An ESM Study: Exploring the Influence of Moral Licensing on Food Purchasing Behaviour

Bachelor's Thesis
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Abstract

This study explored the influence of moral licensing, a behavioural mechanism whereby previous moral actions warrant immoral behaviours, on unhealthy food purchases. Utilising an Experience Sampling Method (ESM), a sample of twenty-four participants was assessed three times a day, across a seven-day period. The participants were assessed on their reported moral licensing tendencies, as well as their food purchasing behaviour. Moral licensing was assessed using a set of four statement items, while reported food purchases were categorised using Nova, a classification system that sorts food items based on the degree to which they are processed. Despite frequent reports of moral licensing tendencies and unhealthy food purchases, the multilevel analysis between moral licensing and unhealthy food purchases revealed no significant effect. The results suggest that moral licensing may have limited applicability in the domain of food-related decisions, underscoring the importance of exploring domain and contextual elements in consumer behaviour. In light of future research, the current study calls for a larger and more diverse sample, as well as the consideration of employing qualitative methods to further enhance the understanding of moral licensing in relation to food purchasing.

Key words: Moral Licensing, Food Purchasing, Experience Sampling Method (ESM)

Introduction

Food is a vital aspect of human vitality and has subsequently played a fundamental role in human existence (Rotberg, 1983). During the Palaeolithic Era, early humans predominantly obtained food through hunting and gathering, a tedious and physically demanding process (Huebbe & Rimbach, 2020). In accordance with evolution, this process has advanced from livestock and agricultural systems to the full industrialisation of food supplies. This shift, influenced by technological, scientific, and cultural advancements, ultimately increased the abundance of food (Layton et al., 1991).

In light of the affluent nature of the modern food culture, individuals have access to an abundance of food products and services. This abundance enables food groups to be categorised into distinctive classifications that often reflect societal, cultural, or health-related domains (Furst et al., 2000). A noteworthy classification is the distinction between healthy and unhealthy food products, which distinguishes the variations in cholesterol, sugar, sodium, or fat percentages (Furst et al., 2000). The distinction between hedonic and utilitarian products is another way of classifying food. Hedonic purchases are largely driven by intrinsic desires and the anticipation of a reward, often evoking feelings of pleasure or guilt depending on the context (Vale & Duarte, 2013). Conversely, utilitarian products are characterised by extrinsic motivation and driven by pragmatism, typically aimed at supporting goal-directed behaviours such as sustaining a healthy diet. In their study, Vale and Duarte (2013) identified hedonic items as including beverages, alcoholic drinks, and processed meats, whereas utilitarian items included fruits, vegetables, dairy, and fresh meat.

Additionally, as research has expanded within the domain of food classifications, researchers have also garnered significant interest in consumer behaviour and consumption. Literature highlights that the extent to which psychological factors shape a consumer's values and purchasing habits is determined by consumers' moral principles (Hochstein et al., 2024). Value-based purchasing may provide insights into these moral principles, exploring consumers' tendencies to make purchases based on perceived punishment or reward (Casey, 2017). In the context of food purchases, foods that are deemed unhealthy are often moralised in a negative light, often leading to self-imposed criticism and restriction after consumption (Askegaard et al., 2014). Conversely, healthier food choices are associated with morality and virtue, reinforcing positive

emotions and behaviours. Comprehending consumers' classifications of food categories and their subsequent food choices is essential in predicting purchasing behaviour and clarifying consumers' alignments of what is healthy and unhealthy (Furst et al., 2000). Furthermore, these classifications can provide insights into whether moral values drive individuals toward certain food choices, a concept that is closely related to the moral licensing theory.

Moral Licensing

Monin & Miller (2001) were the first to establish the moral licensing theory, also referred to as self-licensing, stating that individuals who had set their moral credentials in a particular domain through past behaviour are more likely to express ideas that differ from politically appropriate norms. More specifically, individuals felt licensed to express racially insensitive views after taking part in non-prejudice behaviours, such as selecting an individual of a minority group within a hiring scenario. The concept was further defined by Blanken et al. (2015), who widened its scope beyond political stance, framing moral licensing as the tendency for individuals who initially engage in morally positive behaviour to feel licensed to engage in immoral actions, thereby increasing the likelihood of subsequent unethical behaviours. The prevalence of this effect can be observed across various domains, impacting both interpersonal and intrapersonal interactions. Within the context of decision-making, moral licensing has been researched very closely. It is thought that a regulatory mechanism can drive individuals to balance their moral states by compensating for either moral or immoral acts (Reeves, 2016). This tendency to 'balance' is also closely related to the concept of moral cleaning, whereby engaging in immoral behaviour diminishes one's moral self-worth, leading one to engage in moral acts (Sachdeva et al., 2009).

With regard to food choices, various studies have examined moral licensing. Upon the completion of a demanding task, individuals were more likely to indulge in hedonic foods, with earned moral credit justifying indulgence (Witt Huberts et al., 2011). Moreover, moral licensing opportunities were reported in relation to food temptations (Prinsen et al., 2018). The dynamics of moral licensing have further been examined, suggesting that individuals who hold back on their shopping choices may later favour indulgent food options, illustrating how initial self-control can license indulgent consumption (Mukhopadhyay and Johar, 2009). Moreover, in relation to compensatory behaviour, health-conscious food choices made earlier on during the day licensed subsequent indulgent choices, such as a dessert (Askegaard et al., 2014). Using an ESM framework, a study has also looked into

While the aforementioned studies focus on moral licensing and various aspects of consumer behaviour, they do not directly address moral licensing in relation to consumers' decisions between healthy and unhealthy food choices. This is especially crucial, as understanding the influence of moral licensing in food choices could explain the processes underlying decision making and can also aid in understanding the effects of moral licensing on food purchasing behaviour. Previous research on moral licensing has predominantly focused on indulgent behaviour (Mukhopadhyay & Johar, 2009; Witt Huberts et al., 2011), failing to address its influence on healthy and unhealthy food purchasing behaviour. Furthermore, numerous studies have been situated in controlled laboratory settings and under fabricated scenarios (Monin & Miller, 2001; Sachdeva et al., 2009; Blanken et al., 2015), limiting the ecological validity of the study. In addition, these studies fail to capture within-person processes that may underlie moral licensing. Prior studies largely focus on between-subject or cross-sectional designs, which fail to account for individual variations and patterns over time.

Given the potential variations and fluctuations in moral licensing behaviour across various contexts, it is appropriate to use the Experience Sampling Method (ESM), a validated assessment method that acquires real-time sample observations and reports (Verhagen et al., 2016). The use of an ESM not only provides real-time insights into psychological mechanisms but also helps in observing sequences in cognition and executive functions as they fundamentally occur in participants' daily lives (Conner et al., 2009). In combination with the ESM design, the current study integrated a photo diary method, which allows for a minimally obtrusive data collection. By reducing reliance on retrospective recall, this method ensures that ecological validity is accounted for by offering contextual accuracy and precision in self-reports (Bolger et al., 2003; Shiffman et al., 2008). Hence, the integration of both the ESM design and the photo diary method is valuable in providing a unique opportunity to investigate how moral licensing manifests in real-life food purchasing decisions across time. To our knowledge, there are no studies that have explicitly examined the effects of moral licensing on food purchasing behaviour.

As it stands, the understanding of the influence of moral licensing in the context of real-life food purchasing behaviour is limited, with nutritional variations in the context of moral licensing remaining underexplored. Collectively, the utilisation of the ESM and the photo diary method offers a unique lens into exploring moral licensing as it naturally unfolds, addressing long-

standing methodological gaps in research. By exploring this gap, the study aims to gain a valuable understanding of the dynamics of these variables. Hence, the hypothesis to be tested is as follows:

"A Positive Association is Predicted Between Moral Licensing and Consumers' Decisions to Purchase Unhealthy Foods"

Methodology

Design

This study employed a longitudinal observational design using the experience sampling method (ESM). Repeated measures were gathered three times a day over seven consecutive days. The present study focuses on the dynamics between moral licensing and food purchasing behaviour, specifically whether moral licensing has an effect on unhealthy food purchases.

This study forms a part of another study that focuses on the influence of mood states on unhealthy food purchasing behaviour. Although data collection was conducted together, both studies were led by their own hypothesis and the analyses were conducted independently.

Participants

For this study, the participants were acquired through convenience sampling. The participants either chose to participate through a promotional message distributed by multiple researchers on WhatsApp or located the study through SONA. A total of 24 participants ($N = 24$) filled out the questionnaire, of which 18 were female ($M_{age} = 22.12$, $SD = 2.04$), 5 were male ($M_{age} = 22.0$, $SD = 1.87$), and 1 was non-binary ($M_{age} = 20$). The nationality of participants consisted of German (79.2%), followed by Lithuanian (8.3%), Dutch (4.2%), Turkish (4.2%), and Spanish (4.2%). Moreover, the majority of the sample included individuals who completed Secondary Education (91.6%), but also those who have obtained a Bachelor's (4.2%) and Vocational Training (4.2%). Participants were included in the final data set when meeting the requirements of being at least 18 years old and having adequate proficiency in the English language. Moreover, participants were required to have a device with an established internet connection, a browser, and access to the App Store or Play Store.

Materials

To administer the study, the TIIM App (Twente Intervention and Interaction Machine) was utilised. The platform is designed to administer longitudinal, Experience Sampling Method (ESM), Ecological Momentary Assessment (EMA), and intervention studies to assess participants under scheduled conditions.

Daily Measures

Moral Licensing. To assess moral licensing, four items assessing license opportunity were derived from a study conducted by Prinsen et al. (2018). The initial 20 items were reduced to 4 items to minimise the potential burden on participants, and they were selected based on the highest reported frequencies in the original study and the relevance to the current research context. To assess moral licensing, participants were presented with four statements; namely, (1) "I was on the right track.", (2) "I did my best.", (3) "I did something good.", (4) "I made good intentions.". The aforementioned items were answered with either a "Yes" or a "No" (see *Figure* 1). The internal consistency of the items was deemed acceptable ($\alpha = 0.77$), deeming the moral licensing scale to be reliable in its use within the current study.

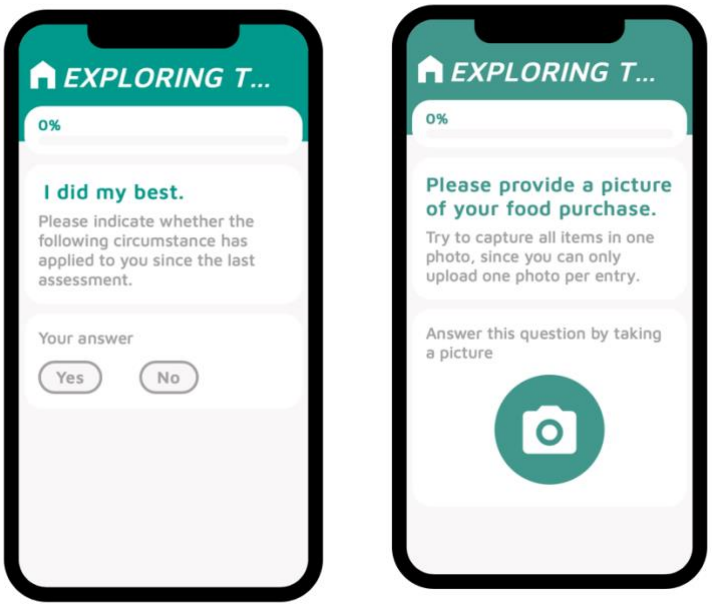
Food Purchasing Behaviour. To assess the food purchasing behaviour, participants were asked whether they had made any food purchases since the last assessment. In response to the question, they had the option to indicate "Yes" or "No". Upon selecting "Yes", they had to indicate whether they had a picture of the food or if they were able to take one. In the case that they took a picture, they were redirected to the next page and were instructed to upload a picture of their food purchase (see Figure 1)... Given the layout of the item on TIIM, participants were permitted to upload no more than one photo. In the case that the participants were unable to provide a picture, they had to select "No". Upon doing so, the participants were redirected to the next page where they were presented with the Healthy and Unhealthy Eating Behaviour Scale (HUEBS), which is often used to assess healthy and unhealthy eating behaviours (Guertin et al., 2020). The twenty-two-item scale consisted of twelve healthy food classifications and ten unhealthy food classifications (see *Appendix D*). Food categories such as fruits, vegetables, and whole grains are considered healthy, while refined grains, processed meats, and pastries are unhealthy. If applicable, the participants were able to select up to 22 items from the list and were only allowed to select each item once per entry, even in cases where several food items corresponded to the same classification.

The responses to the HEUBS were then analysed and categorised by the researchers under the four levels of the Nova classification system (Monteiro et al., 2018). The classification sorts food items based on the degree to which they are processed. It includes four levels of classifications, namely, (1) unprocessed or minimally processed foods, (2) processed culinary ingredients, (3) processed foods, and (4) ultra-processed foods. The HEUBS descriptions aided in categorising food groups that could consistently fit into the NOVA classification system, enhancing accuracy

in assessing the degree of food processing. Examples provided by Monteiro et al. (2018) on established examples of food items in correspondence to the NOVA system were also utilised to further classify the categories. In the context of the present study, higher NOVA scores were indicative of processed, unhealthy food purchases.

Figure 1

Example Items: Moral Licensing & Food Purchasing Behaviour



Procedure

To administer the study, approval from the University of Twente Ethics Committee was requested. Once approved, the study was published on SONA (Study Number 250589), a participant recruitment platform employed by the University of Twente. Participants meeting the requirements and signing up for the study were directed to a link from SONA containing the necessary instructions to download the TIIM App through the App Store or Play Store on their mobile device. Once they had access to the application, they were required to provide a unique letter code or scan a QR code to access the study and become a registered participant. Visualisations of the TIIM app interface as seen by the participants can be found in *Appendix B*.

The first section of the questionnaire included a welcome page highlighting the purpose of the study and instructions. This was followed by an informed consent form, which provided a detailed description of participants' rights to the anonymity and confidentiality of the data

gathered, as well as their right to withdraw at any point within the duration of the study. After agreeing to partake in the study, a set of demographic questions pertaining to age, gender, nationality, and education level were presented. The participants were then prompted to complete daily measures on moral licensing, as well as on their food purchasing choices. They had the option to either provide a photo of their food purchase or provide its description.

The participants were asked to fill in the questionnaires three times a day, at 10 A.M., 2 P.M., and 6 P.M. Each questionnaire was available for four hours after the notification was sent (see *Appendix C*), after which participants were no longer able to fill it in. Moreover, no reminders were sent in case participants did not respond.

The data collection period took place between April 12th, 2025 and May 10th, 2025. Upon the completion of the study, the participants received no incentive for their participation in the study.

Data Analysis

In order to analyse the data gathered from the questionnaire, data was derived from the TIIM Dashboard and transferred onto R Studio (Version 2024.12.1+563).

All preparations, transformations, and visualisations of the data were carried out under the following packages: dplyr, ggplot2, and psych (Wickham et al., 2019; Wickham, 2016; Revelle, 2019). The multilevel analysis was carried out using the lme4 and the lmertest packages (Bates et al., 2015; Kuznetsova et al., 2017). The scripts for the aforementioned analyses can be found in Appendix E.

Due to technical issues on the TIIM Dashboard, there were missing responses among participants. Despite this, a substantiated decision was made to retain the data and include all participants within the analyses. This decision was warranted by the understanding that the technical malfunction was external to the researchers and out of their control.

To examine variations in moral licensing, items within the moral licensing scale were averaged per measurement. To identify within-person variations, the moral licensing scores were centred per participant, enabling the analysis of deviations in an individual's typical moral licensing behaviour and the predicted food purchasing behaviour. Additionally, a lagged variable was created by shifting the group-mean centred scores by one time point to assess temporal influences.

Prior to the main analysis, a manipulation check was conducted to assess whether food purchasing behaviour predicted moral licensing. Although this was separate from the hypothesis, it was assessed to validate the association of moral licensing and food purchasing behaviour. Using a linear-mixed effects model, the analysis aimed to examine whether unhealthy food purchases have an association with moral licensing to begin with. Within this model, the unhealthy food purchases scores were the predictor variable, while the mean moral licensing scores were the outcome variable.

For the main analysis, a linear mixed-effects model (LMM) was used, as the data included repeated daily measures nested within individuals. Integrating this model analysis within-person differences, while considering onset variations amongst participants. The multilevel model examined the potential influences of moral licensing on unhealthy food purchases. As so, the lagged moral licensing scores were set as the predictor variable, while the unhealthy food purchases were the outcome variable. Both moral licensing and NOVA scores were set as fixed effects. Although the study employed a longitudinal design, time was not set as a fixed or random effect. Alternately, each observation was treated as an independent point nested in participants, with a random intercept accounting for the repeated measure. No additional covariance structures were implemented.

Results

Descriptive Statistics

Following the administration of the survey, the data consisted of 24 participants, with an average of 10.58 (*SD* = 6.11) observations per participant. This yields a total of 254 measurements across the specified measurement period. The mean across all moral licensing items was 0.84 (*SD* = 0.28), indicating that moral licensing behaviour was reported in 84% of responses. Moreover, with a mean of 2.80 (*SD* = 1.33), food purchases were frequently reported along the 'processed' end of the NOVA classification system.

The categories in *Table* 1 demonstrate reported food categories that were derived from HEUBS and adapted by the researchers to enhance the interpretation of descriptive data. Frequently reported food categories include snacks, sugary sweetened beverages or alcohol, and prepackaged foods. *Table* 2 displays a summary of moral licensing and NOVA scores across all three measurements. Between each iteration, the average moral licensing scores were 0.85 (Morning), 0.89 (Evening), and 0.76 (Night), while the average NOVA scores were 2.60, 2.86, and 2.94, respectively.

Table 1

Frequencies of Reported Food Categories and NOVA

Category	Amount	NOVA
Fruits and Vegetables	44	1
Snacks	40	4
Sugar Sweetened Beverages or Alcohol	34	4
Prepackaged Food	19	4
Dairy Products	21	2-4 (Low Fat Dairy vs Highly Processed Dairy)
Pasta	3	1
Bread Products	11	1-3 (Whole Grain Bread vs White Bread)
Meat	8	1,4 (Lean Meats vs Fatty Meats)
Water or Tea	5	1

Eggs	4	1
Other	29	1-4

Table 2

Descriptive Statistics of Moral Licensing and Nova

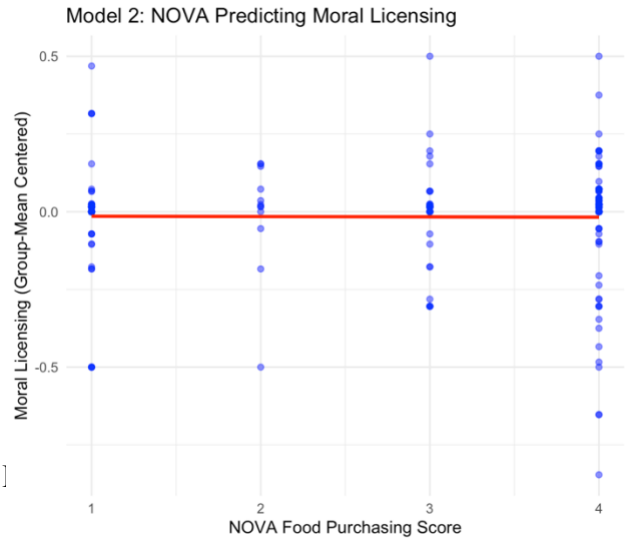
Iteration	Moral Licensing		Nova	
	M	*SD*	*M*	*SD*
Morning	0.85	0.24	2.60	1.31
Evening	0.89	0.22	2.86	1.34
Night	0.76	0.38	2.94	1.32
Overall	0.84	0.28	2.80	1.32

Manipulation Check

The manipulation check evaluated whether unhealthy food purchases influenced moral licensing. The model revealed that there was no significant effect of the nutritional quality of food purchasing on moral licensing, β = -0.001, SE = 0.09, $t(205.28)$ = -0.11, p = .91. The random intercept variance is 0.001 (SD = 0.03), and the residual variance is 0.02 (SD = 0.17). *Figure* 2 displays the manipulation check results.

Figure 2

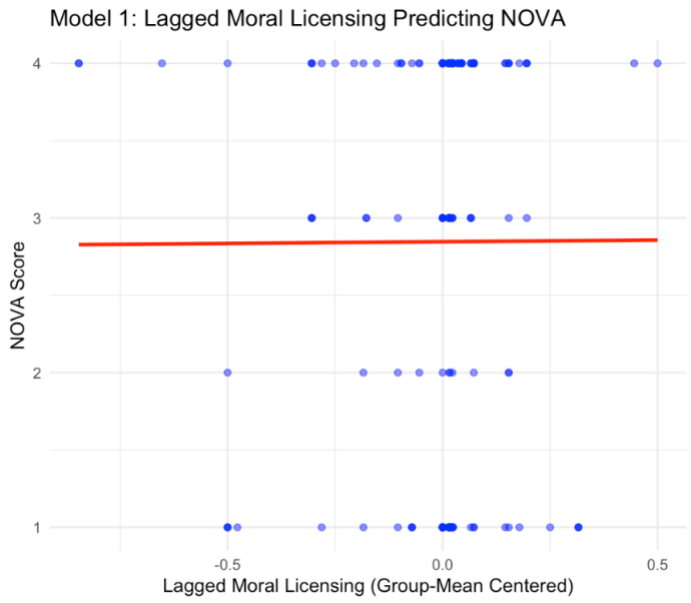
Scatterplot of Manipulation Check



The results of the multilevel model analysis were not significant, $\beta = 0.02$, SE = 0.53, $t(182.85) = 0.04$, $p = .97$, revealing that moral licensing does not affect subsequent unhealthy food purchases. Random intercepts were accounted for participants, with a variance of 0.26 ($SD = 0.51$). The residual variance is 1.47 ($SD = 1.21$). A visualisation of the results is displayed in *Figure* 3.

Figure 3

Scatterplot of Multilevel Analysis Model



Note. Reported observations are represented by the blue dots. The red line represents the fitted regression line of the multilevel model analysis. The slope indicates no significant effect between lagged moral licensing and Nova scores.

Discussion

The current study aimed to explore the influence of moral licensing on consumers' decisions to purchase unhealthy food. Using the moral licensing theory, it was hypothesised that individuals who reported moral licensing tendencies subsequently purchased unhealthy food. With repeated daily measures over seven days, participants were instructed to report their moral licensing tendencies and food purchasing behaviours. Based on the input, participants frequently reported feeling morally licensed and purchasing unhealthy foods, but no quantifiable effect was examined between them.

Theoretical Implications

The current study aligns with an expanding body of research that questions the rigour of moral licensing in the context of consumerism. Based on a previous ESM study, while participants reported potential licensing opportunities in light of food temptations, it did not predict indulgent food choices (Prinsen et al., 2018). Similar to the current study, participants reported licensing opportunities on a recurrent basis, but it failed to have a direct effect on food choices. The observed pattern suggests that individuals may endorse moral licensing thoughts that may not explicitly manifest into behavioural outcomes. This may imply that morality might have limited effects in food purchasing consumer contexts.

A possible explanation lies in the applicability of the context, whereby moral licensing effects may be more likely to occur when there's a perceived psychological connection to the subsequent behaviour (Effron et al., 2012). It can be assumed that participants may perceive their moral acts as unrelated to the domain of food purchasing, hindering any licensing effects. Instead, it is plausible that contributing factors such as self-control and practicality in food choices may override the influence of moral licensing in the process (Askegaard et al. 2014).

While the current findings are explicable by previous studies, they also deviate from well-established research on the effects of moral licensing in laboratory settings. Studies examining moral licensing in relation to indulgent behaviour typically primed moral behaviour or used salience to remind participants of their prior good deeds (Khan & Dhar, 2006; Witt Huberts et al., 2011). This contrasts with the design of the current study, whereby participants were independent in their food choices and were not exposed to any manipulations. This may imply that moral salience is a determining factor and that moral licensing may only occur when individuals are made aware of their previous moral conduct.

It is also important to acknowledge the manipulation check conducted on the influence of food purchases on moral licensing, which produced no significant result. This further substantiates the notion that moral licensing may not play a leading role in unhealthy food purchases. In other words, if food choices do not elicit moral deliberations, then the likelihood that the reverse occurs is improbable. Literature suggests that label colours often drive food-related decisions more than morality, indicating that nutritional choices in food are rather heuristic and have fewer associations with moral licensing effects (Schuldt, 2013). This strengthens the outcomes of the hypothesis that moral licensing may not play a consistent role in guiding food-related choices under naturalistic, unmanipulated contexts.

Limitations

In consideration of the findings of the current study, several limitations must be acknowledged and examined. Future research can employ the insights of the current study in order to gain a more comprehensive understanding of the associations between moral licensing and food purchasing behaviour.

The restraints in obtaining an adequate sample size, as well as the sample characteristics, must also be noted. Based on sample literature, an adequate sample size for a study utilising a Linear Mixed Model design should be above 30 (Maas & Hox, 2005). Smaller sample size weakens the ability to detect existing associations, hence leading to non-significant results even when an effect may exist (Button et al., 2013). The current study also relied on convenience sampling, which limited the reach of the study amongst potential participants. This resulted in a sample size limited to university students and young adults, which may further explain the resulting findings of the study. With a sample predominantly consisting of university students, it is expected that financial means may be limited. In the absence of adequate financial resources, it may be possible that participants felt psychologically licensed but unable to act due to financial constraints.

It is important to consider that participants also reported purchasing unhealthy foods and especially snacks, regardless of licensing effects. This is likely due to the fact that university students are characterised by unhealthy eating habits such as snacking, as ultra-processed foods are often cheaper in comparison to minimally processed products and comply with the convenience of students (Bernardo et al., 2017; Aceves-Martins et al., 2022). Given that food purchasing

decisions are being skewed in accordance with sample characteristics, the true nature of potential licensing effects was not captured.

An additional limitation to be considered is the lack of contextual information in the data collected. For instance, while the HEUBS descriptions were useful in categorising the processing level of purchases, the quantity of foods purchased was ambiguous. This left room to question whether participants categorised multiple products under one category, or whether one item coincided with one description. This is crucial to note that the potential inconsistencies in adequately categorising food categories may lead to faulty interpretations of the final result.

Applications in Future Research

In relation to the limitations of the study, a number of points can be taken into account for future research. Firstly, studies aiming to conduct further research must consider obtaining a larger sample size. By using alternative methods to convenience sampling, these efforts will ensure greater reliability in the results, as more information will be gathered to provide a better understanding of moral licensing dynamics. Additionally, attention should be drawn to the recruitment of a diversified sample with heterogeneous characteristics. By doing so, studies can examine the variables beyond a sample of students and in a wider population. This will reduce the chances of running into any shortcomings, such as probable financial constraints and tendencies towards unhealthy food purchases.

To further develop the findings of the study, future research should also explore the possibility of collecting data on internal processes, such as reflections on perceived moral stances and motivations behind food choices. The current study found insignificant results in relation to moral licensing and unhealthy food purchases, and suggested that morality may not be applicable in the context of food choices. By capturing insights into participants' subjective experiences, future research could confirm these suggestions, as well as establish developed findings on moral licensing. Hence, incorporating methods such as ESM diary entries of follow-up interviews could further enhance insights into how moral licensing influences food purchasing behaviour. Researchers can do so by adopting a mixed-methods study by implementing qualitative methods to help interpret these internal mechanisms. With this, quantitative methods will aim to capture behavioural patterns and variations in moral licensing across time, while qualitative methods will capture and gather rich insights into participants' reflections and rationale for their morality and purchases.

Conclusion

To conclude, the study set out to explore the influence of moral licensing on unhealthy food purchasing behaviour. The uniqueness of the study lies in the use of the Experience Sampling Method (ESM), bringing real-time insights into moral licensing states and reported food purchases. Over a period of seven days, the researchers collected repeated entries on moral licensing behaviour as well as photo diaries and descriptions of food purchases. The results of the study produced no significant association between moral licensing and unhealthy food purchases. A manipulation check, which aimed to examine the influence of unhealthy food purchases on moral licensing, also revealed a non-significant effect.

Despite this, the findings contribute to broader theoretical deliberations on moral licensing dynamics and the multifaceted nature of cognitive mechanisms and decision-making in consumer contexts. Future studies should consider implementing larger samples with diverse characteristics, as well as incorporating qualitative methods to assess measures of internal processes that underlie morality in food decisions. The consideration of these factors can contribute to a holistic understanding of how moral licensing influences food purchases.

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Appendices

The following section contains complementary information that was referenced in the main text of the thesis. They are displayed below to provide further comprehensibility and clarity to the methodology of the study.

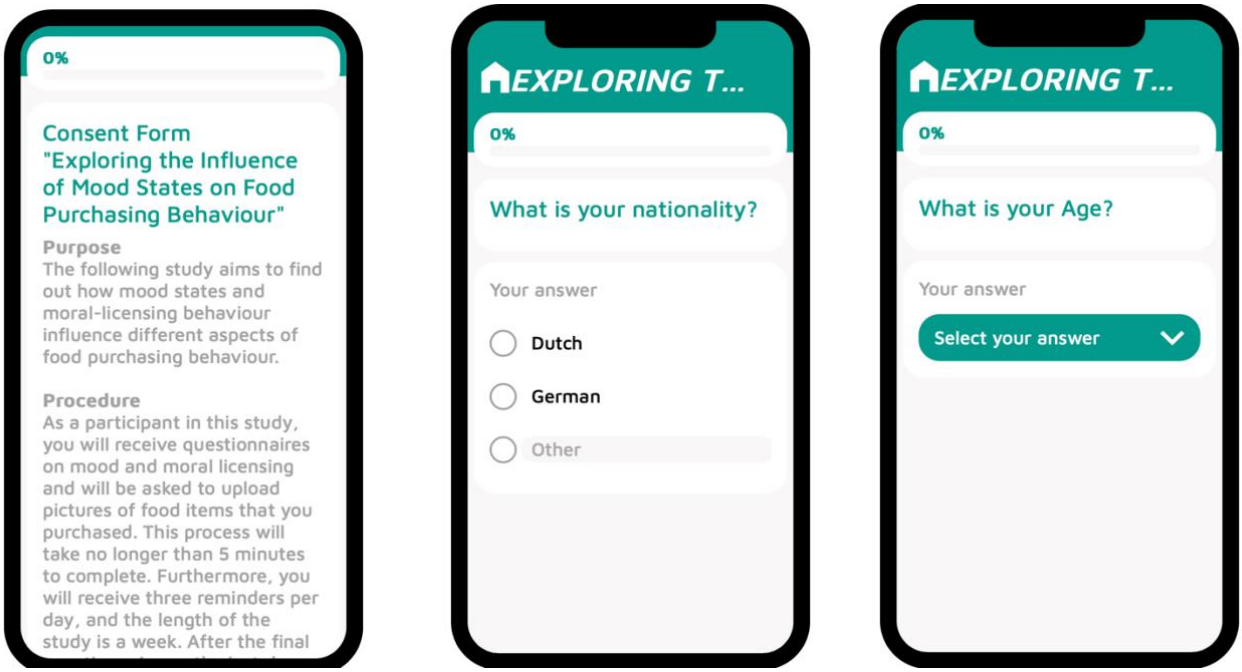
Appendix A

AI Statement

During the preparation of this work, I used MyBib to store and generate references in APA 7th Edition format, Google Scholar to brainstorm and browse academic sources, as well as Microsoft Word's built-in Editor for grammatical and clarification suggestions. After using these tools, I thoroughly reviewed and edited the content as needed, taking full responsibility for the final outcome.

Appendix B

TIIM App Interface



Note. The images are captured from the subscription page of the TIIM app.

Appendix C

Questionnaire Entry Schedule

Time of Day	Notification	Response Window
Morning	10:00 A.M.	Till 1:59 P.M
Afternoon	2:00 P.M.	Till 5:59 P.M.
Evening	6:00 P.M.	Till 9:59 P.M.

Appendix D

HEUBS Item List

Items
Fruits
Vegetables
Whole grains (e.g., brown rice, buckwheat, quinoa, oats)
Foods that are low in saturated fats and cholesterol
Foods that are high in monounsaturated and polyunsaturated fats (e.g., fish, olive oil, avocados, nuts and seeds)
Natural sweeteners (e.g., raw honey, maple syrup, coconut sugar, dates)
Water
Foods that are boiled, steamed, grilled, or poached
Lean meats, such as poultry, fish, and eggs
Low-fat dairy products (e.g., low-fat milk, yogurt, sour cream, cheese)
Legumes (e.g., beans, lentils, peas, peanuts)
Refined grains (e.g., white rice, white bread, white flour)
White sugar or artificial sweeteners

Snack foods, such as chips, chocolate, and/or candy
Sugar-sweetened beverages, such as soft drinks, fruit juices, and sports drinks
Foods that are deep-fried (e.g., fries, fried chicken)
Frozen and/or pre-packaged meals
Processed meats, such as sausages, bacon, and/or cold-cuts
Salty food
Fast-food
Pastries and/or baked goods (e.g., croissants, pie, cake, muffins, brownies)
Alcohol

Appendix E

R Script

```
# Load Required Packages
library(dplyr)
library(ggplot2)
library(psych)
library(lme4)
library(lmerTest)
library(readxl)
library(stringr)

# Clean column names
colnames(ml_demographics) <- trimws(colnames(ml_demographics))  # remove extra space from column names

# Total number of participants
```

```
n_participants <- n_distinct(ml_demographics$participant_id)

# Gender distribution
gender_counts <- ml_demographics %>%
  group_by(gender) %>%
  summarise(count = n()) %>%
  mutate(percentage = round(100 * count / sum(count), 1))

# Age statistics
mean_age <- mean(ml_demographics$age, na.rm = TRUE)
sd_age <- sd(ml_demographics$age, na.rm = TRUE)

# Nationality distribution
nationality_counts <- ml_demographics %>%
  group_by(nationality) %>%
  summarise(count = n()) %>%
  mutate(percentage = round(100 * count / sum(count), 1))

# Education level distribution
education_counts <- ml_demographics %>%
  group_by(`education_level`) %>%
  summarise(count = n()) %>%
  mutate(percentage = round(100 * count / sum(count), 1))

# Age statistics by gender
age_by_gender <- ml_demographics %>%
  group_by(gender) %>%
  summarise(
    mean_age = mean(age, na.rm = TRUE),
    sd_age = sd(age, na.rm = TRUE),
    n = n()
```

```
  )

# Output results
n_participants
gender_counts
mean_age
sd_age
nationality_counts
education_counts
age_by_gender

# Compute Moral Licensing Mean Score
license_vars <- c("license_1", "license_2", "license_3", "license_4")
ml_items$mean_license <- rowMeans(ml_items[, license_vars], na.rm = TRUE)

# Descriptive Statistics
summary(ml_items$NOVA)
sd(ml_items$NOVA, na.rm = TRUE)
summary(ml_items$mean_license)
sd(ml_items$mean_license, na.rm = TRUE)

# Cronbach's Alpha
alpha(ml_items[, license_vars])

# Group-Mean Centering and Lagging
ml_items <- ml_items %>%
  group_by(participant_id) %>%
  mutate(
    person_mean_license = mean(mean_license, na.rm = TRUE),
    license_centered = mean_license - person_mean_license,
    lagged_license_centered = lag(license_centered)
```

```
  ) %>%
  ungroup()

# Predicting NOVA from Lagged Moral Licensing (Hypothesis)
ml_items_filtered <- ml_items %>%
  filter(!is.na(lagged_license_centered), !is.na(NOVA))
model1 <- lmer(NOVA ~ lagged_license_centered + (1 | participant_id), data =
ml_items_filtered, REML = FALSE)
summary(model1)

# Predicting Moral Licensing from NOVA (Manipulation Check)
ml_items_model2 <- ml_items %>%
  filter(!is.na(NOVA), !is.na(license_centered))
model2 <- lmer(license_centered ~ NOVA + (1 | participant_id), data = ml_items_model2,
REML = FALSE)
summary(model2)

# Predictions for Visualisation
ml_items_filtered$pred_NOVA <- predict(model1, newdata = ml_items_filtered, re.form = NA)
ml_items_model2$pred_license <- predict(model2, newdata = ml_items_model2, re.form = NA)

# Scatterplot for Main Hypothesis
ggplot(ml_items_filtered, aes(x = lagged_license_centered, y = NOVA)) +
  geom_point(alpha = 0.5, color = "blue") +
  geom_line(aes(y = pred_NOVA), color = "red", linewidth = 1) +
  labs(
    title = "Model 1: Lagged Moral Licensing Predicting NOVA",
    x = "Lagged Moral Licensing (Group-Mean Centered)",
    y = "NOVA Score"
  ) +
  theme_minimal()
```

```
# Scatterplot for Manipulation Check
ggplot(ml_items_model2, aes(x = NOVA, y = license_centered)) +
  geom_point(alpha = 0.5, color = "blue") +
  geom_line(aes(y = pred_license), color = "red", linewidth = 1) +
  labs(
    title = "Model 2: NOVA Predicting Moral Licensing",
    x = "NOVA Food Purchasing Score",
    y = "Moral Licensing (Group-Mean Centered)"
  ) +
  theme_minimal()

# Mean per Participant
mean_per_participant <- ml_items %>%
  group_by(participant_id) %>%
  summarise(
    mean_NOVA = mean(NOVA, na.rm = TRUE),
    mean_license = mean(mean_license, na.rm = TRUE)
  )

participant_stats <- mean_per_participant %>%
  summarise(
    mean_NOVA = mean(mean_NOVA, na.rm = TRUE),
    sd_NOVA = sd(mean_NOVA, na.rm = TRUE),
    mean_license = mean(mean_license, na.rm = TRUE),
    sd_license = sd(mean_license, na.rm = TRUE)
  )
#Observations Iterations Mean Scores
ml_items %>%
  group_by(participant_id) %>%
  summarise(
```

```
    n_observations = n(),
    n_iterations = n_distinct(Iteration),
    mean_moral_licensing = mean(mean_license, na.rm = TRUE),
    mean_NOVA = mean(NOVA, na.rm = TRUE)
  ) %>%
  print(n = Inf)
# Mean per Measurement
ml_items %>%
  mutate(time_of_day = str_extract(Iteration, "morning|evening|night")) %>%
  group_by(time_of_day) %>%
  summarise(
    moral_license_mean = mean(mean_license, na.rm = TRUE),
    moral_license_sd   = sd(mean_license, na.rm = TRUE),
    NOVA_mean          = mean(NOVA, na.rm = TRUE),
    NOVA_sd            = sd(NOVA, na.rm = TRUE)
  ) %>%
  bind_rows(
    ml_items %>%
      summarise(
        time_of_day = "Overall",
        moral_license_mean = mean(mean_license, na.rm = TRUE),
        moral_license_sd   = sd(mean_license, na.rm = TRUE),
        NOVA_mean          = mean(NOVA, na.rm = TRUE),
        NOVA_sd            = sd(NOVA, na.rm = TRUE)
      )
  )
# Observation Count per Participant
obs_per_participant <- ml_items %>%
  group_by(participant_id) %>%
  summarise(n_obs = n())
```

```
mean_obs <- mean(obs_per_participant$n_obs)
sd_obs <- sd(obs_per_participant$n_obs)
min_obs <- min(obs_per_participant$n_obs)
max_obs <- max(obs_per_participant$n_obs)
```