across situations. Interestingly, high levels of pulling can emerge across situations when pulling is either focused or automatic.

The existence of subtypes, together with their number and associated characteristics, continues to be an important issue in the trichotillomania literature (Flessner, Conelea, et al., 2008; Grant & Chamberlain, 2021a; Grant et al., 2021). Based on the results observed here, however, it is not clear how compelling these typologies are. When examining Figures 1 and 3, strong well-differentiated clusters of pulling subtypes do not emerge. Instead, there simply seems to be tremendous variability in the processes associated with pulling for different individuals, together with large situational effects and situation-individual interactions.

If the type of pulling someone exhibits is related to the efficacy of treatment, then continuing to establish subtypes is important (McGuire et al., 2020). As our findings suggest, though, the most important differences may exist at the level of individuals, not at the level of subtypes. If so, then trying to fit individuals into pulling subtypes may not be all that useful or beneficial for designing effective interventions. Within potential subtypes, large individual variation may affect treatment outcomes significantly. For this reason, it may be more useful if treatment focuses on the individual and is tailored to what influences that individual's pulling most.

Limitations

One significant limitation of this study is the correlational nature of its design and results. Although these results are informative and provide a rich description of individual differences in trichotillomania, they do not establish causality. We cannot conclude what may cause someone to pull their hair but can only conclude that certain factors are associated with pulling. We cannot be sure, for example, that removing external triggers in an environment will reduce pulling frequency and urge strength, even though they are highly correlated with one another. Exploring these relationships further with causal methods offers a useful avenue for future research, especially for developing effective treatments. Nonetheless, even if a process does not cause pulling, its relationship to pulling can still be useful in treatment for a variety of reasons. For example, knowing that external cues are strongly associated with pulling offers a potential target for managing pulling. The external cues may not cause the pulling, but learning to avoid them may minimize encountering correlated factors that together play causal roles.

Another significant limitation is that we do not use the SAM^2 TAI to predict actual pulling experience in everyday life. More specifically, we do not verify that the levels of pulling and urges that an individual indicates in the SAM^2 TAI for each situation actually occur when these situations are experienced. An important issue for future research is to establish whether the SAM^2 TAI offers accurate predictions of pulling in actual situations, together with accurate trait-level measures across them.

Conclusion

The SAM^2 offers a novel approach to assessing the important condition of trichotillomania. By assessing hair pulling in situations, it becomes possible to establish rich descriptive profiles of pulling for individuals and to further examine how individuals vary in their situational profiles. In addition, the SAM^2 TAI exhibits high levels of test reliability, construct validity, and content validity. By evaluating processes extracted from existing models of trichotillomania, it became possible to establish the processes associated with pulling at both the group and individual levels. Establishing such relationships can play an important role in defining trichotillomania and in determining effective treatments for reducing it.

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