Psychological and Demographic Predictors of Plastic Bag Consumption in Transaction Data

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Abstract

Despite the success of plastic bag charges in the UK, there are still around a billion single-use plastic bags bought each year in England alone, and the government have made plans to increase the levy from 5 to 10 pence. Previous research has identified motivations for bringing personal bags to a supermarket, but little is known about the individuals who are continuing to frequently purchase single-use plastic bags after the levy. In this study, over a million loyalty card transaction records from a high-street health and beauty retailer were harnessed to study 12,968 individuals' bag buying behaviour (analysed using descriptive statistics). Statistical regional differences in plastic bag buying throughout the UK occurred. From the transaction data 2,326 frequent single-use plastic bag buyers were identified and matched randomly to infrequent buyers, creating a balanced sub-sample which was used for predictive modelling ($N=4,652$). For each individual in the modelling sample, their transaction data was matched to questionnaire responses measuring demographics, shopping motivations, and individual differences. Using this data, an exploratory machine learning approach was utilised to investigate the demographic and psychological predictors of frequent plastic bag consumption. It was found that frequent bag buyers spent more money in store, were younger, more likely to be male, less frugal, open to new experiences, and more displeased with their appearance (compared with infrequent bag buyers). Interestingly, environmental concerns did not predict plastic bag consumption, highlighting the disconnect between predicting pro-environmental attitudes and real world environmental behaviour.

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Introduction

Plastic Bag Charges

In 2014, 7.6 billion plastic bags were used by customers of English supermarkets (GOV, 2015; WRAP, 2015). That is on average 140 bags per person (GOV, 2015), and equates to approximately 61,000 tonnes of plastic (Smithers, 2016). Plastic bags are typically made from non-biodegradable high density polyethylene (HDPE), a material sourced from fossil fuels (Edwards & Fry, 2011). As well as the energy and oil used to create them, most bags are not recycled (Monaghan, 2018) and negatively impact the environment when littered or inadequately disposed of (Jambeck et al., 2015). Plastic bags contribute to the 12.7 million tonnes of plastic that end up in our seas each year (Jambeck et al., 2015), polluting the waters and harming marine wildlife (Jambeck et al., 2015). Many national and local governments have introduced policies to try to reduce the number of bags used (Clapp & Swanston, 2009), these include bans (e.g. in Kenya (NEMA, 2018)), and mandatory charges (e.g. in Ireland in 2002 (Anastasio and Nix, 2016)). In October 2015, England followed Scotland, Wales, and Northern Ireland in introducing a mandatory 5 pence charge for single use plastic bags, in an attempt to reduce the number of single-use plastic being consumed.

In England, the 5 pence charge has been successful in reducing the number of bags used by shoppers (DEFRA, 2018b) mirroring findings from other countries (Australia, 2015; Block, 2013; Haoran, 2010; Poortinga, Whitmarsh, & Suffolk, 2013; Scottish Government, 2015; Welsh Government, 2016). England's six-month review post-levy showed that the number of single-use plastic bags had dropped by more than 85% to around 500 million in six months (DEFRA, 2018b). People's attitudes towards the levy had also changed (Poortinga, Sautkina, Thomas, & Wolstenholme, 2016; Thomas, Sautkina, Poortinga, Wolstenholme, & Whitmarsh, 2019). A longitudinal survey found that six months after the levy, there was increased support for the charges, and

improved awareness of the environmental impact of household plastic waste (Poortinga et al., 2016; Thomas et al., 2019). When the surveyed respondents reduced their plastic bag consumption, it was reported to be for both financial and environmental reasons (Jakovcevic et al., 2014; Poortinga et al., 2016). Despite the reduction in plastic bag consumption, a supermarket observational study showed that there were no changes in the number of customers bringing personal bags, such as rucksacks, to the supermarket. The use of ‘bags for life’, however, did double after the levy – suggesting shoppers were replacing single-use bags with bags for life (Poortinga et al., 2016).

Studying real world environmental behaviour unobtrusively, whilst retaining detailed information about the individual, is a difficult task. Diary interview studies have teased out people’s motivations and attitudes for buying plastic bags (Poortinga et al., 2016), but when using smaller samples it is harder to attest generalisability to the findings. Questionnaire and longitudinal surveys have reached a wider participant pool (He, 2010; Poortinga et al., 2016; Sharp, Høj, & Wheeler, 2010), but self-reported behaviour measures can be affected by social desirability bias (Van de Mortel et al., 2008) or miss-remembering (Jakovcevic et al., 2014). Kormos and Gifford (2014), in a meta-analysis, found that 79% of the variance in the association between self-reported pro-environmental behaviour and objective pro-environmental behaviour remained unexplained. In other words, self-reported environmental behaviour does not strongly predict objective measures of environmental behaviour. This is especially troubling when interventions and campaigns are being devised on the results of studies using self-reported measures of behaviour. Therefore, if actual behaviour can be measured accurately and objectively on a large scale, along with peoples psychological attributes and demographic information, more accurate insights into who and what drives plastic bag buying in the real world can be made - and used to more accurately inform future policy decisions.

Demographic Predictors of Environmental Concern

Understanding the profile of people who frequently buy plastic bags, in spite of the levy, is important for planning future plastic reduction interventions, legislation, and campaigns. Previous research has shown that people concerned with the environment are more likely to be younger, female, have more money, and a higher education than people less concerned with the environment (Davidson & Freudenburg, 1996; Hines, Hungerford, & Tomera, 1987; Kalof, Dietz, Guagnano, & Stern, 2002; Zelezny, Chua, & Aldrich, 2000). Unsurprisingly, pro-environmental individuals have been shown to hold positive environmental attitudes (Dunlap, Van Liere, Mertig, & Jones, 2000), be well informed on the impact of their behaviour (Frick, Kaiser, & Wilson, 2004), and demonstrate concern over the natural world (Bamberg & Möser, 2007). However, whether this more general profile of pro-environmental individuals fits *specifically* those who avoid purchasing single-use plastic bags, has not yet been fully studied.

Observers in Jakovcevic et al. (2014) and Poortinga et al.'s (2016) supermarket observational study, estimated bag buyers' age and gender. The latter found that in England the use of single-use plastic bags decreased from 53% to 23% among men, and from 55% to 20% among women after the levy. Shoppers estimated to be 18-44 years bought the most plastic bags, whilst older people (estimated to be 65 years or over) bought the least - despite research suggesting older people are less concerned about the environment (Gifford & Nilsson, 2014). This supports literature finding that younger adults have greater concerns about the environment, but older adults engage in more pro-environmental behaviours (Arcury & Christianson, 1993; Honnold, 1984; Klineberg, McKeever, & Rothenbach, 1998). Given this, certain actions or behaviours, such as plastic bag buying, may be less driven by environmental concern, and more by other factors - perhaps frugality (Tapia-Fonllem, Corral-Verdugo, Fraijo-Sing, & Durón-Ramos, 2013), anti-consumerism (Jackson, 2012), or being motivated to save money (Jakovcevic et al., 2014; Poortinga et al., 2016).

Personality and Environmental Concerns

Research has demonstrated that personality can influence people's levels of environmental concern. Early studies found that pro-environmental attitudes were associated with being more liberal (Arbuthnot, 1977) and conscientious (Pettus & Giles, 1987). Recent research has focused on using the Big Five framework (Costa & MacCrae, 1992) for measuring personality using the orthogonal trait dimensions of *openness to new experiences* (intellectual, complex); *conscientiousness* (dependable, self-disciplined); *extraversion* (fun, enthusiastic); *agreeableness* (sympathetic, warm); and *neuroticism* (anxious, easily upset). Milfont and Sibley (2012) showed that on both an individual level and national level, agreeableness, conscientiousness, and openness to new experiences positively predicted environmental engagement (Borden & Francis, 1978; Hirsh, 2010; Milfont & Sibley, 2012). Hirsh and Dolderman (2007) and Hirsh (2010) also found that high agreeableness and openness (strongly), as well as neuroticism and conscientiousness (weakly) positively related to environmental concern. Another study found that agreeableness and conscientiousness were positively related to recycling behaviours (Swami, Chamorro-Premuzic, Snelgar, & Furnham, 2011). Neuroticism has additionally been found to positively relate to certain aspects of environmental engagement (Wiseman & Bogner, 2003). Evidence for the role of extraversion, however, has been mixed.

Openness to new experiences has consistently been found to relate to pro-environmental activities in both a community sample and an undergraduate student sample (Fraj & Martinez, 2006; Markowitz, Goldberg, Ashton, & Lee, 2012). Markowitz et al. (2012) suggested that high levels of aesthetic appreciation, creativity, and inquisitiveness, rather than altruism, may motivate pro-environmental actions. People high in openness have a greater willingness for change, to break with convention, and experience new ways of doing things (Markowitz et al., 2012). Individuals high in openness are also driven by aesthetic appreciation and intellectual curiosity - both of which can positively influence one's interest in nature and environmentalism (Hartig, Kaiser, & Bowler, 2001; Hirsh & Dolderman, 2007). In summary, multiple studies have

found that different personality traits, namely openness and agreeableness, but also conscientiousness and neuroticism, positively relate to environmental concerns and engagement. However, the extent to which these relationships translate from generalised pro-environmental attitudes and activities to the purchasing of plastic bags in the real world is not known.

Engaging in environmental behaviours involves, not just the motivation or intention to do so, but additionally the self-discipline and belief in the behaviour's impact (Axon, 2017; Van der Linden, Maibach, & Leiserowitz, 2015). A greater internal locus of control (the degree to which people believe that they have control over the outcome of events in their lives) has been associated with stronger pro-environmental intentions and behaviour in a variety of different countries including both Germany and Japan (Ando, Ohnuma, Blöbaum, Matthies, & Sugiura, 2010), Australia (Fielding & Head, 2012) and Canada (Abrahamse, Steg, Gifford, & Vlek, 2009). This highlights that when studying real world behaviour, it is not just the motivations for that behaviour (i.e. the related beliefs and attitudes) that are important - but also the dispositional traits which affect whether an action is carried out or not. These factors which can increase the likelihood of a motivation to act translating to a behaviour include: self-control, impulsivity, future focus, propensity to plan ahead, and self-efficacy - none of which are *explicitly* measured using the Big Five.

Future orientation (or having a future time preference) is the tendency to establish goals and to plan strategies for meeting long-term obligations (Corral-Verdugo, Fraijo-Sing, & Pinheiro, 2006); it is also positively related to sustainable behaviour (Corral-Verdugo et al., 2006; Joireman, Van Lange, & Van Vugt, 2004; Urien & Kilbourne, 2011). Frugality or “thriftiness” is defined by being economic with resources, and antagonist to consumerism (Jackson, 2012) and materialism (Goldsmith & Flynn, 2015). Consumerism is one of the stand out causes of environmental problems (Tapia-Fonllem et al., 2013). As well as frugal people having reduced consumption, frugality affects the type of items purchased, and the methods used for waste disposal. Various studies have demonstrated frugality's relationship with

pro-environmental behaviours (Gatersleben, Murtagh, & Abrahamse, 2014; Pepper, Jackson, & Uzzell, 2011; Tapia-Fonllem et al., 2013). As well as impacting through self-transcendent values such as unity with nature (Todd & Lawson, 2003), there is also a self-enhancement aspect of frugality which relates to pro-environmental behaviours - ambition, self-control, and consumer independence (Goldsmith & Flynn, 2015). Lastly, low impulsivity (akin to high self-control) relates negatively to the ability to plan ahead (also captured in time preferences), and thus would be expected to negatively relate to those environmental behaviours that require some degree of forethought or planning. Although people higher in openness are also often more impulsive (McCrae, 1993), there is limited literature explicitly on the relationship between the inhibition of impulses and pro-environmental behaviour.

Personality and Plastic Bag Purchasing

Personality has been shown to predict environmental concerns, engagement and self-reported behaviours. Yet, how this literature translates specifically to bag buying behaviour in the real world is uncertain for the following three reasons:

- 1) One environmentally conscious behaviour does not always predict another. There is some evidence for environmental *behaviour spillover* (where one ecological behaviour can lead to another) from plastic bag reduction to other ecological behaviours (Lanzini & Thøgersen, 2014; Thomas, Poortinga, & Sautkina, 2016), but it does not always occur (Poortinga et al., 2013; Thøgersen & Ölander, 2003). It can depend on the type of behaviour and the cost of that behaviour (Lanzini & Thøgersen, 2014); and in some cases one behaviour could even reduce the propensity to behave environmentally friendly in other areas (Thøgersen & Ölander, 2003). Ego-depletion theory (Baumeister, Bratslavsky, Muraven, & Tice, 1998) proposes people have a finite amount of will-power or self control. Once this is used up, people are unable to exert the same level of self control on subsequent, often unrelated tasks or choices. For example: “I spent ages

sorting the recycling this morning - I didn't have the time or energy to organise bringing a bag for life with me". Thus the factors predicting one environmental behaviour (recycling household waste) may not be predictive of another (bringing a personal shopping bag to the store) - particularly if one behaviour is habitual and the other is not.

2) Limitations exist on the extent to which environmental attitudes and intentions generalise to actual pro-environmental behaviour. For example, Diamantopoulos, Schlegelmilch, Sinkovics, and Bohlen (2003) showed that socio-demographic variables could define consumer profiles for environmental knowledge and attitudes, but were limited for actual behaviour. Environmental knowledge and values have been found to account for only 40% of the variance in ecological behavioural intentions, which in turn explains just 75% of the variance in ecological behaviour (Kaiser, Wölfling, & Fuhrer, 1999). Thus, it is uncertain whether the same personality traits which influence environmental concerns in the literature, predict actual pro-environmental behaviour - specifically the purchasing of plastic bags.

3) Studies which measure self-reported behaviour using questionnaires may be affected by bias (Van de Mortel et al., 2008) or poor memory (Jakovcevic et al., 2014), and may not truly represent behaviour occurring in the real world (Kormos & Gifford, 2014). Kormos and Gifford (2014) did not find a strong association between self-reported pro-environmental behaviour and objective behavioural measurements. Thus, it cannot be assumed that theories and models constructed on self-reported behaviour, transfer to behaviour measured in the real world.

Measuring Environmental Behaviour in Big Data

Until recently, objective environmental behaviour has been hard to measure on a large scale, as it has typically involved observing people in the real world without them knowing (Kormos & Gifford, 2014; Poortinga et al., 2016), gaining peer ratings (which

can be equally biased/inaccurate) (Chao & Lam, 2011), or looking at household meter readings (which are often not at the level of the individual) (Fuj, Hennessy, & Mak, 1985). Field studies allow researchers to study a behaviour from a snapshot in time at a particular location, however they cannot measure the regularity, trends, or patterns in an individual's behaviour. Today, people leave a substantial amount of data in their wake. Smart meters installed into homes, smart appliances, mobile phone records, apps, and transaction records are all sources of data which can now be used to study real world ecological behaviour unobtrusively. Using loyalty cards and personal accounts, researchers can now track and record individual's environmental behavioural patterns over time and space. With permission, this behaviour can additionally be paired to self-reported psychological information. This research exploits such a unique dataset to study the psychological and demographic predictors of frequent plastic bag consumption as it occurs in the real world.

Aim

In this study, a data driven approach was used to investigate who were continuing to frequently purchase plastic bags in England after the 5p levy was brought in. A dataset consisting of millions of transaction records matched to questionnaires measuring demographics, shopping motivations (including questions on environmental concerns), and individual differences were harnessed to predict and explain the plastic bag buying behaviour. Participants' survey responses were linked with their transaction records measuring retrospectively their plastic bag purchases. Using this sample, the first aim was to produce descriptive statistics on the distribution of bag buying in the UK stores studied, over time and geographical space.

Subsequently, the aim was to build a model to predict frequent plastic bag buyers. As using real world behaviour records didn't allow for the control of confounding variables whilst the behaviour was being measured, extraneous variables such as shopping frequency were statistically controlled for by inputting them into the model. Deviating from the more traditional hypothesis driven approach allowed for an

inductive exploration of a much larger number of possible explanations. Because of this exploratory approach, particular caution was taken to ensure “p-hacking as procedural overfitting” (Yarkoni & Westfall, 2017) was not occurring (further discussed in the section Controlling for Multicollinearity, Overfitting, and False Discovery Rates).

Predictions

A priori predictions were made about which variables were expected to predict frequent plastic bag purchasing. These predictions were based on two different streams of reasoning 1) the characteristics of people who *intend* to not consume plastic bags (Jakovcevic et al., 2014; Poortinga et al., 2016); and 2) the characteristics influencing people’s ability to *convert* intentions to behaviour (Bamberg & Möser, 2007; Hines et al., 1987).

Firstly, based on previous findings about the motivations for bag purchasing (Jakovcevic et al., 2014; Poortinga et al., 2016; Sun, Wang, Li, Zhao, & Fan, 2017), it was expected that a person who was motivated to save money, or had concern for the environment, would intend to bring their own bags to the store instead of purchasing single-use ones. Therefore, it was predicted that frequent bag buyers were more likely to have a higher income, spend more money in store, be less frugal, and have less concern for the environment than infrequent plastic bag buyers.

Secondly, as *intending* to reduce plastic bag consumption and actually doing so are not the same (Bamberg & Möser, 2007; Diamantopoulos et al., 2003), many factors can disrupt a motivation or intention converting to behaviour (Kaiser et al., 1999; Sun et al., 2017). Bringing a personal bag to the store is often a required antecedent to refusing a plastic bag at the till, and requires forethought and planning. In other words, if someone was motivated to refuse plastic bags to save money or to help the environment, they could still end up buying bags because they had not adequately planned ahead or had purchased more items than intended on the spur of the moment. Thus, it was predicted that impulsiveness (measured using BAS scales, and self-control) would positively predict regular plastic bag purchasing.

These hypotheses did not comprise exhaustively the factors investigated. This research also constitutes a bottom-up exploratory investigation into the demographic and psychological variables affecting single use plastic bag consumption. Consequently, this left the current authors open to report and discuss all findings (not just those attached to the hypotheses). Therefore, the data available was also utilised to explore the open ended question: who frequently buys plastic bags?

Method

Participants

Online surveys were sent to 80,000 members of the retailer's internal consumer panel. There were 12,968 responses fully completed and matched to participants' purchasing data on their loyalty card. From this data a balanced binary sample was extracted ($N=4,652$) containing frequent and non frequent bag buyers. See the Procedure section for the full details on how this was done. (For clarity, Table 1 displays the different samples that were utilised in the following analyses).

Materials

Online Survey. The survey used in this study was a generalised survey, which was designed with the intention of studying, more generally, which psychological factors affect different purchasing behaviours. The survey questions can be categorised into three groups: socio-demographics, psychological characteristics, and shopping behaviours/motivations.

Socio-demographics: The socio-demographic questions comprised of age, gender, marital status, current occupation, annual household income, highest education qualification, (self reported) geographical region, how many people they live with, and how many children they have.

Psychological characteristics: The psychological characteristics measured included time preferences - assessed by the three questions 'Would you rather have £25/£45/£55 now, or £75 later?' (Reimers, Maylor, Stewart, & Chater, 2009), self

Table 1
The different samples and their uses in the analysis

Sample	Use	N	Area covered
The store's internal consumer panel	The pool of participants the survey was sent to	80,000	UK
The fully-completed questionnaire responses which were successfully linked to respondent's loyalty card transaction data	Used to produce descriptive statistics on plastic bag buying	12,968	UK
The number of identified frequent plastic bag buyers in the transaction data	Used to create a balanced modelling sample	2,326	England
The modelling sample created from the <i>frequent</i> bag buyers being matched to an equal number of <i>infrequent</i> bag buyers	Used to extract the important predictors of plastic bag buying	4,652	England
The 80% of the modelling sample used for training	To train the logistic regression model	3,722	England
The 20% of the modelling sample used for testing	To test the logistic regression model	930	England

control (Tangney, Boone, & Baumeister, 2018), impulsiveness using the Behavioural Activation Scales (BAS) (Carver & White, 1994) measuring reward responsiveness (BAS-RR), drive (BAS-D) and fun seeking (BAS-FS), and the Ten Item Personality Inventory (TIPI) version of the Big Five (Gosling, Rentfrow, & Swann Jr, 2003)¹.

Shopping behaviours and motivations: The items measuring shopping motivations included an eight item frugality measure (Lastovicka, Bettencourt, Hughner, & Kuntze, 1999), a shopping impulsivity scale (Rook & Fisher, 1995), and a series of questions about different shopping motivations which included two questions on environmental concerns: 'Environmental considerations affect the products that I purchase'; and 'I am concerned about climate change (also known as global warming)' ². A correlation

¹ The TIPI measure was used as the final generalised questionnaire asked a large number of questions, and an extended measure of the Big Five would have significantly increased the time it took to complete the questionnaire, and thus the likelihood of participants dropping out.

² It is worth noting here that the questions and measures used in this study were not designed for the sole purpose of understanding plastic bag purchasing, and in this way could be considered secondary

matrix of the interrelationships between measures can be found in Figure 3, and a link to a full copy of the survey sent to participants can be found in Appendix A.

Transaction Data. The study utilised, under informed consent, historical transaction (purchase) records for the survey respondent from a high-street health and beauty retailer, recorded as part of the retailer’s loyalty card scheme. Permission to access the data was provided explicitly as part of the survey. Before the individual’s purchasing data was analysed, it was pseudo-anonymized to link the questionnaire responses with the transaction data prior to full anonymization. No incentives were offered for taking part in the study. This study received full ethical approval from the university.

In order to consider repeat purchasing behaviour of single use plastic bags, data was extracted for a period of 9 months following the introduction of the 5p levy in England on the 5th of October 2015. Over this period the data included the shop location, all participants’ purchases and their value (grouped by transaction). Purchases of single use plastic bags are explicitly recorded in this data.

Feature Engineering. The survey data and the associated 9 months of transaction data formed the available features for the study. Focusing on understanding the underlying motivations of consumers who frequently purchase single use plastic bags, the majority of the independent variables (input features) were drawn from the survey data with only a single input feature (average monthly spending) included from the transaction data. The dependent variable was coded from the objective transaction data.

Engineering the dependent variable: Plastic bag sales were coded in the data for shoppers in England after the 5p levy was brought into action on the 5th October 2015. This meant that every time a bag was purchased using a loyalty card information on that transaction was recorded, including a description of the type of bag purchased. Although bags for life can also threaten our marine environments (DEFRA, 2018b), at this time they were seen as the pro-environmental choice (Poortinga et al., 2016). Bags

data.

for life were therefore not included, as the analysis wanted to capture the characteristics of those individuals whose behaviour was least impacted by the 5p levy intervention. Therefore, the bags in this study are either the single-use or medium-strength plastic bags for which the levy applies.

The total quantity of transaction data which was linked to the survey participants (with complete questionnaires) consisted of 1,284,825 distinct transactions from 1,222 different stores by 12,968 people across the UK. The total number of plastic bags bought by this sample was 20,504. Using this data, the percentage of times each person bought a plastic bag in England (when the data suggested they had bought enough items to warrant needing one) was calculated. This was done by only analysing the shopping trips where either one of the two following conditions were satisfied: 1) they had 3 or more items in their ‘basket’ (used here to denote the items bought in one transaction, not a physical basket), or 2) they had a basket volume of over 2,225 ml (approximately an 8th of the total volume of a standard carrier bag volume (18 litres)).

By only analysing these higher-quantity baskets, baskets where a customer buys only a couple of items that could fit in their pocket/hands are not included in the analysis. Therefore, the measure of bag buying used here is the proportion of times a person makes a single-use plastic bag purchase when a bag was deemed to be required to carry their shopping. If a bag was not brought when the conditions for needing one were satisfied, it was inferred that they either bought their own bag to the store, made an effort to carry multiple items or a large volume of items by hand, or bought a bag for life³.

Independent Variable Encoding: Before being entered into the logistic regression model, categorical variables were dummy coded, giving a total of 92 predictors. For income (which was not strictly an ordinal variable due to the ‘prefer not to say’ category) the lowest income category ‘Less than £25,000’ was removed as the reference class. For the rest of the variables the most frequent class was the reference class, in order to compare the effects of smaller groups to the larger normative group. For

³ Of course other circumstances may have arisen that cannot be known about, such as buying a single-use plastic bag from another high street retailer prior to shopping at the store in question

loyalty card use the reference group was ‘every time’, for shopping frequency ‘once a fortnight’, for the people you are living with this was ‘partner’, for marital status ‘married’, for occupation ‘intermediate manager/professional/administrative’, for highest qualification ‘bachelors’ degree, and for region the most common was ‘Yorkshire’.

Although shopping frequency was being controlled for by engineering the outcome variable using the percentage of times a person bought a bag (when one was required), it was further controlled for by including self reported shopping frequency, loyalty card use, and average monthly spend (calculated from the transaction data) as features in the model. To aid interpretation, all continuous variables were mean centred and standardised before being input into the model. The descriptives of the continuous independent variables from the balanced modelling sample can be viewed in Table 2. The full list of features used are available in the full results table in Appendix C.

Procedure

Using transaction data as a measure of behaviour, as well as an inductive exploratory approach, meant that some additional procedural steps were required. This section describes first how a smaller sub-sample was extracted for modelling, containing an equal number of frequent and non frequent bag buyers. It then describes how, because of the large number of variables being investigated, multicollinearity, overfitting, and false discovery rates (FDR) were controlled for.

Creating a Balanced Modelling Sub-sample. From the whole surveyed sample ($N=12,968$) 56% had never bought a single-use plastic bag. Of those who had bought a bag at least once, the proportion of purchases that included a single-use bag, when they had bought enough items/volume of items to suffice needing one (see section on engineering the dependent variable) is plotted in Figure 1. Only 1,014 people had bought a bag on 50% or more of their bag-warranting visits. Because of the non-normal distribution (positive-skew) of bag buying behaviour, and the fact that this investigation was particularly interested in the sub-group of individuals who *frequently* bought plastic bags, rather than predict the percentage of trips a bag was bought, a

binary outcome variable was created to divide people into frequent and infrequent bag buyers. For this, a cut-off percentage value was selected that weighed up a) extracting a sample of people who really were repeatedly buying plastic bags, with b) the size of the sample attained (i.e. avoiding throwing too much data away). It was decided that because of the strong positive skew in Figure 1, the cut-off of buying a bag 25% or more of the bag-warranting shopping trips was sufficient to separate frequent bag buyers from less frequent bag buyers (the norm in the data).

Therefore, individuals who bought bags on 25% or more occasions, and who had fully completed the questionnaire, made up the positive class in the modelling sub-sample ($N=2,326$). An equal number of infrequent bag buyers (people who bought a plastic bag with less than 25% of their bag warranting visits) were then randomly sampled - producing the balanced modelling sample of 4,652. The descriptives of the continuous independent variables from the balanced modelling sample are shown in Table 2.

Figure 1. A graph to show the distribution of plastic bag purchases when enough items or volume of items to warrant needing one were purchased. Those who never purchased a bag (0%) ($N=8,546$) are not represented in this graph. The cut-off of 25% or more determined the frequent bag buyers.

Controlling for Multicollinearity, Overfitting, and False Discovery

Rates. *Multicollinearity:* As this analysis involved interpreting the standardised β

values (which are affected by multicollinearity) in the context of predictive variable importance, the degree of collinearity between variables was checked using the Variable Inflation Factor (VIF). Four variables had a VIF above the chosen threshold of 2.5 (Allison, 2012)⁴: ‘Happiness’ and ‘Satisfaction with life’ were highly correlated, as were ‘Living on own’, and ‘Marital Status: Single’. To ensure the multicollinearity did not interfere with the variable importance measure, Satisfaction and Happiness were combined into a single well-being variable (Diener, Lucas, Oishi, et al., 2002), and ‘living on own’ was removed. The model was re-fitted to check the VIF levels and all were subsequently below the 2.5 threshold (‘Well-being’ = 1.45, ‘Marital Status: Single’ = 1.64).

Overfitting: Notably the decision to include a large number of variables in the model’s selection pool brings with it an increased risk of over-fitting. Without care, a sample fit statistic can be produced that is unrepresentative of the general population. This issue is known as ‘procedural overfitting’, (Yarkoni & Westfall, 2017) and an inadvertent form of p-hacking. Such dangers can be mitigated against through the rigorous use of cross-validation and, for logistic regression, the use of regularisation parameters (Ng, 2004), and/or recursive feature elimination (Pedregosa et al., 2011). The key to the cross-validation approach well established in computational science and of growing use in the traditionally inferential statistical sciences (Dahl, Grotle, Benth, & Natvig, 2008; Yarkoni & Westfall, 2017) lies in the iterative use of hold-out data partitions to ensure that the selected model specification (in this case, the independent features and meta-parameters controlling regularisation) is the one that optimally generalises to out-of-sample data.

First, 20% ($N=930$) of the sample were excluded at random, and this data was set aside as the “unseen” test data for evaluating the final model’s performance. The remaining 80% ($N=3,722$) of the data were used within a k-fold cross validation procedure (where $K=5$ (Bishop, 2006)) to repeatedly train and evaluate (1) multiple different logistic regression variants based on different levels of regularisation via a

⁴ This threshold, in the context of the large dataset, is particularly stringent (O’Brien, 2007).

systematic search over a range of parameterisations (grid search, see Appendix B) and (2) recursive feature elimination.

K-fold cross validation was used to recycle data for training and testing within the 80% training sample (see Figure 2). The data was divided into K equal samples (folds). One fold becomes the test set, and the remaining folds are the training data. This process is repeated, computing the performance statistic of interest for each of the hold-out folds until each fold has been the test data (K times). The average of the performance statistic across all folds is then calculated. To evaluate the performance of different (regularisation) parameters the Mean Absolute Error (MAE) was used. To select the final features, the Area Under Curve (AUC) score was measured within the recursive feature elimination procedure (using cross validation). This procedure identified just one variable which could be removed without affecting the AUC score, indicating its redundancy. This variable was *Duration*, which measured the time it took the person to complete the online questionnaire. Removing Duration left us with a total of 92 predictor variables, which were all entered into the final regularised regression model.

Figure 2. The cross-validation paradigm used in this study to prevent *p*-hacking

Once the final logistic regression model was selected, the model's performance was tested on the unseen (20%) test data. The model's accuracy was evaluated using the F_1 score. The F_1 score combines both recall (the percentage of total relevant results

correctly classified) and precision (the percentage of correctly classified results in the positive/relevant class) to indicate performance whilst balancing type 1 and type 2 error. Testing the model on data that is unseen by the algorithm provides a score indicating how the model is expected to generalise. This estimation is generally much more conservative than performance measures calculated by fitting a model to 100% of the data (Yarkoni & Westfall, 2017).

As a result of the model selection procedure above, and evaluating the model performance on how well it generalises to new data, p-hacking as procedural overfitting is avoided. At this point, the methodology returns to a more traditional analysis when investigating the significance of the predictive variables using standardised β values, and controlling for the likelihood of some variables being significant by chance using the Benjamin-Hochberg false discovery procedure⁵.

False Discovery Rates: The final step of the analysis was to extract the significant predictive variables of frequent bag buying behaviour from the model. Due to having a large number of independent variables, the likelihood of some variables being significant by chance was controlled for using the Benjamini–Hochberg false discovery procedure with a q -value of 0.05 (Benjamini & Hochberg, 1995). The q -value is the expected proportion of false positives among all features as or more extreme than the observed one. Therefore a q -value threshold of 0.05 yields a FDR of 5% among all features called significant⁶. By only reporting variables which passed the Benjamini–Hochberg test, the likelihood of type 2 error was increased (missing a positive result) in order to reduce the likelihood of a type 1 error (false discovery) (Benjamini & Hochberg, 1995). Thus, as well as tuning meta-parameters and using out of sample testing to increase the generalisability of the model, this conservative approach to analysing the statistical significance of the predictive variables helped ensure the replicability of the findings.

⁵ It is noted that the use of cross-validation can theoretically be extended to address issues of p-hacking within variable importance calculations, however, its use is not widespread and as such more traditional approaches were preferred for this work.

⁶ This is not to be confused with a p -value threshold (alpha) of 0.05, which yields a false positive rate (FPR) of 5% among all *truly null* features.

Results

Descriptive Statistics

Before predicting frequent bag buying using the modelling sample, descriptive statistics were first produced on the whole sample ($N = 12,968$) to investigate the distribution of bag sales over time and geographic space. Overall, a very small sample of people were frequently buying plastic bags, with 56% of the full sample having not bought a single-use plastic bag at all, and just 18% being characterised as *frequent* bag buyers. The descriptive statistics for the continuous independent variables can be found in Table 2. The weekly plastic bag sales in England (per 1,000 items) in the 9 months following the levy can be viewed in Figure 5. Across the UK, more bags per 1,000 items were bought during the Christmas festive period (week 50-53: 7th December to the 3rd January). In the 9 months proceeding the levy start date (15th October 2015) plastic bags bought per week per 1,000 items in England show a significant linear decrease ($t(40) = -3.55, p = 0.001, R^2 = 0.24$). However, as the data on plastic bag consumption prior to the levy was not available, or a full years data after the levy, it cannot be determined whether this decrease in bags is related to the levy, or an annual seasonal trend (more bags bought around Christmas and fewer in the summer).

Table 2
Descriptive statistics for the continuous independent variables in the modelling sample

	Min	Max	Mean	SD
Average Monthly Spend (£)	2.67	380.44	42.40	27.35
Age (years)	17	95	50	15
Extroversion	1	7	4.05	1.55
Agreeableness	1	7	5.51	1.12
Openness	1	7	4.85	1.19
Conscientiousness	1	7	5.81	1.10
Emotional Stability	1	7	4.69	1.47
Well-being	0	10	7.18	1.89
Self-control	1.15	5	3.31	0.66
Frugality	1	6	4.56	0.88
Shopping Impulsivity	1.11	5.11	2.73	0.86
BAS-RR	1.20	4	3.22	0.46
BAS-FS	1	4	2.77	0.53
BAS-D	1	4	2.44	0.64
SM1: I would rather stick to a brand I usually buy...	1	7	4.51	1.57
SM2: I enjoy taking chances in buying unfamiliar brands...	1	7	3.97	1.50
SM3: If I like a brand I rarely switch...	1	7	4.65	1.54
SM4: I would not mind paying more for high quality...	1	7	5.43	1.23
SM5: I only buy products I trust.	1	7	5.26	1.40
SM6: Product quality is extremely important...	1	7	6.12	1.05
SM7: I am pleased about the way I look...	1	7	4.32	1.54
SM8: When I feel good about my looks, I am happier...	1	7	5.78	1.19
SM9: When I see a mirror, I "check myself out"...	1	7	3.90	1.75
SM10: Environmental considerations affect the products that I purchase.	1	7	4.43	1.52
SM11: I am concerned about climate change...	1	7	5.05	1.55

Note: SM refers to Shopping Motivation, so that SM1 refers to the first item on the Shopping motivation questionnaire (and so on). For the full SM items see Appendix C. SD = Standard Deviation.

Figure 3. Correlation matrix of the continuous independent variables and the dependent variable in the modelling sample. ‘Bag Buying’ where 1 = frequent bag purchasing and 0 = infrequent. The lower section of the matrix displays the Pearson r correlation coefficients. The upper section shows the significance levels where *p<0.05; **p<0.01; ***p<0.001. SM1: ‘I would rather stick to a brand I usually buy...’, SM2: ‘I enjoy taking chances in buying unfamiliar brands...’, SM3: ‘If I like a brand I rarely switch...’, SM4: ‘I would not mind paying more for high quality...’, SM5: ‘I only buy products I trust...’, SM6: ‘Product quality is extremely important to me...’, SM7: ‘I am pleased about the way I look...’, SM8: ‘When I feel good about my looks, I am happier...’, SM9: ‘When I see a mirror, I “check myself out”...’, SM10: ‘Environmental considerations affect the products that I purchase...’, SM11: ‘I am concerned about climate change...’

Figure 4. A graph to show the number of sales of single use plastic bags per 1000 items purchased in England each week by the survey sample ($N = 12,968$). Week 44 is the week of Halloween, week 48 the week black Friday occurred, and week 52 is the week of Christmas.

The distribution of plastic bag sales were then compared across different regions within the UK (see Figure 5). Northern Ireland had the highest percentage of bags per 1,000 items bought, followed by Scotland, Wales, and regions of North West England. Regions in the South West of England (Cornwall and Devon) people had bought the lowest number of bags per items. An ANOVA showed that these differences in the number of plastic bags purchased by region were significant ($F(11, 1210) = 8.8, p < 0.001, \eta_p^2 = 0.07$).

At a country level, bonferroni corrected t-tests showed that in England significantly fewer plastic bags were bought per 1,000 items than in Northern Ireland ($t(36) = -3.23, p < 0.001, d = 0.85$), Scotland ($t(115) = -4.03, p < 0.001, d = 0.65$) and Wales ($t(62) = -3.00, p < 0.001, d = 0.87$) but there were no statistically significant differences between the latter three countries. A multi-level model with random intercepts for store type showed that the significant country-level differences in plastic bag consumption remained when the types of store (i.e. chemist, high street (small or large), convenience,

or travel store) were accounted for ($F(3,1211) = 26.40, p < 0.001$).

Figure 5. A map of the UK showing in each region the standardised percentage of bags sold by the retailer per number of transactions in that region. The standardised bag sales were calculated using the full survey sample of 12,968 people.

Prediction Results

To investigate who frequently bought plastic bags, a logistic regression model was optimised on training data (see Methods section) to predict frequent and infrequent bag buyers in an unseen test dataset. The logistic regression, when tested on the 20% balanced unseen data ($N=930$), classified frequent bag buyers and infrequent bag buyers correctly in 67% of cases (F_1 score = 0.67). The model was equally good at classifying frequent and infrequent bag buyers (see Figure 6 for the confusion matrix).

When the model was fitted to the whole sample of data to extract variable importance, the McFadden pseudo R^2 value (McFadden et al., 1973) for the model was 0.13. Twenty-five variables were significant predictors of bag buying frequency with a threshold of $p < 0.05$. After the Benjamini–Hochberg false discovery procedure ($q=0.05$,

see *Methods* section) 10 of those remained significant predictors of frequent bag buying: Age (negatively), Average monthly spend (positively), Gender (Male positively), Frugality (negatively), Openness (positively), the question ‘I am pleased with the way I look’, and the self reported “home” geographical regions ‘West Midlands’, ‘North West’, ‘North East’, and ‘East Anglia’. The 10 predictors and their direct correlations with the dependent variable, standardised beta regression coefficients with 95% confidence intervals, and p -values can all be viewed in Table 3. Notably the two questions measuring environmental concerns were not significant, and neither were impulsivity measures. A full output of all the logistic regression features, their beta coefficients, and p -values can be found in *Appendix C*.

Figure 6. Confusion matrix for the logistic regression predicting the test data. 0 = infrequent bag buyers, 1 = frequent bag buyers.

Discussion

Until now very little has been known about the type of people who regularly buy plastic bags. This study used a mass transaction dataset linked to a personality questionnaire to profile the psychological and demographic predictors of regular plastic bag buying. As predicted, infrequent single-use plastic bag buyers were more frugal and spent less money in store, suggesting shoppers are motivated to go bag-free by saving money. Interestingly, and contrary to hypotheses, climate change concern did not predict single-use plastic bag purchasing - suggesting concern for the environment was not motivating the behaviour.

Table 3
Logistic regression model predicting frequent plastic bag buyers

	<i>Frequent plastic bag buyers</i>		
	pearson <i>r</i>	β coefficients and 95% CIs	Odds Ratio
Age (years)	-0.30	-0.60***[-0.70,-0.50]	0.96
Average monthly spend (£)	0.20	0.43***[0.35,0.51]	1.02
Gender: Male		0.21***[0.15,0.28]	2.15
Frugality	-0.16	-0.21***[-0.29,-0.13]	0.78
Openness	0.09	0.14***[0.06,0.22]	1.12
Region: West Midlands		0.12**[0.05,0.19]	1.68
SM7: I am pleased about the way I look	-0.04	-0.13**[-0.20,-0.05]	0.92
Region: North West		0.12**[0.04,0.19]	1.51
Region: North East		0.11**[0.04,0.18]	1.60
Region: East Anglia		0.10**[0.03,0.17]	1.68

*Note: Significance levels are * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. The coefficients reported in the table are the standardised β coefficients with standardised 95% confidence intervals. The pearson r squared is provided to show the correlation with the outcome variable for continuous independent variables only. The significant variables are ranked by the size of the absolute β coefficients. The beta coefficient represents the degree of change in the dependant variable for every 1-unit (standard deviation) of change in the predictor variable.*

It was additionally anticipated that a lack of self-control or heightened impulsiveness would play a role in people forgetting to take personal bags to the store - and hence would positively predict single use plastic bag purchasing. This was not the case, however high openness did. Overall the results highlight the differences between predicting environmental concerns and predicting a specific environmental behaviour in the real world.

Descriptives Discussion

Overall a very small sample of people were frequently buying plastic bags, with over half of the full survey sample having not bought a single-use plastic bag in the 9 months after the levy. This is very encouraging, and corroborates evidence from DEFRA (2018b) that the levy is working to reduce single use plastic bag consumption. Statistics on plastic bag use concentrate on bags bought from the top 7 supermarket chains (DEFRA, 2018b) and less is known about the bag sales from non-supermarket retailers. The findings suggest that the success of the levy in reducing single-use plastic

bags in supermarkets has extended to high-street health and beauty retailers.

In the 9 months following the levy, the sales of plastic bags per items bought significantly decreased. However, because the data did not extend to after the 9 months it could not be determined whether the trend was levy related or a seasonal bag purchasing trend (more around Christmas, and less in the summer). Consumers may be buying more plastic bags around Christmas for practical reasons, for example, they don't want others to see their gift purchases, to protect purchases from the weather, or it might make returns easier. Alternatively, the increase around Christmas could reflect a change in customers' psychological states. For example, greater present buying may lead to a greater focus on materialism, which could drive high consumption high throw-away behaviours. This is supported by average monthly spend being the strongest predictor after age of regular plastic bag consumption in the logistic regression model. Alternatively, people may be more stressed over the festive period, leading to greater disorganisation, and less planning of shopping trips. Overall, these findings suggest that plastic bag reduction campaigns targeted during the festive period could have considerably more impact than those targeted in the summer months.

The geographic distribution of the bag sales in the full sample, per number of items bought, showed evidence of a North-South divide in the UK. People in Northern Ireland, Scotland, the North West, and Wales purchase more bags than people in Southern regions. At a country level, England significantly had less bag sales per one thousand items than Northern Ireland, Scotland, and Wales. This shows the short-term effectiveness of the levy as an intervention in England, but highlights that an indifference to the levy in the other countries, which introduced the levy earlier, could have occurred. Wales introduced the 5p levy in 2011, then Northern Ireland and Scotland followed in 2013 and (October) 2014 respectively. National statistics showed a large decrease in bag sales in these countries initially post-levy (DAERA, 2018; Scottish Government, 2015; Welsh Government, 2016), but after a number of years the levels are significantly higher than that in England recently post-levy.

Some variants exist in the levies across the different UK countries in terms of

price, and also the type of bag the charges applied for. England, for example, was the only country where only *plastic* bags were charged, whilst for the other countries the levy applied to paper bags as well (Thomas et al., 2019). Still, it is possible the results indicate that the short term effects of the levy are much greater than the long term effects. In (southern) Ireland a plastic bag levy was introduced in 2002, and initially bag use reduced by 94% (Convery, McDonnell, & Ferreira, 2007). However, after the initial drop plastic bag use started to rise again (Clarke, 2014; Xanthos & Walker, 2017). The data may be showing some indication of an increased indifference to bag charges in Wales, Northern Ireland, and even Scotland just a year later.

Demographic Predictors

The logistic regression model used age as the greatest predictor, where younger people were more likely to be frequent single-use plastic bag buyers - replicating Poortinga et al. (2016)'s findings. This is contrary to the literature that finds younger people care more about the environment (Hines et al., 1987), but in line with the findings that suggest younger people are less likely to participate in pro-environmental behaviours (Arcury & Christianson, 1993; Honnold, 1984; Klineberg et al., 1998). It is suspected that the results can be explained by people who are older being better at planning ahead and bringing personal bags to the store. This corroborates previous research (Poortinga et al., 2016) suggesting that future plastic bag reduction efforts should concentrate on targeting younger people with interventions or plastic bag alternatives to make it easier to make a plastic free choice at the till. An increased focus on targeting young people and children will also help to ensure longer term societal change, as these are our future actors. Further, children can be important social influences on their peers, parents, and community (Hartley, Thompson, & Pahl, 2015).

It was expected that higher income would predict frequent plastic bag buying, as people with a lower income would be more motivated to save money. This was not the case, but it was found that spending more money in store positively predicted bag purchasing. This stands against literature suggesting that pro-environmentalists tend to

be middle or upper-middle class individuals (Balderjahn, 1988; Howard, Delgado, Miller, & Gubbins, 1993) and suggests the mechanism behind bag buying may be more dispositional (i.e. wanting to be frugal, or less materialistic/consumerist) than circumstantial (needing to save money). This may change however, as the government plan to increase the levy in price (DEFRA, 2018a), and retailers are already placing their own higher charges on plastic bags.

Environmental Concern

The ecological motivations for bag buying behaviour were evaluated using two questions: one on consumer environmental considerations, and the other measuring climate change concern. Contrary to hypotheses neither questionnaire items related to bag buying behaviour. This indicates a disconnect between peoples' concerns on climate change and the act of buying a plastic bag. Plastic consumption, until recently, has been viewed in the public sphere as a separate issue (one of littering) to that of greenhouse gasses causing global temperatures to rise (Royer, Ferron, Wilson, & Karl, 2018). Recent research has now connected the two environmental issues revealing that as light breaks down plastic, two of the most problematic greenhouse gases, methane and ethylene, are released (Royer et al., 2018). In research by Sun et al. (2017) it was stated as "obvious" that environmental concern predicts willingness to use plastic bags. However, the findings suggest that the relationship between environmental concerns and plastic bag consumption is more complex.

The questionnaire items used to measure environmental concerns were not selected for the sole purpose of studying plastic bag purchasing, and thus may not fully capture what it means to care about the environment (or not). In spite of this, it is significant that general climate change concern and a pro-environmental behaviour (reducing plastic bag waste) show no statistically significant relationship. This particularly highlights the dissociation between measuring environmental concerns and actual pro-environmental behaviour in the real world. Education on the relationship between plastic bag consumption and climate change could help reduce the number of

plastic bags being bought - as those concerned about global warming will be more aware of the detrimental effects, subsequently helping to fuel motivation to stop purchasing plastic bags.

Psychological Predictors

As hypothesised, frugality negatively predicted bag buying behaviour - reflecting economic and ecological motivations. Frugality, often seen as the antithesis of consumerism and materialism (Jackson, 2012), also reflects the values of an older generation/past-era of “make do and mend”, pre-dating the throw-away culture of today’s society. Honnold (1984) demonstrated that the miss-match between younger people showing more environmental concerns and older people partaking more in pro-environmental activities could be explained by era differences in society. This suggests that placing more value on thriftiness once again in society, particularly for the younger generations, could improve adherence to single-use plastic reduction strategies.

Our final prediction was that trait impulsivity (measured using BAS and self-control scales) would predict plastic bag consumption - where the more impulsive (and less self-control someone has) the more likely they would be to frequently buy plastic bags. It was reasoned that the propensity to plan ahead (synonymous with low impulsivity) is important for bringing personal bags to the store, and thus refusing plastic bags at the till. However, none of impulsivity, future focus, or self control indicators were significant in the prediction model. This may be in part because the frugality measure used in this study encapsulated forward thinking and planning (as well as thriftiness). For example, the question ‘there are things I resist buying today so I can save for tomorrow’ is tapping into immediate impulse control for a greater reward in the future. People who orient their thoughts towards the future are more likely to plan their shopping trips, increasing the likelihood of bringing personal bags to the store. Furthermore, holding the future in greater esteem than the present may lead future focused people to consider the effect of today’s actions on tomorrow’s environment, in line with theory of psychological distance (Spence, Poortinga, & Pidgeon, 2012).

Despite the literature finding that traits openness, conscientiousness, agreeableness, and neuroticism significantly predict environmental concern and engagement (Hirsh, 2010; Milfont & Sibley, 2012), the results showed that only openness significantly predicted plastic bag buying. The results showed that people who are open to new experiences are *more* likely to frequently buy plastic bags - the opposite to what was expected from the literature (which finds individuals high in openness to be more concerned and engaged with the environment). This difference could be either because there is something uniquely different about plastic bag buying and its drivers, compared to other ecological activities; or because this study measured a real world behaviour, and this is somewhat removed from self-reported behaviours and measures of environmental concern/engagement (Kormos & Gifford, 2014). As environmental concerns themselves were not predictive of the bag buying behaviour, it is imagined that the latter is a more likely explanation. This has implications for policies which are informed by research using self-reported behavioural measures.

It was suspected that the facets of openness most predictive of bag buying are those tapping into impulsiveness, rather than intellect and liberalism (McCrae, 1993). This is supported by the positive correlation between openness and BAS in the data (see Figure 3). However, facet level openness was not measured, and it is recognised that there are limitations in using the low resolution measure of the big five (TIPI) (Gosling et al., 2003). Thus, this is highlighted as an area which would benefit from further investigation. Despite this limitation, the results suggest that strategies for reducing plastic bag purchasing could benefit from making reduced consumption novel, exciting, cutting-edge, and of great importance - appealing to shoppers high in openness.

An unexpected finding was that frequent bag buyers rated themselves as being less pleased with how they look (an item on the shopping motivation scale - see Appendix A for a full set of the questions) compared with infrequent bag buyers. In the data, people who were not happy with how they look had lower well-being, lower self-control, and were also more neurotic (see the correlations in Figure 3). Interestingly, this single question about appearance appears to capture a broader sense

of dissatisfaction with oneself and a lack of self-efficacy (which has been shown to be important for engaging in environmental behaviours (Axon, 2017; Van der Linden et al., 2015)). This questionnaire item being a significant predictor of bag buying was an interesting surprise result - one of the advantages of the inductive exploratory approach (not being constrained by the use of theory for model specification) that was harnessed in this study. Further research could look further into the effect image dissatisfaction has on other pro-environmental and pro-social behaviours.

Methodological Discussion

Using a mass transaction dataset to study human behaviour allowed for the examination of the predictors of a specific ecological behaviour in the real world. The inductive approach utilised in this study can be both hypothesis generating as well as testing. Considering a large number of potential explanatory features, while directly guarding against overfitting and procedural p-hacking, expanded the opportunity for knowledge discovery and reduced the likelihood of an unmeasured confounding variable affecting the results and their interpretation (Julious & Mullee, 1994) (see *The Simpson's Paradox* (Simpson, 1951)). Overfitting and procedural p-hacking was mitigated through the use of cross-validation in conjunction with regularisation and recursive feature elimination. This methodology directly measures the reported relationships' ability to generalise, helping to ensure that the effects are more than just an artefact of the sample (Yarkoni & Westfall, 2017). Statistical significance of variables were then considered, whilst directly controlling for the large number of variables through the use of the Benjamin-Hochberg false discovery procedure. As human interactions with the world are so complex, an almost infinite number of variables can influence behaviour. Thus, in using real world data, smaller effect sizes were found, as expected (Matz, Gladstone, & Stillwell, 2017), compared to those that come from a controlled lab-based experiment.

There is great potential for big data to reveal previously undetectable insights about sub-groups underrepresented in society, or behavioural change over time.

However, there is also the danger, if treated the same as small data, of over-fitting models and extracting false or inaccurate insights. There is a difference in extracting variable importance for prediction rather than for explanation (Grömping, 2009). For example, impulsivity may have not been a significant predictor of bag buying (as hypothesised) because of its negative correlation with age, and age's strong positive effect on bag buying. In the regression it is likely that age is masking the effect of its correlates (impulsivity, self-control, shopping impulsivity, agreeableness, and neuroticism) (see Figure 3). Depending on the end goal, such variables could be reduced to a latent factor or principle component to improve prediction power (at the loss of fine grain information) (Harrell Jr, Lee, Califf, Pryor, & Rosati, 1984); or modelled using Directed Acyclic Graph (DAG) Bayesian networks (Nielsen & Jensen, 2009) or Structural Equation Modelling (SEM) to try to unpick the exact causal pathways.

How decisions get made in the real world necessitates that policy makers work with a simple and useful model, as they need to trust and understand the information on which they are basing key decisions. In such cases, finding a few key predictors is often more worthwhile than modelling a complex network of interrelated features. Thus the zero-order correlations in Figure 3 could be useful for practical applications when cost:benefit ratios need to be considered. For example, despite age and frugality being related, by incorporating domain knowledge and judgement it is concluded that age is more useful for *targeting* individuals than frugality (but it cannot be changed through interventions, like thriftiness potentially can). Age has a greater correlation coefficient with the dependent variable; trait levels are harder to detect within people, yet age is instantly observable; and if one causes the other, it is age than causes increased frugality, not the other way around (Roberts, Walton, & Viechtbauer, 2006; Specht, Egloff, & Schmukle, 2011). Yet, age cannot be manipulated through interventions in the same way thriftiness potentially can. Thus, the interaction between the variables also becomes important if interventions are to be targeted towards particular sub-groups of people in the real world.

Overall, this paper argues that big data is an important addition to the study of

human behaviour in Psychology. However, researchers must utilise the appropriate methods of model specification and evaluation (such as K-fold cross validation and out of sample testing), to ensure models do not over-fit. This may require the use of non-traditional psychological methods or statistics (Breiman et al., 2001), but will help to minimise false positives and ensure the findings that emerge are replicable and generalise to a wider population.

Summary

Bans and levies are not the only mechanisms to reduce single use plastics (Xanthos & Walker, 2017) - knowing whom and how best to target people is important to avoid a plateau, or future increases, in bag sales, as observed in Ireland (Clarke, 2014). This study has highlighted predictive features of regular bag buyers: namely being younger, spending more, being male, less frugal, high in openness, and being displeased with their appearance. Notably environmental concerns were not significant predictors. This profile is dissimilar from that of pro-environmental individuals in the literature and suggests that bag buying behaviour results less from concerns over global warming, and more from the ability to translate an intention to a behaviour. This is likely due to the forwards planning required for bringing personal bags to the store (Sun et al., 2017). It is also suspected that the bag buyers are more materialistic and consumerist as they spent more money in store and rate themselves lower in frugality. Whether these effects are caused by age or just correlates is not explicitly tested here, but is less important when identifying subgroups such as 'young people' for future campaigns to target.

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Appendix A

Link to the full survey

A copy of the full survey that was sent to participants can be found here: «removed for anonymity during review».

Appendix B

Meta-Parameters

The meta (or *hyper*) parameter values considered in the grid search for the logistic regression were: the type of regression (characterised by different loss functions and regularisation schemes); the cost (or 'C'); and the tolerance (epsilon). The grid search iterated through the following values for each meta parameter. For the type of regression: L2-regularised logistic regression (primal), L2-regularized L2-loss support vector classification (dual), L2-regularized L2-loss support vector classification (primal), L2-regularized L1-loss support vector classification (dual), L1-regularized logistic regression, and L2-regularized logistic regression (dual). Different cost values were: 1,2,3,4. The different tolerance values were 0.0001,0.001,0.01,0.1,0.5. This grid was finalised after ensuring that a value at either end of the grid, for any of the parameters, had not been selected (so the algorithm was not being limited by the parameter values being manually provided).

Appendix C

Full results table

Table C1

Full results table from the logistic regression model predicting frequent bag buying. Table ordered by p-value from low to high.

	Independent Variables	Beta coefficient	p-value
1	Age	-0.600	0
2	Average Monthly Spend (£)	0.430	0
3	Gender: Male	0.210	0
4	Frugality	-0.210	0
5	Openness	0.140	0.001
6	Region: West Midlands	0.120	0.001
7	SM7	-0.130	0.001
8	Region: North West	0.120	0.002
9	Region: North East	0.110	0.002
10	Region: East Anglia	0.100	0.004
11	Shopping frequency: Every day	-0.090	0.007
12	Agreeableness	0.090	0.011
13	Region: London	0.080	0.019
14	SM6	0.090	0.020
15	Shopping frequency: Once in 2-3 months	-0.080	0.021
16	Income: Prefer not to say	-0.100	0.025
17	Shopping frequency: Once a month	-0.080	0.027
18	BAS-RR	0.100	0.030
19	Live with: Solo, children	0.080	0.032
20	Marital status: Divorced	0.080	0.036
21	Qualification: GCSE	0.090	0.037
22	Income: £150,000 or more	-0.070	0.038
23	SM9	0.070	0.046
24	Region: Yorkshire	0.070	0.047
25	Time preference: £40 now, not £70 in 3 months	0.100	0.049
26	Region: South East	0.070	0.054
27	Marital status: Widowed	0.060	0.066
28	Qualification: School	0.070	0.074
29	Marital status: Other	0.060	0.091
30	Shopping frequency: Twice a week	0.060	0.091
31	SM2	0.070	0.094
32	SM11	-0.070	0.096
33	Occupation: Skilled manual worker	0.060	0.110
34	Region: Wales	0.060	0.118
35	Live with: Partner, children	0.060	0.121
36	Region: East Midlands	0.060	0.125
37	SM3	0.060	0.127
38	Qualification: Postgraduate	0.060	0.143
39	Region: Northern Ireland'	0.050	0.153
40	Shopping frequency: More than twice a week	0.050	0.167
41	Card usage: Never	0.070	0.169
42	Occupation: self-employed/own business	0.050	0.175
43	Marital status: Single	-0.060	0.183
44	SM4	0.050	0.192
45	Qualification: PhD	-0.040	0.205
46	SM5	0.050	0.208

	Independent Variables	Beta coefficient	<i>p</i> -value
47	Time preference: £55 now, not £70 in 3 months	0.050	0.243
48	Card usage: Hardly ever	0.040	0.267
49	Well-being	-0.040	0.270
50	Extroversion	0.040	0.307
51	Qualification: AS-level	-0.030	0.314
52	Qualification: A-level	0.040	0.316
53	Shopping Impulsivity	0.050	0.317
54	Region: Scotland	0.040	0.318
55	Region: South West	0.030	0.319
56	Income: £35,000 to £49,999	-0.040	0.351
57	Occupation: Retired/Semi-retired	-0.040	0.357
58	Occupation: Full-time carer of other household member	0.030	0.392
59	SM1	-0.040	0.413
60	Shopping frequency: Every 6 months or less	-0.030	0.432
61	Qualification: Advanced	-0.030	0.440
62	Occupation: Homemaker	0.030	0.474
63	Occupation: Casual worker	0.020	0.508
64	Income: £25,000 to £34,999	-0.030	0.527
65	Card usage: Most of the time	0.020	0.568
66	Live with: Adults (non-family)	0.020	0.571
67	Live with: Adults (family)	0.020	0.620
68	Qualification: BTEC	0.020	0.636
69	Shopping frequency: Once every 4-6 months	-0.020	0.644
70	Income: £50,000 to £74,999	-0.020	0.647
71	Card usage: Sometimes	-0.020	0.651
72	Qualification: Masters	0.020	0.659
73	Marital status: Separated	-0.010	0.672
74	Emotional Stability	-0.020	0.672
75	Time preference: £25 now, not £70 in 3 months	-0.020	0.686
76	Occupation: Unemployed/long-term sickness	-0.010	0.701
77	BAS-D	-0.020	0.709
78	Occupation: Other	0.010	0.715
79	Occupation: Semi/unskilled manual work	0.010	0.716
80	Income: £100,000 to £149,999	-0.010	0.721
81	Conscientiousness	0.010	0.726
82	SM10	0.010	0.731
83	Occupation: Higher managerial/professional/admin.	0.010	0.769
84	Occupation: Student	-0.010	0.782
85	Self-control	-0.010	0.795
86	Occupation: Supervisory/clerical/junior manager./admin	0.010	0.824
87	SM8	0.010	0.835
88	Qualification: Other	0.010	0.851
89	Income: £75,000 to £99,999	0.010	0.888
90	Shopping frequency: Once a week	0	0.902
91	Shopping frequency: Don't know	0.090	0.904
92	BAS-FS	0	0.933

Note: Significance levels and beta coefficients are rounded to three decimal places. Shopping motivation (SM) questions: SM1= 'I would rather stick to a brand I usually buy than try something I am not very sure of.' SM2= 'I enjoy taking chances in buying unfamiliar brands just to get some variety in my purchases.' SM3= 'If I like a brand I rarely switch from it just to try something new.' SM4= 'I would not mind paying more in order to get a high quality product.' SM5= 'I only buy products I trust.' SM6= 'Product Quality is extremely important to me.' SM7= 'I am pleased about the way I look.' SM8= 'When I feel good about my looks, I am happier and have a better outlook on life.' SM9= 'Whenever I see a mirror, I "check myself out" to see how I look.' SM10= 'Environmental considerations affect the products that I purchase.' SM11= 'I am concerned about climate change (also known as global warming).'