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Sustainable products and conceptual processing fluency

Investigating dynamics among implicit attitudes, explicit attitudes, and buying intent for sustainable products through priming paradigm

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This master thesis is a part of the Master of Science in Economics and Business Administration program with a major in Marketing and Brand Management (MBM) at the Norwegian School of Economics (NHH). Writing this thesis enabled me to combine my interests in the topics of consumer behaviour and sustainable marketing. I was excited to attempt to incorporate insights on consumer cognition into the study of green consumer choices. This thesis became a valuable and educational journey, full of motivating challenges, learning, and growth.

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Abstract

In today's information-dense environment, people struggle to filter through the abundance of content from social media, emails, newsletters, and advertisements, while companies battle for the slightest chance of getting their communication efforts noticed by the desired segments. Due to such intense competition for attention, marketers not only utilize consumers' direct information processing but also rely on their peripheral and implicit cognition. With that in mind, when it comes to marketing sustainable offers, a significant amount of misunderstanding, distrust, perceptual barriers, and ignorance still has to be overcome. The purpose of this master thesis was to explore how unconscious information processing mechanisms influence green consumer choices. More specifically, this study addresses how priming for conceptual processing fluency can affect consumer preferences for sustainable products. The effects of sustainability and product category concepts were compared.

A classical experiment with the pre-post test design was conducted online to identify the dynamics in participants' implicit and explicit attitudes and buying intention, based on the VABH framework, depending on what type of context they were primed for. It involved a non-probability self-selected sample of NHH students, who completed IATs and answered questionnaires regarding imaginary cleaning products before and after treatment. One of the products was regular, while the other one had prominent eco-friendly features. The treatment in experimental groups consisted of a concentration task and an advertisement exposure.

The findings were consistent with the adopted VABH theory. Both concepts used in priming facilitated stronger guidance of buying intention by attitudes. Eco-friendly context strengthened the influence of explicit attitudes on buying intent, which was positive for green product and negative for regular one. Product category context strengthened the negative effect of explicit attitudes on buying intent for the conventional product. The significance of interactions of priming and implicit attitudes was inconsistent, likely due to the insufficient statistical power of tests.

Keywords: *green products, IAT, explicit attitudes, implicit attitudes, consumer preferences, buying intention, sustainable consumer behaviour, priming, processing fluency*

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List of abbreviations

APE – Associative-Propositional Evaluation

AVE – Average Variance Extracted

CFA – Confirmatory Factor Analysis

CR – Construct Reliability

DV – Dependent Variable

fMRI – Functional Magnetic Resonance Imaging

IAT – Implicit Association Test

IV – Independent variable

MOA – Motivation-Opportunity-Ability

OLS – Ordinary Least Squares

SEM – Structural Equation Modeling

SOA – Stimulus-Onset Asynchrony

TBP – Theory of Planned Behaviour

TRA – Theory of Reasoned Action

VABH – Value – Attitude – Behaviour Hierarchy

VIF – Variance Inflation Factor

1. Introduction

1.1 Backgrounds on green consumption

Remarkably, only forty years ago, the world population was twice smaller than it is today (United Nations, 2020) and it is projected to grow further to 9.7 billion people by 2050 (United Nations, 2019). This implies tremendous increases in food and energy demand, leading to further natural resource exhaustion and environmental degradation. Therefore, people may need to rely not only on technological solutions but also on changing their lifestyles and consumption patterns. Stricter environmental regulations and increasing stakeholder pressure are moving corporate players towards sustainable practices (Paul et al, 2016). There are multiple types of environmentally conscious behaviour, one of them being environmental purchasing. It stands for buying and consuming products that are more sparing for the environment (Mainieri et al., 1997). Such products are commonly called green products. Shamdasani et al. (1993) define them as "products that will not pollute the earth or deplore natural resources and can be recycled or conserved" (Paul et al., 2016, p. 123).

Even though sustainable behaviour has recently been growing among individuals (French & Showers, 2008) and companies, green product consumption is often impeded by fluctuating consumer preferences (Ha and Janda, 2012), barriers in consumer perception (Vantomme et al., 2004; Lin & Chang, 2012), concerns for greenwashing (Kangun et al., 1991; Peattie, 2010), and lack of consumer awareness (Wheeler et al., 2013). Eco-friendliness can even become a liability when strength-related product attributes are valued (Luchs et al., 2010). The positive environmental and societal impact of green products leads to strong associations with generosity but also weak associations with competency, efficiency, and effectiveness (Aaker et al., 2010 as cited by Lin & Chang, 2012). Consequently, misperceptions about green products often lead to larger than necessary amounts of product used, fostering product waste (Lin & Chang, 2012).

1.2 Backgrounds on limited information processing

Consumers are bombarded with thousands of advertising messages on a daily basis (Gritten, 2007). Meanwhile, the processing capacity of a person is limited. Every second, a human is able to only process approximately 50 bits of information while being exposed to 11 million bits (Wilson, 2002 as cited in Plassman et al., 2011). This means that most of the information remains unnoticed. Moreover, while being exposed to advertising materials, consumers often devote their attention to other tasks, limiting their capacity for ad processing even further (Plassman et al., 2011). In these conditions of intense competition for consumer attention and increasing likelihood of marketing communication not being processed consciously, the study of unconscious processing mechanisms becomes particularly relevant.

1.3 Research Questions

Sustainable consumption and consumer perception of green products have been a subject of multiple studies. The general findings demonstrate that people tend to hold positive evaluations of green practices and state to be positively predisposed to eco-friendly products and brands. However, these self-reported attitudes often do not match the actual consumer choices (De Pelsmacker et al., 2005; Lane & Potter, 2007), with the bulk of green products being overlooked. This dissonance is related to the attitude-behaviour gap (Jacobs et al., 2018), which can be caused by a range of issues, from lack of trust (Chen & Chang, 2013), to low understanding of how one's individual green purchase can contribute to the global cause (Joshi & Rahman, 2015), to perceptual barriers (Tan et al., 2016).

Many of these preventing factors are not consciously recognised by consumers, meaning that unconscious processing has a substantial influence on green product consumption. The studies applying the knowledge about unconscious processing to green product consumption are rather scarce. Therefore, this thesis aims to explore the possible ways of facilitating the unconscious positive change in consumer perception of green products. One of the commonly known methods of affecting consumer perceptions is priming. Priming enables exposure to a stimulus which at a later encounter becomes easier to process, making a person more positively predisposed to the target connected with that stimulus (Stafford, 1996). Such effect occurs largely due to the processing fluency, which can be triggered by prior exposures or the aesthetic appeal of an object (Labroo et al., 2008). Existing research shows that consumers base their product evaluations and brand choices not only on the available information but also on how easily they can process it (Lee & Labroo, 2004). Based on these findings, we can formulate our research questions as follows.

RQ1: Can priming for processing fluency enhance consumer preference for sustainable products?

RQ2: Do the effects of priming for conceptual processing fluency on preference and buying intent for sustainable products differ depending on the concept utilized in a prime?

1.4 Structure

As we have established the direction and the research questions, we can proceed with the further organisation of this thesis. Chapter 2 will present relevant theories for developing concepts and measures for the research. More specifically, it will discuss attitude formation, implicit and explicit attitudes, unconscious processing, processing fluency, priming and cause involvement. Based on that, Chapter 3 will continue with the description of the methodology applied in experiment design. Afterwards, Chapter 4 will present the analysis of collected data and the results of the conducted experiment. Further, Chapter 5 will be dedicated to the discussion of the received results. Lastly, implications, strengths, weaknesses, validity, and suggestions for future research will be presented in Chapter 6.

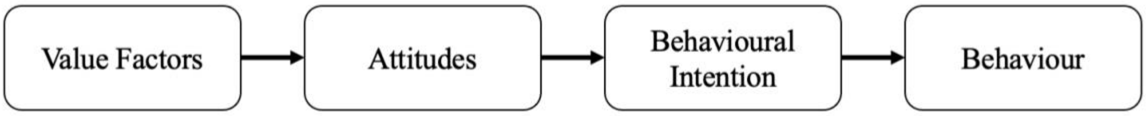
2. Theory

This chapter presents theoretical background for the further research. We will first establish the general concept of consumer attitudes as a potential tool for influencing consumer judgements of green products. Afterwards, we will analyse the distinction between implicit and explicit attitudes. Further, we will explore at the existing research on changing consumer attitudes and take a closer look at the cases of green products. In order to track the attitude formation and attitude change even closer, we will then present the insights from neuroscientific research. We will continue with reviewing the processing fluency theory and defining the concepts of perceptual and conceptual fluency. Lastly, our hypotheses and their theoretical justifications will be introduced.

2.1 Behavioural models

In order to influence consumer behaviour, which is the act of purchasing a product or a service (Ajzen, 2008), one needs to analyse its drivers. Attitudes are considered to contribute significantly to the forecasting of behaviour (Adams, 1964; Homer and Kahle, 1988; Do Paço et al., 2013). According to the Theory of Reasoned Action (TRA), developed by Ajzen & Fishbein (1975), behaviour depends on behavioural intention, which is influenced by attitudes and subjective norms. The stronger the behavioural intention is, the higher the likelihood of behaviour occurring is (Ajzen, 1991). Specific attitudes were found to be better predictors of the buying intent and the purchasing behaviour than general attitudes (Ajzen & Fishbein, 1975). Therefore, the term “attitude” will imply attitude towards a specific product further in the text. The Value-Attitude-Behaviour Hierarchy (VABH) takes a step further and considers the influence of values on attitudes, which lead to behaviour (Homer & Kahle, 1988). Homer and Kahle (1988, p. 638) refer to Rokeach's (1973) definition of values as an “enduring belief that one mode of conduct or end-state is personally preferable”. A value system is an organisation of these beliefs based on their importance (Homer & Kahle, 1988).

Figure 1. Theoretical model, based on VABH (Homer & Kahle, 1988)



Due to the time restrictions of this master thesis, we decided to observe the effects of attitude change on behavioural intention only. Exploring the true effects on the actual behaviour would require observation of customers in real shopping situations, which, in our case, would be hard to achieve for a large sample. Creating an artificial shopping situation in a laboratory could provide insight into the final purchasing behaviour, but it would exclude most of the external influences, and, thus, differ from a realistic environment. Therefore, as we are focusing on the attitude change, we believe that limiting the study up to the intention level will be sufficient for deriving valuable implications.

2.2 Defining Attitudes

According to Sarnoff (1960), an attitude reflects a favourable or an unfavourable predisposition towards an object. For a long time, an attitude was regarded as a product of conscious processing (Dijksterhuis, 2004). However, frequent weak correlations between directly reported attitudes and the following behaviour suggested that consumer attitudes could have some yet unexplored dimensions (Wicker, 1969 as cited by Madhavaram & Appan, 2010). Later social psychology theories have recognised that there are two types of attitudes, implicit and explicit ones (Wilson et al., 2000; Greenwald, et al., 2002; Olson and Fazio, 2001). Consumer’s implicit and explicit attitudes towards the same object can differ significantly (Rydell & McConnell, 2006). For instance, Ewing et al (2008) conducted a study where they saw the influence of Pavlovian conditioning for controversial celebrity endorsers on implicit and explicit brand attitudes. The results showed that implicit and explicit attitudes were uncorrelated. Deliberating about the controversial behaviour of endorsers negatively impacted only explicit attitudes, while the physical attractiveness of celebrities positively influenced only implicit attitudes.

2.2.1 Implicit Attitudes

As the type of attitudes is defined by the cognitive operations they involve (Strack & Deutsch, 2004), implicit attitudes are evaluative responses that consumers may be unaware of (Madhavaram & Appan, 2010). Even though people do not have conscious access to these attitudes (Rydell & McConnell, 2006), they influence consumer brand preferences (Ewing et al., 2008) and affect consumer behaviour (Wilson et al., 2000 as cited by Madhavaram & Appan, 2010). Implicit attitudes are believed to emerge from affective automatic reactions (Rudman, 2004 as cited by Ewing et al., 2008), and can predict subtle spontaneous behaviours (Rydell & McConnell, 2006; McConnell & Leibold, 2001). Since implicit attitudes typically predict immediate emotional reactions (Songa et al., 2019), they are more prognostic of purchasing behaviour in cases of time pressure (Dijker & Koomen, 1996 as cited by Songa et al., 2019).

In order to trace the attitude dynamics, Gawronski and Bodenhausen (2006) developed the associative-propositional evaluation (APE) model. The model suggests that implicit attitudes develop from associative processes. Hence, when an attitude object is encountered and triggers certain associations, implicit attitudes are activated. These associations, in their turn, generally lay outside of consumer's control and are persistent over time (Ewing et al., 2008). Experiments conducted by Rydell & McConnell (2006) demonstrated that small amounts of counter-attitudinal information did not affect implicit attitudes, meaning that most of persuasion techniques may be less effective than expected. That is supported by the fact that implicit attitudes are governed by the slow-learning associative system of reasoning, and tend to change slowly (Rydell & McConnell, 2006).

2.2.2 Explicit Attitudes

Explicit attitudes are more in line with the regular understanding of an attitude (Madhavaram & Appan, 2010), and are more cognitive (Rudman, 2004 as cited by Ewing et al., 2008). According to the aforementioned APE model, explicit attitudes are subject to propositional processes, tapping into knowledge and beliefs (Gawronski and Bodenhausen, 2006). Qualitatively different from implicit attitudes, explicit attitudes depend on truth judgements and are consciously controlled (Ewing et al., 2008). These attitudes are good predictors of deliberative judgements towards objects (Rydell & McConnell, 2006; McConnell & Leibold, 2001) and self-reported emotional reactions (Songa et al., 2019). As explicit attitudes involve the quick-learning, rule-based system of reasoning, they change faster in response to new information (Rydell & McConnell, 2006).

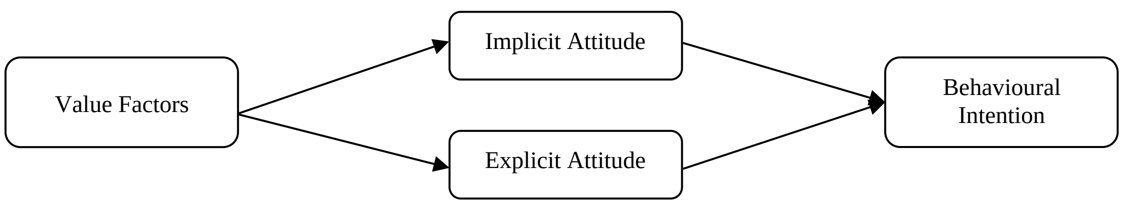
Since it was proven that implicit and explicit attitudes towards various sustainability aspects have weak correlations (Beattie & Sale, 2011 as cited by Songa et al., 2019; Wicker, 1969), it is important to address both of them in order to successfully market a green product (Songa et al., 2019).

2.2.3 Attitudes Towards Green Products

The research on the direct and indirect measurements of implicit and explicit attitudes towards sustainable products provides some curious findings. For instance, sustainable logos were found to cause more positive explicit and implicit reactions than regular logos did. In cases when people spent more time viewing an eco-friendly logo, their positive implicit attitudes led to increased positive neurophysiological reactions, while the relationship between explicit attitudes and explicit emotional evaluations did not change (Songa et al., 2019).

Another study conducted by Richetin et al. (2016) demonstrated that both implicit and explicit attitudes towards organic food brands can become more positive when a self-referencing technique is applied. Moreover, in their case, implicit attitudes change served as a mediator for the explicit attitudes change, brand identification, and hypothetical purchase choice. The effects of self-referencing were preserved even after the procedure of removing the pairing with self (Richetin et al., 2016). These findings once again prove the importance of considering implicit attitudes on par with explicit ones, when pursuing a positive attitude change towards green products.

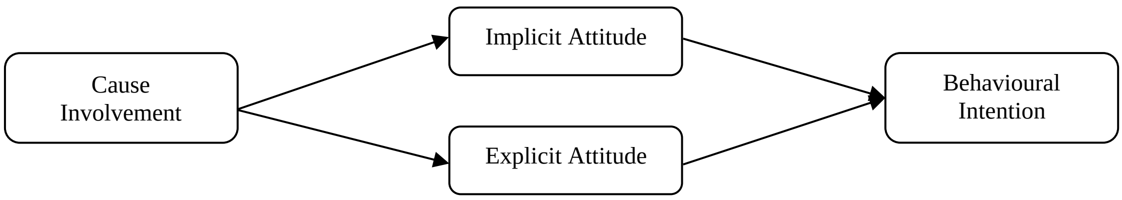
Figure 2. Theoretical model including implicit and explicit attitudes differentiation



2.3 Defining Values Through Cause Involvement

As it was mentioned earlier, values were found to affect attitudes and behaviour (Williams, 1979; Carman, 1977; Becker & Connor, 1981). For instance, Homer and Kahle (1988) showed that people with stronger internal values strived for more control and therefore put more effort into food purchasing, trying to choose the most nutritious and natural products. Moreover, they demonstrated that values can be categorised not only by internal/external and personal/impersonal dimensions but also according to the importance of their fulfilment. While considered on their own, values are one of the most abstract concepts (Homer & Kahle, 1988), but when combined with needs and interests, they comprise a more specific notion of personal relevance (Zaichkowsky, 1985) or cause involvement (Grau and Folse 2007). Patel et al. (2017, p. 6) refer to the simplified definition of cause involvement developed by Rothschild (1984), which is “the relevance that the consumer feels in response to cause exposure”. Therefore, we would like to narrow our focus to cause involvement in our discussion of the relationships between values and attitudes. The resulting adjusted VABH model is presented in Figure 2.

Figure 3. Theoretical model adjusted for the purposes of present research



2.4 Unconscious Information Processing and Attitude Formation

2.4.1 The Controversy of Unconscious Processing

A lot of research has been dedicated to identifying the possible influence of subliminal stimuli on the formation of brand preference and brand attitude. Janiszewski (1988, 1990, 1993) demonstrated that unconsciously processed information can affect brand attitudes while Shapiro et.al (1997) found the effects of such processing on consideration sets (Shapiro et al. 1999). Other findings prove subliminal stimuli to be effective when related to the current consumer goals. For instance, Karreman, Stroebe, and Claus subliminally primed participants with the words “Lipton Ice” or a neutral word consisting of the same letters while controlling for their thirst levels. Afterwards participants could choose between a thirst-quenching Lipton Ice or another beverage. The study revealed that people were more likely to choose Lipton Ice after they were primed with the brand-related word, but only when they were thirsty (Karremans et al., 2005).

Nevertheless, this line of research was met with scepticism. Broyles’ 2006 review of nearly 50 years of findings in subliminal advertising concluded that most of the effects were derived in highly artificial conditions, suggesting the lack of convincing evidence of its impact on consumer attitudes (Brintazzoli et al., 2012). The effects of unconscious stimuli in a more realistic context were explored by Brintazzoli et. al (2012) in their masked priming experiment involving famous brand logos presented consciously and unconsciously. The results revealed that brand logos can have a significant priming effect on brand names and brand-related words but only in the conscious condition.

2.4.2 Neuroscientific Findings on Unconscious Processing

In order to derive more precise conclusions about unconscious consumer behaviour, we would like to incorporate the insights from neuroscience in our analysis. Some findings suggest that human choices can be guided without explicit deliberation or attention to the focus task (Tusche et al. 2010). As noted by Tusche et al. (2010), activations in certain areas of the brain were found to be connected to product-related preference, attractiveness judgments (Lebreton et al., 2009; Luu and Chau, 2009), and financial decision-making and preference-related processing (Knutson and Bossaerts, 2007).

Matching activation theory and gaze-selectivity have also been proven to influence consumer choice and brand evaluation (Janiszewski, 1990; Shapiro et al., 1997; Glaholt & Reingold, 2009; Reutskaya et al., 2011). The hemispheric advantage theory is based on the idea that brain hemispheres have different processing styles. The right hemisphere is considered compatible with the processing of music and visuospatial information, relying on its ability to simultaneously integrate multiple chunks of information (Janiszewski, 1988). The left hemisphere is associated with counting, phonetic and syntactical processing, based on its ability to store and combine serially presented events or stimuli (Janiszewski, 1988). If a stimulus is present to the right of the focal point of the visual system, it is believed to be processed by the left hemisphere and vice versa (Janiszewski, 1988). Relying on this knowledge, Janiszewski (1988) conducted an experiment where he placed different types of ads in a digital magazine so that they would be processed by the desired hemisphere and saw how that affected later evaluations of those ads. For instance, when a pictorial ad was placed to the left from the editorial, thus processed by the right hemisphere, it was later evaluated more favourably. This suggests that hemispheric instantiation can influence preference formation (Janiszewski, 1988).

Tusche et al. (2010) used fMRI screening to investigate brain activity and consumer choices in high- and low-attention situations. The high-attention group was asked to evaluate individually presented different car images, while the low-attention group had to complete a fixation task. During the fixation task, an image of one of those cars passively appeared in the background for 2.4 s. Afterwards, both groups were asked whether they would purchase a car from that image. The results showed that distributed activation patterns in the insula and the medial prefrontal cortex reliably encoded subsequent consumer choices in both high- and low-attention groups (Tusche et al. 2010). This means that consumer choices can be formed without explicit deliberation or attention to a product (Tusche et al. 2010).

2.4.3 Implicit Memories

Consumer decisions can also be influenced by implicit memories, meaning by information encoded in the brain but without a deliberate attempt to retrieve it (Shapiro et al., 2010). Research shows that implicit memories are used in response-biases, such as increased preference for previously seen information (Schacter,1987, as cited by Shapiro et al., 2010). This is consistent with the idea of processing fluency when a person mistakes the familiarity of a previously seen stimulus for the preference for that stimulus (Seamon et al. 1995, as cited by Shapiro et al., 2010). Implicit memories have been found to strongly correspond with consumer judgements in cases when explicit memories were not involved. Moreover, implicit memories based on perceptual information are found to be preserved in the human memory longer than explicit ones based on semantic information (Shapiro et al., 2010). These memories may be preserved even with divided attention, meaning that the exposure had an impact, even at a subconscious level (Shapiro et al., 2010).

2.5 Processing Fluency Theory

One's attitude towards a brand can be changed by incidental exposure to an ad even without explicit memories of that ad (Shapiro, 1999; Laran et al., 2010). Mere exposure research demonstrates that the reason for that can be the catalyzed memory retrieval. If a person has been recently exposed to an object, it becomes more accessible in the memory, making it easier for the person to identify and recognize the object (Jacoby and Dallas 1981, as cited by Lee & Labroo, 2004). According to the processing fluency theory, prior exposure to a stimulus leads to easier processing of this stimulus at a later encounter (Bornstein and D'Agostino, 1994, as cited by Janiszewski & Meyvis, 2001). When such a stimulus is encountered, people often do not have the explicit memories of the prior exposure, thus misattribute the ease of processing to liking, truth, familiarity or acceptability (Janiszewski & Meyvis, 2001; Shapiro, 1999). These attributions are automatic and do not require conscious processing (Janiszewski & Meyvis, 2001). However, if a person is aware of the prior exposure, they are able to correctly attribute the processing fluency to the previous exposures instead of liking (Janiszewski & Meyvis, 2001). There are also sources of processing fluency different from prior exposure, leading to similar effects on attitudes and liking (Janiszewski & Meyvis, 2001). For instance, research suggests that variables affecting the aesthetic appeal of a pictorial stimulus, such as symmetry, clarity, and figure-ground contrast, impact processing fluency even in a single exposure (Labroo et al., 2008).

2.5.1 Processing Fluency Dynamics

It is important to note that processing fluency is not a monotonously increasing function of repeated exposures (Janiszewski & Meyvis, 2001). The change in processing fluency is based on the opponent processes of sensitization and habituation to a stimulus at any point in time. Increased frequency of exposures can lead to boredom and, thus, to less positive evaluations of a stimulus (Bornstein et al., 1990 as cited by Lee & Labroo, 2004). Consequently, these negative associations with the stimulus can counterweight the positive effect of processing fluency and even to less favourable attitudes towards the target object (Lee & Labroo, 2004). Dual-process theory suggests that repeated exposure leads to increased preferences towards familiar stimuli rather than to novel ones, but this advantage tends to disappear with time. That is due to the fact that additional exposures to a stimulus resulted in habituation. In a series of experiments, Janiszewski & Meyvis (2001) demonstrated that consistently with the dualprocessing model, stimuli familiarity and exposure schedule affected sensitization and habituation, leading to changes in processing fluency and consequently in consumer judgements.

2.5.2 Types of Processing Fluency

Processing fluency can be categorised into two types, conceptual and perceptual fluency (Janiszewski & Meyvis, 2001). Both types can be facilitated by prior exposure, yet they are independent of each other, having their unique antecedents and consequences (Cabeza and Ohta 1993; Lee 2002, as cited by Lee & Labroo, 2004).

2.5.2.1 Perceptual Fluency

Perceptual fluency occurs when exposure to a stimulus creates feature-based (for example, shape or brightness) representation in the memory, which during subsequent exposure leads to easier encoding and processing of the stimulus (Shapiro, 1999). It is considered to be most effective when the features of the stimuli shown during prior and later exposures exactly match each other (Roediger, 1990 as cited by Shapiro, 1999). Redhead (1996) suggested that perceptual fluency leads to stronger results when a product's features are first encountered in isolation, meaning without any context. Otherwise, a consumer may extract fewer features than presented during judgement or mix contextual and product features. Later, the consumer would not be able to differentiate them, which would lead to weaker perceptual fluency. Consequently, in a real-life context, perceptual fluency would have the most positive outcome when a person is first exposed to an ad featuring a product alone, not embedded in a scene, and later encounters a product alone as well, since the match between perceived features would be the strongest (Shapiro, 1999). Shapiro (1999) experimentally determined that such unconscious influence is likely to occur only in cases when the advertised product has an unfamiliar shape.

2.5.2.2 Conceptual Fluency

On the contrary, if an ad demonstrates a product embedded in a context, semantic analysis occurs, meaning that conceptual fluency is activated (Shapiro, 1999). Conceptual fluency occurs when exposure to a stimulus creates meaning-based representation, leading to easier encoding and processing of the information later (Shapiro, 1999). In other words, once stimuli come to mind more readily, and their meanings are grasped more easily, they are easier to process (Lee &Labroo, 2004). Conceptual fluency can potentially increase over time, thus is more sensitive to repeated exposure (Janiszewski & Meyvis, 2001). Shapiro (1999), as cited by Janiszewski & Meyvis (2001) also proved that increasing unidimensional complexity of stimuli led to increased conceptual fluency. He found that conceptual fluency was increased once he added a consistent background to a product display scene. On the contrary, when an inconsistent background was added, no change in fluency was identified (Janiszewski & Meyvis, 2001). In case of an incidental ad exposure, semantic processing is facilitated when the consistent context is added (Shapiro, 1999). Shapiro (1999) also showed that when products were advertised embedded in consistent context, increased conceptual fluency led to a higher likelihood of those products being included in consideration sets. Building upon these findings, Lee and Labroo (2004) conducted three experiments, in which they determined that people develop more positive attitudes towards a product if their conceptual fluency is increased by presenting a product in predictive context or primed by a related construct. For example, in one of the experiments, they first asked people to either evaluate an ad for mayonnaise or an ad for multivitamins and then asked them to evaluate a ketchup bottle. People evaluating the mayonnaise ad expressed a stronger liking for ketchup. The researchers suggest that this was due to both items, mayonnaise and ketchup, being meaningfully connected and belonging to the same associative network “condiments” (Lee & Labroo, 2004). At the same time, the negative valence of conceptual fluency, such as when priming hair conditioner with a lice-killing shampoo, can lead to unfavourable attitudes (Lee & Labroo, 2004).

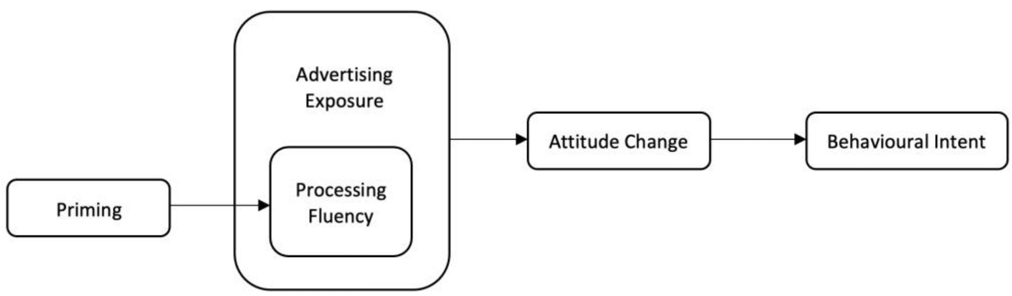
Although it would be insightful to explore both processing fluency types, we would like to focus only on conceptual fluency. Since it is already proven to foster the formation and change of attitudes, we would like to take a step further and compare the attitudes dynamics when different consistent concepts are activated. The neural representations of concepts can be activated prior to the exposure to a target object in the process of priming (Stafford, 1996).

2.6 Priming

The traditional view of priming as a paradigm was developed in the works of Higgins and his colleagues, among whom were Bargh & Lambardi (1985) and Herr (1986) (Stafford, 1996). It was based on the principle that when a stimulus matched a judgement situation, it would unconsciously activate appropriate mental constructs, thus positively influence the judgement of the category (Stafford, 1996). In line with this view, appropriate media context would serve as a prime for an ad, and a salesperson's interaction could prime for judgement heuristics (Stafford, 1996). Since this interpretation of priming might be unrealistic for many selling encounters, when buyers are highly involved and wary of the influence attempts, the new view of priming also considered the effects in cases when buyers would consciously recognise the stimuli (Stafford, 1996). Priming effects in such cases were frequently found absent or even negative (Martin, 1986; Martin et al., 1990, as cited by Stafford, 1996).

Priming effects are influenced not only by the target behaviour implied by the tactic but also by the tactic itself (Laran et al., 2010). For instance, brands produce priming effects, while slogans tend to produce reverse priming effects (Laran et al., 2010). This could be explained by the principle of automatic correction against persuasion. According to correction research, when consumers encounter a source of unwanted bias, it activates mental processes and behaviours to correct for its potential influence (Petty et al., 1998, as cited by Laran et al., 2010). If such a stimulus is encountered frequently, the correction behaviour can become unconscious. In the experiments conducted by Laran et al. (2010), when slogans were perceived as persuasion techniques, they caused an automatic reverse priming effect. However, when the consumer focus was shifted to the creativity of the slogans, desired priming effects were achieved.

Figure 4. Theoretical model of processing fluency



2.7 Hypotheses

Previous studies found both implicit and explicit attitudes predictive of conventional product choice. For instance, Berger and Mitchell (1989) showed that attitude accessibility and attitude confidence, increased through ad exposure, correlated with brand evaluations. Before we check the effects of treatment, we need to ensure that the relationships between attitudes and behavioural intention, which is buying intent in our case, are in line with our version of the VABH model. Positive change in attitudes is expected to result in higher product evaluations. Therefore, we hypothesize the following for green products:

- H1: Implicit attitudes towards a green product will affect the buying intent
- H2: Explicit attitudes towards a green product will affect the buying intent

Since explicit attitudes and buying intention are both self-reported measures, and we do not put respondents under time pressure, it is highly likely that both of them will be assessed cognitively, hence the respondents will exert control over their evaluations. The same nature of processing applied to reporting of these two measures could result in them being stronger correlated with each other than with subconscious IAT measure. For instance, in the study by Songa et al. (2019) explicit attitudes were better predictors of self-reported emotions, while implicit attitudes were stronger related to uncontrolled reactions. Therefore, explicit attitudes will most likely be a stronger predictor of buying intention than implicit attitudes will be, leading to the following hypothesis:

- H3: The effect of explicit attitudes on the buying intent will be stronger than the effect of implicit attitudes

By introducing a consumer to contextual cues, one can change what information is accessible in consumer memory and how easily it can be processed, which in turn affects consumer judgements and choices (Labroo et al., 2008). As Lee and Labroo (2004) state, referring to the work of Nedungadi (1990) and Whittlesea (1993), conceptual fluency can be facilitated by predictive context or indirect priming that does not involve the target object. In their own study, priming a consumer with product-category related primes led to easier ad processing and higher evaluations of the target products. We would like to use these paradigms to build upon the aforementioned hypotheses, which suggest that implicit and explicit attitudes will positively affect the buying intent for green products. We suggest that by priming predictive context we could enhance the positive influence of attitudes on buying intent. If a person focuses on a text describing the typical situation in which a target product is used, the cluster of associations related to that product category should be activated. Consequently, when the person encounters the target product, they will process it easier, which we expect to be reflected in their increased liking of that product. With the goal of comparing the priming effects for both attitude types, we hypothesize that:

- H4: Priming with a product category related prime will positively affect the relationship between implicit attitudes and purchase intention for a green product
- H5: Priming with a product category related prime will positively affect the relationship between explicit attitudes and purchase intention for a green product

One of the goals of our research is to compare the effects of conceptual priming with two different target-consistent contexts. Besides the product category, green products should be closely associated with environmental friendliness (Wang & Horng, 2016). Therefore, we believe that a prime that would activate consumers' mental representation of the eco-friendliness concept can facilitate conceptual fluency in a similar manner as the product-category prime. Hence, we hypothesize that:

- H6: Priming with an eco-friendliness related prime will positively affect the relationship between implicit attitudes and purchase intention for a green product
- H7: Priming with an eco-friendliness related prime will positively affect the relationship between explicit attitudes and purchase intention for a green product

Consumers tend to put more effort into consciously processing the information presented in ads when the subject is relevant for them (Haugtvedt & Petty, 1992). On the contrary, when they perceive it as irrelevant, the processing is reduced mostly to peripheral levels, leading to slighter changes in attitudes (Subroto & Samidi, 2018). We could, therefore, assume that when a person interested in environmental issues sees an ad for an eco-friendly product, they will put more effort to evaluate the information than a person not interested in the topic. Consequently, the person with higher cause involvement will be more likely to have an increased preference for a green product after viewing the ad than a person with low cause involvement would be. Considering the fact that implicit attitudes change slower than explicit ones (Rydell & McConnell, 2006; Ewing et al., 2008), we hypothesise that:

- H8: After viewing a green product ad, explicit attitudes towards green product will correlate with cause involvement stronger than implicit attitudes towards green product will.

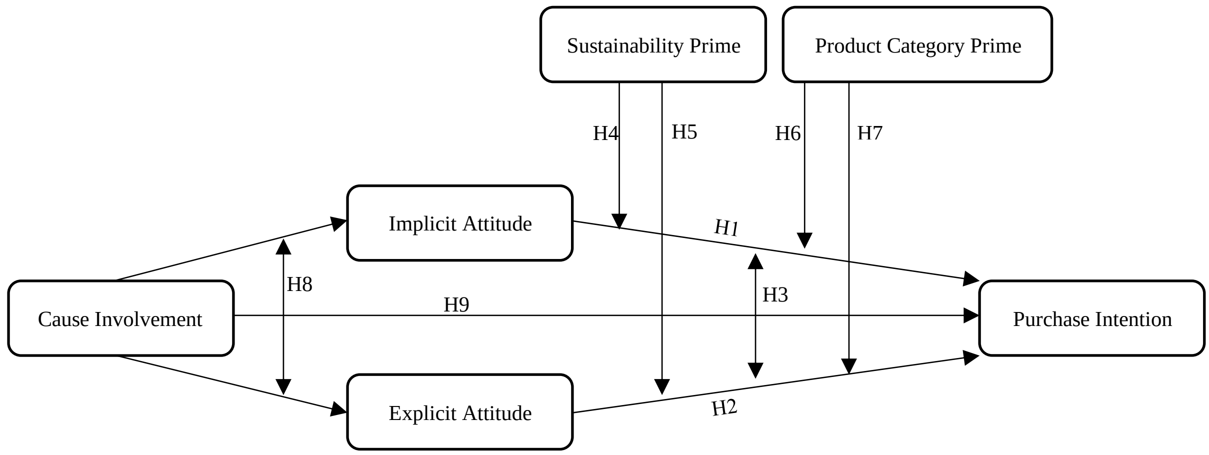
As discussed earlier, values, or cause involvement in our case, express stable beliefs and serve as a basis for attitudes and behaviours (Shin et al., 2017). Researchers identified that values serve as predictors of sustainable consumer behaviour (Ladhari & Tchetgna, 2015; Jacobs et al., 2018). In several studies, values related to environmental protection, in particular, served as predictors of sustainable consumer behaviour (Diamantopoulos et al., 2003; Shaw et al., 2005; Jägel et al., 2012). Furthermore, environmental concern was proven to affect consumers' behaviour and desire to purchase green products (Minton & Rose, 1997; Esmaeilpour & Bahmiary, 2017). Based on these findings and the VABH model, we hypothesize that:

- H9: Cause involvement for sustainable consumption will positively affect the purchasing intention for a green product.

Li et al. (2008) recorded brain potentials to see the effects of individual sensitivity to threat on effects of affective priming and discovered that personal differences indeed affected priming results. In similar logic, personal differences regarding sensitivity to environmental friendliness could affect the results of priming for eco-friendliness context. In our case, this "sensitivity" is reflected in cause involvement. We can also suggest that consumers who express stronger cause involvement for sustainable consumption will have a stronger mental representation of the eco-friendliness concept, which a priori will be activated easier than for those people who do not have a strong connection with the topic. Consequently, we hypothesize that:

- H10: In cases of high cause involvement, the effects of sustainability related prime will be stronger than the effects of product category related prime.

Figure 5. Conceptual model



*H10: In cases of high cause involvement, the effects of sustainability related prime will be stronger than the effects of product category related prime

3. Methodology

This chapter will present the logic behind the way in which the research was undertaken. Saunders et al. (2009) propose that methodology implies understanding not only how the research should be conducted but also “the theoretical and philosophical assumptions upon which research is based and the implications of these for the method or methods adopted”. Therefore, here we will present the choices of research design, experimental design, including measurements and instruments adopted, sampling and data collection, as well as reliability and ethics discussion.

3.1 Research design

Gerring (2012) refers to research design as selection and arrangement of evidence, hence the plan of solving a research problem. According to Saunders et al. (2009), it is a general plan to investigate a research problem by answering research questions.

The purpose of the research dictates the choice of a research method (Saunders et al., 2009). Saunders et al. (2009) define three general types of research methods, including exploratory design, descriptive design, and explanatory design, also known as causal inference (Breivik, 2019a). Exploratory design is dedicated to clarifying and framing the research problem (Breivik, 2019a), while descriptive design serves to describe populations (Breivik, 2019a), “to portray an accurate profile or persons, events or situations” (Saunders et al., 2009, p. 140). Explanatory design focuses on “studying a situation or a problem in order to explain the relationships between variables” (Saunders et al., 2009, p. 591). The purpose of this research is to identify the influence of priming for contextual fluency on consumer attitudes towards green products and consequent preference and buying intent. Moreover, we would like to see whether the effects of this priming will vary depending on consumer’s personal involvement with green causes. Therefore, explanatory research would be the most fitting method for the present study. Since we developed hypotheses based on developed theory, tested those hypotheses, and analysed the results considering the given theoretical frameworks, we used the deductive approach (Saunders et al., 2009).

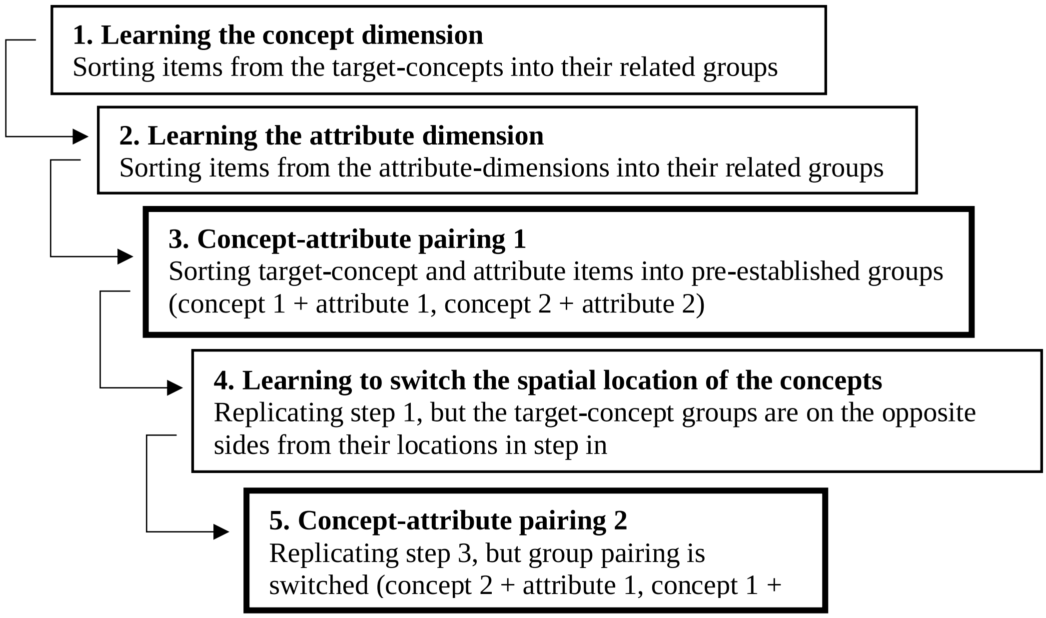
Explanatory design can be supported by various research strategies (Saunders et al., 2009). Since the research questions of this study focus on identifying causal effects, we chose to conduct an experiment. It serves to establish only two possible explanations for the observed effects, which include the effects of the independent variables (IV) and the chance factor (Haslam & McGarty, 2006). Experiment also enables the researchers to have more control over the variables (Haslam & McGarty, 2006) while manipulating the explanatory mechanism. We decided to conduct a between-subject study, meaning that participants were divided into groups, each exposed to different treatments. This type of study helps prevent the transfer of the effect from one treatment to another, as each participant is only exposed to one type of treatment. Since our experiment included experimental groups and a control group, it can be categorized as a classic experiment (Saunders et al., 2009). In order to check whether the manipulation of the IV led to a change in the dependent variables (DV), we had to compare the states before and after the manipulation for both the control and the experimental groups. Ceteris paribus, the difference in the comparison could be attributed to the manipulation. The three treatment groups were subjected to manipulation in a form of a prime exposure and an ad exposure, while the control group was not exposed to any of the IVs. In order to check for the effects of priming on ad effectiveness, the third group was exposed to an irrelevant prime, which was designed not to cause processing fluency, thus served as a control group for priming manipulation.

3.2 Experimental design

3.2.1 Implicit Association Test design

The collection of the quantitative data was conducted in different forms for implicit and explicit attitudes. Implicit attitudes were measured with the help of the Implicit Association Test (IAT). In our experiment, the IAT sections were integrated into the Qualtrix survey with the help of the code developed by iatgen project (Carpenter et al., 2019). IAT test is especially useful in measuring “socially significant associative structures” (Greenwald et al, 1998). Since green consumption is surrounded by a high degree of social influence (Peattie, 2010; Salazar et al, 2013; Wu & Chen, 2014), thus can be considered as a sensitive topic, often leading consumers to intentionally adjust their self-reported answers to fit under a desirable social norm, it fits the experiment at hand well. It is a computer-based test, that measures how many milliseconds it takes a subject to associate the target-concept discrimination with the attribute dimension (Greenwald et al, 1998; Litwin & Boyol Ngan, 2019). A participant is asked to pair a concept, placed centrally on the computer screen, with one of the two contrasting attributes, placed to the left and right from the target-concept, by pressing related keyboard buttons correctly and as fast as possible. IAT measures the strength of an association and works on the principle that under time pressure repeatedly activated association will be more automatic and an association with this attitude will be faster (Greenwald et al, 1998; Litwin & Boyol Ngan, 2019). Researchers believe that such automatic associations activated under time pressure are based on the well-established attitudes of a respondent (Litwin & Boyol Ngan, 2019). After completing a pairing task, a participant has to complete a reverse pairing task. The difference in performance speed constitutes the basis of IAT measurement. The standard IAT test consists of five blocks of tasks, with the third and the fifth blocks providing the critical data:

Figure 6. IAT blocks, based on Nosek et al., 2005



Consistent with the topic of the research, the target-concept groups were selected to represent a green product and a non-green product. Nosek et al. (2005) point out that, based on the work of Greenwald et al. (1998), the number of items per group could vary from 5 to 25 without affecting the magnitude of answer latencies. The most efficient approach was proven to include a few items that represent the group extremely precisely, which results in higher construct validity than having many less precise items (Nosek et al., 2005). Therefore, for the present study we chose to have 5 items per group. To select the items for the product groups, we reviewed the studies on the consumer-perspective green product associations and definitions conducted by Durif et al. (2010), Nguyen et al. (2020), Saravanaraj et a. (2017), Wang and Horng (2016). The only available example of IAT items for general green product concept was present in the work of Wickmann and Brente (2013), which also guided our choice. The items for the green product group included “Sustainability”, “Recycling”, “Reduced Packaging”, “Biodegradable”, “Non-toxic”, “Environmentally Conscious”. The items for the non-green product group included “Convenience”, “Heavy Packaging”, “Non-biodegradable”, “Regular”, “Pollution”, “Cost-saving”. They were chosen with the goal to reflect the lack of features expressed in the green products group’s items, and to express that these products are typically easier to produce and more abundant on the conventional market.

The items for both attribute dimension groups were adopted from the datasets of experiment materials provided at the Project Implicit website. The items chosen for the positive attribute dimension were "Laughter", "Happy", "Joy", "Love", "Glorious", "Pleasure", "Peace", and "Wonderful". The negative dimension items included "Failure", "Agony", "Awful", "Nasty", "Terrible", "Horrible", "Hurt", and "Evil".

3.2.2 Online survey structure

In order to collect the quantitative cross-sectional data on explicit attitudes we decided to conduct a survey in a form of a self-administered online-based questionnaire. According to Saunders et al. (2009), this research strategy is generally perceived as a reliable low-cost tool in collecting large amounts of primary generalizable data. Surveys often include a questionnaire, which Burns et al. (2017, p. 216) define as “the vehicle used to present the questions the researcher desires respondents to answer”. Questionnaires play an important role in marketing studies, as they enable researchers to convey research objectives through specific and standardized questions, speed up the data analysis process, maintain the respondents’ motivation, and provide data for reliability and validity evaluations (Burns et al., 2017). Nevertheless, this technique also entails reduced control over the response situation, implying higher risks of distraction or misinterpretation of the tasks. It is, therefore, highly important to construct the questionnaire carefully in order to achieve truthful responses and to avoid errors caused by question bias or response fatigue. Framing and order of the questions can influence the responses (Burns et al., 2017), therefore we strived to avoid leading, loaded, double-barrelled, and overstates questions. We also followed Burns et al. (2017) recommendation to ensure that questions were focused, brief, grammatically simple, and clear (Appendix L).

Since we wanted to see the dynamics between variables when a person had the treatment, we decided to use a pre-post design. This means that participants had to complete the IAT and the survey before and after having the treatment. While it is excellent for making a precise comparison between the prior and the later relationships between variables, such a design also imposes a testing threat. The change in these relationships might happen not due to the treatment, but because a participant might get more adjusted to the testing itself. However, we believe that the nature of the IAT test and the questionnaire do not develop specific skills or knowledge, thus should not cause such an issue. However, it is worth noting that the questions in the pre-test section of the experiment might prep the participants for the topic of the research, making them even more predisposed towards a green product ad, and more receptive to the green products presented in the survey.

Table 1. Experiment groups

	Pre-test	Treatment	Post-test
Group 1	IAT, questionnaire	Product category prime + ad exposure	IAT, questionnaire
Group 2	IAT, questionnaire	Sustainability prime + ad exposure	IAT, questionnaire
Group 3	IAT, questionnaire	Irrelevant prime + ad exposure	IAT, questionnaire
Group 4	IAT, questionnaire	Irrelevant task	IAT, questionnaire

3.2.3 Prime design

In order to activate the relevant clusters of associations before the participants viewed the advertisement and evaluated the products, they were asked to complete a priming exercise. The task was the same for all treatment groups and included reading a short text and selecting certain words from it by clicking on them. To control for the between-group differences, all the texts were article extracts from online magazines or newspapers of approximately the same size. Meanwhile, each group had its own text and topic for the word selection. The first group's text was an extract from a *Business Insider* article on at-home cleaning products. Participants were asked to select words related to cleaning, since their text aimed at priming the product category associations. The second group read a piece from a digital magazine *dezeen*'s article on a designer who used bio-fabrication to create environmentally friendly product packaging. They were asked to select sustainability related words, as their text was meant to stimulate associations with sustainability. The third group also had to complete a task to have their experience as similar as possible to that of the other two treatment groups. The only difference was in their prime being designed not to trigger any relevant associations for the advertisement and the products reviewed later. Their text included an abstract from a *New York Times* film review, and participants had to select words related to movies.

3.2.4 Advertisement design

After completing the priming task, participants were asked to review an advertisement for an imaginary sustainable laundry detergent. Existing sustainable detergents were purposefully avoided to prevent any external influence on consumer perception. If participants would have previously seen or interacted with the product shown in the ad, even without explicit memories of it, their prior experience could influence the effect of the ad which would be impossible to control for (Northup & Mulligan, 2014). The advertisement consisted of an image of a bottle in front of a laundry basket, hence the product was placed in a relevant context, to achieve conceptual processing fluency (Shapiro, 1999). The packaging was designed to mention the sustainable product features, as well as its functionality. The image was supported by text, which gave more detail on both the cleaning and the sustainable properties of the product.

3.2.5 Irrelevant treatment design

The control group was exposed to the same pre-post design as the treatment groups were but did not have to complete the priming exercise and review the advertisement. Instead, after completing the pre-test, the participants in this group were offered to read a poem not related to the topic of the research. By having the control group complete both pre-test and post-test, it was possible to have its experience as similar to that of the treatment groups as possible. It would also enable us to check for the potential effects of the test repetition.

3.2.6 Product design

Products used to measure the attitudes and purchase intention were designed from scratch for the same reasons as the product in the advertisement. Throughout the experiment, participants saw two cleaning sprays in the pre-test and two dish soaps in the post-test. The pairs differed in order to avoid possible prepping of the post-test evaluations. If participants evaluated the same products in both tests, their second evaluations could be influenced by the familiarity of the products. Both pairs belonged to the same product category, which was cleaning products. Since sustainable product features were proven to create perceptual barriers when shopping for cleaning supplies (Luchs et al., 2010; Newman et al., 2014), this product category was particularly interesting to include in the experiment. The cleaning spray and the dish soap can be generally considered routine purchases, which are often analysed superficially, according to the Motivation-Opportunity-Ability (MOA) model (Hoyer et al., 2013). Each pair contained one regular and one sustainable product. The difference between the appearance of the two products was minimised to reduce the influence of external factors, such as product shape, background colour, or mage brightness, on consumer evaluations. The packaging for both products in a pair contained the same figures, similar elements, and approximately the same amount of information.

Nevertheless, it was also important to ensure that participants could correctly differentiate the products from each other. Conventional products' packaging mentioned functional properties and was predominantly blue-coloured, as is commonly used in real-life products to achieve association with cleanness (Ko, 2011, Pancer et al., 2017) and competence (Labrecque & Milne, 2012). Green products' packaging mentioned not only functional but also sustainable properties featured nature-associated green colour (Naz & Epps, 2004; Labrecque et al., 2013) and nature-inspired textures, which are cues that help activate environmental schema and categorize the product as eco-friendly (Pancer et al., 2017).

No additional information, such as product description, ingredient list, or price, was presented in the experiment. That was done in order not to overload the participants, considering the experiment's high demand for time and attention. Moreover, in typical for cleaning products low-effort purchasing behaviour, easily processed aspects, such as visuals, play a more important role for decision-making, since consumers tend to process information peripherally (Hoyer et al., 2013). Therefore, we assume that presenting the product images only would be sufficient for collecting data on consumers' preferences.

3.2.2 Measurements

Attitudes towards a green product were measured with the help of the IAT and a questionnaire (Appendix L). Implicit attitudes were calculated based on the difference in the latencies of responses to the pairing and the reverse-pairing steps of the IAT. To create a construct for the overall explicit attitude towards a product, we relied on the items used in related studies. In the study on eco-labelling effects, Gosselt et al. (2019) used a bipolar scale to measure the attitude towards a brand, which included "dislike-like", "unfavourable-favorable", "negative-positive", and "socially irresponsible-socially responsible" items. This construct was previously found to be reliable by Nan and Heo (2007), with the Chronbach's alpha equal to 0.84 (Gosselt et al., 2019). Another study on the perceived importance of sustainability in fish consumption measured the general consumer attitude towards the product using items such as "bad-good", "negative-positive", and the attribute-beliefs based items such as "unhealthyhealthy”, “safe-unsafe” (Verbeke et al., 2007). We adopted this approach by first asking the participants to individually rate the green and the conventional product on the following dimensions: “bad-good”, “safe-unsafe”, “unfavourable-favourable”, “worthless-valuable”, “useless-useful”, “negative-positive” using a 1-5 scale. Secondly, the participates evaluated the two products relative to each other on the “interesting”, “pleasant”, “attractive”, and “beneficial” dimensions, using a 1-5 thermometer scale, with 1 meaning “conventional product is more interesting” and 5 meaning “green product is more interesting”. This approach was adopted from Richetin et al. (2016) study on implicit and explicit attitudes towards organic foods. In order to get an explicit measurement more comparable with the relative D-score, a relative explicit attitude was created, which could be interpreted as an “explicit preference for sustainable products. It was calculated as the difference between explicit attitude towards a green product and explicit attitude towards a conventional product collapsed with the thermometer measurement.

Purchasing intent was more straightforward in measuring than general attitudes. Therefore, we adopted a three-item measure previously used by Putrevu and Lord (1994), Lii and Lee (2012), and Patel et al. (2016). We asked participants to rate how much they agreed with the following statements: “I will try the product”, “I will consider purchasing the product next time”, and “It is very likely that I will buy the product”. These questions consisted of a Likert scale from 1 to 5, with 1 meaning “completely disagree” and 5 meaning “completely agree”.

Cause involvement measure, with the Chronbach’s alpha of 0.74, was adopted from Patel et al. (2016), being also previously tested by Maheswaran and Joan (1990), and by Grau and Folse (2007). Participants were asked to indicate statements about sustainability and green consumption using a 1 to 5 semantic scale with the following items: “unimportant / important”, “means nothing to me / means a lot to me”, “personally irrelevant / personally relevant”, “doesn’t matter a great deal to me / matters a great deal to me”, “no concern to me / great concern to me”. The statements used for the measure were adopted from Cho (2015), who used them to measure environmental involvement.

3.3 Sample & Data Collection

Since the goal of this thesis was to explore the influence of different types of conceptual priming on consumer’s implicit and explicit green product evaluations, the target population would be all consumers who face the choice between green and conventional products. With such a broad criterion, it would be impossible to control for individual between-subject differences which could affect the findings. For achieving stronger demographic and psychographic homogeneity among participants, NHH students of master, bachelor, and Ph.D. levels were chosen as the target sample. In terms of awareness about and exposure to sustainable products, we assume that the selected sample should have a similar level of both. Since all the contacted students live in Norway, at least for the time of their study program, they are exposed to the same market of consumer goods, hence the same representation of green products. In the context of the same university, students are exposed to events and business course discussions on the topic of sustainability to approximately the same degree. That is why we believe that extreme outliers in such a sample should be unlikely.

Non-probability self-selection sampling technique was used, as it enabled the quick collection of responses (Saunders et al., 2019). Considering the highly demanding in terms of the time and attention nature of the online experiment, it was important for us to get exposure to a large number of potential respondents to account for the expectable drop-outs. The anonymised link to the online survey, which included the IATs, the treatment, and the questionnaires, was shared with 2954 students via email, which resulted in 125 surveys being started. Two weeks after the first email, a follow-up email was sent to those students who had not yet started the survey. The invitation to the experiment was also shared through social media, such as Facebook resulting in 26 additional responses. One of the main reasons for the low response rate could be that most of the responses were collected in early June when students tend to be occupied with preparation for exams. A high drop-out rate was also expected because students could not participate from their mobile phones or tablets, as the IAT section required an analogue keyboard. Therefore, if they opened the invitation from their mobile devices, which happens often, they were most likely to postpone the experiment and eventually forget about it. Moreover, due to the coronavirus pandemic happening during the period of this master thesis, and the studying process being carried out online, students may have felt less interested in completing extra online work. Nevertheless, the final sample size of 82 responses in the pre-test and 60 responses in the post-test ensured that we had more than 10 cases per parameter, which is a common rule of thumb in working with structural equation modelling (Wolf et al., 2013).

3.4 Quality of Research Design

3.4.1 Reliability

Hair et al. (2019, p. 13) define reliability as "the degree to which the observed variable measures the "true" value and is "error free"; thus, it is the opposite of measurement error". It refers to the consistency of findings depending on the data collection techniques and analysis procedures (Saunders et al., 2009). Reliable measures should provide identical or near-identical results if the study is replicated (Burns et al., 2017).

To reduce the possible biases in research design that could affect the reliability of findings, we ensured to follow the academic recommendations on questionnaire design (see section 3.2.2). Moreover, the use of composite measures for explicit reactions enabled us to derive a more comprehensive measurement of the concept. Such technique allows researchers to shape the concepts more precisely and rely on multiple indicators instead of a single perspective (Burns et al., 2017). Researcher error was also reduced, as the explicit responses were measured quantitatively, with 5-point Likert scales, and there was no personal contact with participants during the experiment.

Moreover, a detailed explanation of the experiment structure and IAT instruction was carefully created to reduce unintentional respondent error. A prompter between the treatment and post-test sections of the experiment helped to fight the attention lag and keep the participants alert (Burns et al., 2017). As we provided respondents with anonymity and confidentiality of their answers, the intentional respondent error was less likely. In order to avoid respondent bias, which is possible in the self-selection sampling, there was no specification of the actual topic of the research in the invitations to the online experiment.

The reliability of implicit measurement was found to be stronger than in other latency-based measures (Nosek et al., 2007). Test-retest, a common assessment of reliability, for the IAT is also considered acceptable and sensitive to trait-specific and occasion-specific variations (Schmukle and Egloff (2005), as cited by Nosek et al., 2007).

3.4.2 Validity

Validity refers to the accuracy of the measurements and concerns the potential systematic error (Breivik, 2019b). According to Burns et al. (2019, p. 215), it is "It is an assessment of the exactness of the measurement relative to what actually exists". There are several types of validity that need to be accounted for and can apply to both measurements and research design.

Content validity ensures that the scale items correspond with the conceptual definitions (Hair et al., 2019) and cover them adequately (Saunders et al., 2009). The concepts investigated in this study were defined based on an extensive review of academic literature, and the questions covering them were adopted from measurement scales already tested in related studies, ensuring the content validity of our measurements. Construct validity "refers the extent to which your measurement questions actually measure the presence of those constructs you intended them to measure" (Saunders et al., 2009, p. 373). A more detailed evaluation of this validity type and the confirmatory factor analysis are described in a later chapter (see section 4.2).

Internal validity is "the extent to which findings can be attributed to interventions rather than any flaws in your research design" (Saunders et al., 2017, p.143). Having a control group in our experimental design enabled us to reduce the threats to internal validity since it was exposed to the same external factors as the experimental groups, hence the manipulation of the independent variables, such as primed concepts, should be the only explanation for the differences among the groups (Saunders et al., 2017). Moreover, random assignment lowered the threat that a high concentration of similar personal characteristics of participants in one group would affect the differences of responses from another group (Saunders et al., 2017). In comparison with a field experiment conducted in a natural setting, our design helped to significantly reduce the possible influence of external factors and provide participants with necessary conditions for the IAT. However, as the experiment was conducted digitally, it could not secure the same level of internal validity, as a laboratory experiment would. The main causes for a possible decrease in internal validity are further discussed in section 6.3 of this thesis.

External validity refers to the "extent to which the results of an analysis can be generalized to other contexts" (Hair et al., 2019, p. 373). While experiments allow having higher internal validity, it is generally considered hard to ensure a high external validity at the same time. As discussed earlier, the selected sample was supposed to be homogenous in terms of age, income, and sustainable awareness. Hence, it would be more appropriate to imply that our findings can be generalised among young adults having experience of living in Norway. However, a replication of the study with a larger sample and more control for socio-demographic differences would be preferable.

4. Data Analysis

This chapter presents the overview of the data collected through the survey and the results of the conducted experiment. We will start with the description of the dataset, check for the construct validity, describe the variables and finalize with the testing of our hypotheses. For organising and processing the data we used RStudio Version 1.2.1335, IBM SPSS Statistic 26, and PROCESS macro Version 3 developed by Hayes (2017). For calculating the D-scores of the IAT test, the code provided by iatgen project (Carpenter et al., 2017) was used.

4.1 Data description

The dataset consisted of one file with 141 responses, which was used to calculate the composite measures for each explicit construct and to calculate the D-scores for pre-test and post-test IATs. Afterwards, the outcome files were merged together, and responses with incomplete pre-tests were removed. This gave us a total of 82 pre-test responses and 60 post-test responses. To ensure that the manipulation took place, the completeness of the priming task was controlled for. Respondents that did not select any words from the text in the priming task, thus did not pass the manipulation check, were removed from the final sample. The participants were equally distributed across the four experimental groups, yet due to the randomness of dropouts, the final group sizes were not strictly equal. The control group and the sustainability related prime group both had 20 responses in the pre-test and 17 responses in the post-test. The product category related prime group had 18 responses in the pre-test and 12 responses in the post-test. The irrelevant prime group had 20 responses in the pre-test and 12 responses in the post-test.

Before proceeding with the analysis, we analysed the data distribution with the help of skewness and kurtosis indexes. There is no strict consensus about what index values should be considered normal. Many scientists conservatively consider the skewness and kurtosis values of -1/1 range to be excellent (Field, 2009). Meanwhile, some researchers also accept more flexible skewness ranges of -2/2 (George & Mallery, 2016) and -3/3 (Kline, 2011) as normal. Kline (2011) also suggests that the kurtosis index within -10/10 values is non-problematic. All variables in our dataset were negatively skewed within the -2/2 range, which means that there were more responses on the right side of the distribution (Gravetter & Wallnau, 2013), implying prevailing positive evaluations. Explicit attitude (-1.004) and buying intent for green product (-0.956) after the treatment were the most skewed, with the highest likelihood of the means potentially being less representative of the central tendency (Saunders et al., 2009). Kurtosis values, in our case, laid within -3/3 range, with explicit attitudes before (2.427) and after (2.332) the treatment having the most extreme values. Buying intent for the green product after the test (1.005) also stood out with a high value. In our dataset there were variables with positive kurtosis values, signifying a more peaked distribution compared to the normal one, and variables with negative kurtosis and flatter than a normal distribution (Saunders et al., 2009). Even though the data was not symmetrical, and there were some outliers, based on the index ranges proposed by Kline (2011) and George and Mallery (2016) we could consider our data distribution well within the norm for conducting further statistical tests.

Table 2. Descriptives statistics

Variable	Mean	Std. Dev.	Min.	Max.	Skewness	Kurtosis
Implicit pre	0.53	0.31	-0.38	1.19	-0.38	0.34
Implicit post	0.49	0.30	-0.28	1.04	-0.30	-0.52
Explicit pre	0.25	0.30	-0.63	1.28	-0.35	2.43
Explicit post	0.18	0.36	-1.00	0.90	-1.00	2.33
Buying intent green pre	3.47	0.94	1.00	5.00	-0.71	0.32
Buying intent green post	3.61	0.95	1.00	5.00	-0.96	1.01
Buying intent conventional pre	2.83	0.97	1.00	5.00	-0.38	-0.56
Buying intent conventional post	2.88	0.90	1.00	4.33	-0.70	-0.27
Cause involvement	4.04	0.65	2.40	5.00	-0.44	-0.25

4.2 Construct validity

Before proceeding with the hypothesis testing, it is also important to ensure that items in our measurements accurately reflect the theoretical constructs we want to analyse. According to Hair et al. (2019, p.162), "construct validity is the extent to which a scale or set of measures accurately represents the concept of interest". One of the tools to test for construct validity is confirmatory factor analysis (CFA) (Kline, 2011). The degree of association between two items in CFA is factor loading. Ideally, intercorrelation is considered significant when loadings are higher than 0.7, but loadings higher than 0.5 are also accepted (Hair et al., 2019). Since implicit attitudes were measured separately, we will only consider "explicit attitude", "buying intention" and "cause involvement" constructs here. We used the same measurements in pre-test and post-test, which resulted in some of them representing one factor in the CFA, and some being divided into two. It is also worth noting that even though there are separate factors reflecting green and conventional products measurements in our CFA, their items are identical, and the difference was created only by the images accompanying them. The thermometer questions "AB.compare_1", "AB.compare_4", in the pre-test, and "AB.compare_1.1", and "AB.compare_4.1", in post-test, which asked to evaluate products relative each other, were found problematic. They were tested twice, in a test with green product items and in one with conventional product items. These questions either cross-loaded or did not load on the same factors as the other two items in the constructs. Therefore, they were removed from further analysis.

Convergent validity presumes that a set of items measures the same construct if they are highly intercorrelated. It can be tested with the average variance extracted (AVE) statistic. As a rule of thumb, AVE is considered to indicate adequate convergence when it has the value of 0.5 or higher (Fornell & Larcker, 1981; Hair et al., 2019). In our case, the only potential candidate for deletion was the explicit attitude towards a green product in the pre-test, with a rather low AVE of 0.38, meaning that its items may hold more error than variance in common with the factor they load on (Hair et al., 2019). It would normally become a candidate for deletion, but since its items are identical to the items in other explicit attitude measures, which had acceptable AVE scores, we did not consider it problematic. Cause involvement had an AVE only 0.01 shy of the commonly accepted 0.5 threshold and was accepted, considering its high Cronbach's alpha. This statistic is often used to assess interrelatedness among the items, or internal consistency of the measurements (Osburn, 2000; Saunders et al., 2009). Cronbach's alpha is considered acceptable when its value exceeds 0.7 (Hair et al., 2019). In our case, all the measurements had alphas above 0.7, meaning that the responses to questions within each measure were consistent enough to be considered reliable for composite measure constructing. There are some concerns, however, about the robustness of Cronbach's alpha estimate (Cortina, 1993). Another indicator of convergent validity is construct reliability (CR), which should ideally exceed 0.7 value (Hair et al., 2019). In our case, CR statistics was satisfactory for all constructs.

Discriminant validity reflects how unique and distinct from other measures each construct is. One of the ways to check for discriminant validity is to compare the AVE scores of two constructs with their correlation estimate (Hair et al., 2019). Fornell and Larcker (1981) suggest that discriminant validity is established when the square root of AVE for a construct is larger than any of its correlation estimates with other constructs. In our case, all measurements had the square root of AVE exceeding their correlation estimates with other constructs. Therefore, we can consider that our measures are different from one another.

Table 3. Confirmatory factor analysis, including loadings, CR, AVE and Cronbach's alpha

Construct		***Items***	***Loading***	***CR***	***AVE***	***α***
Explicit attitude - *green* product	pre-test	Bat_1	0.80	0.88	0.54	0.89
		Bat_2	0.77			
		Bat_3	0.86			
		Bat_4	0.55			
		Bat_5	0.63			
		Bat_6	0.77			
	post-test	Aat2_1	0.93	0.94	0.72	0.95
		Aat2_2	0.78			
		Aat2_3	0.87			
		Aat2_4	0.72			
		Aat2_5	0.84			
		Aat2_6	0.92			
Explicit attitude - *conventional* product	pre-test	Aat_1	0.81	0.89	0.58	0.91
		Aat_2	0.75			
		Aat_3	0.83			
		Aat_4	0.69			
		Aat_5	0.46			
		Aat_6	0.95			
	post-test	Bat2_1	0.69	0.90	0.59	0.93
		Bat2_2	0.84			
		Bat2_3	0.81			
		Bat2_4	0.82			
		Bat2_5	0.64			
		Bat2_6	0.78			
Explicit comparison	pre-test	AB.compare_1	0.42	0.74	0.51	0.79
		AB.compare_2	0.92			
		AB.compare_3	0.72			
		AB.compare_4	-			
	post-test	AB.compare_1.1	-	0.80	0.66	0.80
		AB.compare_2.1	0.65			
		AB.compare_3.1	0.95			
		AB.compare_4.1	-			
Buying intent - *green* product	pre-test	B.PI_1_A	0.90	0.87	0.70	0.91
		B.PI_2_A	0.82			
		B.PI_3_A	0.78			
	post-test	A.PI_1	0.90	0.90	0.86	0.92
		A.PI_2	0.86			
		A.PI_3	0.85			
Buying intent - *conventional* product	pre-test	A..PI_1	0.90	0.86	0.67	0.91
		A..PI_2	0.80			
		A..PI_3	0.74			
	post-test	B.PI_1.1	0.81	0.85	0.66	0.93
		B.PI_2.1	0.80			
		B.PI_3.1	0.82			
Cause involvement		CI_1	0.69	0.82	0.49	0.83
		CI_2	0.58			
		CI_3	0.51			
		CI_4	0.85			
		CI_5	0.82			

*Extraction Method: Principal Axis Factoring. Rotation method: Oblimin with Kaiser Normalization.

Table 4. Discriminant validity analysis, including factor intercorrelations, AVE and √AVE

Pre-test Green Product						
Factor	**AVE**	**√AVE**	**1**	**2**	**3**	**4**
1. Attitude	0.54	0.73	1			
2. Cause involvement	0.49	0.70	0.32	1		
3. Buying intent	0.70	0.84	0.40	0.22	1	
4. Comparison	0.51	0.71	0.26	0.13	0.22	1
Post-test Green Product						
Factor	**AVE**	**√AVE**	**1**	**2**	**3**	**4**
1. Attitude	0.72	0.85	1			
2. Cause involvement	0.49	0.70	0.38	1		
3. Buying intent	0.86	0.93	-0.50	-0.21	1	
4. Comparison	0.66	0.81	-0.38	-0.21	0.39	1
Pre-test Conventional Product						
Factor	**AVE**	**√AVE**	**1**	**2**	**3**	**4**
1. Attitude	0.58	0.76	1			
2.Cause involvement	0.49	0.70	0.15	1		
3. Comparison	0.51	0.71	-0.16	0.29	1	
4. Buying intent	0.67	0.82	0.53	0.06	-0.25	1
Post-test Conventional Product						
Factor	**AVE**	**√AVE**	**1**	**2**	**3**	**4**
1. Attitude	0.66	0.81	1			
2.Cause involvement	0.49	0.70	-0.01	1		
3. Comparison	0.66	0.81	0.18	-0.326	1	
4. Buying intent	0.66	0.81	0.48	-0.286	0.312	1

4.3 Hypotheses testing

Due to the sample not being rather small, the individual analysis of each experimental group was not powerful enough to provide statistically significant results. Therefore, it was not feasible to conduct analysis comparing the changes between pre-test and post-test relationships in each group individually. Nevertheless, we could still explore the potential influence of priming by applying a multiple regression analysis for the whole sample.

4.3.1 Multiple OLS regression analysis

Multiple regression analysis is an extension of the simple linear regression analysis, which allows to check for the simultaneous influence of several IVs on the DV (Darren & Malley, 2016). It is one of the most commonly used dependence techniques in research concerning predictions and explanations (Hair et al, 2019). The effects tested in the regression models demonstrate the influence of IVs Implicit Attitude, Explicit Attitude, Cause Involvement, Sustainability Related Prime, and Product Category Related Prime on the DV Buying Intention. Even though our hypotheses focus on the effect for the green product, the regression analysis was conducted for conventional products as well, since it is insightful to compare the results.

Bivariate correlation analysis showed that implicit attitudes after the treatment correlated neither with the buying intent for the green product (R = 0.094, p = 0.483) nor with the buying intent for the regular one (R = -0.086, p = 0.523). Considering that implicit attitudes are hard to change, and there could be almost no difference between before and after the treatment states (supported by the paired-samples T-test: t=1.743, p=0.087), the pre-test Implicit Attitude variable, which had linear relationship with post-test buying intent, was used. Thus, we should keep in mind that the potential processing fluency caused by priming did not affect implicit attitudes directly in our example. Yet, there could be an interaction effect of fixed implicit attitudes and priming on the formation of the explicit buying intent, meaning that the influence of implicit attitude could still vary depending on the presence of the prime.

Explicit Attitude variable was taken from the post-test, as it significantly correlated with the post-test buying intent for both products (R = 0.459, p = 0.000 for green product, and R = -0.321, p = 0.012 for regular one).

Including the irrelevant prime variable and its interaction terms in the models neither added to the coefficient of determination nor had any statistically significant influence on the IV. Therefore, while it would be a factor to consider in between-group comparisons, it was not used in the overall multiple regression analysis.

For the regression analysis to yield meaningful results, the dataset had to fit under several conditions. The relationship between IVs and DVs has to be linear (Hair et al., 2019). Curve estimation analysis and visual evaluation of scatterplots (Appendix D) were conducted regarding the relationships among all IVs and DVs. Linearity was established for all relationships except for the one between implicit attitudes and the buying intent for the green product. Due to the small sample size the curve estimation analysis did not have enough statistical power to clearly establish linearity. Nevertheless, the linear model was the closest one to being statistically significant for this relationship, and we assume that with a larger sample size the relationship would most likely be linear.

Moreover, the data should demonstrate homoscedasticity, meaning that the error terms should be constant across the range of the IVs (Hair et al., 2019). This condition was checked for by analyzing the scatterplots of residuals and predicted DV (Appendix E) and by conducting the Breusch-Pagan test (Appendix F). The residual scatterplots did not have any prominent patterns, implying that the data did not have the heteroscedasticity problem. The results of the visual analysis were backed up by the Breusch-Pagan test (Appendix F), which consisted of a linear regression with all our IVs and the squared residual values as the DV. It revealed that the IVs did not affect the residuals (with p = 0.888 in green product's case and p = 0.224 in conventional product's case, we could not reject the H_0 hypothesis of constant variance). Therefore, we can assume that our data met the homoscedasticity requirement.

Further multiple regression assumption is the normality of the error term distribution. Considering the small sample size, the normal probability plots served as a better estimate than the histograms of residuals (Hair et al., 2019), and, therefore, were visually analysed (Appendix G). The residuals in our plots followed the diagonal line representing the normal distribution closely, implying the normal distribution of error term.

The next assumption is the independence of the error term. It implies that predicted values should not be influenced by any IV. Hair et al. (2019) suggest testing this assumption by visual examination of the plots of residuals against any possible grouping variable. In our case the plots (Appendix H) demonstrated scattered distributions of residuals, meaning that the data is in line with this assumption.

Furthermore, regression analysis assumes that there is no multicollinearity in the dataset. Bivariate correlations among the IVs were below 0.7, meaning there were no high correlations (Saunders et al., 2009). The tolerance levels of each IV were above 0.7, signifying a high amount of IV that cannot be explained by the other IVs (Hair et al., 2019). Multicollinearity is also measured with the variance inflation factor (VIF), which reflects how much the standard error could be affected. According to Saunders et al. (2009), the VIF values between 0 and 10 are preferable. In our case, VIF values ranged from 1.13 to 1.35 (Appendix I). Therefore, we can conclude that there is no correlation between IVs that could impede the analysis of individual effects of those variables.

4.3.2 Results of the OLS analysis

We have constructed several models, checking separately for the direct effects of the IVs (Model 1- Model 3), and for the moderating effects of priming (Model 4 – Model 10) and environmental cause involvement (Model 11 – Model 12). Model 7 had the highest coefficient of variance, explaining 37.8% of the change in the buying intent for the green product. Model 6 and Model 11, which checked for the moderating effects of sustainable prime of both primes and cause involvement, also had a high coefficient of variance, explaining 35.4% of the change in buying intent for green product and 36.4% of buying intent for the conventional product.

- H1: Implicit attitudes towards a green product will affect the buying intent for green product

According to model 11 implicit attitudes positively affected the buying intent ($\beta = 0.370$, $p = 0.033$). However, in the models which do not control for moderating variables, the effect of implicit attitude is present in the conventional product's case only. Therefore, we can assume that H1 is partially confirmed.

- H2: Explicit attitudes towards a green product will affect the buying intent for green product

In models controlling for the direct effects only (Model 1, Model 2, Model 3), explicit attitudes influenced the buying intent for the green product. In most of the models including moderating effects, explicit attitude also had a direct effect on buying intent for the green product. However, it is worth noticing that when the interaction term of attitudes and involvement was controlled for, the impact of explicit attitudes lost its statistical significance. Meanwhile, the influence of explicit attitudes on buying intent for the conventional product was present in all models. Considering the direct effects only, we can consider H2 confirmed.

- H3: The effect of explicit attitudes on the buying intent will be stronger than the effect of implicit attitudes

In models considering only the main effects, explicit attitudes had a statistically significant effect on the buying intent for the green product, confirming H3. In most of the models, explicit attitudes had larger beta coefficients than implicit attitudes did in the case of the conventional product as well, further supporting the hypothesis about the difference in effect strengths of the two attitude types.

- H4: Priming with a product category related prime will positively affect the relationship between implicit attitudes and purchase intention for a green product

None of the models revealed statistically significant interaction effects of product category related priming on the relationship between implicit attitudes and buying intent for the green product. Therefore, H4 is rejected. The same held in the case of the conventional product.

- H5: Priming with a product category related prime will positively affect the relationship between explicit attitudes and purchase intention for a green product

Similar to the outcome for the implicit attitudes, the influence of explicit attitudes on buying intention for the green product was not influenced by product category related priming. H5 cannot be supported. Meanwhile, in the case of the conventional product, the moderating effect of this prime type on the relationship was present in every model which included it ($\beta = 0.684$, $p = 0.003$ according to Model 11).

- H6: Priming with an eco-friendliness related prime will positively affect the relationship between implicit attitudes and purchase intention for a green product

The influence of implicit attitude on buying intention was moderated by the sustainability related priming, but the effect was negative in all the models controlling for this factor ($\beta = -0.335$, $p = 0.033$, according to Model 11). The effect was also negative for the conventional product's case. H6 is not supported.

- H7: Priming with an eco-friendliness related prime will positively affect the relationship between explicit attitudes and purchase intention for a green product

All models controlling for the sustainable prime interactions revealed that the presence of prime positively affected the relationship between explicit attitudes and buying intent for the green product ($\beta = 0.343$, $p = 0.010$, according to Model 11). Therefore, H7 can be considered confirmed. As for the conventional product, eco-friendly prime had a positive effect on the relationship between explicit attitudes and buying intent too.

- H8: After viewing a green product ad, explicit attitudes towards green product will correlate with cause involvement stronger than implicit attitudes towards green product will

Bivariate correlation analysis revealed that cause involvement correlated stronger with implicit attitudes ($R = 0.322$, $p = 0.011$) than with explicit attitudes ($R = 0.207$, $p = 0.107$) before the treatment. After the treatment, however, the opposite was true and the correlation with explicit attitudes ($R = 0.369$, $p = 0.004$) was stronger than with implicit attitudes ($R = -0.054$, $p = 0.683$). Therefore, H8 is supported.

- H9: Cause involvement for sustainable consumption will positively affect the buying intention for a green product.

In the majority of the models, cause involvement did not have a statistically significant influence on the buying intent for the green product. Nevertheless, we can see that the direction of the relationship was positive in cases of green product and negative in cases of conventional product. Simple linear regression analysis showed that cause involvement positively affected the buying intent for the green product ($\beta = 0.280$, $p = 0.031$) and negatively affected it in the case of the conventional product ($\beta = -0.273$, $p = 0.035$). In multiple regression models, the main effect could disappear in cases of full mediation through the attitudes. That is why we tested the indirect effects with PROCESS macro Version 3 (Hayes, 2017), based on the percentile bootstrap estimation approach (Shrout & Bolger, 2002). The analysis (Appendix J1) revealed that explicit attitudes indeed fully mediated the effects of cause involvement on buying intent for the green product ($\beta = 0.225$, 95% CI 0.0047, 0.5688). In models 10 and 11, controlling for the moderation of both primes simultaneously, while the direct effect of explicit attitude could disappear because of complete moderation, cause involvement statistically significantly influenced the buying intent for the green product at 90% confidence level ($\beta = 0.256$, $p = 0.056$, according to Model 11). Consequently, H9 is supported.

- H10: In cases of high cause involvement, the effects of sustainability related prime will be stronger than the effects of product category related prime.

To test this hypothesis, the dataset was divided into the high involvement group (responses equal or larger than the median 4) and the low involvement group (responses lower than the median 4). The regression analysis for the low involvement group did not have enough statistical power, and the models were insignificant, thus making the comparison of effects impossible. Moreover, from the previous analysis, we saw that product prime did not affect the green product's case, meaning that the effects of the green prime would be stronger at any level of cause involvement. Nevertheless, we could still check for the three-way interaction effects of cause involvement, priming, attitudes on buying intent considering the whole sample. The results revealed that there was no three-way interaction (Appendix K), meaning that H10 is not confirmed.

Table 5. OLS models 1 – 3

DV: Buying intent	Model 1		Model 2		Model 3	
Product type	Green	Conv.	Green	Conv.	Green	Conv.
Implicit Attitude	0.080	-0.263	0.046	-0.232*	0.101	-0.207
Explicit Attitude	0.425	-0.258	0.387	-0.223*	0.404	-0.215
Cause involvement	-	-	0.123	-0.114	0.145	-0.104
Sustainability prime	-	-	-	-	-	-
Product category prime	-	-	-	-	-	-
Implicit_x_Explicit	-	-	-	-	0.281	0.129
Implicit_x_green_prime	-	-	-	-	-	-
Explicit_x_green_prime	-	-	-	-	-	-
Implicit_x_product_prime	-	-	-	-	-	-
Explicit_x_ product _prime	-	-	-	-	-	-
Implicti_x_involvement	-	-	-	-	-	-
Explicit_x_involvement	-	-	-	-	-	-
Green_prime_x_involvement	-	-	-	-	-	-
Product_prime_x_involvement	-	-	-	-	-	-
Adjusted R^2	0.169	0.128	0.167	0.123	0.231	0.124

* - significant at 90% confidence interval
Statistically insignificant results are light-grey coloured

Table 6. OLS models 4 – 6

DV: Buying intent	Model 4		Model 5		Model 6	
Product type	Green	Conv.	Green	Conv.	Green	Conv.
Implicit Attitude	0.064	-0.238	0.111	-0.217	0.269	-0.066
Explicit Attitude	0.365	-0.226	0.384	-0.217	0.239	-0.444
Cause involvement	0.144	-0.051	0.155	-0.046	-	-
Sustainability prime	-0.170	0.106	-0.149	0.116	-0.132	0.102
Product category prime	0.091	0.211	0.061	0.197	-	-
Implicit_x_Explicit	-	-	0.253	0.115	0.201*	0.089
Implicit_x_green_prime	-	-	-	-	-0.208	-0.242*
Explicit_x_green_prime	-	-	-	-	0.348	0.373
Implicit_x_product_prime	-	-	-	-	-	-
Explicit_x_ product _prime	-	-	-	-	-	-
Implicti_x_involvement	-	-	-	-	-	-
Explicit_x_involvement	-	-	-	-	-	-
Green_prime_x_involvement	-	-	-	-	-	-
Product_prime_x_involvement	-	-	-	-	-	-
Adjusted R^2	0.187	0.130	0.236	0.127	0.357	0.252

* - significant at 90% confidence interval
Statistically insignificant results are light-grey coloured

Table 7. OLS models 7 - 9

DV: Buying intent	Model 7		Model 8		Model 9	
Product type	Green	Conv.	Green	Conv.	Green	Conv.
Implicit Attitude	0.261	-0.061	0.111	-0.301	0.080	-0.294
Explicit Attitude	0.170	-0.428	0.529	-0.418	0.473	-0.405
Cause involvement	0.195	-0.044	-	-	0.147	-0.034
Sustainability prime	-0.121	0.100	-	-	-	-
Product category prime	-	-	0.089	0.131	0.121	0.124
Implicit_x_Explicit	0.211	0.087	0.190	0.334	0.204	0.330
Implicit_x_green_prime	-0.234*	-0.236*	-	-	-	-
Explicit_x_green_prime	0.364	0.369	-	-	-	-
Implicit_x_product_prime	-	-	0.121	0.124	0.101	0.128
Explicit_x_ product _prime	-	-	-0.220	0.336*	-0.187	0.329*
Implicti_x_involvement	-	-	-	-	-	-
Explicit_x_involvement	-	-	-	-	-	-
Green_prime_x_involvement	-	-	-	-	-	-
Product_prime_x_involvement	-	-	-	-	-	-
Adjusted R^2	0.378	0.239	0.216	0.183	0.218	0.168

* - significant at 90% confidence interval
Statistically insignificant results are light-grey coloured

Table 8. OLS models 10 – 12

DV: Buying intent	Model 10		Model 11		Model 12	
Product type	Green	Conv.	Green	Conv.	Green	Conv.
Implicit Attitude	0.319*	-0.153	0.370	-0.111	0.377	-0.116
Explicit Attitude	0.311	-0.694	0.176	-0.757	0.099	-0.725
Cause involvement	-	-	0.256*	0.093	0.434	0.019
Sustainability prime	-0.120	0.160	-0.068	0.242	-0.051	0.277*
Product category prime	0.040	0.160	0.107	0.210*	0.119	0.224*
Implicit_x_Explicit	0.126	0.335	0.306	0.562	0.327	0.550
Implicit_x_green_prime	-0.234	-0.153	-0.335	-0.195	-0.285*	-0.159
Explicit_x_green_prime	0.320	0.470	0.343	0.436	0.389	0.433
Implicit_x_product_prime	-0.002	0.048	-0.108	-0.027	-0.102	-0.059
Explicit_x_ product _prime	-0.134	0.482	-0.125	0.684	-0.100	0.671
Implicti_x_involvement	-	-	-0.199	-0.306	-0.236	-0.283
Explicit_x_involvement	-	-	-0.125	0.185	-0.148	0.194
Green_prime_x_involvement	-	-	-	-	-0.185	-0.024
Product_prime_x_involvement	-	-	-	-	-0.139	0.131
Adjusted R^2	0.326	0.362	0.354	0.364	0.348	0.346

* - significant at 90% confidence interval
Statistically insignificant results are light-grey coloured

4.4 Summarised results

Figures 6 and 7 depict the empirical results of the proposed conceptual model regarding green and conventional products respectively. The relative strength of relationships, expressed through standardized beta weights, for the green product's case was taken from Model 7, as it had the highest coefficient of variance, and there were no significant interactions of product category prime. The strength of the mediation effect was taken from the percentile bootstrap estimation analysis (see Appendix J1). The beta coefficients for the conventional product's case were adopted from model 11, as it included effects of both primes simultaneously.

Buying intention for the green product was influenced by implicit and explicit attitudes, cause involvement, and sustainability concept priming. Meanwhile, the intention to buy a conventional product was affected by implicit attitudes, explicit attitudes, sustainability, and product category related primes. Although cause involvement also negatively affected buying intention for the conventional product when considered separately from other variables, when analysed together with other factors, its effect became less prominent. Based on that, the relationships between IVs and DVs are consistent with the theoretical background. The effects of primes differed depending on the type of attitude and the type of product. Sustainable concept prime positively moderated the impact of explicit attitudes on buying intent for both product types. It negatively moderated the impact of implicit attitudes, significantly in green product case and insignificantly in conventional product case. Product category prime did not have effects on the intention to buy a green product, but positively moderated effects of explicit attitudes on buying intent for the conventional product. Figures 6 and 7 demonstrate the relationships among variables for green and conventional product cases respectively.

Table 9 contains the results of hypotheses testing, with a 95% confidence interval. Since the hypotheses aimed at exploring the relationships for green product only, results from conventional product's case are not included.

Figure 7. Empirical results of conceptual model green product case

(Based on Model 7 and percentile bootstrap estimation analysis)

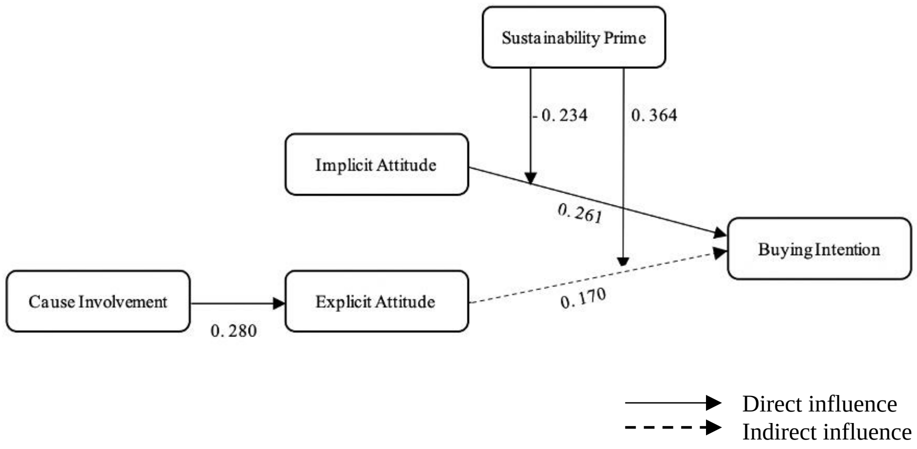


Figure 8. Empirical results of conceptual model conventional product *case*

(Based on Model 11)

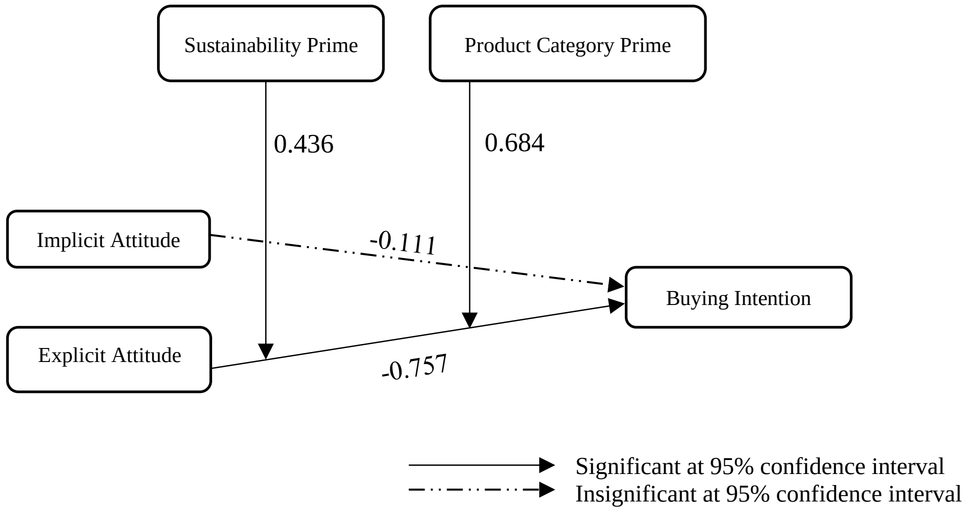


Table 9. Hypotheses rejection/support

	Relationship	Model	Direction	β	p	Result
H1	*Implicit attitude → Buying Intent*	2 7	+ +	0.046 0.261	0.716 0.047	**Partially supported**
H2	*Explicit attitude → Buying Intent*	2	+	0.387	0.004	**Supported**
H3	*Explicit attitude → Buying Intent > > Implicit attitude → Buying Intent*	1 - 5	+			**Supported**
H4	*Product category prime → (Implicit attitudes → Buying intent)*	11	+	- 0.108	0.523	Not supported
H5	*Product category prime → (Explicit attitudes → Buying intent)*	11	+	- 0.125	0.578	Not supported
H6	*Sustainable prime → (Implicit attitudes → Buying intent)*	11	+	- 0.335	0.033	Not supported
H7	*Sustainable prime → (Explicit attitudes → Buying intent)*	11	+	0.343	0.010	**Supported**
H8	*Bivariate correlation analysis*					
	Cause involvement ↔ explicit attitudes > > Cause involvement ↔ implicit attitudes		Direction	R	p	
	Cause involvement ↔ implicit attitudes		-	0.054	0.683	**Supported**
	Cause involvement ↔ explicit attitudes		+	0.369**	0.004	
H9	*Percentile bootstrap estimation analysis, see Appendix J*					
	Cause involvement → Buying intent	Direction	β	LLCI	ULCI	
	Direct effect	+	0.205	-0.178	0.590	**Supported**
	Indirect effect	+	0.225	0.005	0.569	
H10	*Three-way moderation, see Appendix K*					
	Cause involvement → sustainability related prime > Cause involvement → product category prime		Direction	β	p	
	Cause involvement → (sustainable prime → implicit attitude)		+	0.421	0.147	
	Cause involvement → (sustainable prime → explicit attitude)		-	0.834	0.119	Not supported
	Cause involvement → (product category prime → implicit attitude)		+	0.073	0.819	
	Cause involvement → (product category prime → explicit attitude)		-	0.025	0.897	

**** -** Correlation is significant at 0.01 level

5. Discussion

Earlier, we have attempted to test the effects of environmental cause involvement, implicit attitudes, and explicit attitudes on buying intention for green product. We have also considered the effect of two primes facilitating conceptual processing fluency. One of the main goals of this thesis was to explore the possible ways of increasing the likelihood of a sustainable product being chosen instead of a regular one. Therefore, we explored how the presumed effects of priming for conceptual fluency would compare between these two product types. In this chapter, we will discuss the result obtained from testing our hypotheses in relation to our research questions:

RQ1: How does priming for processing fluency affect consumers' buying intention for sustainable products?

RQ2: Do the effects of priming for conceptual processing fluency on preference and buying intent for sustainable products differ depending on the concept utilized in a prime?

5.1 General discussion

5.1.1 Direct effects and mediation

To test the hypotheses in our research model we used structural equation modelling in SPSS software. From literature, we know that purchasing behaviour is shaped by many factors, including buying intention, attitudes, subjective norms (TRA), perceived behavioural control, beliefs, motivation (TPB), and multiple external influences. In this project, we decided to narrow our focus down to the mechanisms between buying intent, attitudes, and values, constructing our research model based on VABH theory. We are interested in exploring the unconscious processes behind the purchasing decision making regarding sustainable products, and, therefore, we differentiated attitudes into implicit and explicit ones. We used several models to test the main effects of IVs Cause Involvement, Implicit Attitude, and Explicit Attitude, and indirect effects of moderating variables Green Prime and Product Prime on the DV Buying Intent. As demonstrated in Table 9, not all of our hypotheses were confirmed.

Before discussing the effects of priming manipulations, we needed to ensure that the core of our research model was in place. This was monitored with the help of hypotheses H1, H2, and H9, which were all confirmed. Accounting for the direct effect of IVs, Models 1 and 2 revealed that Explicit Attitudes had a positive effect on the Buying Intent for the green product and a negative effect on the Buying Intent for the conventional one. Implicit attitudes in these models were reflected in the case of the conventional product, having a negative effect on the buying intention. Therefore, the relationships between attitudes and behavioural intent in our experiment were consistent with the existing research.

The effect of Cause Involvement on Buying Intent could potentially be invisible in those models, if it was fully mediated by attitudes, following the VABH model. According to Baron and Kenny (1986), mediation occurs when there is no significant direct effect of the IV on the dependent one, but a significant relationship between the IV and mediator is present, as well as a significant effect of the mediator on the DV is. The percentile bootstrap estimation approach (Shrout & Bolger, 2002) to evaluating mediating effects revealed that the direct effect of cause involvement, indeed, did not appear in those models because it was completely mediated by explicit attitudes (see Appendix J1). Hence, when cause involvement is considered alone, it influences buying intent, but when it is considered simultaneously with explicit attitudes, it affects them first, influencing the buying intent indirectly. The indirect effect of cause involvement on buying intention had a positive direction, which also is in agreement with the VABH framework as the theoretical background of our conceptual model. A simple linear regression demonstrated that cause involvement influenced implicit attitudes as well ($\beta = -0.322$, $p = 0.011$), also potentially consistent with the VABH model considering the type of attitude is not specified in it. However, implicit attitudes did not mediate the relationship between cause involvement and buying intent (Appendix J2, Appendix J3).

We can also notice the interaction term between Implicit and Explicit attitudes in affecting the buying intent present in all models that included it (Models 5 – 7, Models 10 – 12). There is a potential pattern in the relationships between the variables. The interaction term is in most cases only present in the conventional product's case, where only explicit attitudes have a direct effect on the buying intent. The influence of the interaction term is positive in all models, with varying strength degrees. In these models, the effect of explicit attitudes on intent to buy the green product was insignificant, which could be due to present effects of cause involvement, an IV correlating with explicit attitudes. The interaction term of implicit and explicit attitudes was also insignificant in those cases. Consequently, we could suggest that for the conventional product, implicit attitudes did not affect the buying intent directly, but moderated the effects of explicit attitude on it. Yet, due to the lack of consistency among the models (Models 6 and 7 do not follow the suggested pattern), a more statistically powerful analysis would provide more explanations.

In the same models, implicit attitudes had a statistically significant negative effect on the intention to buy a conventional product. Hypothetically, in the case of a choice between a green and a conventional product, this could indirectly benefit the buying intention for a green product. The effects of implicit and explicit attitudes on buying intent for the conventional product were almost equal in strength when moderating effects were not considered.

5.1.2 Moderating effects of priming

Relying on the knowledge about conceptual processing fluency, we wanted to see how it could be applied to shifting consumer preferences towards sustainable products. Our first research question addressed the possible effects of priming for conceptual fluency on buying intention. Considering the processing fluency mechanisms, we assumed that priming would not have a direct effect on buying intent, but rather influence it indirectly through attitudes by making the green products demonstrated in the experiment easier to process. We were interested in seeing whether the potential impact of priming would apply differently to implicit and explicit attitudes' effects, considering the difference in the nature of these attitude types.

5.1.2.1 Moderating effect of sustainability related prime

In all models we could see a statistically significant influence of the interaction between explicit attitudes and sustainability related prime on the buying intent for the green product, confirming positive moderating effects. In models 7, 11, and 12, including all IVs, the main effect of explicit attitude disappeared when the interaction with moderator term was introduced. The main effect could have been reduced because of the correlation between the IV and the interaction term ($R = 0.417$, $p = 0.001$), meaning that it could still be present but less visible in the models. Moderation implies that the direction and strength of the effect of IV on the DV depend on the level of the moderator (Frazier et al., 2004). Green Prime was a dichotomous categorical variable indicating whether the priming was present or not. Therefore, from our results, we can interpret that when a person experienced a sustainability related prime, the positive effect of explicit attitude on buying intent for the green product was stronger than when they did not. By asking a person to focus on sustainability related stimulus, we potentially created a context relevant for the green product, which, consistently with the works of Shapiro (1999), Lee and Labroo (2001), Janiszewski and Meyvis (2001), should have made the processing of a product with salient sustainable features easier than the processing of a conventional product with no sustainability related features. This interpretation can also be supported by the spreading activation view on priming, which suggests that word-primes can activate relevant nodes in lexical and semantic networks, facilitating the processing of evaluatively consistent targets (Klauer et al., 2009). The ease of processing resulted in a stronger positive relationship between a person's directly reported preference for a green product and their intention to purchase that product. We need to keep in mind that our explicit attitude variable was calculated as a relative measurement, which should be interpreted as a directly reported preference between green and conventional products. Thus, we could suggest that when people evaluate a green product and had their mental representation of the "sustainability" concept recently activated, their intention to buy this product will be more in line with their explicit preference for it.

The significance of the interaction between sustainability related prime and implicit attitudes was inconsistent among the OLS models. When analysing this relationship, we should also remember that the implicit attitude variable was recorded before prime exposure, thus the processing mechanisms involved were likely not the same as in the case with the explicit attitude. Implicit attitude variable that was recorded after the prime exposure would make the comparisons of the two attitude types more robust, but it was not used in our SEM analysis since it did not have a significant effect on the buying intention. This could happen due to fewer post-test responses leading to the lower statistical power of the multiple regression test. Models 7 and 11 had the most weight in explaining the variations in the buying intent for the green product. Model 7 tested the interactions of green prime only, while model 11 included the interactions of the green and the product category prime simultaneously. The interaction of implicit attitudes and sustainable prime was significant at 90% and 95% confidence intervals in models 7 and 11 respectively, having a negative direction. Consequently, we can interpret that the relationship between the unconscious preference for green products and intention to purchase a green product could become weaker if a person was exposed to a sustainable prime. This contradicts our suggestion that priming should have a positive impact on the relationship between unconscious attitude and buying intent. Since the result of our experiment had an opposite direction to what we expected, it could be regarded as a reversed priming effect (Klauer & Musch, 2003). Although the research of reversed priming still needs more consistent replications, there are diverse theories that aim to explain the causes of reversed priming. Klauer et al. (2009) provide an overview of potential explanations, which include, but are not limited to, high-frequency targets (Chanet al.,2006), masked priming (Banse, 2001), pronunciation tasks, and high anxiety among participants (Berner & Maier, 2004), and emphasis on speed and accuracy (Wentura, 1999; Glaser, 2003). Unfortunately, none of these explanations fit well with our experimental design. From a different perspective, we could assume that, since we are testing the simultaneous effects of implicit and explicit attitudes, sustainable prime may stimulate the dominance of conscious preference over the unconscious one in influencing the purchasing intention.

5.1.2.2 Moderating effect of product category related prime

The hypothesised mechanism behind the product category prime was similar to that of the sustainable prime. Working with the text about cleaning items was supposed to create a relevant context for the target product and facilitate its easier processing. None of the analysed SEM models indicated a statistically significant interaction of this prime with either attitude type, meaning that priming with product category concept had no moderating effects for intention to buy a sustainable product.

There are several ways we can interpret this outcome. Firstly, we can assume that product category is simply not an effective enough construct for creating predicting context and triggering conceptual processing fluency. However, this line of thought is inconsistent with the findings of Lee and Labroo (2004), who successfully used the product category for this purpose.

Another explanation could be connected with our experimental design. The blocks that tested associations for the green product in IAT tests asked participants to concentrate on sustainability related words, which could act as a prime too. Especially if we consider that the test was taken two times throughout the experiment, the possibility of unintentional priming becomes even higher. Deutsch and Gawronski (2009) explored the contrast effects of double priming, which occurred when two “opposing” primes were presented in close succession. The effects of the second prime were stronger when the first prime was evaluatively inconsistent with it. Scherer and Lambert (2009) mention that double priming effects can also be explained as a reversed effect of stimulus-onset asynchrony (SOA). When SOA, the period between the onset of one stimulus and the onset of the following stimulus, is long, reversed priming effects may occur (Klauer et al., 2009). In cases of double priming with the same type of prime, the second stimulus does not carry new information and perceived SOA becomes twice longer than in double priming with inconsistent primes (Scherer & Lambert, 2009). Applied to our case, this would imply that the effect of IAT as a prime would be stronger when it was preceded by the product category prime than when it was preceded by the sustainability related prime. Hypothetically, if such an effect took place, the post-test IAT could override the moderating effect of the product category prime. It is important to note that the examples discussed in research literature have evaluative primes, while in our case the primes were not evaluative. Furthermore, we would need to control for the priming effect of IAT to draw a reliable conclusion, which is impossible in our case, since all experimental groups were exposed to IAT. Therefore, the reason why product category prime did not have an expected effect remains open for further investigation.

5.2 Priming effects: green vs conventional product case

Our second research question aimed at exploring the differences in the effects between the two concepts used for priming. Since there was no interaction of product category prime with attitudes for green product, we cannot make the necessary comparisons. Nevertheless, we can notice the differences among prime effects in the case of conventional product. Models 10, 11, and 12 show that both types of primes had a moderating effect on the relationship between explicit attitudes and buying intention for conventional product. Models 6 and 7 show that sustainable prime interacted with explicit attitudes at 95% confidence level, and with implicit attitudes at 90% confidence level. Models 8 and 9, which had a relatively low coefficient of determination, show that product category prime interacted with explicit attitudes at a 90 % confidence level. There was an interesting pattern across all models, which demonstrated that the product category prime only had moderating effects for the intention to buy conventional product, while sustainability prime affected buying intention for both products.

Let us take a closer look at the interactions with explicit attitudes. Moderating effect of sustainable prime had a positive direction, meaning that it strengthened the negative influence of explicit preference for green product on the buying intent for conventional product. Similarly, product category prime’s interaction had a positive direction, meaning it also strengthened the negative relationship between explicit attitude and buying intent. The effects of green prime are in line with our expectations, as the context it created was not consistent with conventional product's features and resulted in a stronger preference and buying intent for green product.

Meanwhile, the effects of product category prime are puzzling. It would be easier to understand if this prime benefited the buying intent for conventional product, as the target's processing should have become easier after concentration on the text about cleaning. It would also be logical if this prime's interaction with attitudes towards green product positively affected the buying intent, since it exhibited cleaning attributes and matched the primed context. However, this prime strengthened the negative effect of explicit preference on intent to buy a conventional product. We should take into account that the explicit attitude is a relative measure in our experiment. Therefore, when a person had a mental representation of the "cleaning" context activated before product evaluations, their buying intention was more likely to be consistent with their explicit preference between the green and conventional products. If they explicitly preferred green product over conventional one, they would be more likely to form an intention to buy a green product. In the opposite case, if they preferred a conventional product, they would be more likely to intend to purchase it instead of a green one. Nevertheless, it is unclear why the same relationship was not reflected directly on the intention to buy a sustainable product.

Implicit attitudes did not have a statistically significant influence on the buying intent for conventional product in our experiment. Therefore, we could only see the influence of priming on the relationship between explicit attitudes and buying intent. However, it is worth noting that the interaction term for both product category and sustainability product primes, and implicit attitudes had a negative direction, similar to the green product's case.

6. Implications

In this chapter we will discuss the several aspects in which the present research extends existing studies on consumer behaviour and priming. Furthermore, we will present the ways our findings could be valuable for application in a business setting. The main limitations of the study will be presented afterwards, as well as the possible ways they could influence the validity and reliability of our research. The discussion on how the present study could assist the further research of consumer attitudes and green consumption will finalise this chapter.

6.1 Theoretical Implications

The main theoretical interest of this study was to apply the knowledge on unconscious information processing to exploring the dynamics in consumer preferences for sustainable products based on the priming paradigm. A growing body of research has been dedicated to consumer behaviour regarding green products. Yet, the majority of such studies operate with explicitly reported data. As we have discovered in the literature review section, uncontrolled cognitive processes can also influence consumer decisions (Janiszewski & Wyer, 2014). We decided to study how such processes influence consumer preferences for green products specifically, by using explicit and implicit measurements. We observed that the same priming manipulations yielded different results in cases of a sustainable and a conventional product from the same product category. Therefore, we suggest that this research contributes to a better understanding of consumer perceptions of green products.

One of our goals was to extend the current research on conceptual processing fluency by comparing the effectiveness of two primes containing different contexts. The works on stimulating processing fluency reviewed for this project mostly considered the effects of consistent/inconsistent stimuli and positive/negative evaluative stimuli (Yi, 1990; Shapiro, 1999; Lee & Labroo, 2004; Reber et al., 2004; Labroo et al., 2008; Northup, 2019). In our project, we investigated whether the effects of two stimuli, sustainability context and cleaning products context, which were both consistent with the target, sustainable cleaning product, would differ. Our results showed that the two primes acted differently depending on the type of product. When the context was related to product category, it was reflected in conventional product's case, but not in sustainable product's case. The prime with sustainability related context interfered with both product types. Relying on Tversky and Kahneman (1973, p. 208) definition of conceptual fluency as "the ease with which instances or associations come to mind”, we could suggest that even if a non-evaluative lexical prime is consistent with a target stimulus, its effectiveness might vary depending on which association cluster it is meant to activate.

We have also attempted to check whether the potential differences in the effectiveness of these primes depended on other factors influencing attitudes, such as values. In our study, we did not find any significant influence of the value for environmental concern, presented as cause involvement, on the performance of primes. Neither did priming significantly influence the relationship between participant’s established views on environmentally friendly behaviour and their attitudes towards eco-friendly products. Yet, we believe that including additional factors from such behavioural models as VABH, TRA, and TPB into the analysis of priming effectiveness gives a broader perspective on studying how unconscious processing affects consumer preferences and buying behaviour.

Furthermore, we have taken a more detailed approach towards the conceptual model of VABH theory by dividing the attitude factor into two categories, implicit and explicit attitudes. In our example, we saw that the two types of attitudes interacted differently with the buying intention, with the value factor (which in our case was expressed through cause involvement) and with external moderators. Therefore, by concentrating only on explicitly measured attitudes, researchers might miss valuable information regarding consumer behaviour. We believe that applying the two-type attitude approach to related theoretical frameworks, such as TRA, and TPB, could benefit marketeers’ deeper understanding of consumer psychology.

6.2 Managerial Implications

The present research aims to provide valuable insight for managers, marketers, and online retailers. One of the main areas that could benefit from our findings is advertising. Yi (1990) states that the effectiveness of an ad and its influence on brand evaluations depends on which of product attributes primed by the ad’s contextual factors. Northup and Mulligan (2014) note that in advertising conceptual priming may be more relevant than perceptual priming. Our research design, which compares two conceptual primes, fits well under this criterium. In choosing an advertising strategy, the work of Lee (2002) highlights the importance of knowing the elaborative processes guiding customers’ purchasing decisions. The influence of conceptual priming was found to be more effective in situations of memory-based consumer choices, while perceptual priming was more preferable for stimulus-based choices. If we know that a customer is going to base their decision not as much on the information presented in the physical environment, but rather on the information retrieved from memory, advertising strategy employing scripts and storytelling that motivate relevant context is recommended (Lee, 2002). Our findings support these ideas, by demonstrating that when sustainable attributes of a cleaning product are primed, a person is more likely to intend to purchase a green product according to their explicit preference between green and conventional products. Thus, if a marketing manager of a sustainable product knows that their lead is positively predisposed to green products, activating their associations with sustainability prior to the product exposure would increase the chances of the lead moving forward in the acquisition funnel. If an e-commerce store owner offers sustainable and conventional ones but wishes to increase the sales of the former, priming the functional attributes of the products prior to product exposure could also benefit their goals. The opposite would supposedly hold true in cases when the leads are known to evaluate non-green products higher. In such cases, our findings suggest refraining from activating either sustainability or functionality-related associations.

The present research also contributes to the knowledge of online marketers. In our experiment, the prime and the buying decision followed each other immediately, which is more likely to be replicated in an online shopping situation. According to our findings, primes strengthened the impact of explicit preference on the buying intention, meaning that it would be more effective to use them in situations when customers tend to make conscious, non-impulsive decisions. For instance, if we know that a potential buyer has a high enough motivation for elaboration (Petty and Cacioppo (1986) provide a detailed framework for elaboration likelihood theory), integrating a sustainability related text into their customer journey, would stimulate the positive impact of their conscious preference for green products on their buying decision. At the same time, we would recommend avoiding using conceptual priming in cases of emotional or time-pressured purchasing, since the influence of implicit preference, which usually drives the decision making in such situations, may become weaker. As the influence of implicit attitudes becomes weaker, it provides more room for other factors to impact the consumer choice, and consequently more risk that those factors will not work in favour of a sustainable product.

6.3 Limitations

One of the central concerns regarding the validity of our finding is caused by the small sample size. The survey initially collected 141 responses, which after data cleaning provided us with only 60 fully completed responses. Saunders et al. (2009) note that usually, a sample size of 30 or more should have a very close to normal sampling distribution for the mean. They also refer to Stutely (2003) when giving the rule of thumb of having at least 30 responses in each controlled category within a sample. In our case, the experimental groups in the post-test were significantly smaller than that. Therefore, we were not able to make reliable between-group comparisons utilizing T-tests and ANOVA. A larger sample would also enable us to trace the changes in pre-test and post-test responses more closely, possibly identifying the direct effects of our moderating variables. Nevertheless, we could still analyse the relationships between DV and IV, as well as interaction with moderators, in the context of the whole sample.

The self-selecting sampling method also could influence the reliability of our findings. According to Saunders et al. (2009), this method has a low likelihood of a sample being representative. This can mainly happen if participants express a certain level of interest in the research topic, which could affect their responses. The invitation to our online experiment did not provide details about the topic and goals of the study, only mentioning that it concerned consumer attitudes. Therefore, we assume that the decision to participate in the experiment was not affected by participants' possible interest in sustainable consumption or unconscious consumer processing. No incentives were attached to the invitation for the online experiment either, reducing the risk of respondents joining solely for the chance to get a prize and answering inattentively.

The measures for ensuring external and internal validity tend to contradict each other, making it hard to simultaneously ensure both of them at a high level. Conducting an experiment allowed us to reduce the influence of external factors on the explored relationships, thus, to increase the internal validity of the study. Nevertheless, we should be cautious of the fact that the experiment was conducted online and did not accommodate for close supervision of the participants. Detailed instruction was provided at the beginning of the assessment to ensure that participants were prepared for the structure and the duration of the experiment. Special attention was dedicated to properly explaining the instructions for taking the IAT, aiming to reduce the drop-out rate and the stress levels during the test. We had no control over the possible external destructions that participants might have encountered during the experiment.

The overall time each participant took to complete the assessment was recorded, enabling us to control for extreme outliers, but we were not able to check how much time participants spent on each stimulus and how long were the breaks between stimuli exposures. Ideally, we would have to conduct the experiment offline, making sure that respondents complete all the tasks in the same environment. Unfortunately, as the COVID-19 pandemic situation escalated during the time of this master's thesis, personal interactions with large numbers of people became practically impossible. Hence, the online experiment was conducted.

It is important to admit that the present research conditions were considerably different from the daily consumer experience. To increase the external validity and make our finding more representative of a real-life situation involving purchasing decision making, an overt field study could be undertaken. It would enable us to observe a more natural behaviour of people choosing between sustainable and conventional product options after being primed for a certain concept. We could additionally obtain information on how consumers would react to various aspects of product packaging, shelf space, and price. Considering our lack of resources, and the required amount of attention to external influences, this option was not feasible for the current project.

While the IATs measured the attitudes toward the general concept of green products, the questionnaires asked participants to evaluate specific dummy products. This could lead to a slight inconsistency in what the two types of attitudes focused on. The concepts in the IATs were not the dummy products due to the limitations in our technical capabilities for integrating IAT in Qualtrix, which allowed us to include all parts of the online experiment in one platform and provide a smooth experience for participants. The explicit attitudes were collected for dummy products and Since the idea behind the experiment was to explore consumer attitudes to green products in general, we believe that both measurements in our study were appropriate and comparable.

Pretest - posttest study design could also hinder the internal validity of our study. When completing the pre-test, participants were asked to work with sustainable/conventional products in the IAT and to evaluate a sustainable and a conventional product explicitly. Although the inclusion of conventional products was supposed to make the topic of the research less obvious, there is a high likelihood of participants realising what the study was about. In case it was true, their evaluations in the post-test could be affected and adjusted to be more socially desirable. Paired sample T-tests between pre-test and post-test IVs did not reveal a statistically significant difference, implying that the pre-test should not have affected the answers after the treatment. The IAT on its own could also inform the participants about the topic of the study and stimulate participants to evaluate products differently from how they would without completing the implicit measurement test. Such concern could be prevented if physiological and neuroscientific tools for measuring implicit reaction were used. However, due to financial restrictions and COVID-19 related social distancing requirements of this research, IAT was the only reliable tool available for us.

Despite the limitations presented above, we were able to obtain valuable knowledge about implicit and explicit aspects of consumer preferences towards sustainable products, and the way they tend to interact with regards to conceptual priming for two different consistent contexts.

6.4 Future Research

The priming process in the present experiment was detached from any specific marketing context. Further research could add external factors, such as the medium which facilitates exposure to priming, into the conceptual model. For example, it would be a valuable insight to know that a conceptual prime is more likely to yield desired results when used in a social media advertisement rather than in a print advertisement. In a recent study, Dennis et al. (2020) explored the effects of numeric and semantic priming on willingness to pay applied to an e-commerce website. Their results suggested that there was a difference between priming effects in offline and in online settings. Therefore, pursuing this research direction with regards to sustainable products has great potential in helping marketers develop advertising campaigns.

In our study, we could see how conceptual priming affected the strength of influence of attitudes on buying intention. Yet, due to the small sample size, we could not properly check for the directs effects of primes on attitudes and on buying intention, as it was done in previous research (Labroo et al., 2008; Shen & Chen, 2007; Gifford & Comeau, 2011; Loebnitz & Aschemann-Witzel, 2016). Therefore, our first recommendation for future research would be to replicate the experiment using a larger sample, which would give the between-group comparisons more statistical power. In that case, a researcher could proceed by comparing the changes between before- and after-treatment states, and compare the strength of that change between different experiment groups. Based on our current findings we can make practical recommendations regarding the work of implicit and explicit attitudes relatively one another.

However, by identifying the direct effects of priming, we will be able to address each attitude type individually, providing marketers of sustainable products with more robust advice.

For a deeper understanding of unconscious consumer processing in the context of green consumption, one could utilize implicit priming techniques. The participants in our experiment were aware of the stimuli they were exposed to. Hence, only explicit priming was involved. Comparing our results with a study that would also prime for sustainable and product category contexts, but overtly, could reveal interesting patterns in consumer psychology. Mikulincer et al. (2011) conducted a study of similar nature, comparing the effects of implicit and explicit priming for security context on the performance in creative tasks. They discovered that both priming techniques enhanced creativity, but only explicit priming was moderated by external factors. While the ethicality of using subliminal priming is controversial, solely from the perspective of consumer psychology, it would be enlightening to test whether the outcome would be similar when priming varying concepts targeting sustainable products.

The present project included artificial brands in order to prevent the influence of participants' personal experience on the results. While it gave us more control over the factors that were involved in the studied relationships, it also made our findings more general. Based on our results, we can make implications regarding the interactions of priming, attitudes, and buying intentions towards a more obstruct idea of green products and conventional products. Replicating the experiment with existing brands would provide a more realistic view of the cognitive processes involved. It would also enable one to control for the possible influence of brand-related factors, such as brand positioning and various aspects of brand personality, on the effectiveness of differing conceptual primes.

Use of a more precise measurement of implicit attitudes would also further benefit this research. IAT only provided us with an understanding of whether a person perceived green and conventional products as positive or negative when evaluating them against one another. Luo et al. (2006) integrated fMRI into their research of implicit evaluations of legal and illegal behaviours and found specific brain activity patterns that correlated with congruent and incongruent conditions. As was mentioned in the theory chapter of this thesis (see section 2.2.1), Songa et al. (2019) measured implicit attitude as uncontrolled psychophysiological reactions, such as pupil dilation, facial expressions, and eye movement. Adopting a similar approach would enable one to derive implicit evaluations of sustainable products without reference to conventional products. Thus, researchers would get more specific data on the unconscious perception of green products. Meanwhile, experiment participants would need to evaluate fewer items and, consequently, be less likely to become subjects of respondent fatigue.

Since our sample represents a highly homogenous group in terms of socio-demographic characteristics, future research could benefit from diversifying the sample to be more representative of the population of green domestic product consumers. In the case of our sample, participants predominantly reported positive attitudes towards green products, thus the effects of primes benefited the intention to buy green products over conventional ones. However, in potential segments that would not be as positively predisposed to sustainable products, this mechanism could create an opposite effect and foster a tendency to purchase conventional products. Therefore, controlling for the possible influences of gender, education level, parental status, or geographical location on the attitudes, behavioural intentions, and the effectiveness of priming could reveal new interesting patterns in consumer psychology and provide a more comprehensive view on sustainable consumption.

6.5 Conclusion

This thesis contributes to the field of marketing research by exploring the influences of environmental cause involvement, implicit and explicit attitudes, and conceptual fluency priming with different contexts on the intention to purchase sustainable products. Our explanatory research demonstrated the differences in the dynamics between priming and other variables depending on the concept primed and the product type.

This study intended to compare the differences in the means and the relationships between attitudes and buying intention among the groups primed for different concepts or not primed at all. Moreover, the comparisons of the states before and after the treatment were accounted for in the research and experiment design. However, due to the small sample size, such comparisons became unfeasible. Nevertheless, OLS models explaining up to 37.8% of the variance in buying intent for green and conventional products demonstrated the influence of priming on the formation of the buying intention through moderation of the effects of implicit and explicit attitudes. The relationships among cause involvement, attitudes, and buying intention were consistent with the adopted VABH model.

According to our findings, if a person had a mental construct of sustainability explicitly activated in their memory before exposure to a sustainable product, their intention to buy such a product is more likely to be consistent with their explicit preferences between green and conventional products. In case when a product category construct is activated, their intention to choose a conventional product from this category will be more consistent with their explicit preferences. It is important to note that these proposed cognitive mechanisms would be expected in a situation where both green and non-green products are available to choose from. There is also a chance that in the case of sustainability concept activation, the intention to purchase a sustainable product will be less in line with implicit preferences. However, further replications with experimental conditions of more robust validity would be necessary to support these suggestions.

As researchers get access to increasingly advances tools for investigating consumer psychology and cognitive nuances, a great opportunity arises to apply such capabilities in sustainability related marketing studies. This thesis demonstrates that incorporating the knowledge on conscious and unconscious information processing could assist marketers to successfully communicate the value of green offerings. While people growing more knowledgeable of their consumption choices, and companies being likely to increase investments in sustainable practices, we could soon expect more interest in similar studies. We believe that with the development and implementation of strong ethical guidelines, such knowledge could assist in developing effective marketing strategies, bringing brands and consumers even closer together.

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Appendix

Appendix A: Images

Appendix A.1. Advertisement of the imaginary sustainable product

Appendix A.2. Pre-test product pair

Appendix A.3. Post-test product pair

Appendix B: Priming materials

Treatment groups	Text	Task
Group 1 (product category prime)	"I've found that once I start cleaning one of the rooms in my apartment, I get into a productive groove that whisks me from the bathroom and kitchen to the living room and bedroom with montage-like ease. Having both the mental strength to clean and a proper toolkit of products on hand helps me reach this cleaning groove and get the chore over as quickly and seamlessly as possible. If you're equipped with thorough, durable, and easy-to-use cleaners and appliances, you can clean your entire home and barely break a sweat in the process." (Chen, 2020).	Please read the text and select all the words related to **cleaning**: (for each word you find relevant - press on the word, then press "select" button)
Group 2 (sustainability prime)	"Chile-based designer Margarita Talep has created a sustainable, biodegradable alternative to single-use packaging, using raw material extracted from algae. Disappointed by the abundance of non-recyclable materials currently used to contain food products, Talep decided to develop her own eco-friendly packaging that would stand in for plastic. "I believe that bio-fabrication will be an important part of future industries," said Talep. "As long as all the processes of extracting these raw materials and their	Please read the text and select all the words related to **sustainability**: (for each word you find relevant - press on the word, then press "select" button)

	manufacture are done with environmental awareness."" (Hitti, 2020).	
Group 3 (irrelevant prime)	"As he did in "Fantastic Mr. Fox," Mr. Anderson tells his tale primarily using stop-motion animation, an artisanal process that creates the illusion of movement frame by frame with objects like puppets. This being a Wes Anderson production, it is also visually seductive, filled with perfectly aligned cubistic trash, gleaming pools of toxic liquid and walls of colored glass bottles that glow like stained-glass windows on a sun-drenched morning. And yet, time and again, Mr. Anderson pulls you hard into "Isle of Dogs." His use of film space, which he playfully flattens and deepens, is one of his stylistic signatures; he likes symmetry and, in contrast to most directors these days, does a lot inside the frame." (Dargis, 2018).	Please read the text and select all the words related to **movies**: (for each word you find relevant - press on the word, then press "select" button)

Appendix C: Construct validity analysis

Construct	Items	Question	Loading	CR	AVE	α
Explicit attitude - *green* product (pre-test)		Please indicate how you would rate product A on the following dimensions:		0.75	0.38	0.89
	Bat_1	Bad / Good	0.69			
	Bat_2	Unsafe / Safe	0.48			
	Bat_3	Unfavourable / Favourable	0.62			
	Bat_4	Worthless / Valuable	0.58			
	Bat_6	Negative / Positive	0.67			
Explicit attitude - *conventional product* (pre-test)		Please indicate how you would rate product A on the following dimensions:		0.86	0.56	0.92
	Aat_1	Bad / Good	0.73			
	Aat_2	Unsafe / Safe	0.67			
	Aat_3	Unfavourable / Favourable	0.78			
	Aat_4	Worthless / Valuable	0.71			
	Aat_6	Negative / Positive	0.83			
Explicit comparison (pre-test)		Please rate products A and B relative each other on the following dimensions:		0.66	0.49	0.88
	AB.compare_2_A	Product A is more pleasant than product B/ Product B is more pleasant than product A	0.69			
	AB.compare_3_A	Product A is more attractive than product B/ Product B is more attractive than product A	0.71			
Explicit attitude - *green* product (post-test)		Please indicate how you would rate product A on the following dimensions:		0.92	0.71	0.95
	Aat2_1	Bad / Good	0.89			
	Aat2_2	Unsafe / Safe	0.77			
	Aat2_3	Unfavourable / Favourable	0.88			
	Aat2_4	Worthless / Valuable	0.79			
	Aat2_6	Negative / Positive	0.87			
Explicit attitude - *conventional*		Please indicate how you would rate product A on the following dimensions:		0.90	0.63	0.93
	Bat2_1	Bad / Good	0.80			
	Bat2_2	Unsafe / Safe	0.76			

product (post – test)	Bat2_3	Unfavourable / Favourable	0.83			
	Bat2_4	Worthless / Valuable	0.78			
	Bat2_6	Negative / Positive	0.81			
Explicit comparison (post-test)		Please rate products A and B relative each other on the following dimensions:		0.66	0.49	0.80
	AB.compare_2	Product A is more pleasant than product B/ Product B is more pleasant than product A	0.69			
	AB.compare_3	Product A is more attractive than product B/ Product B is more attractive than product A	0.71			
Buying intent -*green* product (pre-test)		Imagine product B is real. Please choose the option that best describes your opinion:		0.87	0.68	0.91
	BPI_1_A	I will try the product	0.83			
	BPI_2_A	I will consider purchasing the product next time	0.85			
	BPI_3_A	It is very likely that I will buy the product	0.80			
Buying intent -*green* product (post-test)		Imagine product B is real. Please choose the option that best describes your opinion:		0.88	0.71	0.92
	API_1	I will try the product	0.86			
	API_2	I will consider purchasing the product next time	0.86			
	API_3	It is very likely that I will buy the product	0.80			
Buying intent - *conventional product* (pre-test)		Imagine product B is real. Please choose the option that best describes your opinion:		0.79	0.56	0.91
	API_1_A	I will try the product	0.85			
	API_2_A	I will consider purchasing the product next time	0.72			
	API_3_A	It is very likely that I will buy the product	0.66			
Buying intent - *conventional product* (post-test)		Imagine product B is real. Please choose the option that best describes your opinion:		0.77	0.52	0.93
	BPI_1	I will try the product	0.70			
	BPI_2	I will consider purchasing the product next time	0.71			
	BPI_3	It is very likely that I will buy the product	0.76			
Cause involvement		For each statement, please choose the option that best reflects your opinion:		0.84	0.52	0.84
	CI_1	The state of environment is important / unimportant for me	0.71			
	CI_2	The way environment affects the quality of life is irrelevant / relevant for me	0.65			
	CI_3	Making sacrifices to protect environment means nothing / means a lot to me	0.59			
	CI_4	The way my actions affect the environment does not matter a great deal / matters a great deal to me	0.82			
	CI_5	Maintaining sustainable habits is no concern / a big concern to me	0.80			

Appendix D: Curve estimation for regression analysis

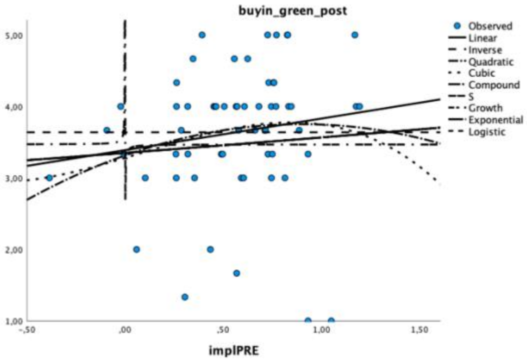
Appendix D1: Curve estimation for regression analysis - Green product

Model Summary and Parameter Estimates

Dependent Variable: buyin_green_post

	Model Summary					Parameter Estimates			
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	,022	1,297	1	57	,260	3,389	,442		
Logarithmic[a]	.	.	.	.	.	.	.		
Inverse	,000	,000	1	57	,999	3,638	-1,069E-5		
Quadratic	,030	,852	2	56	,432	3,315	,974	-,542	
Cubic	,031	,586	3	55	,627	3,280	,822	,140	-,496
Compound	,003	,186	1	57	,668	3,350	1,064		
Power[a]	.	.	.	.	.	.	.		
S	,001	,034	1	57	,855	1,244	,000		
Growth	,003	,186	1	57	,668	1,209	,062		
Exponential	,003	,186	1	57	,668	3,350	,062		
Logistic	,003	,186	1	57	,668	,299	,939		

The independent variable is implPRE.

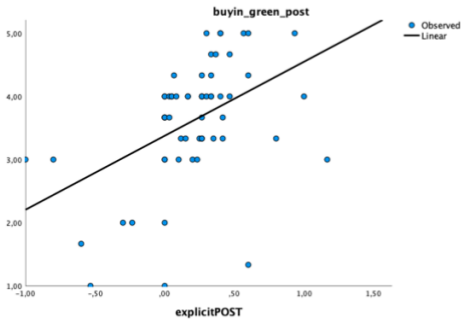


Model Summary and Parameter Estimates

Dependent Variable: buyin_green_post

	Model Summary					Parameter Estimates	
Equation	R Square	F	df1	df2	Sig.	Constant	b1
Linear	,211	15,501	1	58	,000	3,377	1,172

The independent variable is explicitPOST.

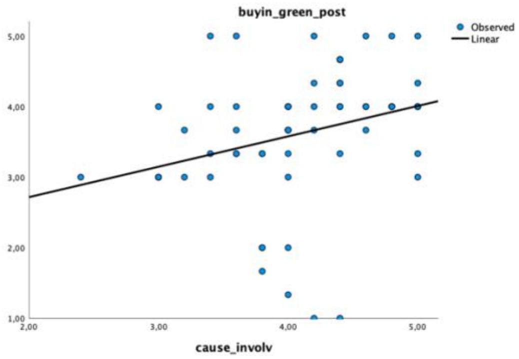


Model Summary and Parameter Estimates

Dependent Variable: Zscore(buyin_green_post)

	Model Summary					Parameter Estimates	
Equation	R Square	F	df1	df2	Sig.	Constant	b1
Linear	,078	4,917	1	58	,031	-,019	,295

The independent variable is Zscore(cause_involv).



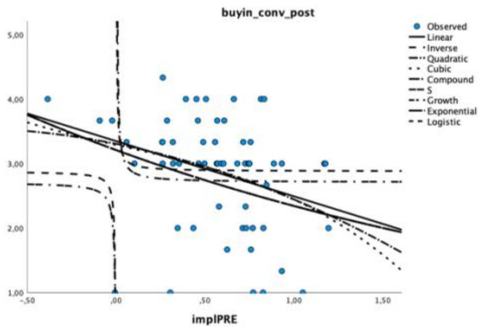
Appendix D2: Curve estimation for regression analysis - Conventional product

Model Summary and Parameter Estimates

Dependent Variable: buyin_conv_post

	Model Summary					Parameter Estimates			
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	,093	5,866	1	57	,019	3,348	-,856		
Logarithmic[a]	.	.	.	.	.	.	.		
Inverse	,055	3,318	1	57	,074	2,879	,010		
Quadratic	,096	2,972	2	56	,059	3,306	-,552	-,310	
Cubic	,096	1,955	3	55	,131	3,289	-,627	,026	-,244
Compound	,064	3,891	1	57	,053	3,209	,730		
Power[a]	.	.	.	.	.	.	.		
S	,085	5,313	1	57	,025	,996	,005		
Growth	,064	3,891	1	57	,053	1,166	-,315		
Exponential	,064	3,891	1	57	,053	3,209	-,315		
Logistic	,064	3,891	1	57	,053	,312	1,370		

The independent variable is implPRE.

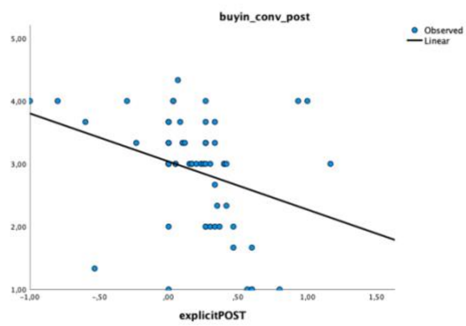


Model Summary and Parameter Estimates

Dependent Variable: buyin_conv_post

	Model Summary					Parameter Estimates	
Equation	R Square	F	df1	df2	Sig.	Constant	b1
Linear	,103	6,649	1	58	,012	3,036	-,765

The independent variable is explicitPOST.

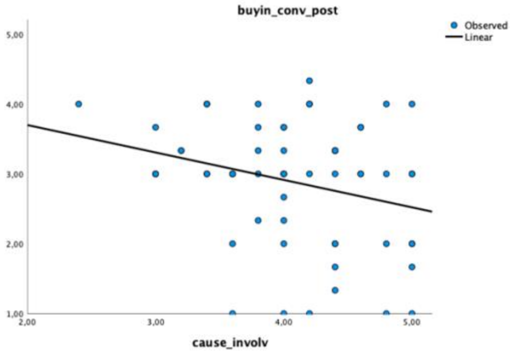


Model Summary and Parameter Estimates

Dependent Variable: Zscore(buyin_conv_post)

	Model Summary					Parameter Estimates	
Equation	R Square	F	df1	df2	Sig.	Constant	b1
Linear	,074	4,655	1	58	,035	,018	-,288

The independent variable is Zscore(cause_involv).



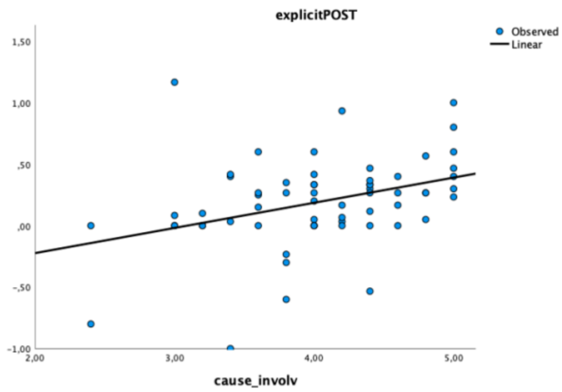
Appendix D3: Curve estimation for regression analysis – Attitude types

Model Summary and Parameter Estimates

Dependent Variable: explicitPOST

	Model Summary					Parameter Estimates	
Equation	R Square	F	df1	df2	Sig.	Constant	b1
Linear	,131	9,078	1	60	,004	-,633	,205

The independent variable is cause_involv.

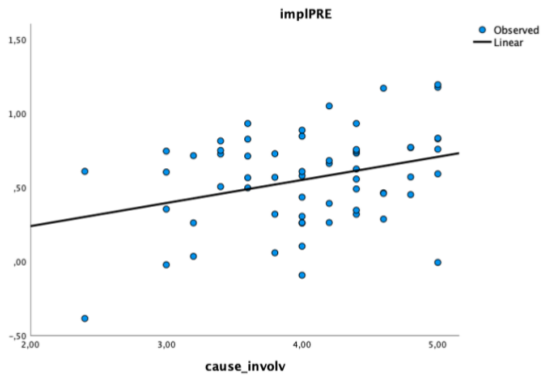


Model Summary and Parameter Estimates

Dependent Variable: implPRE

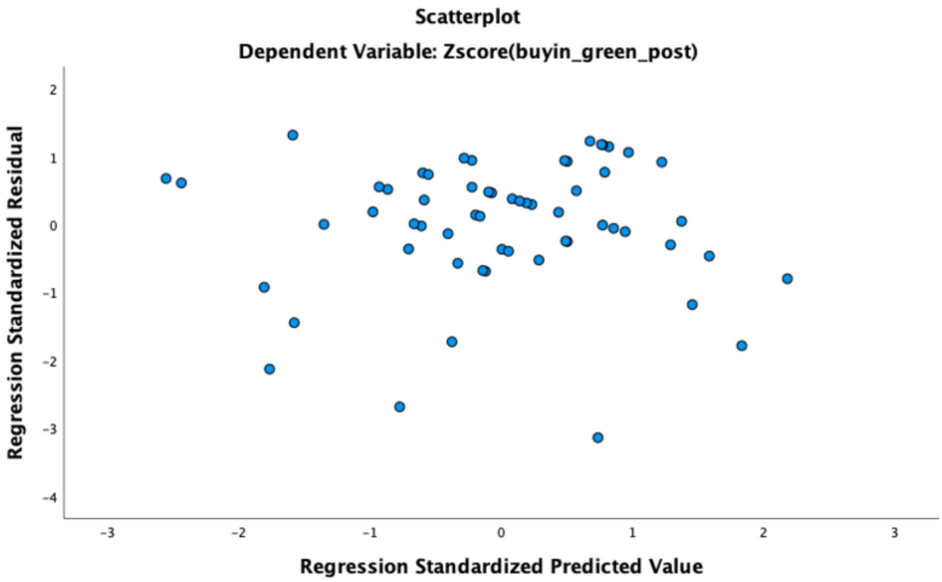
	Model Summary					Parameter Estimates	
Equation	R Square	F	df1	df2	Sig.	Constant	b1
Linear	,104	6,844	1	59	,011	-,073	,156

The independent variable is cause_involv.

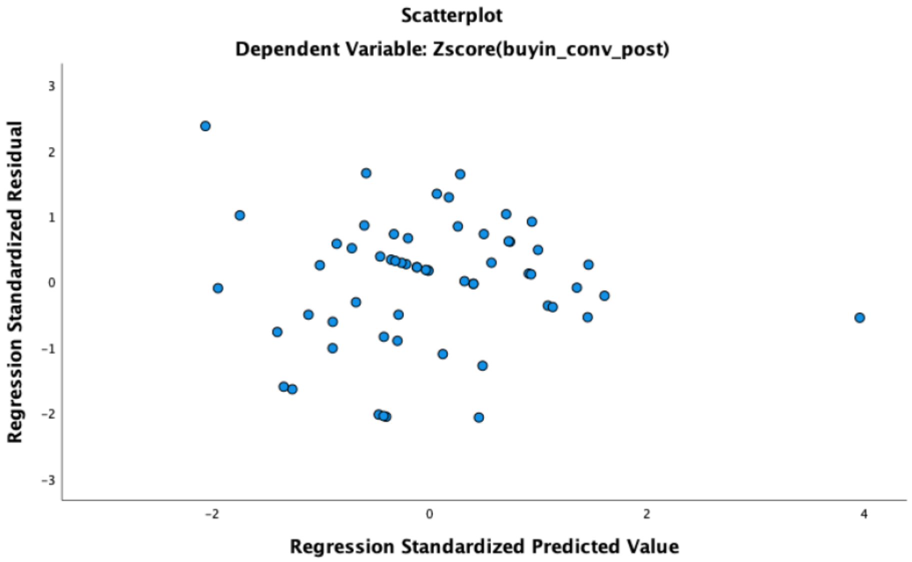


Appendix E: Heteroscedasticity scatterplots

Appendix E1: Heteroscedasticity scatterplots – Green product



Appendix E2: Heteroscedasticity scatterplots – Conventional product



Appendix F: Breusch-Pagan test regressions

Appendix F1: Breusch-Pagan test regressions - Conventional product

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5,730	5	1,146	1,443	,224[b]
	Residual	42,077	53	,794		
	Total	47,806	58			

a. Dependent Variable: squareRES_CONV

b. Predictors: (Constant), product, explicitPOST, implPRE, green, cause_involv

Appendix F2: Breusch-Pagan test regressions - Green product

ANOVA[a]

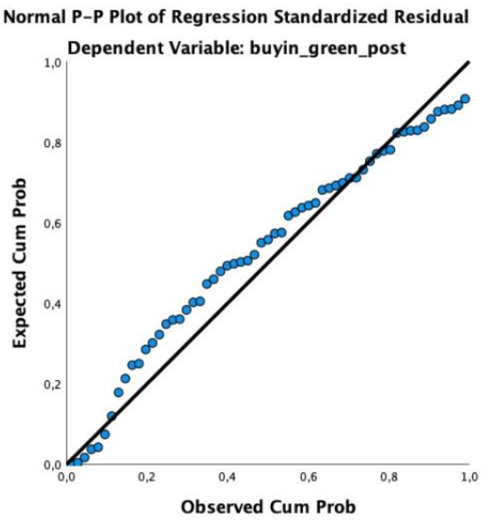
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2,638	5	,528	,337	,888[b]
	Residual	82,946	53	1,565		
	Total	85,584	58			

a. Dependent Variable: squareRES_GREEN

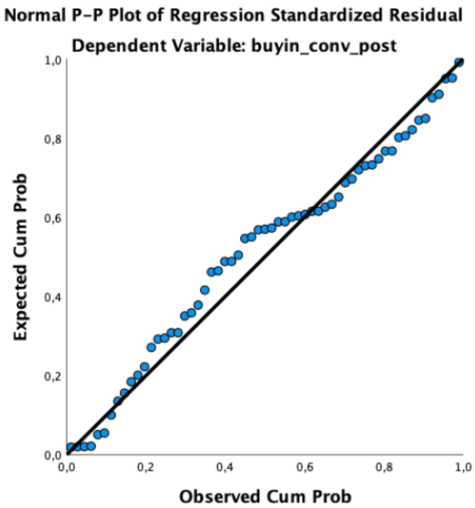
b. Predictors: (Constant), product, explicitPOST, implPRE, green, cause_involv

Appendix G: Normal probability plots

Appendix G1: Normal probability plots – Green Product

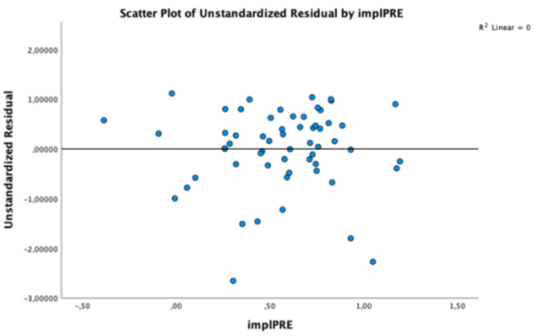


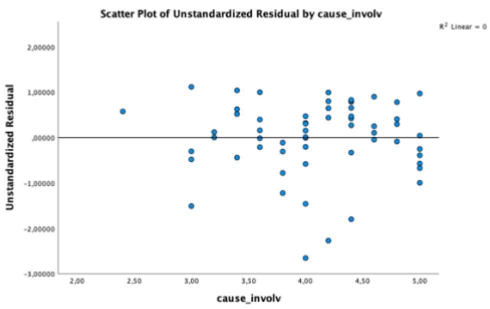
Appendix G2: Normal probability plots – Conventional Product

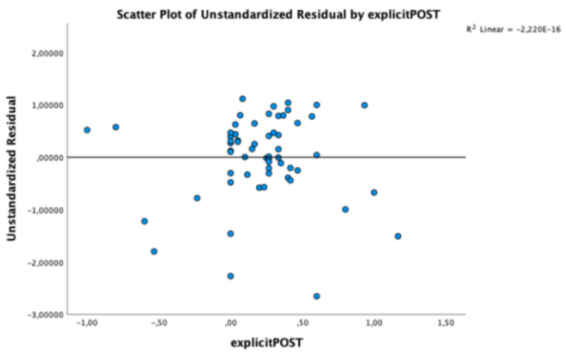


Appendix H: Independence of error scatterplots

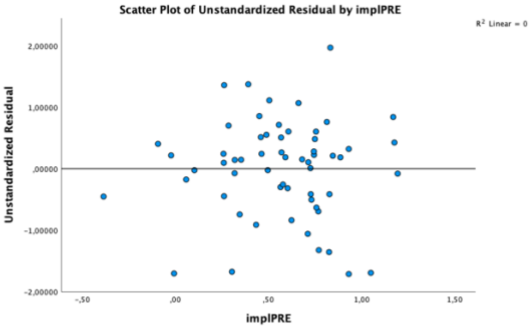
Appendix H1: Independence of error scatterplots - Green product

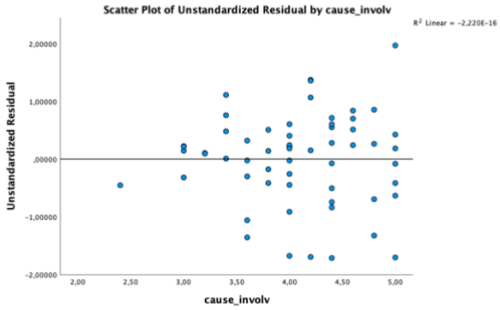


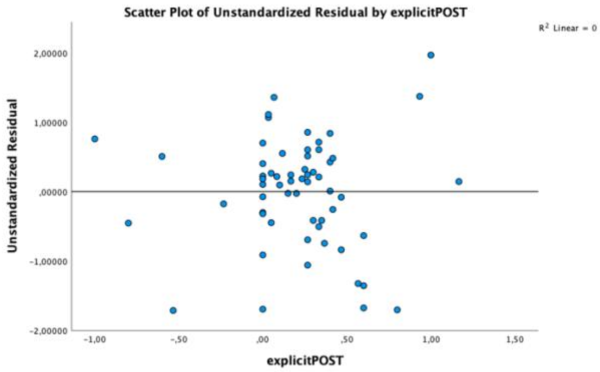




Appendix H2: Independence of error scatterplots - Conventional product







Appendix I: Multicollinearity test

Correlations

		implPRE	explicitPOST	cause_involv
implPRE	Pearson Correlation	1	,172	,322*
	Sig. (2-tailed)		,184	,011
	N	82	61	61
explicitPOST	Pearson Correlation	,172	1	,363**
	Sig. (2-tailed)	,184		,004
	N	61	62	62
cause_involv	Pearson Correlation	,322*	,363**	1
	Sig. (2-tailed)	,011	,004	
	N	61	62	62

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	2,512	,835		3,007	,004		
	implPRE	,191	,373	,064	,512	,611	,886	1,129
	explicitPOST	,922	,322	,365	2,868	,006	,866	1,155
	cause_involv	,216	,207	,144	1,044	,301	,740	1,352
	green	-,350	,262	-,170	-1,333	,188	,858	1,166
	product	,205	,296	,091	,693	,491	,806	1,241

a. Dependent Variable: buyin_green_post

Appendix J: Mediation analysis, developed by Hayes (2017), based on Shrout and Bolger (2002)

Appendix J1: Mediation analysis, developed by Hayes (2017), based on Shrout and Bolger (2002) - Green product, mediation through explicit attitudes

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : bgp
    X  : ci
    M  : exp

Sample
Size:  60

Custom
Seed:     10000

**************************************************************************
OUTCOME VARIABLE:
 exp

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3550      ,1261      ,1240     8,3654     1,0000    58,0000      ,0054

Model
              coeff         se          t          p       LLCI       ULCI
constant     -,6742      ,3056    -2,2065      ,0313    -1,2859     -,0626
ci            ,2144      ,0741     2,8923      ,0054      ,0660      ,3627


**************************************************************************
OUTCOME VARIABLE:
 bgp

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,4758      ,2264      ,7273     8,3422     2,0000    57,0000      ,0007

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,5636      ,7705     3,3271      ,0015     1,0206     4,1066
ci            ,2054      ,1920     1,0698      ,2892     -,1791      ,5900
exp          1,0512      ,3180     3,3054      ,0016      ,4144     1,6881

************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:
 bgp

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2796      ,0782      ,8518     4,9172     1,0000    58,0000      ,0305

Model
              coeff         se          t          p       LLCI       ULCI
constant     1,8548      ,8009     2,3159      ,0241      ,2516     3,4581
ci            ,4308      ,1943     2,2175      ,0305      ,0419      ,8197

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,4308      ,1943     2,2175      ,0305      ,0419      ,8197

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,2054      ,1920     1,0698      ,2892     -,1791      ,5900

Indirect effect(s) of X on Y:
        Effect     BootSE   BootLLCI   BootULCI
exp      ,2254      ,1485      ,0047      ,5688


 *********************** ANALYSIS NOTES AND ERRORS ************************

 Level of confidence for all confidence intervals in output:
   95,0000

 Number of bootstrap samples for percentile bootstrap confidence intervals:
   10000

 ------ END MATRIX -----
```

Appendix J2: Mediation analysis, developed by Hayes (2017), based on Shrout and Bolger (2002) - Conventional product, mediation through explicit attitudes

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : bcp
    X  : ci
    M  : exp

Sample
Size:  60

Custom
Seed:     10000

**************************************************************************
OUTCOME VARIABLE:
 exp

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3550      ,1261      ,1240     8,3654     1,0000    58,0000      ,0054

Model
              coeff         se          t          p       LLCI       ULCI
constant     -,6742      ,3056    -2,2065      ,0313    -1,2859     -,0626
ci            ,2144      ,0741     2,8923      ,0054      ,0660      ,3627

**************************************************************************
OUTCOME VARIABLE:
 bcp



 Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3629      ,1317      ,7137     4,3217     2,0000    57,0000      ,0179

 Model
              coeff         se          t          p       LLCI       ULCI
 constant    4,0722      ,7633     5,3352      ,0000     2,5438     5,6007
 ci          -,2617      ,1902    -1,3756      ,1743     -,6426      ,1192
 exp         -,6114      ,3150    -1,9406      ,0573    -1,2422      ,0195

 ************************** TOTAL EFFECT MODEL ****************************
 OUTCOME VARIABLE:
  bcp

 Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2726      ,0743      ,7477     4,6555     1,0000    58,0000      ,0351

 Model
              coeff         se          t          p       LLCI       ULCI
 constant    4,4844      ,7504     5,9760      ,0000     2,9823     5,9866
 ci          -,3928      ,1820    -2,1577      ,0351     -,7571     -,0284

 ************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

 Total effect of X on Y
      Effect         se          t          p       LLCI       ULCI
      -,3928      ,1820    -2,1577      ,0351     -,7571     -,0284

 Direct effect of X on Y
      Effect         se          t          p       LLCI       ULCI
      -,2617      ,1902    -1,3756      ,1743     -,6426      ,1192

 Indirect effect(s) of X on Y:
         Effect     BootSE   BootLLCI   BootULCI
 exp     -,1311      ,1188     -,4273      ,0316

 *********************** ANALYSIS NOTES AND ERRORS ************************

 Level of confidence for all confidence intervals in output:
   95,0000

 Number of bootstrap samples for percentile bootstrap confidence intervals:
   10000

 ------ END MATRIX -----
```

Appendix J3: Mediation analysis, developed by Hayes (2017), based on Shrout and Bolger (2002) - Green product, mediation through implicit attitudes

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : bgp
    X  : ci
    M  : implPRE

Sample
Size:  59

Custom
Seed:     10000

**************************************************************************
OUTCOME VARIABLE:
 implPRE

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3221      ,1037      ,0912     6,5982     1,0000    57,0000      ,0129

Model
              coeff         se          t          p       LLCI       ULCI
constant     -,1029      ,2628     -,3915      ,6969     -,6292      ,4234
ci            ,1635      ,0637     2,5687      ,0129      ,0361      ,2910

**************************************************************************
OUTCOME VARIABLE:
 bgp


Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2813      ,0791      ,8379     2,4057     2,0000    56,0000      ,0995

Model
              coeff         se          t          p       LLCI       ULCI
constant     1,9771      ,7978     2,4781      ,0163      ,3788     3,5753
ci            ,3792      ,2039     1,8597      ,0682     -,0293      ,7876
implPRE       ,2016      ,4015      ,5021      ,6176     -,6028     1,0060

************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:
 bgp

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2738      ,0750      ,8269     4,6199     1,0000    57,0000      ,0359

Model
              coeff         se          t          p       LLCI       ULCI
constant     1,9563      ,7915     2,4716      ,0165      ,3713     3,5413
ci            ,4121      ,1917     2,1494      ,0359      ,0282      ,7961

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,4121      ,1917     2,1494      ,0359      ,0282      ,7961

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,3792      ,2039     1,8597      ,0682     -,0293      ,7876

Indirect effect(s) of X on Y:
            Effect     BootSE   BootLLCI   BootULCI
implPRE      ,0330      ,0760     -,1364      ,1816


*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  10000

------ END MATRIX -----
```

Appendix J4: Mediation analysis, developed by Hayes (2017), based on Shrout and Bolger (2002) - Conventional product, mediation through implicit attitudes

```
Run MATRIX procedure:

**************** PROCESS Procedure for SPSS Version 3.5 ****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : bcp
    X  : ci
    M  : implPRE

Sample
Size:  59

Custom
Seed:     10000

**************************************************************************
OUTCOME VARIABLE:
 implPRE

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3221      ,1037      ,0912     6,5982     1,0000    57,0000      ,0129

Model
              coeff         se          t          p       LLCI       ULCI
constant     -,1029      ,2628     -,3915      ,6969     -,6292      ,4234
ci            ,1635      ,0637     2,5687      ,0129      ,0361      ,2910

**************************************************************************
OUTCOME VARIABLE:
 bcp


Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3536      ,1250      ,7122     4,0012     2,0000    56,0000      ,0238

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,3453      ,7355     5,9075      ,0000     2,8718     5,8187
ci           -,2679      ,1880    -1,4250      ,1597     -,6444      ,1087
implPRE      -,6865      ,3702    -1,8545      ,0689    -1,4282      ,0551

************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:
 bcp

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2670      ,0713      ,7427     4,3759     1,0000    57,0000      ,0409

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,4159      ,7501     5,8870      ,0000     2,9138     5,9180
ci           -,3801      ,1817    -2,0919      ,0409     -,7440     -,0162

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI
     -,3801      ,1817    -2,0919      ,0409     -,7440     -,0162

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
     -,2679      ,1880    -1,4250      ,1597     -,6444      ,1087

Indirect effect(s) of X on Y:
            Effect     BootSE   BootLLCI   BootULCI
implPRE     -,1123      ,0978     -,3538      ,0132


*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  10000

------ END MATRIX -----
```

Appendix K: Three-way moderation analysis

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,507[a]	,257	,187	,84515	,257	3,667	5	53	,006
2	,738[b]	,544	,339	,76183	,287	1,941	13	40	,054

a. Predictors: (Constant), product, exp, implPRE, green, ci

b. Predictors: (Constant), product, exp, implPRE, green, ci, implPRE_involv, expl_prod_involv, explPOST_green, involv_green, explPOST_involv, implPRE_green, involv_prod, implPRE_explPOST, implPRE_prod, impl_green_involv, explPOST_prod, impl_prod_involv, expl_green_involv

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13,096	5	2,619	3,667	,006[b]
	Residual	37,857	53	,714		
	Total	50,953	58			
2	Regression	27,737	18	1,541	2,655	,005[c]
	Residual	23,215	40	,580		
	Total	50,953	58			

a. Dependent Variable: bgp

b. Predictors: (Constant), product, exp, implPRE, green, ci

c. Predictors: (Constant), product, exp, implPRE, green, ci, implPRE_involv, expl_prod_involv, explPOST_green, involv_green, explPOST_involv, implPRE_green, involv_prod, implPRE_explPOST, implPRE_prod, impl_green_involv, explPOST_prod, impl_prod_involv, expl_green_involv

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	95,0% Confidence Interval for B Upper Bound
1	(Constant)	2,512	,835		3,007	,004	,836	4,187
	implPRE	,191	,373	,064	,512	,611	-,557	,939
	exp	,922	,322	,365	2,868	,006	,277	1,567
	ci	,216	,207	,144	1,044	,301	-,199	,632
	green	-,350	,262	-,170	-1,333	,188	-,876	,176
	product	,205	,296	,091	,693	,491	-,388	,798
2	(Constant)	-,351	1,551		-,226	,822	-3,485	2,784
	implPRE	1,341	,613	,452	2,188	,035	,102	2,580
	exp	,092	,464	,036	,197	,845	-,847	1,030
	ci	,796	,353	,529	2,253	,030	,082	1,509
	green	-,014	,304	-,007	-,045	,964	-,628	,601
	product	,279	,282	,125	,989	,328	-,291	,850
	implPRE_explPOST	,375	,171	,557	2,197	,034	,030	,720
	implPRE_green	-1,506	,662	-,883	-2,275	,028	-2,844	-,168
	explPOST_green	2,862	1,172	1,300	2,442	,019	,493	5,230
	implPRE_prod	-,209	,372	-,119	-,562	,577	-,961	,542
	explPOST_prod	,047	,446	,026	,105	,917	-,855	,948
	implPRE_involv	-,390	,230	-,562	-1,697	,098	-,854	,074
	explPOST_involv	-,082	,157	-,113	-,525	,603	-,399	,234
	involv_green	-,435	,375	-,193	-1,160	,253	-1,193	,323
	involv_prod	-,316	,313	-,192	-1,008	,320	-,949	,318
	impl_green_involv	1,090	,698	,443	1,561	,127	-,322	2,502
	impl_prod_involv	,114	,256	,132	,446	,658	-,403	,631
	expl_green_involv	-2,048	1,246	-,854	-1,644	,108	-4,566	,470
	expl_prod_involv	-,171	1,217	-,023	-,140	,889	-2,631	2,290

Tree-way interactions

a. Dependent Variable: bgp

Appendix L: Questionnaire

Incorrect device

The survey software has detected that you are attempting to take this survey from an incompatible device. The survey contains questions that will only function correctly on a computer with a keyboard. Please open this survey from a computer with a keyboard.

Introduction

Hello and thank you for for taking part in this experiment! Your insight means a lot for my project and I hope you will have fun while participating!

You will be asked to do 3 things:

- take **2** simple 5-minute Implicit Association Tests
- complete a mini-task
- look at some made-up products and share you opinions about them

We will start off with an Implicit Association Test that will help us register attitudes you might not know about or not be able to report. It will consist of 7 short blocks, and you will see the instructions before the test begins. During the test you can only press letter "E", "I" or "Space". Don't worry if you see a red cross, just

retry.

After the first test you will see a couple questions about some made-up products, followed by a mini-task.

Then comes the **second test**, and the second batch of product-related questions -> and we are done!

Remember: there are no right or wrong answers, and your help is highly appreciated.

Your responses are anonymous, all the data will be used for academic purposes only and **kept confidential**.

IAT

Please indicate how you would rate product A on the following dimensions:

bad	○	○	○	○	○	good
unsafe	○	○	○	○	○	safe
unfavourable	○	○	○	○	○	favourable
worthless	○	○	○	○	○	valuable
useless	○	○	○	○	○	useful
negative	○	○	○	○	○	positive

Please indicate how you would rate product B on the following dimensions:

bad	○	○	○	○	○	good
unsafe	○	○	○	○	○	safe
unfavourable	○	○	○	○	○	favourable
worthless	○	○	○	○	○	valuable
useless	○	○	○	○	○	useful
negative	○	○	○	○	○	positive

Please rate products A and B relative each other on the following dimensions:
(choose the statement that reflects your opinion best, on the scale from 1 to 5)

A)

B)

Product **A is more interesting** than product B	○	○	○	○	○	Product **B is more interesting** than product A
Product **A is more pleasant** than product B	○	○	○	○	○	Product **B is more pleasant** than product A
Product **A is more attractive** than product B	○	○	○	○	○	Product **B is more attractive** than product A
Product **A is more beneficial** than product B	○	○	○	○	○	Product **B is more beneficial** than product A

Imagine product A is real. Please choose the option that best describes your opinion:

A)

	Highly disagree	Somewhat disagree	Neutral	Somewhat agree	Highly agree
I will try the product	○	○	○	○	○
I will consider purchasing the product next time	○	○	○	○	○
It is very likely that I will buy the product	○	○	○	○	○

Imagine product B is real. Please choose the option that best describes your opinion:

B)

	Highly disagree	Somewhat disagree	Neutral	Somewhat agree	Highly agree
I will try the product	○	○	○	○	○
I will consider purchasing the product next time	○	○	○	○	○
It is very likely that I will buy the product	○	○	○	○	○

treatment section

Intro for the 2nd part

2/3 are done, and You are doing great!

Now we are ready for **the second** Implicit Association Test and product-related questions.

IAT

Please indicate how you would rate product A on the following dimensions:

bad	○	○	○	○	○	good
unsafe	○	○	○	○	○	safe
unfavourable	○	○	○	○	○	favourable
worthless	○	○	○	○	○	valuable
useless	○	○	○	○	○	useful
negative	○	○	○	○	○	positive

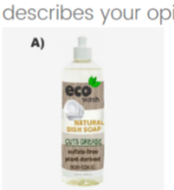
Please indicate how you would rate product B on the following dimensions:

bad	○	○	○	○	○	good
unsafe	○	○	○	○	○	safe
unfavourable	○	○	○	○	○	favourable
worthless	○	○	○	○	○	valuable
useless	○	○	○	○	○	useful
negative	○	○	○	○	○	positive

Please rate products A and B relative each other on the following dimensions:
(choose which statement reflects your opinion best, on the scale from 1 to 5)

Product **A is more interesting** than product B	○	○	○	○	○	Product **B is more interesting** than product A
Product **A is more pleasant** than product B	○	○	○	○	○	Product **B is more pleasant** than product A
Product **A is more attractive** than product B	○	○	○	○	○	Product **B is more attractive** than product A
Product **A is more beneficial** than product B	○	○	○	○	○	Product **B is more beneficial** than product A

Imagine product A is real. Please choose the option that best describes your opinion:



	Highly disagree	Somewhat disagree	Neutral	Somewhat agree	Highly agree
I will try the product	○	○	○	○	○
I will consider purchasing the product next time	○	○	○	○	○
It is very likely that I will buy the product	○	○	○	○	○

Imagine product B is real. Please choose the option that best describes your opinion:

	Highly disagree	Somewhat disagree	Neutral	Somewhat agree	Highly agree
I will try the product	○	○	○	○	○
I will consider purchasing the product next time	○	○	○	○	○
It is very likely that I will buy the product	○	○	○	○	○

Cause involvement

For each statement, please choose the option that best reflects your opinion:
(you can choose on the 1 - 5 scale)

The state of environment is **unimportant** for me	○	○	○	○	○	The state of environment is **important** for me
The way environment affects the quality of life is **irrelevant** for me	○	○	○	○	○	The way environment affects the quality of life is **relevant** for me
Making sacrifices to protect environment **means nothing** to me	○	○	○	○	○	Making sacrifices to protect environment **means a lot** to me
The way my actions affect the environment **does not matter a great deal** to me	○	○	○	○	○	The way my actions affect the environment **matters a great deal** to me
Maintaining sustainable habits is **no concern** to me	○	○	○	○	○	Maintaining sustainable habits is **a big concern** to me

Appendix M: SPSS output OLS regressions

Appendix M1: Model 1

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,445[a]	,198	,169	,85430

a. Predictors: (Constant), exp, implPRE

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10,083	2	5,041	6,908	,002[b]
	Residual	40,870	56	,730		
	Total	50,953	58			

a. Dependent Variable: bgp

b. Predictors: (Constant), exp, implPRE

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3,281	,231		14,193	,000
	implPRE	,237	,360	,080	,659	,513
	exp	1,074	,307	,425	3,502	,001

a. Dependent Variable: bgp

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,397[a]	,158	,128	,82793

a. Predictors: (Constant), exp, implPRE

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7,196	2	3,598	5,249	,008[b]
	Residual	38,386	56	,685		
	Total	45,582	58			

a. Dependent Variable: bcp

b. Predictors: (Constant), exp, implPRE

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3,410	,224		15,219	,000
	implPRE	-,739	,348	-,263	-2,120	,038
	exp	-,616	,297	-,258	-2,072	,043

a. Dependent Variable: bcp

Appendix M2: Model 2

Appendix M2: Model 2 – Green Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,458[a]	,210	,167	,85545	,210	4,876	3	55	,004

a. Predictors: (Constant), ci, implPRE, exp

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10,704	3	3,568	4,876	,004[b]
	Residual	40,249	55	,732		
	Total	50,953	58			

a. Dependent Variable: bgp

b. Predictors: (Constant), ci, implPRE, exp

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2,601	,774		3,362	,001	1,050	4,151
	implPRE	,138	,376	,046	,366	,716	-,616	,891
	exp	,978	,324	,387	3,020	,004	,329	1,628
	ci	,185	,201	,123	,922	,361	-,218	,588

a. Dependent Variable: bgp

Appendix M2: Model 2 – Conventional Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,410[a]	,168	,123	,83021	,168	3,711	3	55	,017

a. Predictors: (Constant), ci, implPRE, exp

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7,673	3	2,558	3,711	,017[b]
	Residual	37,908	55	,689		
	Total	45,582	58			

a. Dependent Variable: bcp

b. Predictors: (Constant), ci, implPRE, exp

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	4,006	,751		5,335	,000	2,501	5,511
	implPRE	-,652	,365	-,232	-1,787	,080	-1,383	,079
	exp	-,532	,314	-,223	-1,692	,096	-1,162	,098
	ci	-,162	,195	-,114	-,832	,409	-,553	,229

a. Dependent Variable: bcp

Appendix M3: Model 3

Appendix M3: Model 3 – Green Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	,458[a]	,210	,167	,85545	,210	4,876	3	55	,004
2	,533[b]	,284	,231	,82179	,074	5,598	1	54	,022

a. Predictors: (Constant), ci, implPRE, exp

b. Predictors: (Constant), ci, implPRE, exp, implPRE_explPOST

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10,704	3	3,568	4,876	,004[b]
	Residual	40,249	55	,732		
	Total	50,953	58			
2	Regression	14,485	4	3,621	5,362	,001[c]
	Residual	36,468	54	,675		
	Total	50,953	58			

a. Dependent Variable: bgp

b. Predictors: (Constant), ci, implPRE, exp

c. Predictors: (Constant), ci, implPRE, exp, implPRE_explPOST

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	Upper Bound
1	(Constant)	2,601	,774		3,362	,001	1,050	4,151
	implPRE	,138	,376	,046	,366	,716	-,616	,891
	exp	,978	,324	,387	3,020	,004	,329	1,628
	ci	,185	,201	,123	,922	,361	-,218	,588
2	(Constant)	2,336	,752		3,109	,003	,830	3,843
	implPRE	,299	,367	,101	,815	,419	-,437	1,036
	exp	1,021	,312	,404	3,275	,002	,396	1,646
	ci	,218	,194	,145	1,123	,266	-,171	,606
	implPRE_explPOST	,190	,080	,281	2,366	,022	,029	,350

a. Dependent Variable: bgp

Appendix M3: Model 3 – Conventional Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,410[a]	,168	,123	,83021	,168	3,711	3	55	,017
2	,429[b]	,184	,124	,82995	,016	1,034	1	54	,314

a. Predictors: (Constant), ci, implPRE, exp

b. Predictors: (Constant), ci, implPRE, exp, implPRE_explPOST

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7,673	3	2,558	3,711	,017[b]
	Residual	37,908	55	,689		
	Total	45,582	58			
2	Regression	8,386	4	2,096	3,044	,025[c]
	Residual	37,196	54	,689		
	Total	45,582	58			

a. Dependent Variable: bcp

b. Predictors: (Constant), ci, implPRE, exp

c. Predictors: (Constant), ci, implPRE, exp, implPRE_explPOST

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	4,006	,751		5,335	,000	2,501	5,511
	implPRE	-,652	,365	-,232	-1,787	,080	-1,383	,079
	exp	-,532	,314	-,223	-1,692	,096	-1,162	,098
	ci	-,162	,195	-,114	-,832	,409	-,553	,229
2	(Constant)	3,891	,759		5,126	,000	2,369	5,413
	implPRE	-,581	,371	-,207	-1,567	,123	-1,326	,163
	exp	-,514	,315	-,215	-1,631	,109	-1,145	,118
	ci	-,148	,196	-,104	-,759	,451	-,540	,244
	implPRE_explPOST	,082	,081	,129	1,017	,314	-,080	,245

a. Dependent Variable: bcp

Appendix M4: Model 4

Appendix M4: Model 4 –Green Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	,507[a]	,257	,187	,84515	,257	3,667	5	53	,006

a. Predictors: (Constant), product, exp, implPRE, green, ci

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13,096	5	2,619	3,667	,006[b]
	Residual	37,857	53	,714		
	Total	50,953	58			

a. Dependent Variable: bgp

b. Predictors: (Constant), product, exp, implPRE, green, ci

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	Upper Bound
1	(Constant)	2,512	,835		3,007	,004	,836	4,187
	implPRE	,191	,373	,064	,512	,611	-,557	,939
	exp	,922	,322	,365	2,868	,006	,277	1,567
	ci	,216	,207	,144	1,044	,301	-,199	,632
	green	-,350	,262	-,170	-1,333	,188	-,876	,176
	product	,205	,296	,091	,693	,491	-,388	,798

a. Dependent Variable: bgp

Appendix M4: Model 4 – Conventional Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	,453[a]	,205	,130	,82673	,205	2,738	5	53	,028

a. Predictors: (Constant), product, exp, implPRE, green, ci

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9,357	5	1,871	2,738	,028[b]
	Residual	36,225	53	,683		
	Total	45,582	58			

a. Dependent Variable: bcp

b. Predictors: (Constant), product, exp, implPRE, green, ci

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	Upper Bound
1	(Constant)	3,490	,817		4,271	,000	1,851	5,129
	implPRE	-,668	,365	-,238	-1,832	,073	-1,400	,063
	exp	-,540	,315	-,226	-1,715	,092	-1,171	,091
	ci	-,072	,203	-,051	-,356	,724	-,479	,334
	green	,207	,257	,106	,805	,424	-,308	,721
	product	,447	,289	,211	1,546	,128	-,133	1,028

a. Dependent Variable: bcp

Appendix M5: Model 5

Appendix M5: Model 5 – Green Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	,507[a]	,257	,187	,84515	,257	3,667	5	53	,006
2	,561[b]	,315	,236	,81926	,058	4,403	1	52	,041

a. Predictors: (Constant), product, Zscore(explicitPOST), Zscore(implPRE), green, Zscore(cause_involv)

b. Predictors: (Constant), product, Zscore(explicitPOST), Zscore(implPRE), green, Zscore(cause_involv), implPRE_explPOST

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13,096	5	2,619	3,667	,006[b]
	Residual	37,857	53	,714		
	Total	50,953	58			
2	Regression	16,051	6	2,675	3,986	,002[c]
	Residual	34,902	52	,671		
	Total	50,953	58			

a. Dependent Variable: bgp

b. Predictors: (Constant), product, Zscore(explicitPOST), Zscore(implPRE), green, Zscore(cause_involv)

c. Predictors: (Constant), product, Zscore(explicitPOST), Zscore(implPRE), green, Zscore(cause_involv), implPRE_explPOST

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	Upper Bound
1	(Constant)	3,664	,162		22,665	,000	3,340	3,988
	Zscore(implPRE)	,058	,114	,064	,512	,611	-,170	,286
	Zscore(explicitPOST)	,340	,119	,365	2,868	,006	,102	,578
	Zscore(cause_involv)	,141	,135	,144	1,044	,301	-,130	,413
	green	-,350	,262	-,170	-1,333	,188	-,876	,176
	product	,205	,296	,091	,693	,491	-,388	,798
2	(Constant)	3,632	,157		23,064	,000	3,316	3,948
	Zscore(implPRE)	,100	,112	,111	,894	,376	-,124	,324
	Zscore(explicitPOST)	,358	,115	,384	3,105	,003	,127	,590
	Zscore(cause_involv)	,152	,131	,155	1,159	,252	-,111	,416
	green	-,307	,255	-,149	-1,202	,235	-,819	,205
	product	,136	,289	,061	,470	,640	-,443	,715
	implPRE_explPOST	,170	,081	,253	2,098	,041	,007	,333

a. Dependent Variable: bgp

Appendix M5: Model 5 – Conventional Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,453[a]	,205	,130	,82673	,205	2,738	5	53	,028
2	,466[b]	,217	,127	,82833	,012	,795	1	52	,377

a. Predictors: (Constant), product, Zscore(explicitPOST), Zscore(implPRE), green, Zscore(cause_involv)

b. Predictors: (Constant), product, Zscore(explicitPOST), Zscore(implPRE), green, Zscore(cause_involv), implPRE_explPOST

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9,357	5	1,871	2,738	,028[b]
	Residual	36,225	53	,683		
	Total	45,582	58			
2	Regression	9,903	6	1,650	2,405	,040[c]
	Residual	35,679	52	,686		
	Total	45,582	58			

a. Dependent Variable: bcp

b. Predictors: (Constant), product, Zscore(explicitPOST), Zscore(implPRE), green, Zscore(cause_involv)

c. Predictors: (Constant), product, Zscore(explicitPOST), Zscore(implPRE), green, Zscore(cause_involv), implPRE_explPOST

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2,739	,158		17,323	,000	2,422	3,057
	Zscore(implPRE)	-,203	,111	-,238	-1,832	,073	-,426	,019
	Zscore(explicitPOST)	-,199	,116	-,226	-1,715	,092	-,432	,034
	Zscore(cause_involv)	-,047	,132	-,051	-,356	,724	-,313	,219
	green	,207	,257	,106	,805	,424	-,308	,721
	product	,447	,289	,211	1,546	,128	-,133	1,028
2	(Constant)	2,726	,159		17,119	,000	2,406	3,045
	Zscore(implPRE)	-,185	,113	-,217	-1,640	,107	-,412	,041
	Zscore(explicitPOST)	-,191	,117	-,217	-1,642	,107	-,425	,043
	Zscore(cause_involv)	-,042	,133	-,046	-,319	,751	-,309	,224
	green	,225	,258	,116	,873	,387	-,292	,743
	product	,418	,292	,197	1,431	,158	-,168	1,003
	implPRE_explPOST	,073	,082	,115	,892	,377	-,091	,238

a. Dependent Variable: bcp

Appendix M6: Model 6

Appendix M6: Model 6 – Green Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	,489[a]	,239	,198	,83945	,239	5,769	3	55	,002
2	,651[b]	,423	,357	,75171	,184	5,530	3	52	,002

a. Predictors: (Constant), green, implPRE, exp

b. Predictors: (Constant), green, implPRE, exp, implPRE_explPOST, explPOST_green, implPRE_green

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12,196	3	4,065	5,769	,002[b]
	Residual	38,757	55	,705		
	Total	50,953	58			
2	Regression	21,569	6	3,595	6,362	,000[c]
	Residual	29,384	52	,565		
	Total	50,953	58			

a. Dependent Variable: bgp

b. Predictors: (Constant), green, implPRE, exp

c. Predictors: (Constant), green, implPRE, exp, implPRE_explPOST, explPOST_green, implPRE_green

Coefficients[a]

Model		Unstandardized Coefficients: B	Unstandardized Coefficients: Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	95,0% Confidence Interval for B: Upper Bound
1	(Constant)	3,384	,235		14,410	,000	2,914	3,855
	implPRE	,289	,355	,098	,815	,418	-,422	1,000
	exp	1,019	,303	,403	3,362	,001	,411	1,626
	green	-,421	,243	-,205	-1,731	,089	-,909	,066
2	(Constant)	3,116	,240		12,986	,000	2,635	3,598
	implPRE	,879	,381	,296	2,305	,025	,114	1,644
	exp	,605	,308	,239	1,964	,055	-,013	1,223
	green	-,270	,222	-,132	-1,215	,230	-,716	,176
	implPRE_explPOST	,135	,074	,201	1,819	,075	-,014	,285
	implPRE_green	-,356	,218	-,208	-1,631	,109	-,793	,082
	explPOST_green	,765	,261	,348	2,928	,005	,241	1,290

a. Dependent Variable: bgp

Appendix M6: Model 6 – Conventional Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,399[a]	,159	,113	,83478	,159	3,470	3	55	,022
2	,574[b]	,329	,252	,76672	,170	4,399	3	52	,008

a. Predictors: (Constant), green, implPRE, exp

b. Predictors: (Constant), green, implPRE, exp, implPRE_explPOST, explPOST_green, implPRE_green

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7,255	3	2,418	3,470	,022[b]
	Residual	38,327	55	,697		
	Total	45,582	58			
2	Regression	15,013	6	2,502	4,257	,001[c]
	Residual	30,569	52	,588		
	Total	45,582	58			

a. Dependent Variable: bcp

b. Predictors: (Constant), green, implPRE, exp

c. Predictors: (Constant), green, implPRE, exp, implPRE_explPOST, explPOST_green, implPRE_green

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	3,392	,234		14,525	,000	2,924	3,860
	implPRE	-,747	,353	-,267	-2,120	,039	-1,454	-,041
	exp	-,607	,301	-,254	-2,013	,049	-1,210	-,003
	green	,070	,242	,036	,291	,772	-,414	,555
2	(Constant)	3,176	,245		12,975	,000	2,685	3,667
	implPRE	-,194	,389	-,069	-,498	,621	-,974	,587
	exp	-1,062	,314	-,444	-3,380	,001	-1,692	-,431
	green	,198	,227	,102	,875	,386	-,256	,653
	implPRE_explPOST	,057	,076	,089	,749	,457	-,095	,209
	implPRE_green	-,391	,222	-,242	-1,757	,085	-,837	,055
	explPOST_green	,776	,267	,373	2,911	,005	,241	1,311

a. Dependent Variable: bcp

Appendix M7: Model 7

Appendix M7: Model 7 – Green Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,500[a]	,250	,195	,84108	,250	4,507	4	54	,003
2	,673[b]	,453	,378	,73931	,203	6,297	3	51	,001

a. Predictors: (Constant), green, ci, implPRE, exp

b. Predictors: (Constant), green, ci, implPRE, exp, implPRE_explPOST, explPOST_green, implPRE_green

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12,753	4	3,188	4,507	,003[b]
	Residual	38,200	54	,707		
	Total	50,953	58			
2	Regression	23,078	7	3,297	6,032	,000[c]
	Residual	27,875	51	,547		
	Total	50,953	58			

a. Dependent Variable: bgp

b. Predictors: (Constant), green, ci, implPRE, exp

c. Predictors: (Constant), green, ci, implPRE, exp, implPRE_explPOST, explPOST_green, implPRE_green

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2,738	,765		3,580	,001	1,205	4,272
	implPRE	,194	,371	,066	,524	,603	-,550	,938
	exp	,929	,320	,368	2,905	,005	,288	1,570
	ci	,176	,198	,117	,888	,379	-,221	,572
	green	-,415	,244	-,202	-1,702	,095	-,904	,074
2	(Constant)	2,013	,705		2,857	,006	,598	3,428
	implPRE	,773	,380	,261	2,034	,047	,010	1,537
	exp	,431	,320	,170	1,344	,185	-,213	1,074
	ci	,293	,176	,195	1,661	,103	-,061	,647
	green	-,248	,219	-,121	-1,133	,263	-,687	,191
	implPRE_explPOST	,142	,073	,211	1,938	,058	-,005	,289
	implPRE_green	-,399	,216	-,234	-1,847	,070	-,833	,035
	explPOST_green	,802	,258	,364	3,106	,003	,284	1,320

a. Dependent Variable: bgp

Appendix M7: Model 7 – Conventional Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,412[a]	,169	,108	,83731	,169	2,754	4	54	,037
2	,575[b]	,331	,239	,77331	,161	4,102	3	51	,011

a. Predictors: (Constant), green, ci, implPRE, exp

b. Predictors: (Constant), green, ci, implPRE, exp, implPRE_explPOST, explPOST_green, implPRE_green

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7,723	4	1,931	2,754	,037[b]
	Residual	37,859	54	,701		
	Total	45,582	58			
2	Regression	15,083	7	2,155	3,603	,003[c]
	Residual	30,499	51	,598		
	Total	45,582	58			

a. Dependent Variable: bcp

b. Predictors: (Constant), green, ci, implPRE, exp

c. Predictors: (Constant), green, ci, implPRE, exp, implPRE_explPOST, explPOST_green, implPRE_green

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	3,985	,762		5,232	,000	2,458	5,511
	implPRE	-,661	,369	-,236	-1,788	,079	-1,401	,080
	exp	-,525	,318	-,219	-1,647	,105	-1,163	,114
	ci	-,161	,197	-,113	-,817	,417	-,556	,234
	green	,065	,243	,033	,266	,791	-,422	,551
2	(Constant)	3,413	,737		4,630	,000	1,933	4,893
	implPRE	-,171	,398	-,061	-,430	,669	-,970	,628
	exp	-1,024	,335	-,428	-3,055	,004	-1,697	-,351
	ci	-,063	,184	-,044	-,342	,734	-,433	,307
	green	,194	,229	,100	,845	,402	-,266	,653
	implPRE_explPOST	,055	,077	,087	,723	,473	-,099	,209
	implPRE_green	-,381	,226	-,236	-1,688	,098	-,835	,072
	explPOST_green	,769	,270	,369	2,847	,006	,227	1,310

a. Dependent Variable: bcp

Appendix M8: Model 8

Appendix M8: Model 8 – Green Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	,459[a]	,211	,168	,85489	,211	4,906	3	55	,004
2	,545[b]	,297	,216	,82998	,086	2,117	3	52	,109

a. Predictors: (Constant), product, exp, implPRE

b. Predictors: (Constant), product, exp, implPRE, implPRE_explPOST, implPRE_prod, explPOST_prod

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10,757	3	3,586	4,906	,004[b]
	Residual	40,196	55	,731		
	Total	50,953	58			
2	Regression	15,131	6	2,522	3,661	,004[c]
	Residual	35,821	52	,689		
	Total	50,953	58			

a. Dependent Variable: bgp

b. Predictors: (Constant), product, exp, implPRE

c. Predictors: (Constant), product, exp, implPRE, implPRE_explPOST, implPRE_prod, explPOST_prod

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	Upper Bound
1	(Constant)	3,204	,245		13,078	,000	2,713	3,695
	implPRE	,270	,362	,091	,748	,458	-,454	,995
	exp	1,081	,307	,428	3,521	,001	,466	1,696
	product	,259	,270	,116	,961	,341	-,282	,800
2	(Constant)	3,109	,275		11,288	,000	2,556	3,662
	implPRE	,329	,405	,111	,813	,420	-,483	1,142
	exp	1,338	,363	,529	3,684	,001	,609	2,067
	product	,200	,269	,089	,745	,460	-,339	,739
	implPRE_explPOST	,128	,108	,190	1,192	,239	-,088	,344
	implPRE_prod	,213	,279	,121	,762	,449	-,347	,773
	explPOST_prod	-,389	,318	-,220	-1,222	,227	-1,028	,250

a. Dependent Variable: bgp

Appendix M8: Model 8 – Conventional Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,439[a]	,192	,148	,81813	,192	4,367	3	55	,008
2	,518[b]	,268	,183	,80110	,076	1,788	3	52	,161

a. Predictors: (Constant), product, exp, implPRE

b. Predictors: (Constant), product, exp, implPRE, implPRE_explPOST, implPRE_prod, explPOST_prod

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8,768	3	2,923	4,367	,008[b]
	Residual	36,814	55	,669		
	Total	45,582	58			
2	Regression	12,210	6	2,035	3,171	,010[c]
	Residual	33,372	52	,642		
	Total	45,582	58			

a. Dependent Variable: bcp

b. Predictors: (Constant), product, exp, implPRE

c. Predictors: (Constant), product, exp, implPRE, implPRE_explPOST, implPRE_prod, explPOST_prod

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	3,291	,234		14,040	,000	2,822	3,761
	implPRE	-,688	,346	-,245	-1,988	,052	-1,381	,006
	exp	-,605	,294	-,253	-2,060	,044	-1,194	-,016
	product	,396	,258	,187	1,533	,131	-,122	,914
2	(Constant)	3,460	,266		13,016	,000	2,927	3,994
	implPRE	-,845	,391	-,301	-2,161	,035	-1,629	-,060
	exp	-1,000	,351	-,418	-2,853	,006	-1,704	-,297
	product	,277	,259	,131	1,070	,290	-,243	,798
	implPRE_explPOST	,213	,104	,334	2,048	,046	,004	,421
	implPRE_prod	,206	,269	,124	,764	,449	-,335	,747
	explPOST_prod	,562	,307	,336	1,827	,073	-,055	1,178

a. Dependent Variable: bcp

Appendix M9: Model 9

Appendix M9: Model 9 – Green Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,482[a]	,232	,175	,85122	,232	4,080	4	54	,006
2	,559[b]	,313	,218	,82864	,081	1,994	3	51	,127

a. Predictors: (Constant), product, exp, implPRE, ci

b. Predictors: (Constant), product, exp, implPRE, ci, implPRE_explPOST, implPRE_prod, explPOST_prod

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11,826	4	2,957	4,080	,006[b]
	Residual	39,127	54	,725		
	Total	50,953	58			
2	Regression	15,934	7	2,276	3,315	,006[c]
	Residual	35,019	51	,687		
	Total	50,953	58			

a. Dependent Variable: bgp

b. Predictors: (Constant), product, exp, implPRE, ci

c. Predictors: (Constant), product, exp, implPRE, ci, implPRE_explPOST, implPRE_prod, explPOST_prod

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2,255	,819		2,754	,008	,614	3,896
	implPRE	,147	,374	,049	,392	,697	-,603	,897
	exp	,954	,323	,377	2,952	,005	,306	1,601
	ci	,251	,207	,167	1,214	,230	-,164	,666
	product	,346	,278	,154	1,244	,219	-,212	,904
2	(Constant)	2,267	,826		2,745	,008	,609	3,926
	implPRE	,238	,413	,080	,578	,566	-,590	1,067
	exp	1,197	,386	,473	3,104	,003	,423	1,971
	ci	,222	,205	,147	1,081	,285	-,190	,634
	product	,270	,276	,121	,980	,332	-,284	,824
	implPRE_explPOST	,137	,108	,204	1,276	,208	-,079	,354
	implPRE_prod	,178	,281	,101	,634	,529	-,385	,741
	explPOST_prod	-,331	,323	-,187	-1,026	,310	-,978	,317

a. Dependent Variable: bgp

Appendix M9: Model 9 – Conventional Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,442[a]	,196	,136	,82404	,196	3,282	4	54	,018
2	,518[b]	,269	,168	,80845	,073	1,701	3	51	,179

a. Predictors: (Constant), product, exp, implPRE, ci

b. Predictors: (Constant), product, exp, implPRE, ci, implPRE_explPOST, implPRE_prod, explPOST_prod

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8,914	4	2,229	3,282	,018[b]
	Residual	36,668	54	,679		
	Total	45,582	58			
2	Regression	12,249	7	1,750	2,677	,019[c]
	Residual	33,333	51	,654		
	Total	45,582	58			

a. Dependent Variable: bcp

b. Predictors: (Constant), product, exp, implPRE, ci

c. Predictors: (Constant), product, exp, implPRE, ci, implPRE_explPOST, implPRE_prod, explPOST_prod

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	3,642	,792		4,596	,000	2,053	5,231
	implPRE	-,642	,362	-,229	-1,773	,082	-1,368	,084
	exp	-,558	,313	-,233	-1,785	,080	-1,185	,069
	ci	-,093	,200	-,065	-,463	,645	-,495	,309
	product	,364	,269	,172	1,352	,182	-,176	,904
2	(Constant)	3,644	,806		4,522	,000	2,027	5,262
	implPRE	-,825	,403	-,294	-2,048	,046	-1,633	-,016
	exp	-,969	,376	-,405	-2,577	,013	-1,724	-,214
	ci	-,049	,200	-,034	-,243	,809	-,450	,353
	product	,262	,269	,124	,973	,335	-,279	,803
	implPRE_explPOST	,211	,105	,330	2,004	,050	,000	,421
	implPRE_prod	,213	,274	,128	,780	,439	-,336	,763
	explPOST_prod	,549	,315	,329	1,744	,087	-,083	1,180

a. Dependent Variable: bcp

Appendix M10: Model 10

Appendix M10: Model 10 – Green Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,492[a]	,242	,186	,84585	,242	4,304	4	54	,004
2	,656[b]	,431	,326	,76943	,189	3,252	5	49	,013

a. Predictors: (Constant), product, exp, implPRE, green

b. Predictors: (Constant), product, exp, implPRE, green, implPRE_explPOST, explPOST_green, implPRE_green, implPRE_prod, explPOST_prod

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12,318	4	3,080	4,304	,004[b]
	Residual	38,635	54	,715		
	Total	50,953	58			
2	Regression	21,944	9	2,438	4,119	,001[c]
	Residual	29,009	49	,592		
	Total	50,953	58			

a. Dependent Variable: bgp

b. Predictors: (Constant), product, exp, implPRE, green

c. Predictors: (Constant), product, exp, implPRE, green, implPRE_explPOST, explPOST_green, implPRE_green, implPRE_prod, explPOST_prod

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	3,340	,259		12,875	,000	2,820	3,861
	implPRE	,300	,358	,101	,837	,406	-,418	1,018
	exp	1,027	,306	,406	3,356	,001	,413	1,640
	green	-,385	,260	-,187	-1,477	,145	-,907	,137
	product	,118	,284	,052	,414	,680	-,452	,687
2	(Constant)	3,022	,325		9,290	,000	2,368	3,675
	implPRE	,945	,492	,319	1,922	,060	-,043	1,933
	exp	,786	,393	,311	2,001	,051	-,004	1,576
	green	-,246	,241	-,120	-1,019	,313	-,730	,239
	product	,090	,265	,040	,341	,735	-,442	,623
	implPRE_explPOST	,085	,107	,126	,799	,428	-,129	,300
	implPRE_green	-,399	,253	-,234	-1,578	,121	-,907	,109
	explPOST_green	,704	,279	,320	2,523	,015	,143	1,265
	implPRE_prod	-,003	,285	-,002	-,011	,992	-,577	,571
	explPOST_prod	-,236	,311	-,134	-,761	,451	-,861	,388

a. Dependent Variable: bgp

Appendix M10: Model 10 – Conventional Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,451[a]	,203	,144	,82002	,203	3,447	4	54	,014
2	,679[b]	,461	,362	,70815	,258	4,682	5	49	,001

a. Predictors: (Constant), product, exp, implPRE, green

b. Predictors: (Constant), product, exp, implPRE, green, implPRE_explPOST, explPOST_green, implPRE_green, implPRE_prod, explPOST_prod

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9,271	4	2,318	3,447	,014[b]
	Residual	36,311	54	,672		
	Total	45,582	58			
2	Regression	21,010	9	2,334	4,655	,000[c]
	Residual	24,572	49	,501		
	Total	45,582	58			

a. Dependent Variable: bcp

b. Predictors: (Constant), product, exp, implPRE, green

c. Predictors: (Constant), product, exp, implPRE, green, implPRE_explPOST, explPOST_green, implPRE_green, implPRE_prod, explPOST_prod

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	3,214	,252		12,778	,000	2,710	3,718
	implPRE	-,705	,347	-,251	-2,029	,047	-1,401	-,008
	exp	-,574	,297	-,240	-1,937	,058	-1,169	,020
	green	,218	,252	,112	,864	,391	-,288	,724
	product	,476	,275	,225	1,731	,089	-,075	1,028
2	(Constant)	3,304	,299		11,037	,000	2,702	3,906
	implPRE	-,429	,453	-,153	-,949	,347	-1,339	,480
	exp	-1,659	,362	-,694	-4,587	,000	-2,387	-,932
	green	,310	,222	,160	1,399	,168	-,135	,756
	product	,340	,244	,160	1,392	,170	-,151	,830
	implPRE_explPOST	,213	,098	,335	2,174	,035	,016	,411
	implPRE_green	-,247	,233	-,153	-1,064	,293	-,715	,220
	explPOST_green	,979	,257	,470	3,812	,000	,463	1,495
	implPRE_prod	,080	,263	,048	,304	,762	-,448	,608
	explPOST_prod	,806	,286	,482	2,817	,007	,231	1,381

a. Dependent Variable: bcp

Appendix M11: Model 11

Appendix M11: Model 11 – Green Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,507[a]	,257	,187	,84515	,257	3,667	5	53	,006
2	,698[b]	,488	,354	,75316	,231	2,962	7	46	,012

a. Predictors: (Constant), product, exp, implPRE, green, ci

b. Predictors: (Constant), product, exp, implPRE, green, ci, implPRE_involv, explPOST_green, implPRE_green, explPOST_involv, implPRE_prod, implPRE_explPOST, explPOST_prod

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13,096	5	2,619	3,667	,006[b]
	Residual	37,857	53	,714		
	Total	50,953	58			
2	Regression	24,859	12	2,072	3,652	,001[c]
	Residual	26,094	46	,567		
	Total	50,953	58			

a. Dependent Variable: bgp

b. Predictors: (Constant), product, exp, implPRE, green, ci

c. Predictors: (Constant), product, exp, implPRE, green, ci, implPRE_involv, explPOST_green, implPRE_green, explPOST_involv, implPRE_prod, implPRE_explPOST, explPOST_prod

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2,512	,835		3,007	,004	,836	4,187
	implPRE	,191	,373	,064	,512	,611	-,557	,939
	exp	,922	,322	,365	2,868	,006	,277	1,567
	ci	,216	,207	,144	1,044	,301	-,199	,632
	green	-,350	,262	-,170	-1,333	,188	-,876	,176
	product	,205	,296	,091	,693	,491	-,388	,798
2	(Constant)	1,431	,856		1,671	,101	-,293	3,155
	implPRE	1,097	,499	,370	2,197	,033	,092	2,102
	exp	,444	,416	,176	1,068	,291	-,393	1,282
	ci	,386	,197	,256	1,963	,056	-,010	,782
	green	-,139	,255	-,068	-,545	,588	-,652	,374
	product	,240	,273	,107	,877	,385	-,310	,790
	implPRE_explPOST	,206	,145	,306	1,428	,160	-,085	,497
	implPRE_green	-,571	,260	-,335	-2,200	,033	-1,094	-,049
	explPOST_green	,756	,282	,343	2,681	,010	,188	1,323
	implPRE_prod	-,189	,294	-,108	-,643	,523	-,781	,403
	explPOST_prod	-,221	,394	-,125	-,561	,578	-1,013	,572
	implPRE_involv	-,138	,134	-,199	-1,028	,310	-,408	,132
	explPOST_involv	-,091	,133	-,125	-,689	,494	-,359	,176

a. Dependent Variable: bgp

Appendix M11: Model 11 – Conventional Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,453[a]	,205	,130	,82673	,205	2,738	5	53	,028
2	,704[b]	,495	,364	,70712	,290	3,778	7	46	,003

a. Predictors: (Constant), product, exp, implPRE, green, ci

b. Predictors: (Constant), product, exp, implPRE, green, ci, implPRE_involv, explPOST_green, implPRE_green, explPOST_involv, implPRE_prod, implPRE_explPOST, explPOST_prod

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9,357	5	1,871	2,738	,028[b]
	Residual	36,225	53	,683		
	Total	45,582	58			
2	Regression	22,581	12	1,882	3,763	,001[c]
	Residual	23,001	46	,500		
	Total	45,582	58			

a. Dependent Variable: bcp

b. Predictors: (Constant), product, exp, implPRE, green, ci

c. Predictors: (Constant), product, exp, implPRE, green, ci, implPRE_involv, explPOST_green, implPRE_green, explPOST_involv, implPRE_prod, implPRE_explPOST, explPOST_prod

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	3,490	,817		4,271	,000	1,851	5,129
	implPRE	-,668	,365	-,238	-1,832	,073	-1,400	,063
	exp	-,540	,315	-,226	-1,715	,092	-1,171	,091
	ci	-,072	,203	-,051	-,356	,724	-,479	,334
	green	,207	,257	,106	,805	,424	-,308	,721
	product	,447	,289	,211	1,546	,128	-,133	1,028
2	(Constant)	2,659	,804		3,306	,002	1,040	4,277
	implPRE	-,311	,469	-,111	-,663	,511	-1,254	,633
	exp	-1,809	,391	-,757	-4,631	,000	-2,595	-1,023
	ci	,132	,185	,093	,716	,477	-,239	,504
	green	,470	,239	,242	1,963	,056	-,012	,951
	product	,446	,257	,210	1,738	,089	-,071	,962
	implPRE_explPOST	,358	,136	,562	2,638	,011	,085	,631
	implPRE_green	-,315	,244	-,195	-1,290	,203	-,805	,176
	explPOST_green	,909	,265	,436	3,434	,001	,376	1,441
	implPRE_prod	-,045	,276	-,027	-,163	,872	-,601	,511
	explPOST_prod	1,143	,370	,684	3,091	,003	,399	1,887
	implPRE_involv	-,201	,126	-,306	-1,593	,118	-,454	,053
	explPOST_involv	,127	,125	,185	1,023	,312	-,123	,378

a. Dependent Variable: bcp

Appendix M12: Model 12

Appendix M12: Model 12 – Green Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	,507[a]	,257	,187	,84515	,257	3,667	5	53	,006
2	,711[b]	,505	,348	,75699	,248	2,452	9	44	,023

a. Predictors: (Constant), product, exp, implPRE, green, ci

b. Predictors: (Constant), product, exp, implPRE, green, ci, implPRE_involv, explPOST_green, involv_green, explPOST_involv, implPRE_green, implPRE_prod, involv_prod, implPRE_explPOST, explPOST_prod

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13,096	5	2,619	3,667	,006[b]
	Residual	37,857	53	,714		
	Total	50,953	58			
2	Regression	25,739	14	1,839	3,208	,002[c]
	Residual	25,214	44	,573		
	Total	50,953	58			

a. Dependent Variable: bgp

b. Predictors: (Constant), product, exp, implPRE, green, ci

c. Predictors: (Constant), product, exp, implPRE, green, ci, implPRE_involv, explPOST_green, involv_green, explPOST_involv, implPRE_green, implPRE_prod, involv_prod, implPRE_explPOST, explPOST_prod

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	Upper Bound
1	(Constant)	2,512	,835		3,007	,004	,836	4,187
	implPRE	,191	,373	,064	,512	,611	-,557	,939
	exp	,922	,322	,365	2,868	,006	,277	1,567
	ci	,216	,207	,144	1,044	,301	-,199	,632
	green	-,350	,262	-,170	-1,333	,188	-,876	,176
	product	,205	,296	,091	,693	,491	-,388	,798
2	(Constant)	,347	1,305		,266	,791	-2,282	2,976
	implPRE	1,116	,502	,377	2,222	,031	,104	2,129
	exp	,250	,453	,099	,552	,584	-,663	1,164
	ci	,653	,311	,434	2,096	,042	,025	1,280
	green	-,104	,260	-,051	-,402	,690	-,628	,419
	product	,267	,278	,119	,959	,343	-,294	,827
	implPRE_explPOST	,221	,146	,327	1,511	,138	-,074	,515
	implPRE_green	-,486	,280	-,285	-1,733	,090	-1,050	,079
	explPOST_green	,856	,295	,389	2,905	,006	,262	1,449
	implPRE_prod	-,179	,302	-,102	-,593	,556	-,789	,430
	explPOST_prod	-,176	,398	-,100	-,442	,661	-,978	,626
	implPRE_involv	-,164	,137	-,236	-1,191	,240	-,441	,113
	explPOST_involv	-,108	,134	-,148	-,806	,424	-,379	,162
	involv_green	-,417	,348	-,185	-1,198	,237	-1,119	,284
	involv_prod	-,228	,293	-,139	-,778	,441	-,819	,363

a. Dependent Variable: bgp

Appendix M12: Model 12 – Conventional Product

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,453[a]	,205	,130	,82673	,205	2,738	5	53	,028
2	,710[b]	,504	,346	,71666	,299	2,948	9	44	,008

a. Predictors: (Constant), product, exp, implPRE, green, ci

b. Predictors: (Constant), product, exp, implPRE, green, ci, implPRE_involv, explPOST_green, involv_green, explPOST_involv, implPRE_green, implPRE_prod, involv_prod, implPRE_explPOST, explPOST_prod

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9,357	5	1,871	2,738	,028[b]
	Residual	36,225	53	,683		
	Total	45,582	58			
2	Regression	22,983	14	1,642	3,196	,002[c]
	Residual	22,599	44	,514		
	Total	45,582	58			

a. Dependent Variable: bcp

b. Predictors: (Constant), product, exp, implPRE, green, ci

c. Predictors: (Constant), product, exp, implPRE, green, ci, implPRE_involv, explPOST_green, involv_green, explPOST_involv, implPRE_green, implPRE_prod, involv_prod, implPRE_explPOST, explPOST_prod

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	3,490	,817		4,271	,000	1,851	5,129
	implPRE	-,668	,365	-,238	-1,832	,073	-1,400	,063
	exp	-,540	,315	-,226	-1,715	,092	-1,171	,091
	ci	-,072	,203	-,051	-,356	,724	-,479	,334
	green	,207	,257	,106	,805	,424	-,308	,721
	product	,447	,289	,211	1,546	,128	-,133	1,028
2	(Constant)	3,090	1,235		2,502	,016	,601	5,579
	implPRE	-,325	,476	-,116	-,683	,498	-1,283	,633
	exp	-1,733	,429	-,725	-4,038	,000	-2,598	-,868
	ci	,027	,295	,019	,091	,928	-,567	,621
	green	,441	,246	,227	1,796	,079	-,054	,937
	product	,475	,263	,224	1,804	,078	-,055	1,005
	implPRE_explPOST	,350	,138	,550	2,537	,015	,072	,629
	implPRE_green	-,257	,265	-,159	-,969	,338	-,792	,278
	explPOST_green	,902	,279	,433	3,235	,002	,340	1,464
	implPRE_prod	-,098	,286	-,059	-,343	,733	-,675	,479
	explPOST_prod	1,121	,377	,671	2,974	,005	,361	1,880
	implPRE_involv	-,186	,130	-,283	-1,427	,161	-,448	,077
	explPOST_involv	,133	,127	,194	1,050	,299	-,123	,389
	involv_green	-,050	,330	-,024	-,153	,879	-,715	,614
	involv_prod	,203	,278	,131	,733	,467	-,356	,763

a. Dependent Variable: bcp