Appetite xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Appetite

journal homepage: www.elsevier.com/locate/appet

Studying human eating behaviour in the laboratory: Theoretical considerations and practical suggestions

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ABSTRACT

Robinson and colleagues (2018) make important first steps in highlighting the shortcomings of laboratory studies of human eating behaviour, and providing some general suggestions to increase methodological and reporting quality. In this commentary, we present additional important theoretical considerations and practical suggestions. First, we discuss the role of situational cues in eating behaviour and highlight the implications for designing ecologically valid laboratory experiments. Next, we discuss food intake in laboratory settings in the context of the distinction between implicit and explicit measures used widely in social psychology, and provide practical recommendations to keep intake a relatively implicit measure. Finally, we recognise that designing optimal experiments requires significant resources so we present a practical procedure to recruit the smallest informative sample via Bayesian sequential hypothesis testing.

Laboratory research has revealed invaluable insights into the psychological mechanisms of human eating behaviour, and is integral for the design of effective interventions to address the current obesity epidemic. We agree entirely with Robinson and colleagues (Robinson, Bevelander, Field, & Jones, 2018) that high levels of experimental control, effective and testable participant blinding, sufficient and justifiable sample sizes, and transparent reporting of study details are critical to improving the quality of laboratory studies of eating behaviour. In our view, however, the characteristics of high-quality laboratory studies extend beyond those highlighted by Robinson and colleagues. In this commentary, we discuss two additional considerations that are likely to moderate the quality and usefulness of laboratory studies of human eating behaviour: (1) the laboratory as an incongruent eating situation and (2) the use of implicit versus explicit measures of intake. In addition, we provide some practical suggestions as to how researchers can readily address these issues in their laboratory study methodologies. Finally, we extend Robinson and colleagues' important suggestion that researchers should ensure sufficient sample sizes to detect the effect of interest. Specifically, we highlight how Bayesian analyses can inform prospective study design to determine optimal sample size, overcoming many of the limitations of classical power calculations and maximising available resources for laboratory studies.

1. The laboratory as an incongruent eating situation

Most researchers would agree that a central goal of conducting laboratory research is to provide insight into 'real world' eating behaviour. Indeed, findings generated in laboratory studies are often used to devise and predict the potential effectiveness of interventions to change behaviour outside of the laboratory (see, e.g. Marteau, Hollands, Shemilt, & Jebb, 2015). In the past few years, however, there has been an increased consideration of the factors that could disproportionately influence eating behaviour in the laboratory. Awareness that eating behaviour is being monitored, for example, has been shown to reduce energy intake in laboratory settings (for a meta-analysis, see Robinson, Hardman, Halford, & Jones, 2015; Robinson, Kersbergen, Brunstrom, & Field, 2014; Robinson, Proctor, Oldham, & Masic, 2016). The presence of others (e.g. the experimenter, other participants) or social cues indicating the eating behaviour of others (e.g. empty food packaging) have also been shown to modulate intake (for an overview, see Cruwys, Bevelander, & Hermans, 2015). Researchers should ensure that they take appropriate steps to mitigate these confounds (e.g. blinding participants to study aims, as suggested by Robinson et al. (2018)).

Importantly, however, we argue that the situational characteristics of the laboratory environment are likely to exert an important, yet overlooked, effect on intake. Whilst laboratory studies are assumed to explain 'real world' eating behaviour, there is a stark contrast between the situational characteristics of laboratory studies and the situational characteristics of field studies conducted in more naturalistic settings

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https://doi.org/10.1016/j.appet.2018.06.001
Received 2 May 2018; Received in revised form 21 May 2018; Accepted 1 June 2018

(e.g. in the restaurant; Papies & Veling, 2013). We argue that this is a major shortcoming of research into human eating behaviour.

Whilst conducting research in traditional laboratory settings affords researchers high experimental control, we argue that it substantially reduces the extent to which laboratory research captures authentic eating behaviour. Crucially, conducting eating research in the laboratory ignores the effects of the typical consumption situation on the desire and motivation to consume and, as a consequence, ignores the effect of the consumption situation on the amount consumed. Recent work on how people represent food demonstrates that people readily think about food in terms of the situational cues associated with consumption (e.g. Papies, 2013; see also; McRae, Cree, Seidenberg, & McNorgan, 2005). When instructed to generate "features that are typically true" of a series of food products in a feature-listing task, consumers spontaneously represented food products in terms of the place in which the food is typically consumed (e.g. "on the sofa"), the people present (e.g. "with friends"), the time of consumption (e.g. "evening"), and the event in which the food is consumed (e.g. "party"), especially if the food was considered to be tempting (e.g. crisps; Papies, 2013). Importantly, the percentage of situational features generated by participants was positively associated with explicit tastiness ratings and desire to consume the foods (Papies, 2013; see also; Keesman et al., 2018). This suggests that the representation of food in terms of situational features can motivate consumption.

The role of situational features in predicting desire for tempting and rewarding food follows directly from the Grounded Cognition Theory of Desire (Papies & Barsalou, 2015; Papies, Best, Gelibter, & Barsalou, 2017). The central premise of this theory is that, for any given experience, situational cues are integrated into complex, associative, multi-modal representations, so-called 'situated conceptualisations'. The situational cues represented within a situated conceptualisation could include, for example, the actions, emotions, or bodily states experienced in a given situation, alongside various other sources of information, such as sensory input, interoceptive states, cognitions, goals, information about time and space, and representations of the objects and people present (Barsalou, 2003, 2016a, 2016b; Papies & Barsalou, 2015). Whilst eating crisps on a Friday evening in front of the TV, for example, consumers may encode a situated conceptualisation that includes the action of reaching for the crisps, the sensory input from the TV screen, the people present, the bodily sensations of sitting on the sofa, the time of day, and so on. Importantly, according to the Grounded Cognition Theory of Desire, encountering any of these situational cues on future occasions can reactivate the stored situated conceptualisation from long-term memory, leading to increased desire and motivation to consume the food (for a review of relevant work in consumer behaviour, see Papies et al., 2017).

When applied to eating research, it follows that situational features of the laboratory environment likely constitute a strong influence on behaviour. Specifically, if there is a large mismatch between the situation in which eating behaviour is studied in the laboratory (e.g. the testing cubicle or room) and the situation in which the food is typically consumed (e.g. at home sitting on the sofa), the effects of previous consumption experiences in motivating consumption will be diminished or even eliminated in the laboratory setting. Thus, the extent to which the laboratory study captures 'real-world' eating behaviour would be reduced significantly. Consistent with this idea, recent work from our lab has shown that instructing participants to immerse themselves in a situation that is *incongruent* with the typical consumption situation for a given food or drink reduces participants' desire, ability to imagine consuming the food or drink, and salivation (as a physiological measure of the preparedness to eat), relative to when participants are instructed to immerse themselves in a context that is *congruent* with consumption (Best & Papies, 2018; Papies & Best, 2018; van Stekelenburg, Smeets, Zandstra, Dijksterhuis, & Papies, 2018).

A number of practical suggestions to improve laboratory studies of eating behaviour follow from this theoretical approach. First and foremost, developing standardised procedures to reduce the incongruity between the situational setting in which eating behaviour is studied in the laboratory and the situation in which the food is typically consumed is a key priority for the field of human eating behaviour. Reducing situational incongruity in the laboratory could be achieved by (1) instructing participants to imagine or cognitively immerse themselves in a situation in which the food is typically consumed (including non-food filler items or task instructions to reduce attention to the food itself; see below), (2) incorporating features of the typical consumption situation into the laboratory setting (e.g. the inclusion of physical cues; as in the use of a 'mock bar' in studies of alcohol consumption, see e.g. Field & Jones, 2017), or (3) using pictorial food stimuli that depict the food item in the situation in which it is typically consumed. Secondly, we recommend that researchers control the time of day in which the intake is measured, such that data collection occurs at the time in which the selected food item is typically consumed (Haynes, Kemps, & Moffitt, 2016). This may be particularly important to consider in single-session laboratory studies in which data collection typically occurs within a wide time window (e.g. 1–5pm) than in studies in which multiple measures of intake are obtained at typical meal times (e.g. breakfast, lunch, dinner). Finally, we suggest that the situational features present in the laboratory context in which data were collected, and the match between these features and typical consumption of the foods in question are clearly reported.

2. Laboratory food intake as an implicit or explicit measure

Whilst collecting data in laboratory settings may reduce the desire and motivation for consumption, another consequence is that conclusions based on laboratory research may underestimate the role of automatic processes involved in 'real world' eating. Research in the habits literature has shown that exposure to situational cues associated with habitual behaviours constitute strong predictors of engagement in implicit, automatic behaviours (for an overview, see Best & Papies, 2017). Individuals who frequently consume popcorn during visits to the movie theatre, for example, eat more popcorn than individuals who rarely consume it, even when the popcorn is stale and thus not particularly enjoyable to consume (Neal, Wood, Wu, & Kurlander, 2011). Importantly, the observed increase in stale popcorn consumption for the strong-habit consumers was observed in a movie theatre context but not in a campus meeting room. Thus, it seems likely that situational cues present in the movie theatre elicited a learned habitual (implicit) consumption response. It follows that intake in laboratory environments could arise via more deliberative processes than in 'real world' settings due to the absence of situational cues that would otherwise elicit habitual, implicit consumption. Next, we consider in more detail whether food intake can be considered an implicit or explicit measure in the laboratory.

The distinction between implicit and explicit measures in psychological research has improved our understanding of the conditions under which participants' motivation to control their behaviour can affect measurement outcomes. This distinction is highly relevant for eating behaviour as a socially sensitive topic, especially for individuals who try to regulate their intake. Implicit measures are defined as outcomes of measurement procedures caused by the to-be-measured attribute in an automatic manner (De Houwer, Teige-Mocigemba, Spruyt, & Moors, 2009), and do not rely on conscious awareness of the measurement process, cognitive resources, goals, or substantial amounts of time on the part of the participant. An attitude measure obtained by administering a reaction-time affective priming task, for example, can be considered implicit to the degree that it operates quickly, without participants' effort, goals to evaluate, or awareness of the measurement (De Houwer et al., 2009; Fazio & Olson, 2003). With explicit measures, on the other hand, participants are typically aware of the measurement process, their goals can affect the measurement outcome, and the measurement process requires time and cognitive resources.

Importantly, most measurement procedures can be considered to have some, but not all, features of automaticity. Implicit and explicit measures should not be seen as a simple dichotomy. In addition, researchers should always specify which features of automaticity are relevant for a given measure that is labelled as 'implicit' (see e.g., De Houwer et al., 2009).

For laboratory studies of human eating behaviour, we argue that it is important to consider whether intake constitutes an implicit or an explicit measure of the underlying construct in question. Whilst participants may be aware of their liking for a given food, for example, they may be less aware of the extent to which liking affects their intake. At the same time, participants will inevitably have some degree of control over their intake and so could deliberately eat less if, for example, they consider it socially appropriate to do so. Thus, participants' conscious goals could moderate the ways in which variables, such as liking, are translated into the measurement outcome. In other words, food intake can be argued to be an implicit measure in terms of resources and awareness but not, per se, with regards to the effects of conscious goals on the measurement process.

Here, we suggest a number of ways in which researchers can keep the measure of intake as implicit as possible to maximise the value of laboratory studies. As eating behaviour is often a socially sensitive issue, individuals who are aware that intake is measured may deliberately control their intake. This is problematic as it affects intake for reasons unrelated to the variables manipulated (see also Robinson, Hardman, Halford, & Jones, 2015; Robinson et al., 2014), and also because the motivation to control intake may vary systematically with characteristics that are of interest to the researchers (e.g. dietary restraint), thus confounding research results. This possibility has several methodological and practical implications. Most generally, research findings are less likely to be systematically affected by this variable if researchers can prevent participants from being motivated to consciously control their intake in the first place. To achieve this, participants should ideally not be aware that intake is being measured. In other words, as long as the socially sensitive nature of the behaviour of interest is not salient, participants will be less motivated to behave in a socially desirable way, and food intake can be regarded as relatively implicit measure. Robinson et al. (2018) suggest participant blinding to experimental manipulations and hypotheses as one important feature of laboratory studies that is often under-reported or underused. Next, we suggest additional ways that researchers can reduce the chances of participants being motivated to control their intake at several different stages of an experiment.

2.1. Design

Participants' awareness of the manipulations and measures of interest are likely to increase with their exposure to them and with multiple measures of intake. As a result, manipulating critical variables between participants, rather than within participants, will help to reduce the likelihood that participants become aware that food intake is being influenced and assessed. At the same time, between-participants designs typically require much larger sample sizes than within-participants designs, and reduce control over potentially confounding between-groups differences. Controlling features of the consumption situation and awareness that intake is being measured may also be more difficult in laboratory studies in which multiple measures of intake are obtained several times a times a day, week, or month. Therefore, the benefits of each design need to be carefully evaluated for each study. If using a within-participants design is the best option, the order of conditions should be counterbalanced and researchers should examine whether the condition order interacts with the effect of interest. We recognise that many studies are not sufficiently powered to detect the effects of trial-, measurement-, or condition- order (as a between-participants factor), but researchers might consider adding trial-, measurement- or condition- order as a covariate to examine the effects of the variable of interest on intake, whilst controlling for order effects and other potential confounds. Furthermore, researchers should also provide descriptive statistics as a function of each counterbalanced condition and measurement (if multiple intake measures were obtained) rather than just averaging over these.

2.2. Recruitment and standardising appetite

During recruitment, potential participants are less likely to become aware of intake measurement if the study is not advertised as being about eating behaviour, if participants have not participated in an eating behaviour experiment in the same laboratory before, and if the researchers avoid instructions on fasting (or other similar) to explicitly standardise appetite. While we agree with Robinson et al. (2018) that standardising appetite is important, we suggest that this can be realised in ways that prevent participant awareness of study goals. Specifically, we suggest that researchers assess participants' levels of experienced hunger and thirst at the beginning of the study. In order to do so unobtrusively, these questions can be intermixed with other questions, for example items on current mood and physical states (e.g., happy, excited, tired, hungry, irritated, calm; see e.g. Robinson, te Raa, & Hardman, 2015; Versluis, Papies, & Marchiori, 2015). Levels of self-reported hunger can then be included as a covariate in analyses of food intake. Standardising pre-experiment hunger in this way may reduce participants' awareness of intake being measured relative to standardising pre-experiment consumption. This approach is especially useful if researchers also try to prevent participant awareness during the completion of laboratory tasks, as described next.

2.3. Laboratory tasks and situational context

An important consideration for capturing implicit eating behaviour is the laboratory task selection and situational context. We suggest that researchers devise and implement tasks in the laboratory in which intake is an incidental component. Whilst we recognise that intake in the commonly used taste-test procedure is predicted by variables associated with consumption (e.g. hunger, liking; Robinson et al., 2017), we argue that participants' awareness of intake being measured, as well as the focus on sensory properties of the food item in the taste-test procedure, likely override more subtle predictors of intake. We therefore suggest that researchers devise and adopt tasks in which eating is incidental and not the main focus of the task (e.g. intake during completion of another task or questionnaire). As a result, participants are likely to be less aware of their intake and, consequently, less motivated and able to monitor it (for a meta-analysis, see Robinson et al., 2013). Furthermore, the introduction of an additional task may have the beneficial outcome of reducing attention to features of the laboratory that are incongruent with the typical consumption situation (for a discussion of the role of contextual congruency on intake; see above).

3. Optimising data collection using Bayesian analyses: recruiting the smallest informative sample

We realise that conducting well-controlled laboratory studies that maintain high ecological validity with naïve participants and intake as a relatively implicit measure requires significant resources in terms of experimenter and participant time. Whilst we fully endorse Robinson and colleagues' suggestion that researchers ensure their studies have sufficient sample sizes, we argue classical power calculations do not readily afford researchers an effective tool to determine optimal sample size. Classical power analyses are often confounded by the requirement to pinpoint a true (or minimally interesting) effect size (Gelman & Carlin, 2014). This is problematic because (1) relevant literature on which to determine a true effect size often does not exist or is not publicly available; (2) previous studies may suggest a range of possible effect sizes, and (3) even if the literature appears to converge on a single

effect size, there is no guarantee that this is the *true* effect size (e.g. due to publication biases, file-drawer effects, etc.). Thus, whilst classical power calculations are effective when the true effect size turns out to be close to the *a priori* estimate they are, in the majority of cases, practically impossible to implement and, most importantly, provide no guarantee that the target sample size is large enough to detect the *true* effect of interest. Here, we suggest using the recently developed procedure of Bayesian sequential sampling as an alternative approach.

Bayesian sequential sampling provides an efficient means to determine optimal sample size and address the limitations of classical power analyses. The basis of Bayesian sequential hypothesis testing is the Bayes factor, which quantifies the relative plausibility of the data under two competing hypotheses (for overviews, see e.g. Dienes, 2011, 2014, 2016; Kruschke & Liddell, 2017; Jarosz & Wiley, 2014; Morey & Rouder, 2011; Rouder & Morey, 2012; Rouder, Speckman, Sun, Morey, & Iverson, 2009; Wagenmakers, Verhagen, & Ly, 2016). Whilst frequentist analyses can only determine whether the null hypothesis should be rejected, Bayes factors continuously allocate evidence between the null and alternative hypotheses and therefore are able to distinguish between 'absence of evidence' and 'evidence of absence' (Dienes, 2014). As such, Bayes factors are increasingly used in psychological research to quantify evidence for the null hypothesis over an alternative hypothesis (denoted as 'BF_{01}') or evidence for an alternative hypothesis over the null hypothesis (denoted as 'BF_{10}'). To provide an example: imagine that a researcher collects data comparing intake from two food types, producing a BF_{01} of 10 for the key comparison of interest. In this scenario, the use of Bayesian analyses would allow the researcher to conclude that the observed data are ten times more likely under the null hypothesis than under the alternative hypothesis. Although Bayes factors are continuous, discrete categories have been established to aid interpretation, such that the observed data can be interpreted as anecdotal, moderate, strong, very strong, or extreme evidence for the presence or absence of an effect (see e.g., Lee & Wagenmakers, 2013).

One of the main advantages of Bayes factors as a means to determine and optimise sample size is that, unlike frequentist analyses, they do not require adjustments for 'peeking' or for multiple comparisons (e.g. Rouder, 2014). As such, researchers can legitimately compute a Bayes factor for the key comparison (or comparisons) of interest at regular intervals during data collection (e.g. after every participant), stopping data collection when a desired level of evidence for the null or alternative hypothesis is obtained (Schönbrodt & Wagenmakers, 2018; Schönbrodt, Wagenmaker, Zehetleitner, & Perugini, 2017). As a general guide, Schönbrodt and colleagues suggest stopping data collection when the Bayes factor for the comparison of interest equals 6 in exploratory research (corresponding to 'moderate evidence'; Schönbrodt & Wagenmakers, 2018) and 10 where more compelling evidence might be desired (corresponding to 'strong evidence'; Schönbrodt & Wagenmakers, 2018; Schönbrodt, Wagenmaker, Zehetleitner, & Perugini, 2017). How often the Bayes factor is computed during data collection, however, is to be decided by the researcher, likely based on practical considerations associated with the specific research design at hand (e.g. participant availability, budget, time, counterbalancing). Note that even if data collection is terminated before the desired level of evidence is reached (e.g. due to the aforementioned practical constraints), the Bayes factor still allows researchers to draw conclusions with respect to the hypothesis of interest. In other words, an 'underpowered' experiment is only uninformative when researchers just report the statistical significance of the effect (Wagenmakers et al., 2015). Bayes factors, on the other hand, make full use of the available evidence, allowing researchers and readers to distinguish whether an 'insignificant' finding reflects support for the null hypothesis or whether more evidence would need to be collected to determine the desired level of evidence for the null or the alternative hypothesis.

In summary, the procedure for using Bayesian sequential sampling is as follows (for more detailed overviews, see Schönbrodt, Wagenmakers, Zehetleitner, & Perugini, 2017; Schönbrodt & Wagenmakers, 2018):

1. *Determine the minimum sample size.* Minimum sample size could be determined using a classical power calculation (e.g. assuming a large effect) or on the basis of practical constraints.
2. *Determine the maximum sample size* that you would be willing to obtain (e.g. taking into participant availability, budget, time, plus the minimally interesting effect size)
3. *Determine the 'data collection intervals'* (i.e. establish how many participants will be added in each iteration of data collection after the minimum sample size has been collected, ensuring that the design is fully counterbalanced after each iteration).
4. *Establish the desired level of evidence for the null or alternative hypothesis* (i.e. how many times more likely must the data be under the alternative hypothesis than under the null hypothesis, or vice versa, in order to have 'satisfactory' evidence, for example a Bayes factor of 6 in exploratory research or 10 where more compelling evidence is required; see Schönbrodt & Wagenmakers, 2018).
5. *Collect data up to the minimum sample size.*
6. *Use the collected data to compute the Bayes Factor for the comparison of interest, adding participants in accordance with the data collection intervals (as determined in step 3.) and re-computing the Bayes Factor after each data collection interval.* Note that Bayes factors can be readily computed using the BayesFactor package in R (Morey, Rouder, & Jamil, 2015) and in JASP, an interfaced spreadsheet program that allows for both frequentist and Bayesian analyses (JASP Team, 2018).
7. *When the Bayes Factor shows the desired level of evidence for the null or alternative hypotheses (as specified in step 4.) or the maximum sample size is reached (as specified in step 2.) stop collecting data and report the final Bayes factor.*

4. Conclusions

Further to the suggestions proposed by Robinson et al. (2018), we argue that the quality of laboratory studies of human eating behaviour would benefit from considering a number of relatively novel theoretically-derived issues and statistical advances. Specifically, we suggest that researchers consider (1) the incongruity between laboratory study context and the situation in which the food in question is typically consumed, and (2) the use of implicit versus explicit measures of intake. Finally, we suggest the use of Bayes factors to determine optimal sample sizes on the basis of the available evidence during data collection, addressing the limitations of classical power calculations and maximising available resources for laboratory studies.

Acknowledgements

We would like to thank Felix D. Schönbrodt for providing helpful feedback on the Bayesian section, and one anonymous reviewer for their comments.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.appet.2018.06.001.

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