The Role of Self-Congruity in Consumer Preferences: Perspectives from Transaction Records

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Declaration

I, Cui Ling Lay, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

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Abstract

Personalised marketing is more persuasive than traditional techniques aimed at the masses, however marketers do not always have access to consumers' private attributes in order to apply these insights. The effect of personalisation is based on an established theory in consumer psychology – self-congruity theory – which posits that individuals prefer products, brands and advertisements that embody characteristics that match with their self-concepts. Self-congruence not only enhances marketing effectiveness, it can also be used to improve consumer well-being. While it has been established that consumers who spend in a way that is more congruent with their personality are happier, clarifications around the types of individuals who are more or less likely to engage in self-congruent spending, as well as the moderating effects on the benefit in happiness from such consumption could inform policy for improving happiness at a collective level.

This thesis contributes to a growing body of research which attempts to understand how consumption patterns are related to consumers' characteristics, its applications in advertising, as well as consumer well-being. By using a dataset containing more than 1 million transactions recorded over a period of 12-months, the thesis demonstrates the value of the digital footprint in the form of bank transactions for enriching our understanding of key questions in consumer research, underpinned by the theory of self-congruity. This thesis combines methods from computational social science with personality psychology to test research questions on consumer preferences. Two components of the thesis focused on the predictive utility of transaction records in inferring consumer attributes with which to personalise advertising, as well as the use of transaction records in examining self-congruence in overall consumption patterns and its relationship with happiness.

Through five empirical studies, this work suggests that consumer attributes such as age and financial distress can be reliably inferred from consumption patterns reflected in transaction records (Chapter 3 and 5). The inferred age can be used to personalise advertisements in order to increase their appeal (Chapter 4). Using an objective measure of self-congruence in overall consumption pattern computed from transaction records and panel ratings, the thesis shows that individuals differ in their tendency to spend in a way that is congruent with their

personality based on their levels of materialism and financial distress (Chapter 6). As the most important predictor of self-congruent spending, financial distress moderates the relationship between self-congruent spending and happiness (Chapter 7). These findings contribute insights into how consumption patterns are related to consumer attributes and usefulness for personalisation in marketing, as well as policy recommendations for improving well-being by targeting consumption patterns in financially distressed individuals. In addition, this thesis also showcases the value of machine learning and large-scale behavioural field data in the study of consumer psychology. Privacy and ethical concerns surrounding automated profiling and microtargeting are also cautioned.

Impact Statement

This thesis meaningfully contributes to the field of consumer psychology by showing that transaction records can offer new insights to key questions around attribute inference, personalised advertising and self-congruence in consumption patterns. Crucially, it advances the increasingly more prominent use of big data and machine learning in the pursuit of consumer insights, by demonstrating the value of such methodology over traditional approaches which are limited by a reliance on self-reported measures of consumption behaviour, low statistical power, risk of overfitting and small sample size. In particular, two key methods are used. First, machine learning models are employed to infer consumer attributes (i.e., age, financial distress). Second, in the investigation of self-congruence effects, an objective measure of self-congruence in overall consumption patterns is computed using a comprehensive record of consumers' spending across different categories, matched with panel ratings of these spending categories' personality. By applying computational methods on large-scale behavioural field data in the examination of consumer phenomena, this thesis successfully builds on the growing body of research bridging the largely separate discourse in psychology and computer science research.

In terms of practical relevance, this thesis shows that one of the most commonly used attributes for personalising advertising – age – can be accurately inferred from transaction records and then used to target consumers with tailored advertisements. This is useful to marketers interested in increasing the appeal of their advertisements. This thesis also provides evidence that subjective feelings of financial distress can be inferred from transaction records with a moderate degree of accuracy. This could be instrumental for policymakers interested in identifying vulnerable individuals and providing them with assistance which may alleviate their negative feelings associated with their financial circumstances, thereby preventing adverse downstream consequences. Further, the thesis also reveals that not only are individuals experiencing financial distress less likely to spend in a way that is congruent with their personality, the increase in happiness from self-congruent spending is more pronounced for these individuals. Thus, these results could inform policy recommendations aimed at increasing self-congruence in overall consumption patterns amongst those who are experiencing financial distress, in order to improve their well-being.

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Chapter 1 – Scope of Thesis

Personalisation increases the persuasive appeal of advertisements. According to self-congruity theory, individuals prefer brands, products and advertisements they consider to be aligned with their self-concept (Kamins, 1990; Sirgy, 1982; Wright, 2016). However, the applicability of insights regarding the persuasive power of personalised advertising is restricted by marketers' limited access to the characteristics of their consumers as well as the accuracy of such information. In order to maximise the potential of personalised advertising, marketers need to first acquire accurate information about consumers' characteristics at scale, and then tailor advertisements to fit with these attributes. Attempts to directly bridge these two processes are rare. While the idea of self-congruity is useful for increasing advertising effectiveness through trait-based personalisation, there is evidence to suggest that self-congruence in consumption plays an important role in consumers' well-being. However, a majority of previous studies assessing self-congruence in consumption have utilised self-reported measures of congruence between a brand and a person, limiting the external validity of such findings. These gaps in the literature can be effectively addressed with novel research methods enabled by advances in big data analytics.

The recent development in the ability to collect, store and analyse data at an unprecedented scale has opened up opportunities for scholars of different fields to formulate new research questions and test them with methodologies that were previously infeasible or impractical. Within the area of consumer psychology, this means that it is now possible for researchers to derive valuable insights into millions of consumers by observing the digital records that are passively and unobtrusively left behind by consumers as they go about their daily lives (Matz & Netzer, 2017). Transaction records provide a comprehensive view of consumers' actual consumption patterns, a measure arguably superior to traditionally used self-reported purchase behaviours which implies purchase intention. As the central focus of this research is to illuminate consumer psychology through consumption patterns, a dataset of over one million passive records of outgoing bank transactions will be used throughout this thesis. Having access to this data allows this research to circumvent some of the limitations of traditional approaches to gather 'human-centric' data about individual consumers in psychology research, including difficulty in scaling, small sample size, and lack of generalisability (Adjerid & Kelley, 2018; Chang et al., 2014; Oswald, 2020; Yarkoni & Westfall, 2017). Due to the large sample size and breadth of variables, this dataset requires computational methods to analyse it effectively that are rarely used within academic psychology or consumer research.

Part 1 – Literature review

The current thesis, therefore, is structured as follows. Part 1 presents an overview of the thesis, and the literature review that outlines the background and rationale of this research. Chapter 2 presents a literature review which outlines of the role of individual differences in consumer behaviour and provides an overview of self-congruity theory. It also details three key areas of research related to self-congruity, particularly the inferences of consumer characteristics, the role of self-congruity in personalised advertising and consumer well-being. The chapter appraises the traditional methods of collecting consumer data, followed by a critical review of the opportunities and challenges offered by the digital records of bank transactions in the investigation of consumer behaviour. Finally, Chapter 2 concludes with the research questions to be explored in the thesis, and an overview of the empirical studies aimed at answering them.

Part 2 – Empirical Studies

Part 2 presents five empirical studies aimed to address the gaps identified in the literature review. The empirical investigation comprised of two components: first, automatic inference of consumer characteristics and personalised advertising, and second, examination of self-congruence effects in overall consumption patterns from transaction records.

The first component assessed the extent to which attributes can be inferred from transaction records and the practical utility of such inferences for personalised advertising through three studies in Chapter 3 to 5. The limited access to accurate consumer attributes which poses as a challenge for marketers interested in personalising advertisements can be overcome with automatic inference of consumer characteristics from their digital footprint at scale using a machine learning model. However, the fixation of existing studies on inferring *Big Five* *personality traits* using *social media data* (see for Azucar et al., 2018 for a meta-analysis) means that how other aspects of consumer self-concept (i.e., demographics and other malleable traits) manifest themselves in different behavioural cues have received little empirical attention in the past. Furthermore, while there are a considerable number of studies investigating the effectiveness of personalised advertisements using actual or inferred traits (e.g., Alhabash et al., 2020; Higgins et al., 2018; Matz, Kosinski, et al., 2017; Roy et al., 2015), there is an apparent gap in studies directly bridging inference of consumer traits and personalising advertisements.

In light of the under-utilisation of transaction records in the investigation of automatic attribute inference using machine learning models (Gladstone et al., 2019), **Chapter 3** explores the potential of bank transactions in predicting consumer's chronological age. This study chooses to focus on inferring consumers' chronological age as it relates to life events that define one's identity (Chamberlain et al., 2017). A follow-up experiment in **Chapter 4** was then conducted to test the extent to which this inferred chronological age can be used to guide personalised advertising, by testing how consumers may react more or less favourably to advertisements tailored to their inferred chronological age using the machine learning model. The focus on Big Five personality in automatic profiling studies also meant that there is a dearth of studies inferring less-stable characteristics from the digital footprint, such as subjective feelings of financial distress. **Chapter 5** sets out to test the potential of transaction records in predicting financial distress. Financial distress was chosen as the focal attribute for inference as it causes severe negative consequences (Glei et al., 2018; Kerr et al., 2017; Sweet et al., 2013), while the taboo around the topic makes it difficult for people to seek urgent help (Starrin et al., 2009).

The second component responded to the limitations of self-reported questionnaires of self-congruence in previous studies by examining self-congruence effects through an objective measure of self-congruence in consumption reflected from transaction records and panel ratings. Transaction records offer a more objective way to measure self-congruence which is able to account for a consumer's overall consumption pattern. While the literature in authenticity suggests that people can differ from each other on the extent to which they behave congruently to their beliefs, values and dispositions (Jongman-Sereno & Leary, 2020;

Wood et al., 2008), evidence on the factors influencing individuals' ability to spend in ways that are congruent with their personality remains rare. In view of this, **Chapter 6** explores the potential correlates of self-congruence in overall consumption, namely chronological age, self-control, materialism and financial distress. Findings demonstrating that spending in ways that fits with one's personality can bring about an increase in happiness (Matz et al., 2016; Petersen et al., 2018; Zhang et al., 2014), but research on the potential moderators of this effect is lacking, which can have important implications for improving policy recommendations. With evidence suggesting detrimental effects of financial distress on well-being, **Chapter 7** investigates whether self-congruent consumption may help those more financially distressed to gain greater happiness than those who are less financially distressed.

Part 3 – Discussion

Part 3 summarises the results of the thesis and its implications. Chapter 8 offers a general discussion of the empirical findings of this thesis, drawing comparison to existing research. This chapter also presents the theoretical and methodological implications of the findings, ending with a discussion of managerial applications as well as ethical concerns that may result from the methods as well as this line of enquiry in psychology.

Chapter 2 – Literature review

Chapter 2 Summary

The chapter begins by outlining the role of individual differences in consumer psychology, and the theory of self-congruity which underpins the relationship between individual differences and consumer behaviour. It appraises the traditional methodologies used in consumer research highlighting the key limitations. As the advancement in technology has allowed people's consumption patterns to be recorded digitally in the form of bank transactions at an unprecedented scale, opportunities are now available to researchers to study consumer behaviour using novel sources of data coupled with more advanced analytical methods. A critical review of the opportunities and challenges offered by the digital records of bank transactions in the investigation of consumer behaviour is outlined. Previous research has shown it is possible to infer individual differences from a variety of digital footprints, highlighting the opportunity for the use of bank transactions in expanding our current understanding of how consumer characteristics may be linked to their consumption patterns. For consumer research to be useful to practice, it is crucial to show practical relevance of individual differences and the concept of self-congruity in altering consumer behaviour in a way that may benefit both marketers and consumers. To this end, two particularly interesting areas are examined: personalised advertising effectiveness and consumers' subjective well-being. The role of self-congruity in personalising advertisements and the relationship between consumption and happiness is outlined, and empirical evidence in these areas is reviewed. This chapter concludes with an overview of the empirical studies which are aimed at answering the gaps identified in this chapter.

2.1 – Individual Differences and Consumer Behaviour

Individual differences play a non-negligible role in determining a range of behaviour and life outcomes (Chamorro-Premuzic & Furnham, 2003; Judge & Kammeyer-Mueller, 2007; Roberts et al., 2007; Shiner et al., 2003). People's consumption and spending behaviours, just like people's behaviours in other domains in life, are influenced by the psychological traits of these individuals (Goldberg, 1976; Wells, 1975). The investigation of consumer characteristics has a long-standing tradition in consumer behaviour research, dating back to 1960s (Grubb & Grathwohl, 1967). Individual differences are "the more-or-less enduring psychological characteristics that distinguish one person from another" (McCrae, 2007, p. 472). These characteristics are the internal and private attributes, abilities, beliefs that make an individual unique, special and different from others (Cross et al., 2003). While some traits may be stable or resistant to change over time (e.g., age, gender, culture, race), some are more adaptive and more malleable (e.g., depression, self-monitoring, learning style (Williamson, 2018).

The incorporation of individual differences in consumer psychology has led to several significant developments in marketing research such as the conceptualisation of psychographics (Wells, 1975) and customer segmentation (Marcus, 1998), which have revolutionised the way marketers advertise, in order to cater to the specific needs of their target customers. There has been a plethora of research demonstrating differences in consumption patterns and brand preferences which vary as a function of individual differences. For instance, men scoring higher in neuroticism preferred "Trusted" brands, while the same brands are preferred by women who are highly conscientious (Mulyanegara et al., 2009). Furthermore, it has been established that cognitively, emotionally and behaviourally, consumers tend to exhibit more positive responses to brands, goods or advertising messages that are aligned with their identities or psychological characteristics (Aaker, 1999; Hirsh et al., 2012; Sirgy, 1985; Wheeler et al., 2005).

2.2 – Self-congruity Theory

A key theory used to explain the links between consumers' characteristics and their consumption is self-congruity theory (Sirgy, 1982). Consistent with the findings demonstrating the role of individual differences in consumer behaviour is the notion that the nature of consumption has become increasingly psychological (Dittmar & Beattie, 1998). In the postmodern society, there is a marked shift in the significance of, and motivations for, buying consumer goods. The former focus on purchasing products to fulfil physical needs has shifted toward using consumer goods as symbols (Solomon, 1983), a way of acquiring, expressing and building one's self-identity (Dittmar, 1992). In other words, people consume not only for economic and practical reasons, but also to fulfil psychological needs (Arnould & Thompson, 2005; Belk, 1988; Levy, 1959).

Previous to the introduction of self-congruity theory, the majority of the approaches that explained consumers' attitudes towards brands and products focused on their utility and performance-related attributes (Sirgy et al., 1991). The self-congruity theory thus addresses the neglect in symbolic or value-expressive attributes by offering a way to model and predict brand attitudes which encompasses both utilitarian and value-expressive attributes (Sirgy et al., 1991). To describe this phenomenon, self-congruity theory proposes that consumers prefer brands and products that they deem to contain personality traits that are congruent with their own (Kassarjian, 1971; Sirgy, 1982). According to self-congruity theory, consumers make comparisons between their perception of a brand image and their own self-concept, and evaluate whether or not the brand is for them, based on how likely it enables their self-concepts to be maintained, reinforced, or enhanced (Sirgy, 2018a). For example, consumers may consider customers of Starbucks as "trendy" and they may also perceive themselves as being "trendy". Hence, there is a match between the brand-user image and consumer's self-concept. On the other hand, there is a mismatch if they do not self-identify as being "trendy". Thus, self-congruity refers to the degree to which consumers identify with the brand, or the users of the brand.

Decades of research in self-congruity effect demonstrate that individuals' preferences across a wide range of domains are associated with their personality. People are more likely to have friends on Facebook that are psychologically similar to them (Youyou et al., 2017), to live in a residential neighbourhood with characteristics that match their psychological needs (Jokela et al., 2015; Rentfrow & Jokela, 2016), to favour the music of artists whose publicly-observable and computer-predicted personality traits are similar to their own (Greenberg et al., 2020). Within the material domain, research has also consistently demonstrated that self-congruity significantly impacts consumption behaviour at different stages of a consumer's life cycle (see Sirgy, 2018a for a review). A meta-analysis of 262 studies in self-congruity found that a match between a brand's user image or personality and the self-concepts of its consumers resulted in consumption-related outcomes at a moderate effect size of $r = .31$ (Aguirre-Rodriguez et al., 2012). The findings indicate that self-congruity effect is robust as it explains approximately 10% of the variance in consumer attitudes, intentions and behaviours, a magnitude which is comparable to other consumer behaviour phenomena (Cohen, 2013; Peterson et al., 1985).

Self-congruity has been found to be associated with a myriad of consumer behaviours, for instance, brand attitude (Liu et al., 2012), purchase intention (Ericksen, 1997; Yu et al., 2013), brand choice (Beerli et al., 2007; Hung & Petrick, 2011; Litvin & Goh, 2002) and brand loyalty (Das, 2014; Liu et al., 2012; Sirgy et al., 2008), as well as marketing success such as promotion effectiveness (Close et al., 2009). Generally, when there is a match between a consumer's self-image and a brand user image, consumers show stronger preferences (Ericksen & Sirgy, 1992), perceive these brands to be of higher value (Baker et al., 2020), evaluate them more positively (Hosany & Martin, 2012; Üner & Armutlu, 2012), be more satisfied with the brands (Aguirre-Rodriguez et al., 2014; Ericksen & Sirgy, 1992; Krishen & Sirgy, 2016), be committed to repurchasing the same brand (Chebat et al., 2009; Kressmann et al., 2006; Yim et al., 2007), and promote the brand to others (Chebat et al., 2010). The effect has also been consistently demonstrated across different cultures (He & Mukherjee, 2007; Kang et al., 2012; Quester et al., 2000), and in a wide range of areas, including retail store choice (Willems & Swinnen, 2011), tourism (Boksberger et al., 2011), the housing market (Sirgy et al., 2005), and even career choice (Nolan & Harold, 2010).

Dimensions of Self-image, Self-concept Motives and Self-congruity

According to Sirgy (1982), self-congruity is multidimensional, comprising of four components: actual self-image, ideal self-image, social self-image and ideal social self-image, each corresponding to four self-concept motives, resulting in four self-congruity (see Table 2.1). When consumers engage in a process of evaluation about goods and services, all four dimensions of the consumer self-concept offer a referent point for comparing and evaluating the appeal of a brand-user image. Self-congruity satisfies self-concept needs, and it is through this that self-congruity exert its impact on how consumers perceive value in pre- and post-consumption stages (Sirgy, 2018a).

Table 2.1 *Dimensions of consumer self-concept, motives and congruity*

	Self	Social
Actual	Actual self-image *(Self-consistency)* Actual self-congruity	Social self-image *(Social consistency)* Social self-congruity
Ideal	Ideal self-image *(Self-esteem)* Ideal self-congruity	Ideal social self-image *(Social approval)* Ideal social self-congruity

Note. Table taken from Sirgy (2018a)

Actual self-congruity is the fit between the brand-user image and the consumer's actual self-image – an assortment of attributes that represents how the consumers truly see themselves (Sirgy, 2018a). The underlying motive is the need for self-consistency which steer consumers into making decisions that are in line with their personal identities (Epstein, 1973; Sirgy, 1986). This motivation is greater especially in consumers who strongly believe in their own identities (Burke & Stets, 2009; Gregg et al., 2011; Sedikides & Strube, 1995). People are inclined to consume commodities that offer them ways to consolidate and validate their personal and social identity, while they avoid those incongruent with their actual self-image which may lead to cognitive dissonance (Festinger, 1957; Sirgy, 1982). Individuals strive to seek confirmation for their current self-perceptions (Swann et al., 1992), which leads to a boost in their self-esteem, facilitation of social interactions, and generation of favourable responses towards the object of evaluation (Sirgy, 2018a). Conversely, a lack of verification of one's self-concept may cause negative affect (Cho & Kim, 2012).

Ideal self-congruity occurs when the following are aligned: the brand-user image and ideal self-image – the set of image attributes that represents how consumers would like to see themselves or what they aspire to be (Hong & Zinkhan, 1995; Malhotra, 1988). Generally, people are drawn to brands or products that augment their sense of self and avoid diminishing of their selves (Sirgy, 2018a). Driven by a motivation for self-enhancement, consumers tend to evaluate products and services more favourably when they perceive them to embody the desirable traits that are consistent with their ideal self-image. They are also more likely to purchase and consume goods and services which they perceive to have the capacity to help them realise their ideal self, and in so doing, serves to boost their self-esteem.

As consumers' characteristics do not exist in a vacuum and are embedded within social contexts, congruity is highly relevant to not only self-image and ideal self-image, but also social self-image and ideal social self-image. Social self-congruity refers to the alignment between consumers' *social self-image* – how consumers believe they are being perceived by significant others – and the brand-user image (Sirgy, 2018a). Finally, ideal social self-congruity is the match between their *ideal social self-image* – how consumers wish to be seen by others – and the brand-user image. The social dimension of selves stems from individuals' identification with different groups and social network that they are part of (e.g., Reed, 2004; Reed et al., 2012). Crucially, the salience of a consumer's social identity becomes stronger as their social network takes on a more central role in their self-concept and becomes more accessible. Some examples of salient social identities include gender, race, religion, occupation, hobbies and activities, all of which are related to demographics and personality to different degrees (Garza & Herringer, 1987). When social identities are reinforced by a newly acquired product, it heightens a consumer's sense of identification with the social groups associated with these identities (Sirgy, 2018a). Similar to personal identity, a lack of reinforcement of social identity can also result in negative emotions such as anxiety and distress (Hung & Petrick, 2011; Sirgy & Samli, 1985).

The widespread usage of the self-congruity theory in explaining various consumer behaviour and outcomes showed that it is a robust framework for understanding consumer preferences. For this reason, it will form the basis of the theoretical framework used throughout this thesis.

2.3 – Inferring Consumer Characteristics

Self-concept comprises different aspects of the self (Malhotra, 1988; Sirgy, 1982), including "one's attitudes, feelings, perceptions, and evaluations of oneself as an object" (Grubb & Grathwohl, 1967, p. 24). How consumers make decisions is intricately linked to different parts of their self-concept, such as their personality, demographics and other psychological attributes (see Section 2.1). Consumers tend to prefer and respond more favourably to products and services that are in line with their self-concepts (Sirgy, 2018a). This makes identifying consumer characteristics an important aspect of an effective marketing strategy. However, consumers' characteristics are not readily accessible by marketers, in particular, private attributes such as personality, attitudes towards products that are not immediately visible in real life or virtual environment. While obtaining information about some demographic attributes (e.g., gender, ethnicity, approximate age group) may be possible to a certain extent if individuals voluntarily share this information, it is often kept private and rarely available. Further, if individuals try to conceal their identity, or pretend to be someone else through their user-generated content on social media, the task of accurately inferring attributes becomes much more difficult (Hinds & Joinson, 2018). Therefore, methods aimed at predicting consumers' attributes based on actual purchasing data offer an opportunity for marketers to infer consumers' attributes from any types of digital footprint that is available, even when such attributes are not readily available.

Consumer characteristics have been considered one of the most important information for companies and marketers to understand the preferences and behaviours of their target customers. First introduced by Smith (1956), market segmentation has quickly become an integral part of modern marketing. It aims at identifying the distinct categories of consumption patterns by splitting a market into several homogenous submarkets (Lin, 2002), which could be based on personality, demographics and other psychological attributes such as values and lifestyle. While early studies in acquiring information about consumer characteristics have relied predominantly on self-reported measures, advancement in the collection, storage and analysis of data has enabled recent research to start using digital footprint data to predict individuals' psychological characteristics at scale (e.g., Gladstone et al., 2019; Kosinski et al., 2013; Qiu et al., 2012; Youyou et al., 2015).

The exponential growth of the Internet and the large number of connected devices has enabled our daily activities to be carried out digitally progressively over time (Lambiotte & Kosinski, 2014), and has led to vast amounts of data and digital footprints being left behind (Kosinski et al., 2016; Mahmoodi et al., 2017). Paired with improved computing power and advanced statistical tools, this conveniently recorded information about *individual* consumers on different parts of the web and in real life can be capitalised to answer some contentious questions in consumer psychology that previous methods were unable to satisfactorily investigate (Lazer et al., 2009; Matz & Netzer, 2017), while also providing opportunities for identifying, understanding and accommodating to consumers' needs with an unprecedented level of specificity. Importantly, it has presented a valuable opportunity to address some of the issues that are associated with traditional approaches to data collection, including a reliance on self-report measures, small sample size and low power.

Digital footprints are the unique sets of digital traces left behind by individuals as they go about their lives on the web or in real life (Weaver & Gahegan, 2007). In the last decade, there has been a surge of research studies linking individual differences and personality traits to a range of digital footprints (see Azucar et al., 2018 for a meta-analysis; Hinds & Joinson, 2018 for a review). For instance, studies have found links between Big Five personality traits and Facebook status updates (Farnadi et al., 2013; Winter et al., 2014), social media activities (Quercia et al., 2012), posted images (Celli et al., 2014; Liu et al., 2016; Skowron et al., 2016), Likes (Kosinski et al., 2013; Youyou et al., 2015), usage behaviour on mobile applications (Huseynov, 2020) and website behaviours (Kosinski et al., 2014). These studies have demonstrated the immense value of big data in expanding our understanding of behaviours, particularly through showing how psychological attributes can be revealed from users' behaviours in a natural online environment. In a more practical sense, the findings have opened up opportunities for marketers to infer and more effectively target consumers based on their characteristics (Matz et al., 2017).

Transaction Records: An Underutilised Data Type

The measurement of consumption behaviour is crucial to producing reliable research in the domain of consumer psychology. Some of the most common traditional approaches for gathering information about individual consumers involve self-reported surveys, small-scale field observations, laboratory experiments and phone interviews (Chi-Hsien & Nagasawa, 2019; Matz & Netzer, 2017). The small sample size and a reliance on self-reported questionnaires mean that these studies often lack ecological validity. Objective measures of consumer behaviour offer an opportunity to overcome these limitations. With the wide adoption of digital banking paired with the increasing availability of consumption behaviour on an unprecedented scale in the past decade, it has become clear that bank transactions may contain the most comprehensive record of a consumer's real purchasing behaviours, making it a rich source of data for researchers interested in expanding knowledge about consumers. Despite the unique value of such datasets, transaction records are rarely used in consumer research. Having access to transaction records enables researchers to move beyond measures of purchase intention to direct observations of consumption patterns for a larger number of highly differentiated products and services at different point in time and locations, which in turn allow for more valuable real-world insights to be extracted in the process.

A key limitation of traditional consumer research that can be circumvented through the use of transaction records concerns small sample sizes (Yarkoni & Westfall, 2017). Traditional studies in consumer behaviour are often underpowered, and difficult to scale which often leads to a small sample size which is associated with other issues such as lack of generalisability. While the routine use of larger samples is a recommendation that has been suggested for decades (Cohen, 1962, 1992), it has not been incorporated effectively until recent advancement in data collection has facilitated this (Sedlmeier & Gigerenzer, 1989). Furthermore, as technology advances in the ability to handle large amounts of data, these methods have now paled in predictive power and would now be considered too conservative for answering certain research questions. In the domain of consumer research, big data methodologies have provided opportunities for researchers to study consumers at scale through the observation of the digital records that are gathered unobtrusively about consumers as they conduct their daily lives.

While previous studies of attribute inferences have successfully overcome limitations around issues of small sample size and self-reported behaviours, their focus on user-generated content (e.g., status updates, blog entries, images) as behavioural cue has meant that these studies may still suffer from the risk of impression management related to self-report. In previous research of attribute inferences, behaviours on different social media platforms were used as input for prediction of psychological attributes, amongst which Facebook is the most popular resulting from the availability of a dataset stemming from the MyPersonality project (Kosinski et al., 2013; see Azucar et al., 2018 for a meta-analysis). However, as social media users employ a wide variety of tactics in order to influence how they are being perceived by others, there is risk of impression management inherent in these datasets (DeAndrea et al., 2018; Walther & Jang, 2012). There is a possibility that people could mask or distort their identity, which can lead to inaccurate conclusions being made about consumer attributes and the types of behaviour that are manifested. In other words, user-generated content may be more indicative of the impression that people intend to give, than who they actually are. By contrast, unobtrusive recording of behaviours allows insights into how consumers' identities are reflected through their largely unmanipulated behaviours, rather than a carefully managed façade or self-reported behaviours. Transaction records are particularly relevant to the domain of consumer psychology as they reflect real-world purchasing behaviour, which makes them a good alternative to user-generated content for examining consumer preferences.

In addition to reducing risks of impression management, transaction records may also offer new insights by offering psychology researchers an opportunity to examine how individual differences may manifest themselves in consumption pattern. Different data types contain information about unique behavioural cues which are revealing of different facets of an individual's psychological attributes (Qiu et al., 2018). For example, Conscientiousness was reflected by the absence of information regarding private geographical location in selfies (Qiu et al., 2015), but not associated with any distinct cues in tweets (Qiu et al., 2012). While cues in selfies were poor signals of Extraversion, the trait was indicated by the frequent appearance of cues signalling positive emotion and words indicating sociability in tweets (Qiu et al., 2012, 2015). Thus, a focus on only the digital footprint on social media means that researchers could be missing valuable opportunities to explore the potential for other data types to infer attributes. Broadly speaking, the use of different data types enables scholars to study behavioural manifestations of psychological characteristics from different perspectives. This increases reliability of their findings and in turn contributes to a more holistic view of human behaviour.

Inference of Demographics and Malleable Traits

In addition to an inclination for user-generated content as a data type for investigation, previous research using computational methods to study individual differences have also predominantly focused on the Big Five personality traits (Azucar et al., 2018). This is likely driven by fact that the Big Five model is the most established personality model in the field of psychology, and using the same individual differences measures allows researchers the ability to draw direct comparisons across domains, providing a universal language to build and unite a discourse around the use of this emergent methodology. However, as studies of this nature have increased over the years, greater value is likely to be gained through an expansion of the types of attributes that can be inferred from these digital footprints. This includes predicting less conventional psychological attributes, such as predicting values (Leutner, 2016), intelligence (Wei & Stillwell, 2017), and sexual orientation (Wang & Kosinski, 2018). While demographics such as age and gender have been investigated frequently as part of these analyses (Hinds & Joinson, 2018; Kosinski et al., 2013), they remain comparatively less frequently studied than personality measures. Reflecting the trends of research linking individual differences and consumer behaviour (Müllensiefen et al., 2018; Sandy et al., 2013), studies using digital footprints suggest that there are markedly stronger links between behaviours on the Internet and demographics (Hinds & Joinson, 2018), compared to personality (Azucar et al., 2018). Thus, for research focusing on inference of consumers' characteristics to be useful to marketing strategy, it is important to employ both demographic and psychographic inferences.

Prior research looking at the effects of demographics and psychographics in consumer behaviour has yielded mixed findings. Of particular relevance is a study employing a large sample of more than 45,000 participants, which compared the relative amount of variance explained by demographic and personality factors in a wide range of outcome variables in product choices, media consumption, as well as political and societal views (Sandy et al., 2013). This study found that Big Five personality traits explained about an equal amount of variance in consumer behaviour. The findings are in line with a previous study showing a roughly equal amount of variance in attitudinal and behavioural criterion variables explained by demographics and psychological variables (Novak & MacEvoy, 1990). However, a more recent study found that demographic variables such as gender and age were more important in predicting the clustering of brand choices, compared to personality variables (Müllensiefen et al., 2018). This is in line with Naseri and Elliot's (2006) findings that socio-demographic variables offer higher explanatory power than non-demographic variables (e.g., shopping orientation, online perception of risk). In light of the mixed findings, Sandy et al. (2013) also showed that there was considerable variation in the relative contribution of demographics and psychographics across different consumer behaviours, pointing to potential nuances in how demographics and psychological variables may play different roles in different consumer behaviours. Altogether, the evidence contradicts the widely accepted proposition that demographic segments do not have much practical value to marketers due to their weak links to marketing variables (Naseri & Elliot, 2006). Rather than choosing to use only demographics or psychological variables in segmenting consumers, these studies indicate that demographics and psychological variables are both useful and it is beneficial for marketers to use both in understanding consumer behaviour.

Another area that is currently underexplored in the literature on automatic inference of attributes is the predictions of malleable characteristics. As mentioned previously, self-concept is the point of reference with which consumers evaluate products or brands, which in turn influences their consumption-related behaviours (Sirgy, 1986). Self-concept is a multifaceted construct (Malhotra, 1988; Sirgy, 1982) spanning different aspects of an individual, thus it is comprised of not only stable, but also malleable traits (Markus & Kunda, 1986). According to Grubb and Grathwohl (1967, p. 24), "the self is what one is aware of, one's attitudes, feelings, perceptions, and evaluations of oneself as an object". In other words, self-concept represents all of an individual's feelings and thoughts related to the self (Rosenberg, 1989), including their personality traits and other psychological characteristics. Depending on the traits, some of them may have profound impact on how consumers evaluate and purchase products and services. Thus, there appears to be a gap such that demographic and malleable traits have received comparably less attention than personality in previous research of attribute inferences. Malleable traits can also affect consumer behaviour, and thus are useful for understanding the psychological processes of consumer preferences.

In relation to the use of transactional records in inferring attributes, a notable study which used a large-scale dataset of bank transactions investigated its potential for predicting Big Five personality from spending categories (Gladstone et al., 2019). While the study has opened up an important discussion on how spending records are related to psychological traits, it did not explore how these purchases may be used to infer demographics or other more malleable traits. As transaction data is also specific to the consumption or financial domain, it presents an opportunity to study how these demographic and malleable characteristics can manifest in consumption patterns. Thus, this thesis aims to capitalise on transaction records and predict a demographic variable, chronological age, as well as a less stable domain-specific trait, financial distress.

2.4 – Personalised Advertising

The association between consumers' characteristics and various consumption related outcomes are well documented. The rise of big data analytics to profile consumers and the increasing ease to microtarget them on different parts of the internet have significantly altered the landscape of marketing. Advertisements are no longer being created to be directed at a broad audience; it has become increasingly commonplace for advertisers to microtarget consumers based on profiles created from on a wide range of data, providing them with demographic or psychological characteristics to reach each individual within the target audience (Smit et al., 2014). The ability to reliably predict consumers' characteristics at scale from passively collected behavioural residues could significantly improve marketing effectiveness and consumer outcomes. Two processes are involved in microtargeting consumers: obtaining profiles of consumers with which to target advertisements with, and personalising advertisement which will be presented to the targeted audiences. While studies in both processes are abundant, there are considerably fewer attempts at bridging how the inference made from the digital footprint can be applied directly in marketing, particularly in improving advertising effectiveness through personalisation.

Customer Segmentation to Personalised Advertisements

Personalised advertising is operationalised as the "strategic creation, modification, and adaptation of content and distribution to optimise the fit with personal characteristics, interests, preferences, communication styles, and behaviours" (Bol, Smit, et al., 2020, pg. 373). Personalising marketing to fit consumers' psychographics and demographics has a long history even before the emergence of digital marketing, with the concept of market segments being first introduced in the 1950's by Smith (1956). The effectiveness of this marketing approach is rooted in self-congruity, which expects that people choose products with images (actual or perceived) that match their psychographic and demographic characteristics (Beatty et al., 1985). Importantly, these concepts highlight the beginning of a shift in marketing towards a more tailored approach, away from a one-size-fits-all approach. It has been consistently found that when advertisements are tailored to a target audience's psychographic and demographic profiles, consumers are more likely to react favourably towards the advertisement and to express intention to purchase the product advertised (Han et al., 2018;

Matz et al., 2017; Winter et al., 2021). In fact, consumers have expressed preference for personalised advertising over general advertising when they are done right (Duran, 2018). The rapid migration toward personalised advertisements that are produced to deliver messages to appeal to the specific preferences of the receivers (Pappas et al., 2017) has led to increased scepticism around the usefulness of the traditional marketing approach aimed at the mass. The fact that consumers are now exposed to a large number of advertisements, estimated at 5,000 a day (Burton et al., 2019), emphasises the relevance of personalisation, which is fundamental for captivating consumers' attention towards information they would otherwise ignore (Morrison, 2016).

Although personalising advertising has been a part of marketers' practice for a long time, developments in digital media, including the rapid growth of social media and the expansion of customer touch points have enabled marketers to personalise their advertising to specific segments of audiences at the scale and level of specificity that were not previously possible. This type of advertising is better able to satisfy consumer needs, as it is able to ensure the timely offer of the relevant product or service, which greatly improves information search process by saving consumers time from having to continue searching (Okazaki et al., 2009; Tam & Ho, 2006). Personalisation encompasses different types of tailoring strategies, including cue-based personalisation, which involves incorporating recognisable aspects of an individual such as their name or picture (Sahni et al., 2018); behavioural targeting, which involves showing consumers products that they have previously purchased or are related to their browsing history (Lambrecht & Tucker, 2013); and trait-based personalisation, which customises advertising message for the same product based on consumers' characteristics (i.e., gender, age, personality) derived from their online behaviours. Even though these demographic and psychographic characteristics may be common to many people, they can be used to refer to an individual person when linked in a precise configuration (Dijkstra, 2008).

Trait-based personalisation refers to advertising content that aligns with a consumer's psychological characteristics (Winter et al., 2021). This type of personalisation requires advertisers to possess information about the consumer's attributes, which has been facilitated by the growth in the size of digital footprints left by consumers and the rapid improvement of machine learning approaches that can be applied in the inference of consumer attributes from a wide variety of data types, and at scale (e.g., Gladstone et al., 2019; Kosinski et al., 2013; Qiu et al., 2015). Marketers can then use these inferred consumer characteristics to tailor their advertisements and target specific audiences to elicit desired responses from these individuals (Winter et al., 2021). Crucially, messages can be modified to become more persuasive based on various aspects of the individual's self-concepts such as demographics, personality, values, beliefs or lifestyle (Hornikx & O'Keefe, 2009). While aspects of marketing communication can be modified to target a focal trait (e.g., the source of the message and transmission channel (Chiu et al., 2014), message framing could also be tailored through alterations of cues in ads, such as visual elements, and the use of celebrity endorser (e.g., Alhabash et al., 2020; Higgins et al., 2018; Matz, Kosinski, et al., 2017; Pradhan et al., 2016; Wright, 2016). For instance, someone introverted will see an advertisement depicting a person having the advertised snack at home alone watching television, whereas someone with high extraversion will be shown an advertisement of the same snack but enjoyed in the presence of other people. Messages that are aligned with the audience's interests or characteristics are evaluated more favourably and are more influential (Crano et al., 2010; Hirsh et al., 2012).

Self-congruity in Personalised Advertisements

The mechanism behind personalised advertisements is rooted in self-congruity, as advertisers present advertising content to target consumers at an individual level by showing them messages that are congruent with their characteristics or preferences (Maslowska et al., 2013). Previous studies have shown that when advertisements match well with the viewers' self-concept, they are more effective compared to those that do not match well (Hong & Zinkhan, 1995; Wang & Mowen, 1997). Driven by the need for self-consistency or self-enhancement (Sirgy, 1982), consumers are more likely to perceive self-congruent messages of which tone and framing are consistent to the recipient's consumer profile, thinking style, beliefs or attitudes as more relevant and persuasive, thus responding to them more positively (Dodoo & Wen, 2019; Heckler & Childers, 1992; Hong & Zinkhan, 1995). The alignment with the brand image necessary for self-congruity to work can be in the form of a retail store's image (Chebat et al., 2006), a brand's website (Chung & Ahn, 2013), elements of product design (Seimiene & Kamarauskaite, 2014), the ethnicity of a service giver (Huang et al., 2013), the gender (Morrison & Shaffer, 2003) and age (Alhabash et al., 2020) as well as the personality of a brand's celebrity endorser (Ambroise et al., 2014; Pradhan et al., 2016).

According to the self-congruity theory, when encountering an advertisement, consumers engage in a process of assessing the brand or product advertised based on the extent to which it is congruent with their self-image. During this process, consumers make inferences as to whether a brand or product is "for-me" or "not-for-me" (Chaplin & John, 2005). Not only do self-concepts affect how an individual evaluates an advertisement, they also make information-processing more efficient by selectively guiding attention to signals that are align with the individual's self-concepts (Markus & Wurf, 1987). While the enhanced processing itself does not automatically lead to more positive attitudes, as the positive attitudes hinge upon the persuasiveness of the message itself, it is likely that aspects of an advertisement that fit with recipients' self-concepts may result in higher perceived relevance, thus activating deeper cognitive processing (Wheeler et al., 2005), in turn increasing the persuasive impact of the message. Furthermore, as people tend to assign higher value to matched features, the argument quality of an advertisement may be perceived as being better. Put simply, an advertising message that is framed to fit with a consumer's self-concept can be processed more easily, resulting in a fluency that is experienced as pleasurable, therefore leading consumers to a positively biased evaluation of the advertised product (Winter et al., 2021).

The effects of self-congruent advertising are well documented; however, some inconsistencies are also noted. Personalisation have been found to increase ad effectiveness in some studies, including Chang (2001) and Hong and Zinkhan (1995) which demonstrated that introverted participants evaluated ads portraying introverted users more positively, while their extroverted counterparts favoured ads that portray extroverted users. Using Facebook targeted audiences, Matz et al. (2017) found that when advertisements are personalised to fit an individual's personality traits (i.e., Extraversion and Openness), they are more likely to click through and also to purchase the item. Beyond personality traits, ad congruence with demographic factors like age and gender, as well as other psychological characteristics, such as regulatory focus, have also been found to improve the persuasive ability of a message (Dijkstra, 2008). Studies have also found that compared to inconsistent role portrayals, those aligned with individuals' inclinations of femininity or masculinity tend to benefit from greater persuasiveness (Jaffe, 1990, 1994). Further supporting evidence was also found for the cultural dimension in terms of collectivism and individualism (Leach & Liu, 1998; Wang & Mowen, 1997). In terms of regulatory focus, when messages are framed to be in line with individuals' regulatory focus (i.e., promotion focus or prevention focus), they were more likely to be responded to favourably (Higgins et al., 2003; Kim, 2006). In a more recent study, Han et al. (2018) found that the persuasive effects of messages in political ads are heightened when tailored to reflect the voters' regulatory focus. However, Winter et al. (2021) found limited persuasive effects of congruence in terms of personality. Specifically, the study showed that messages matched to participants' specific susceptibilities such as towards authorities resulted in an increase in their intentions to engage with the posts, though the effects on consumers' attitudes toward the products depicted in the advertisements were inconsistent (Winter et al., 2021). In all, it appears that the effect sizes of personalisation tend to vary depending on different consumer characteristics and advertisement elements that are being used to enhance congruence.

Consumer Profile in Personalised Advertising

The concept of self-congruity is highly relevant to marketers looking to increase effectiveness in their marketing efforts through personalised advertising. However, for personalised advertising to work at its highest efficacy, two factors are crucial: accurate consumer profiles and persuasive advertisements that are congruent with the viewer. Without either of these, personalised advertisement is unlikely to be at its most effective. To address the lack of research connecting these two processes necessary in personalised advertising, this thesis proposes that automatic inference of consumer characteristics from bank transactions may provide marketers with accurate characteristics of consumers for tailoring their advertisements to. The degree to which inferred consumer characteristics can be used to effectively increase advertising appeal through personalised advertisements is tested.

2.5 – Self-congruence in Consumption

The subject of happiness has been a long-standing topic for debate that has occupied the minds of philosophers and scientists alike. Since the 1970s, the question of whether having more money can buy happiness started to be approached empirically by social scientists (Stanca & Veenhoven, 2015). With an economic recession and mounting debts on both personal and national scales, questions surrounding how people should spend money to attain happiness have started receiving more attention in psychological research. With the key emphasis of economic theories being the association between income and happiness (e.g., Clark et al., 2005; Dehejia et al., 2007; Layard, 2005), these theories postulate that consumption is positively related to happiness (Ackerman, 1997; Noll & Weick, 2015). More specifically, individual members of society are seen as insatiable consumers who can only be meaningfully satisfied from more consumption (Ackerman, 1997; Guillen-Royo, 2011). While a positive relationship has been found between income and happiness, the effect is weak (Clark et al., 2008). Nevertheless, this belief is so widespread that, people continue to pursue monetary goals in the hopes that larger income will make them happier, particularly in the Western world (Howell & Guevarra, 2013).

Psychological studies exploring the question of whether money buys happiness, however, have produced mixed evidence. One of the most prominent findings of the relationship between income and subjective well-being is by Easterlin (1974), who observes that the relationship is paradoxical, such that they are correlated at a given point in time, but happiness does not rise with income over longer time periods. More recently, Easterlin (2001) extended the original findings by suggesting that while income is related to happiness, there is a point of diminishing returns: the material aspirations that many acquire as their incomes rise can undermine the potential gains of happiness. Thirty years after the establishment of this "Easterlin paradox", the concept remains highly relevant and contentious today because it calls into question conventional economic policy that foster income growth as the primary way for improving well-being (Easterlin et al., 2010; Stevenson & Wolfers, 2008).

Self-congruent Spending

The weak links between money and happiness (Diener & Biswas-Diener, 2002; Easterlin, 1974; Kahneman & Deaton, 2010) have led some scholars to argue that the way people choose to allocate their money could shed light on this contentious relationship (Dunn et al., 2011; Howell & Hill, 2009; Howell & Howell, 2008). Put simply, the way that money can bring about happiness is through spending money on the right purchases. Some compelling evidence suggests that the inconsistencies in the literature may be due to self-incongruity in spending patterns (Dunn et al., 2011). As the focus shifts away from identifying happiness-inducing consumption for the mass toward those that benefit individual members of the society, self-congruity theory provides a valuable perspective into the relationship between money and happiness. According to self-congruity theory, when people behave in a way that fits with their actual self-concepts, they experience a sense of coherence resulting from self-consistency, which is characterised by positive emotions (Sirgy, 1982). When the self-concept is confirmed, it augments an individual’s feelings of confidence; conversely, activities that invalidates one’s self-concept can lead to distress (Sirgy, 1982, 1985).

Recent research has emerged in the investigation of the relationship between self-congruity in consumption patterns and consumer well-being. For example, while experiential purchases consistently lead to heightened levels of happiness for experiential consumers, they result in either no increase, or smaller increase in happiness for those preferring material purchases (Zhang et al., 2014). Similarly, pro-social spending increases happiness for consumers with self-transcendental values (a concern for other individuals and entities) but not those who are low on self-transcendence (Hill & Howell, 2014). In terms of self-control, evidence suggests consumers with high self-control experience higher levels of happiness when they have a reason to justify the purchase of indulgent products, while those with low self-control are happier when they do not have a reason to indulge (Petersen et al., 2018). Together, these findings suggest a possibility that may explain the inconsistencies in the links between consumption and happiness, may be found in self-congruity. More broadly in terms of Big Five personality, a recent study found that when individuals spend money in product categories that match with their personality, they are happier, and that this effect is robust as it has been consistently demonstrated both in actual purchases recorded as bank transactions as well as in experimental setting where participants reported significantly higher subjective well-being after purchasing items that fit with their personality (Matz et al., 2016).

Importantly, the study showed that people can gain happiness from spending on a wider range of products and activities that match well with their personality which can meaningfully satisfy their fundamental needs, regardless of how much they actually spend on each of these categories (Matz et al., 2016).

Correlates of self-congruent spending

In general, people are motivated to seek confirmation for their currently held self-views in order to conserve their personal identity (Aguirre-Rodriguez et al., 2012; Burke & Stets, 2009; Cast & Burke, 2002; Swann et al., 1992). However, it is unclear what factors may affect one's motivation or their ability to behave in a way that is self-congruent. While there is established research into self-congruence and happiness, research into the effects of self-congruent spending on happiness is only nascent. There is limited evidence regarding the types of consumers who may be more or less likely to spend more congruently. A further question that stems from this line of research is how the benefit of self-congruent on happiness may differ in strength based on other consumer characteristics. It is possible that certain predispositions, or attitudes may make it more difficult for some people to spend in a way that fits with their personality, therefore impacting their ability to gain happiness in this way.

Transaction Records Reflect Self-congruence in Consumption

While empirical studies investigating the phenomenon of how money is related to happiness have predominantly used income as an indicator of an individual's standard of living, evidence suggests that consumption may in fact be more relevant than income as a measure of utility or satisfaction (Cutler et al., 1991; Headey et al., 2008; Meyer & Sullivan, 2006; Slesnick, 2001). In fact, researchers have argued that income may simply be a noisy signal for consumption in the study of happiness (Dynan & Ravina, 2007; Meyer & Sullivan, 2003). Previous studies on subjective well-being which typically utilised income as a variable were based on a flawed premise that income is converted directly into consumption capitals (MacDonald & Douthitt, 1992). While consumption and income are connected, how much a person consumes may differ significantly from how much money they make due to taxation and other financial behaviours such as saving (Attanasio & Pistaferri, 2016; Meghir &

Pistaferri, 2011). By shifting the focus from a person's income to the composition of their consumption, researchers are now able to formulate and test new research questions regarding how, and why, consumption can improve subjective well-being (DeLeire & Kalil, 2010). Despite the value of consumption in illuminating the relationship between money and happiness, there are far fewer studies linking consumption and happiness compared to those utilising income. As consumption patterns are best observed through records of consumer purchases, transactional data serve as an accurate and comprehensive reflection of consumers' real-world purchasing behaviour. By using transaction records in the examination of self-congruence in consumption patterns, this thesis contributes to the growing body of research aimed at understanding how to improve well-being through consumption.

Another way that transaction records can offer a new perspective into how consumption relates to happiness is by serving as an *objective* measure of self-congruence in *overall* consumption patterns. Previous studies in self-congruence and authenticity were predominantly conducted using self-reported questionnaires. Similar to self-reported consumption behaviour, self-reported measures of self-congruence are limited as they could be faked, and prone to impression management tendencies. Self-assessed authenticity measures appear to be confounded with positivity (Jongman-Sereno & Leary, 2020). For instance, positive actions are perceived as to having a higher degree of authenticity than negative ones (Sheldon et al., 1997). This is true whether or not they are actually aligned with the person's characteristics (Fleeson & Wilt, 2010). Rather than felt authenticity or perceived congruence in consumption, transaction records serve as a more objective indicator of self-congruence or authenticity in spending behaviour.

Importantly, while previous studies that look at congruence in spending are only able to do this for a single brand (see Sirgy, 2018a for a review), having access to the detailed purchasing information in a large number of spending categories and brands allows this thesis to examine self-congruence with not just a small number of brands, but all of an individual's real-world purchases which reflects overall consumption pattern. Notably, the value of such methodology was demonstrated in a recent study which utilised bank transactions to compute a congruence score to indicate a match between an individual's overall shopping basket over the period of 12 months and their Big Five personality (see Matz et al., 2016). This thesis will apply the same method to infer self-congruence in spending in a dataset of a larger scale with involves the aggregation of transactions across bank accounts, and extend the research question to investigate the potential correlates of self-congruence in overall consumption as well as the potential moderating effect of consumer characteristics on the relationship between self-congruent spending and happiness.

2.6 – Overview of Studies

This chapter has reviewed the research underpinned by the theory of self-congruity, including inference of attributes, personalised advertising and the relationship between consumption and happiness. It also outlined the limitations of traditional approach to collecting data about individual consumers in psychology research, as well as the promising outlook of using the large-scale digital footprint in overcoming some of these issues. While the large-scale mining and aggregation of behavioural data is already used extensively in other areas, particularly in the analysis of social media data (see Azucar et al., 2018 for a meta-analysis), studies of consumption patterns using transaction records remain rare (with a few exceptions, e.g., Gladstone et al., 2019; Matz et al., 2016). The literature review identified various opportunities and gaps in the literature which can be effectively responded to with a mixture of transaction records, as well as experiment and survey. Thus, this thesis aims to harness the increasing availability of behavioural field data to make contributions to the consumer psychology literature. The investigation of research questions in three key areas will form the foundation for the following empirical chapters: inference of consumer characteristics, personalised advertising and self-congruence in consumption.

The empirical investigation is comprised of two components: attribute inference from transaction records, and investigation of self-congruence effects in consumption from transaction records. In total, five studies were conducted in this research area, aimed at addressing three key topics (see Table 2.2).

The first component aims to address the gaps within the literature of attribute inference from digital footprints, particularly the preoccupation with inferring *Big Five personality traits* using *social media data*. There is an overlooked opportunity to understand how other consumer characteristics manifest themselves, such as demographics and more malleable traits that form part of an individual's self-concept. Furthermore, with the myriad of data types that represent different behavioural cues and psychological attributes, transaction records allow a more holistic understanding of consumer behaviour to be built. Therefore, this thesis will be exploring the potential to infer two consumer attributes: chronological age as a demographic factor, and subjective feelings of financial distress as a malleable trait, using an underutilised data type, transaction records. While studies inferring personality from digital footprints are plentiful, there are far fewer attempts to directly demonstrate practical relevance of these inferences, particularly in linking attribute inference to personalised advertising. To demonstrate ecological validity of the predictions made using machine learning, this thesis will explore the extent to which inferred chronological age can be used to personalise advertisements and increase viewers' appeal to these ads.

The second component is an examination of self-congruence effects using a more objective measurement of self-congruence in consumption computed via transaction records. The emerging research linking self-congruence in consumption to happiness shows promise for improving consumer well-being. Importantly, studies of self-congruence or authenticity were predominantly investigated using self-reported questionnaires, which suffers from issues related to positive bias. This thesis contributes to the emerging literature concerning self-congruent spending by exploring the potential correlates of self-congruent spending using a more objective measure of self-congruence through transaction records and ratings of spending categories by a separate panel. In doing this, it identifies the types of individuals who are more, or less likely to spend in a way that fits with their personality. To further expand the discourse on the benefits of self-congruent spending on happiness, this thesis will investigate the moderating effect of financial distress on the effect of self-congruence in consumption on happiness.

Table 2.2 *The structure of the empirical studies*

Topic		Study
Consumer attribute inference and personalised advertising	1	Predicting chronological age from bank transactions
	2	Personalising adverts to inferred age
	3	Detecting feelings of financial distress
Self-congruence in Consumption	4	Correlates of self-congruent spending
	5	Self-congruent spending and happiness: Moderating effect of financial distress

Capitalising on the opportunity for transactional records as an underutilised data type, Study 1 addresses one of the empirical gaps in the literature of attribute inference from digital footprints concerning a lack of research in the use of consumers' demographic attributes. This study aims to predict a consumer's chronological age from the amount of money they have spent in each brand over 12 months as reflected in their aggregated bank transactions. A machine learning model was built, and a feature importance analysis was conducted to allow insight into the types of brands that are most revealing of a consumer's age. External validity was also established by comparing the correlations between financial behaviours and age, both actual and inferred.

Study 2 looks to establish a direct link between the use of inferred traits in personalised advertising, which will strengthen the practical relevance of automatic attribute inference. The aim is to investigate the extent to which inferred age can be used to increase appeals of personalised advertisements. To do this, the machine learning model devised in Study 1 was applied onto a new sample of self-reported purchases collected in Study 2, deriving an inferred age for each participant. Then an experiment was conducted to investigate the the extent to which the inferred age can be used to increase appeal towards advertisements when they are matched to participants' inferred age. The experiment involves showing randomly allocated groups of participants advertisements that were matched or mismatched to their age, and then asking them about their attitudes towards these advertisements.

Another gap identified in the attribute inference studies is the dearth of research investigating malleable traits. Rather than stable personality traits or demographic factors, Study 3 examines how accurately a malleable trait such as subjective feelings of financial distress can be predicted from bank transactions. Specifically, this study predicts financial distress from the proportion of money spent in spending categories using a machine learning model. Again, a feature importance analysis was conducted to follow up with the machine learning model to aid the understanding of the types of spending related to financial distress.

While research establishing the links between self-congruent consumption and happiness shows promise for improving consumers' pursuit of happiness through consumption, there is limited evidence of the correlates of self-congruent spending. Importantly, studies in authenticity indicated that individuals differ from one another in their ability to behave authentically, pointing to the possibility that there may be factors that influence the extent to which consumers are capable of spending in a way that is congruent with their personality. Study 4 aims to address this gap by exploring the potential factors that may affect self-congruent spending. A different panel of participants were recruited to rate each spending category on the Big Five personality traits. A basket match score was computed to indicate the strength of match between the personality of the spender and their overall basket personality score. Using correlations and dominance analysis, the study looks at the relationship between personality match in consumption and consumer characteristics such as age, self-control, materialism and financial distress.

As established in Study 4, financial distress is one of the most potent predictors of low self-congruent spending. Considering the effects of self-congruent spending on happiness and the adverse impact of financial distress on consumer well-being, it is useful to know the extent to which the strength of this effect may depend on the level of financial distress an individual is experiencing. In Study 5, the moderating effect of financial distress on the relationship between personality self-congruent consumption and happiness was tested. The interaction effect of financial distress and basket personality match on happiness was then investigated using a moderated regression to determine whether the beneficial effect of self-congruent spending is different for those who are financially distressed compared to their less financially distressed counterparts.

As a body of research, the five studies aims to optimise the strengths of transaction records to investigate the role of self-congruity in consumer preferences, utilising self-congruity theory as a theoretical framework. The findings are particularly relevant to psychology and consumer researchers interested in the potential of machine learning and big data to contribute meaningfully to the field. It also provides implications for marketing practitioners striving to increase the effectiveness of their advertising strategy, and policymakers concerned about the potential consumer privacy issues emanating from the use of machine learning in inferring consumers' private attributes.

Chapter 3 – Predicting Chronological Age from Bank Transactions

Chapter 3 Summary

Age is one of the key consumer attributes with which marketers use to target their customers. However, marketers don't always have access to such information. While automatic inference of consumer attributes from digital footprints can offer a solution to this problem. Previous research has rarely attempted to infer a person's age from their digital footprint, and it is unclear whether accurate predictions can be achieved using transaction records. This study assesses how accurately a consumer's chronological age can be predicted from the brands they purchase. Data collected from a money management app containing more than 1 million transactions from 2,274 users was analysed. By employing machine learning models with consumer spending across 652 brands, the study demonstrates that age can be predicted with a high degree of out-of-sample accuracy (r = .71). Feature importance analysis reveals the spending categories most informative for reliably predicting age, indicating a clear digital divide between generations in their consumption of technology-focused products and services, as well as eating out and supermarket brand preferences. The results also demonstrate that important characteristics and behaviours of consumers (e.g., whether they have children or own their home), as well as their wealth and income, are more strongly correlated with the predictions of age based on brand consumption, compared to real age.

3.1 – Introduction

Emerging forms of data and analytic techniques provide new opportunities to study consumer behaviour. Recent research has developed computational methods to automatically predict consumer's attributes based on the 'digital footprint' left behind by their behaviour (e.g., Kosinski et al., 2013). Despite findings suggesting a greater utility of demographic variables in explaining consumer behaviour (Naseri & Elliot, 2006; Novak & MacEvoy, 1990; Sandy et al., 2013) and personalising advertisements to increase appeal (Bol, Strycharz, et al., 2020; Müllensiefen et al., 2018), studies on automatic attribute inference have focused predominantly on the Big Five personality traits (see Azucar et al., 2018 for a meta-analysis). Among the small number of studies inferring age from digital footprints, the data sources used included cookies from website browsing histories (Hu et al., 2007), the language a person uses online (Sap et al., 2014) and their Facebook Likes (Kosinski et al., 2013). These studies suggest that age can accurately be inferred from consumer's passive online behaviour (e.g., Kosinski et al., 2013; Sap et al., 2014; Youyou et al., 2015).

While previous studies have predominantly used data from social media, there has been comparatively fewer attempts at inferring consumers' characteristics from digital payments (e.g., credit and debit cards, online and mobile payments). For instance, a recent study predicted Big Five personality traits from categories of spending (Gladstone et al., 2019), which demonstrated it is possible to predict Big Five personality with an accuracy of $r = .15$, while specific traits such as materialism was predicted with $r = .33$. The widespread adoption of digital payments means consumers increasingly leave behind a 'digital footprint' in the form of virtual residues of their day-to-day spending. An advantage of using digital forms of payment is that they are used widely across the age spectrum, as 96% of the UK population have a debit card (The UK Cards Associations., 2017). The ubiquity of transaction records may thus provide another universal and rich source of data from which to study consumer attributes across domains.

Predicting Age from Brand Spending

While research in consumer psychology typically focuses on establishing the causal mechanisms and processes underlying behaviour, the goal of this research is on predicting age from brand spending. This study focuses on prediction for three reasons. First, determining which brands provide the most accurate prediction of age offers insight into the generational differences in consumer behaviour, an area that has received little attention to date. Second, understanding the strength of the relationships between brands and age can provide a rich description upon which to build on existing theories, or create new theories about consumer behaviour that can be tested in future research (Yarkoni & Westfall, 2017). For instance, spending has been thought of as being driven by a wide range of factors, including cognitive processes, motivation, attitudes, personality, social influence and influence of advertising (Solomon, 2010). This study will allow researchers to build on some of these perspectives. And third, there is practical value in achieving accurate predictions of consumer characteristics such as age, as it is often the main goal of marketing applications.

Age and Consumption Patterns

The things that people buy change as they age. There are several different reasons brand choice can reveal a person's age. Two different pathways in which age could influence how people consume were identified: self-concept and technology.

According to the concept of self-congruity, consuming a specific brand enables consumers to signal their self-identity, as well as which social groups they align with (Escalas & Bettman, 2005). The consumer behaviour literature has established that people consume branded goods not only for their practical value, but also to fulfil psychological needs (Belk, 1988; D. Lee & Hyman, 2008; Solomon, 1983). Beyond the essential spending necessary to sustain a basic level of living, discretionary spending can reflect who we are as individuals, as product consumption symbolises our personal attributes, personality, motivations and lifestyle (McCracken, 1987; Sirgy, 1982). According to self-congruity theory, consumers purchase products that align with their self-concept (Sirgy, 1982). While a person's age can be judged from their physical appearance or other cues with relative ease, the age of a brand is not always apparent or easily inferred (Ouwersloot & Tudorica, 2001). Although not explicitly a dimension of brand personality, age has been suggested to constitute a part of the imagery associated with typical users of the brand (brand-as-users), thus impression of a certain age could be transferred to a brand through its typical users (Levy, 1959). It is possible that people also consume brands with a brand-as-user image in line with their age-related self-concepts. Thus, this study expects that individuals' brand consumption will reveal aspects of their social identity that are related to their age.

Consumption patterns are likely to look similar among individuals similar in age, as they go through similar age-related life events which further define their identity, such as education, employment, marriage, child birth, and retirement (Chamberlain et al., 2017). As a cohort, people born in a specific time period can also be similarly influenced by changes in the macro-environment, imprinting collectively distinct consumption behaviours (Howe & Strauss, 2000). Individuals treat major life events (regardless of desirability) as stressors, which they attempt to relieve by modifying their behaviours (Lazarus & Folkman, 1984; Pearlin, 1982). This is supported by research demonstrating that individuals initiate, intensify or change their consumption habits in an attempt to relieve their stress (Andreasen, 1984; O'Guinn & Faber, 1989). It is possible that these changes may be observable in different age groups. Furthermore, the normative perspective considers spending behaviour to be the result of the roles people take on and enact at different stages of life (Hagestad & Uhlenberg, 2007). People buy new products that enable them to define their recently acquired role, and discard goods involved in the portrayal of a former role which are no longer relevant to the new role (McAlexander, 1991; Mehta & Belk, 1991). Thus, changes in consumption patterns may signal transition in one's self-concept during different stages of life as people age (Moschis et al., 2005).

Another way that consumers' self-concept may be shared amongst those similar in age is through cohort effects. Individuals are considered to be from a generational cohort if they were born during a limited time period which results in them sharing the same social and historical experiences (Rindfleisch, 1994). The external events that cohorts go through during their highly malleable years of late adolescent/early adulthood tend to be similar, these shared experiences form 'defining moments' that have meaningful impact on their values, preferences, attitudes and purchasing behaviour in ways that remain relatively unchanged with them throughout their entire lifetime (Ryder, 1965). However, time spans defining a generation are not uniform and may vary across countries, while in some cases the later cohorts may even overlap due to their intensive use of the internet (Soulez & Guillot-Soulez, 2011). Nonetheless, since cohort effects are linear, not categorical, changes in their consumption patterns are likely to remain steady over time rather than shifting abruptly at birth-year cut-offs (Reisenwitz & Iyer, 2009; Twenge, 2010).

Altogether, it is reasonable to expect that brand choices will be sufficiently distinctive across different age groups (and sufficiently homogenous within age groups), that these differences can be exploited to model a person's age from their spending. Previous meta-analytic research also showed that younger consumers have higher evaluations of brands with higher levels of competence (Eisend & Stokburger-Sauer, 2013). Although few empirical studies have analysed how brand preferences vary across age groups, several studies show significant age differences in related domains, for instance, in media consumption (Harwood, 1999), and an inclination for older consumers to favour long-established brands (Lambert-Pandraud et al., 2006).

The Current Research

This study investigates the extent to which consumers' age can be accurately predicted from their spending records. Specifically, the approach employed here aggregates the amount consumers spend on different brands, and characterises each user by their purchase history, i.e., their pattern of spending across brands. Age is operationalised as chronological, measured as years lived since birth (Jarvik, 1975), and machine learning models are used to predict consumer age as a function of these spending variables. The aims of the current study are threefold: (1) to investigate how accurately age can be predicted; (2) to determine the types of brand spending which best predict age, and (3) to establish the external validity of these predictions. The focus on this study is not only on the predictions themselves, but also in using these predictions to make inferences about other behaviour.

3.2 – Method

This study utilises spending data aggregated from 2,274 users' bank accounts, obtained from a money management app. Customers' account records provided a daily panel of all debit and credit transactions across each of a customer's bank accounts, tagged in types (e.g., broadband, designer clothes, flights) or brands (e.g., Amazon, Tesco, ASOS). Machine learning algorithms are implemented on the transaction data to predict age from brand spending, and then derive feature importance to determine the brands most important in changing the prediction accuracy of the model. To preserve the information at the lowest level and to provide clarity on the type of brands important in age prediction, brands will be used as features to predict age, and these findings are interpreted using spending categories. Finally, to establish external validity, a series of correlations was run with variables created from both incoming and outgoing transactions tagged in types.

Participants and Procedure

The dataset was collected in 2017 as part of a collaboration with a UK-based money management mobile app. This app aggregates transactions across their individual users' bank accounts and provide them with an online dashboard of their incoming and outgoing money. Participants gave consent to having their personal transaction data used for research. Prior to being subjected to analyses, all customer data was fully anonymised and the research received ethical approval from the university IRB board. In total, 2,274 participants took part in the study. Participants' gender were derived from their first names, which indicated there were 962 males, 294 females, and 1,018 were unidentifiable. The sample size was determined by the available number of transaction data-linked survey responses. The dataset contained 118,597 user-brand pairs with spending totalling over 44 million pounds.

Measures

Brand Spending

The service recorded all transactions including purchases and withdrawals made by individual participants across their bank accounts for a 12-month period prior to the survey date. Through the service, individual transactions were automatically tagged with one of 652 brands (e.g., “Amazon,” “Tesco,” “ASOS”). The transaction data were aggregated across the 12 months to calculate each individual’s total spending on each brand (e.g., the total amount in pounds an individual has spent on Amazon).

Brand Categories

Each of the 652 brands were categorised into 1 of 18 groups, which will be used to ease the interpretation of the findings. This was conducted by me, with no necessary changes confirmed by a research assistant, indicating the categories are face valid.

Age

Participants’ age was obtained from the date of birth provided by users upon the point of service registration (mean = 38.32 years, median = 36, *SD* = 11.77, range = 18-87). The age distribution of the sample is provided in Figure S1 of the supplementary materials. The median age of the UK population was 40.6 (CIA, 2017), meaning the sample was comparable with, but younger than, the population overall.

External criteria

Using self-reported, outgoing and incoming transaction data, external criteria were computed by summing the amount of money within transaction types tagged with related keywords. Information was collected about self-reported income, self-reported investment, self-reported saving using single-item questions asking participants to indicate the amount of money (in pounds) that they have invested in 9 categories (i.e., 0, 0-100, 100-1,000, 1,000-5,000, 5,000-10,000, 10,000-50,000, 50,000, 100,000+), and their income in 8 categories with £10k intervals. Other external criteria computed were home ownership, pension reception, pension income, investment income, investment spending, government benefit, amount invested or saved, spending on children. Table 3.1 reports the descriptions of these external criteria and details how they were calculated.

Table 3.1 *Descriptions of external criteria*

Variable	Description
Pension reception	A binary variable indicating whether a person is receiving pension. Yes if a person has received more than £0 in types tagged with the word 'pension'
Homeowner	A binary variable indicating whether a person owns a home. Yes if a person has spent more than £0 in types tagged with words like 'mortgage', 'home insurance'
Pension income	The amount of pension received. The total amount of incoming money tagged as types including the word 'pension'
Investment income	The amount of investment income received. The total amount of incoming money tagged as types including the word 'investment'
Investment spending	The amount spent in investment spent. The total amount of outgoing money tagged as types including words like 'investment', 'bond' and 'dividend'
Government benefit	A binary variable indicating whether a person is receiving government benefit. Yes if a person has received more than £0 in types tagged with the word 'benefits'
Amount invested or saved	The amount spent in savings or investment. The total amount of outgoing money tagged as types including words like 'saving', 'isa' and 'investments'
Spending on children	A binary variable indicating whether a person is spending on children. Yes if a person has spent more than £0 in types tagged with words like 'nursery', 'child'
Self-reported saving	Self-reported amount of money saved rated in 9 incremental categories
Self-reported investment	Self-reported amount of money invested rated in 9 incremental categories
Self-reported income	Self-reported amount of income rated in 8 incremental categories with £10k intervals

Data Analysis

Model comparison and selection

Machine learning algorithms offers psychology researchers new opportunities for gaining important insights from large-scale behavioural data. While the traditional statistical toolkit is appropriate for the analysis of small-*N* studies in traditional psychology research, it is less suitable for studies that include a large number of variables and observations. Traditional psychological research often uses linear regression to derive insight. The computational approach to data analysis offers researchers a variety of models with which to tackle the same analytical problem. Machine learning models such as decision tree or ensemble methods are likely to show superior performance to linear regressions in most cases, though it has also been shown in several cases that LASSO and linear regression can sometimes outperform ensemble methods (see Minokhin, 2015; Nauman & Nättilä, 2019). They are also able to deal with multi-collinearity much better than linear regression (Ding et al., 2016), which is particularly useful for datasets involving a large number of predictors which can be interrelated. Furthermore, ensemble decision tree-based methods involve feature selection and regularisation and thus are better able to account for non-linear relationships and interactions (Breiman, 2001), as well as the inclusion of a larger number of features without pre-selection (Hua et al., 2005). Gradient boosting methods model errors from previous trees (Friedman, 2001), as opposed to random forest models which average the predictions across all trees. As the different models often result in different degrees of predictive accuracy when applied to datasets differing in nature, I chose to employ a variety of machine learning models in the analysis of this study. For the sake of comparison, correlations between predicted and actual age were used to assess model accuracy as correlations is a common metric that previous studies of similar nature have used.

The dataset was cleaned prior to being entered into the machine learning models. Participants who have spent money in fewer than 1 category, as well as spending categories with fewer than 1 participant who has spent money in them were removed from the dataset. This resulted in a final number of 2,274 participants and 652 brands. The dataset is sparse, with a large number of user-brand pairs with spending amount of 0. However, as machine learning models are able to handle this form of data, the subsequent data analysis procedure was followed.

Machine learning models were implemented in Python using the Scikit Learn (Pedregosa et al., 2011), XGBoost (Chen & Guestrin, 2016) and Skater (Choudhary et al., 2018) packages. The aim was to predict users' age from the amount of money spent on each brand. Because individual techniques rarely provide optimal predictions across different learning problems (Wolpert & Macready, 1997), several models were compared: Linear Regression, LASSO Regression, Random Forest Regressor, Gradient Boosting Regressor and Extreme Gradient Boosting (XGBoost) Regressor. To set-up the models, age was entered as the dependent variable and the 652 brands as independent variables. Due to the high computational power needed, the model was tuned manually by entering different values in each hyperparameter, narrowing down the gaps between the values to find the optimal Pearson's correlation value indicating high predictive accuracy.

To reduce over-fitting on two levels of inferences (i.e., model comparison and selection, (Cawley & Talbot, 2010), a form of cross validation was incorporated within the analysis. Cross validation is a set of procedures that repeatedly partition data in order to simulate replication attempts which provides a study with a computational advantage by avoiding overfitting, which occurs when a statistical model is mistakenly fitted to the peculiarities of a dataset, treating the sample-specific noise as if it were signal (Koul et al., 2018). Through evaluation of the model's performance on an independent dataset (testing set), cross validation prevents overfitting the training data. This process also makes it possible to measure the generalisability of a model, which informs us on how well it is able to predict using an out-of-sample dataset (Varoquaux, 2018). For this study, the nested cross validation technique was employed (Stone, 1974) by separating the data into 10 training and test sets (outer level), and further dividing the training set into 10 training and validation sets (inner level). The inner level was used to identify the best hyperparameters for each model, while the outer level was used to compare all models to select the best performing based on the average and standard deviation of the Pearson correlation coefficient between predicted and actual outcome values, as well as Root Mean Squared Error (RMSE).

3.3 – Results

The results are described in three parts. First, the predictive accuracies of the five machine learning models were compared, followed by an outline of brands that were the best predictors of age. Finally, the categories of spending that were the most important in age prediction are described.

Accuracy of Age Predictions

Table 3.2 summarises the results from each of the prediction models. The results demonstrate that spending on brands provides a strong predictor of age. The best performing model is the XGBoost regressor model, which predicted a person's age with a high degree of accuracy; $r = .70$ expressed as the Pearson correlation coefficient between predicted and actual attribute values. Utilising algorithms of the gradient descent boosting framework which minimises loss as new models are added (Friedman, 2001), XGBoost regressor is a decision-tree-based ensemble method whereby new models are created to predict the residuals or errors of preceding models, which are then compiled to produce the final prediction (Chen & Guestrin, 2016). The hyperparameters of the best performing XGBoost Regressor model was as follows. Max_depth = 5, learning_rate = 0.2, n_estimator = 440, base_score = 0.6, subsample = 0.9, colsample_bytree = 0.5, colsample_bylevel = 0.2, lambda = 60, gamma = 0.0001, min_child_weight = 1, max_delta_step = 0, scale_pos_weight = 1, reg_alpha = 0, objective='reg:linear', booster='gbtree', n_jobs= -1.

Table 3.2

The average Pearson's r and RMSE scores across 10 outer folds of the machine learning models predicting age from amount spent in brands

	Pearson's *r*		RMSE	
	Mean	*SD*	Mean	*SD*
Linear Regression	.29	.14	22.33	11.53
LASSO Regression	.45	.08	11.65	1.59

Random Forest Regressor	.67	.05	8.88	.57
XGBoost Regressor	.70	.04	8.46	.56

The findings show that age can be predicted by spending records with a meaningful level of accuracy using linear methods such as linear and LASSO regression, with the latter showing improvements likely resulting from feature selection and regularisation. However, the random forest model demonstrated a substantial improvement in the accuracy, likely due to the ability of ensemble decision tree-based methods to incorporate non-linear relationships and interactions (Breiman, 2001), as well as the inclusion of a larger number of features without pre-selection (Hua et al., 2005). However, the best performance was provided by XGBoost, a gradient boosting method, which models errors from previous trees (Friedman, 2001), as opposed to random forest models which average the predictions across all trees.

The prediction accuracy of .70 compares favourably with previous research using other forms of behaviour as inputs, including language (.69; Sap et al., 2014) and Facebook Likes (.75; Kosinski et al., 2013). Figure 1 presents the plot of the actual age of participants on the x-axis, and on the y-axis the age predicted by the XGBoost Regressor model. The prediction accuracy appears to be equally accurate for younger and older consumers.

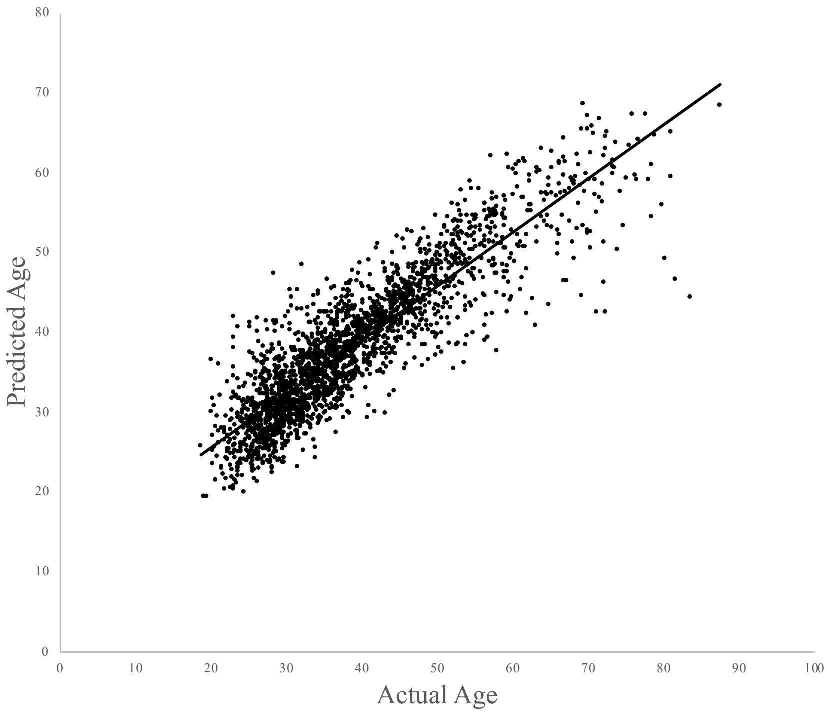

Figure 3.1. A scatterplot of the actual and predicted values of age, taken from the XGboost Regressor model

The Most Predictive Brands

To understand which brands were contributing most to the XGBoost model's predictive accuracy, a feature importance score was calculated for each brand in the model, which is a measure of the extent to which a predictive model depends on a particular feature. Through feature importance, it is possible to understand which features the model is using to learn from. To derive feature importance, the Skater package was employed, which measures a feature's entropy in prediction changes, given perturbations (Choudhary et al., 2018). The more important a feature is, the more a model's decision criteria rely on it, the more likely the predictions are to change as a function of perturbing the feature.

A series of Pearson's correlations was run to obtain the correlation coefficients for all features included. Positive correlations indicate that older people spend more money on the brand, while negative correlations mean younger people purchase more from the brand. Table 3.3 summarises the feature importance and the correlation coefficients for the most predictive brands.

The results show which brands are the most important features for predicting age, as well as whether a particular brand is purchased predominantly by older or younger consumers. The most important brand for the model was Marks and Spencer (M&S), a department and grocery store. M&S is typically considered a brand with an older customer demographic (Michell et al., 1998), providing some face validity to the model's predictions. This was followed in feature importance by: TV licensing, the fee UK households pay to access the British Broadcasting Service (BBC); Just Eat, a home delivery mobile application; B&Q, a homeware store; McDonald's, a fast-food chain; and Sainsbury's, one of the UK's largest grocery chain. Young people were more likely to spend money in fast food brands, while older people appeared to spend more money at supermarkets.

Table 3.3

The brands which best predicted age based on feature importance (> .01)

Brand	Category	Feature importance	*r*
Marks and Spencer	Retail	.053	.173
TV Licensing	Entertainment	.044	.270
Just Eat	Food and Beverage	.036	-.156
B&Q	Home	.030	.149
McDonald's	Food and Beverage	.028	-.097
Sainsbury's	Retail	.026	.107
Subway	Food and Beverage	.024	-.120
DVLA	Transport	.024	.219
Lidl	Retail	.023	.124
H&M	Clothing	.022	-.067
Dominos	Food and Beverage	.022	-.115
Uber	Transport	.020	-.091
Tesco	Retail	.020	.141
ASOS	Clothing	.019	-.087
Nando's	Food and Beverage	.018	-.133
Pret-a-manger	Food and Beverage	.018	-.026
KFC	Food and Beverage	.018	-.076
John Lewis	Retail	.017	.120
Homebase	Home	.015	.105
Next	Clothing	.015	.007
Post Office	Bills	.014	.043
Costa	Food and Beverage	.013	.054
Greggs	Food and Beverage	.013	-.067
TFL	Transport	.012	-.131
Boots	Retail	.012	.064
Which	Retail	.012	.175
Aldi	Retail	.012	.106
Spotify	Entertainment	.011	-.098
Sky	Bills	.011	.172
Starbucks	Food and Beverage	.011	-.019
WHSmith	Books / Stationery	.010	.056
BT	Bills	.010	.167

Note. The correlation coefficients were computed separately from the building of the model.

The Most Predictive Categories of Spending

In order to understand which broad categories of spending cumulatively contributed most to the prediction of age, the feature importance scores of the brands were summed up within each category. By way of illustration, Figure 3.2 presents the relative strength of these categories with a pie chart.

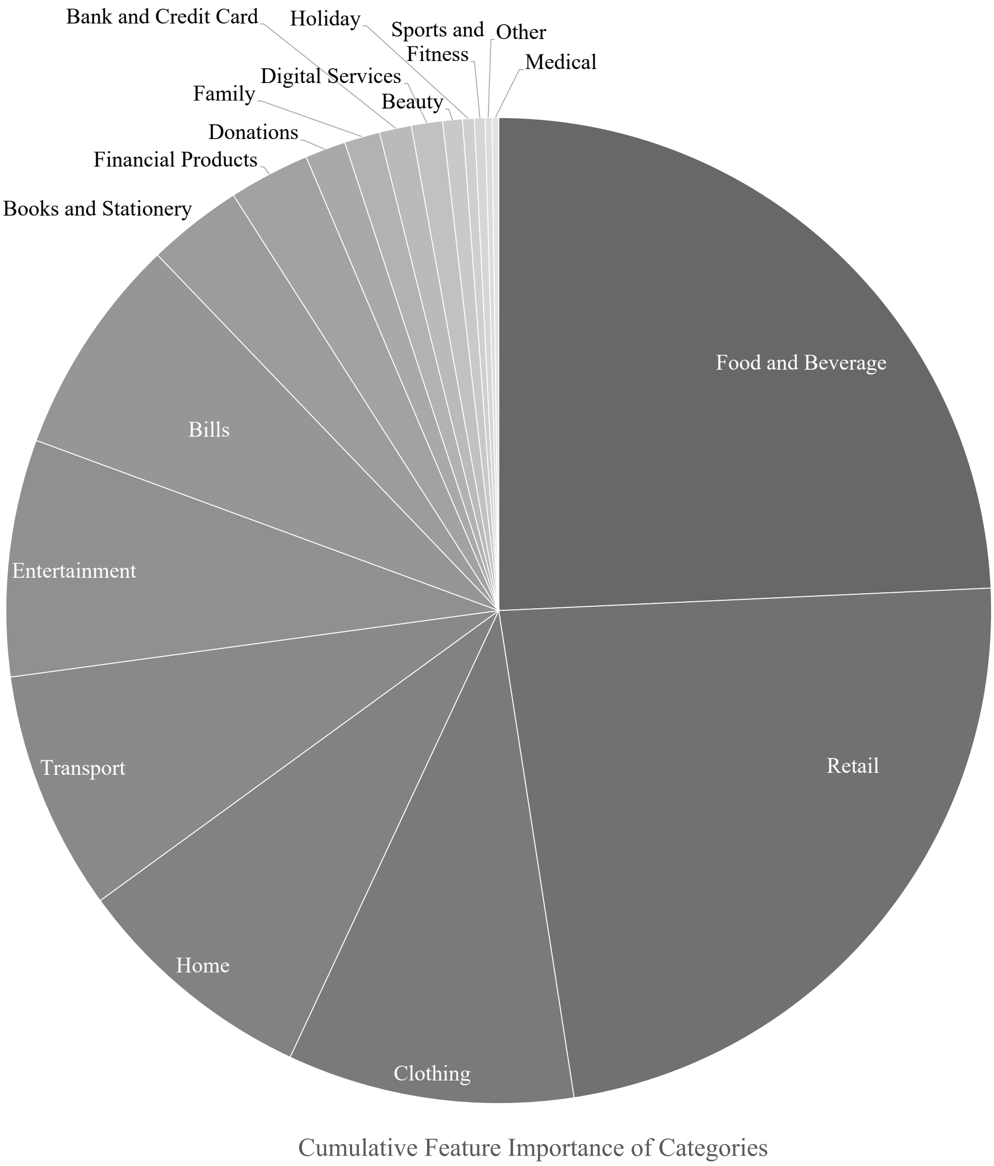

Figure 3.2. Cumulative feature importance of each category in the XGboost regression model

Note. Food and Beverage, $N = 70$; Retail, $N = 57$; Clothing, $N = 100$, Transport, $N = 63$, Bills, $N = 47$.

The five most predictive categories are Food and Beverage (.24), Retail (.23), Clothing (.09), Home (.08) and Transport (.08). This means that the brands of Food and Beverage and Retail are the most impactful in the prediction model. Together, these two categories account for nearly half the predictive accuracy of the model (.47).

Establishing External Validity

The study was motivated to predict age because it is a part of demographic variables which accounts for a large proportion of the unique variance across consumer behaviour (Naseri & Elliot, 2006; Novak & MacEvoy, 1990; Sandy et al., 2013). However, it is difficult to interpret the accuracy score (r = .70) and whether this score has practical relevance. The error that exists between participant's real age and their model-predicted age could either mean the predicted age is a far poorer predictor of real behaviour than actual age, or given that the predictions are based on additional information about each individual these predictions could potentially explain a greater degree of variation in real-life outcomes than actual age.

To assess criterion-related validity, the correlations between several relevant external criteria were compared. Real age, and predicted age, were both used to predict outcomes. In Figure 3.3, the external validity of predicted age (plotted on the y-axis) was higher than that of real age (plotted on the x-axis). If the point is above the line, it means that the model-predicted age is better at predicting the outcome. When below the line, then real age is better. What is particularly striking is that predicted age reliably predicted these external criteria. In 8 out of the 11 correlations, predicted age was also more strongly associated with the external criteria than actual age. For example, the correlation between real age and home ownership was r = .193, while correlation between predicted age and home ownership was r = .256.

When interpreting these results, one might question if there is a difference in use of cash and that this may have an impact on the findings. A Pearson's correlation coefficient was computed between age and cash usage as indicated as the amount of money spent tagged in the "cash" category. The results indicated that although it was significant (p = .02), the effect size was considered very small (r = .05). This means that the impact is likely to be negligible and possibly attributable to other factors.

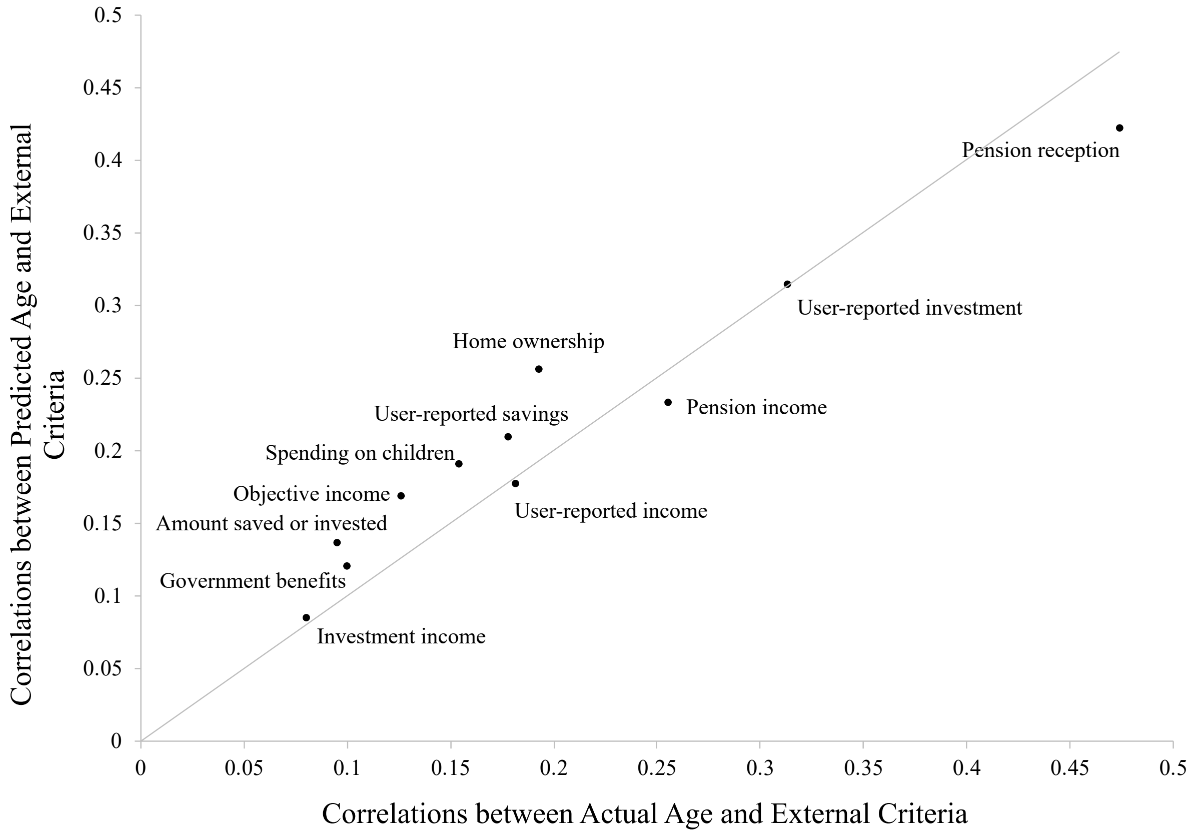

Figure 3.3. Scatterplots of correlations between outcome measures and both actual and predicted age.

3.4 – Discussion

The aims of the current study were threefold. First, this study tested whether a consumer's age can accurately be predicted from the brands they buy. Second, it determined which brands provided the most important signals of age. Third, external validity of these predictions to important outcomes was demonstrated. The results indicated that examining individuals' brand spending over a 12-month period can reliably predict age with an accuracy of .70, expressed by the Pearson product-moment correlation coefficient between the actual and predicted values. This was comparable with past research inferring age from consumer's Facebook Likes (.75; Kosinski et al., 2013) and the language they used online (.69; Sap et al., 2014). The findings suggest that utilising the digital footprint left behind by spending may be just as useful to researchers in predicting consumer characteristics such as age, compared to the use of social media and other forms of online data. The present study makes a unique contribution to the literature in that it explicitly compared the predictive utility of different brands and different types of purchases. As well as demonstrating a high level of predictive accuracy overall, the study also provided descriptions of the brands which contributed the most to the models' accuracy.

The finding that chronological age can be inferred at a high degree of predictive accuracy from transaction records clearly demonstrates that bank transactions are a good source of data for understanding consumer characteristics and their consumption patterns. This is in line with the proposition that transaction records are superior to self-reported purchasing behaviour of a smaller range of products and attitudes often relied upon by traditional consumer research, which have yielded small effect sizes (i.e., less than 10%; Sandy et al., 2013) in explaining the relationship between demographic variables and consumer behaviour. By showing that consumption patterns can predict age with a higher degree of accuracy compared to personality, this study contributes to the debate regarding the usefulness of demographics and psychographics in understanding consumer behaviour. To put these findings into context with prior studies of similar nature, age is predicted using spending records with an accuracy of $r = .70$ in this study, compared to Big Five personality as predicted by Gladstone et al. (2019) at an accuracy of $r = .15$. In line with evidence demonstrating higher explanatory power of demographics compared to personality in the differences in a wide range of consumer behaviour (Naseri & Elliot, 2006; Novak &

MacEvoy, 1990; Sandy et al., 2013), the current results suggest that age may be a more useful segmentation criterion than personality for informing marketing strategy.

The findings are supportive of self-congruity theory (Sirgy, 1982), as there appears to be a strong association between how much people spend in each brand and their age which suggests that people spend in a similar way when they are of similar age, conforming to their age-related self-concept; on the other hand, the difference in where they spend their money increases as the age gap widens. Inspecting the feature importance list of brands (see Table 3.3) and the cumulative feature importance across spending categories (see Figure 3.2), it is apparent that brands belonging to the Food and Beverage and Retail categories were the most influential. This means that consumer's brand preferences in these areas, as measured by which brands they choose to spend their money on, best differentiates themselves from consumers in other age groups. These results confirmed that people buy things not only because of their functional usefulness, but that they express something about themselves (Levy, 1959). While spending on food is a necessity for basic living, which brands an individual chooses to spend their money on within these categories appears to send clear signals about their life-stage and age-related identity. Thus, these trends are indicative of a detectable degree of self-congruence between one's age-related self-concept and brand choices.

Some clear trends emerge from the results. Young people consume more from fast food brands, and older people spend more on supermarket brands. These differences are likely to reflect the different lifestyles of older and younger consumers, with younger consumers valuing convenience while older consumers have more disposable income, are buying for larger households and are more likely to be cooking meals at home. The differences in brand spending may also be explained by young people's preference for experiential purchases (van Boven & Gilovich, 2003), indicated by their inclination to eat out, an activity involving social interactions commonly related to experiential spending (Caprariello & Reis, 2013).

Beyond self-concept, the ability for brand purchases to reveal consumers' age may also be accentuated by the digital divide between younger and older people (Friemel, 2016). The rapid advancement of technology has led the behaviours of the young to increasingly be mediated by technology, in contrast to the old (Kezer, Sevi, Cemalcilar, & Baruh, 2016; Sorce, Perotti, & Widrick, 2005; Olson et al., 2011). While young people are typically early adopters and active users of technology (Vaage, 2013), older people use the Internet less frequently (Office for National Statistics., 2017). While the rise of online shopping has transformed the retail industry, accounting for a growing proportion of total sales (Office for National Statistics., 2018b), the adoption of retail technology has not been universal. Online shopping shapes consumer's spending but that this is moderated by age (Zhang, 2009), due to older people's inexperience with technology, resistance to change and greater risk perception with respect to online shopping (Trocchia & Janda, 2000). Therefore, it was expected that spending mediated by technology (e.g., spending on online-only brands) would reveal age to a greater degree than traditional brands.

The use of online platforms and mobile applications as methods to engage consumers (Izquierdo-Yusta et al., 2016) may help explain young people's tendency to use or shop at brands such as Just Eat, Uber, ASOS and Deliveroo. After all, young people tend to be early adopters and active users of technology (Boyd, 2008), and are more attracted to recently introduced options (Lambert-Pandraud et al., 2006). As digital marketing is highly exposed to young adults who spend a large proportion of their time on the Internet and have grown up surrounded by digital technologies (Montgomery & Chester, 2009), brands that employ this form of marketing may also engage a larger audience of younger consumers. Similarly, industry statistics show that young people prefer on-demand services hosted online such as Netflix, Amazon Prime and YouTube over traditional television (Ofcom., 2018). This is consistent with the current findings that older people spent more on TV licensing, which indicates that they are more likely than young people to engage with traditional media. Altogether, these findings show that brands' use of technology may underlie age differences found in consumption patterns, and that these differences in spending reveal important information about a consumer's age.

The findings showed that age predictions were equally accurate for younger and older consumers, supporting the value of transactions as a good source of data to study behaviours, given its widespread use across the age spectrum. However, the similar predictive accuracy across ages is inconsistent with previous studies suggesting that older people may be less homogeneous than younger groups, as there are more changes in later stages of their lives compared to those in their 20s (Silvers, 1997). Furthermore, the ageing process differs among individuals in terms of their age-related physiological, social and psychological changes (Moschis, 2003), as well as the different life-changing experiences they go through (e.g., divorce, death of a partner). As a result, older consumers may grow to become increasingly disparate in their lifestyles, needs and consumption habits (Moschis, 1996). Thus, replication will be needed to verify this finding, as it may be unique to this dataset.

Practical implications

The findings of the current study have implications that are practically relevant to marketing professionals. As age information is not always available to marketers, it is possible for some companies to profile consumers' age based purely on their spending records. While the exact set of data may not be available to most companies, some may have access to similar data sources. For instance, large retail companies have access to the spending records of their customer database on their own website or shop, certain web companies may collect cookies and information about which websites consumers have purchased from. With the rapidly ageing global population (World Health Organisation, 2018) and growing disparity in resources between the generations with the wealth of the old increasing at a faster pace than the young across many Western countries (Office for National Statistics, 2018a), companies who want to reap the rewards of these demographic and economic shifts must be able to target their products directly to the specific age segments they wish to serve. As the older consumer market is now forecast to be at least as important as the younger consumers upon whom marketers have traditionally focused (Cole et al., 2008), inferred age can be used as a part of business strategy to boost sales through a personalised marketing strategy and item recommendation (Zhao et al., 2014) which can improve user experience and mitigate choice overload (Iyengar & Lepper, 2000; Schwartz & Ward, 2004). When consumers are shown advertisements more relevant to their age, they may respond to these marketing messages more positively, resulting in more positive attitudes and intention to purchase (Alhabash et al., 2020). The insights drawn from current findings regarding the potential mechanisms underlying age-related brand preferences can be used directly to inform the content tailored to specific age groups distributed by different digital marketing tools such that they are more relevant to the social identity and life stages of each age group.

Another practical implication of the current study concerns the establishment of good external validity for predicted age from brand spending. The findings show that inferred age is related to meaningful external criteria at comparable strength to actual age. For businesses interested in predicting financial outcomes of their customers such as home ownership or investment behaviours in order to target prospective customers for products related to these behaviours, the findings indicate that inferred age can be as useful as actual age, or in some cases more useful than actual age, to understand some financial behaviours. More importantly, the methodology used in this study demonstrates the possibility of scaling the acquisition of such information to a larger pool of customers. These predictions can have strong implications for businesses who are interested in incorporating customers' age information as part of their strategy to procure new customers, or market new products to existing ones.

The results of the current study also have important implications for consumer privacy. Consumers who consider age to be sensitive and private information may not wish to disclose their age to marketers or organisations. However, as purchases become recorded automatically by digital payment methods, it becomes increasingly difficult for consumers to avoid being profiled based on their spending. More worrying still, a consumer's age does not only denote their membership of a potential market segment but can also reveal consumers cognitive efficacy. For example, as an individual's cognitive capacities decline with age (Li et al., 2013), the use of inferred age from spending records may be open to potential abuse in identifying age-associated vulnerability to fraudulent sales techniques (e.g., email phishing attacks). This vulnerability may be greater for older adults, due to their lower tendency to employ privacy protection online (Kezer et al., 2016). However, similar risks are posed to younger generations, who are known to be less financial literate than older groups (Lusardi et al., 2010), and therefore may be targeted to engage in harmful financial behaviours (i.e., gambling, payday loans). Therefore, policymakers should consider how regulation might be required to protect consumers from these risks. A recommendation may be to use inferred age information to design educational and outreach programmes aimed at raising awareness around the potential risks of vulnerability-based microtargeting.

Limitations and Future Research

Research using spending to predict consumer characteristics is also likely to require continual updating to remain accurate, as cohort effects in spending (e.g., popularity of categories or brands) will vary over time. For example, several of the most highly predictive brands in this sample have only traded for the past few years, meaning new brands that emerge are likely to continue to have a disproportionate influence on predicting age. As with any age-related studies, the current study is unable to disentangle the confounding effects of period or cohort from age, hence it is not permitted to conclusively determine the effect of age on consumption patterns. Another consideration is the potential narrowing of the age gap in the behaviours of individual consumers, as shown by prior research showing that once individuals become experienced online shoppers their behaviours begin to converge (Hernández et al., 2011). Therefore, age differences in shopping behaviours may become less pronounced, as the already digitalised younger generations grow older, though it remains unclear how adaptive they will be to future consumer technology.

In terms of future research, studies could look into the potential differences in how well chronological and perceived age can be predicted from transaction records. People do not always perceive their cognitive age to be the same as their biological age, and this can influence their purchase behaviour (Barak & Schiffman, 1981) as well as how they understand and interpret advertisements (Bradley & Longino, 2001). There is also some evidence suggesting that chronological age is gradually becoming a less important signal of individuals' experiences of ageing and self-identity, meaning that age-based marketing may shift from a focus on the physical, to appealing more strongly to values, traditions and aspirations (Bradley & Longino, 2001). This means that there is a possibility that predictive models could yield potentially higher degree of accuracy when inferring chronological age, if consumers are spending more closely in line with their cognitive age than their biological age.

Conclusion

In conclusion, this study found that it is possible to reliably predict age from consumer's spending records, with a high degree of predictive accuracy (r = .70). The brands that best distinguish people of different ages are primarily those related to food and retail. Brands using technology in their operation or marketing – such as delivery apps or online clothing shops – were used predominantly by younger consumers, and therefore these types of spending provided a strong signal of age. Thus, these findings demonstrate the digital divide between older and younger consumers, expressed through their brand choices. As this study has shown, age inferred from the XGBoost model with transaction records as input is highly accurate. This information could potentially be used to tailor adverts to consumers to increase their appeal, a proposition that will be tested in the next study. However, the results also raise important questions about consumer welfare and privacy. In future, the accumulation of digital records at larger scales will provide the opportunity to study longitudinally how purchase behaviours change over the lifespan and with increasing computational power and advances in machine learning tools for big data analytics, the prediction of age using bank transactions is expected to become more reliable and accurate.

Chapter 4 – Personalising Adverts Using Inferred Age

Chapter 4 summary

This study addresses the lack of studies directly bridging two processes in personalised advertising (inference of consumer attributes and personalising advertisements), and demonstrates the practical relevance of inferred consumer attributes acquired through predictive models. Prior research has shown that when advertisements are tailored to fit with consumer's characteristics, they are responded to more favourably (Alhabash et al., 2020; Higgins et al., 2018; Matz et al., 2017). One of the ways to tailor advertisements is via advertising endorsers such as celebrities' characteristics, as evidence suggests that when the endorser's age is congruent with viewer's age, they are more likely to engage positively with the advertisements (Alhabash et al., 2020). This study therefore aims to investigate the extent to which age – inferred from the spending preferences of consumers – can be used to tailor advertisements and subsequently increase advertisement appeal. To this end, this study applies the machine learning model built in Chapter 3 to predict age onto a new dataset which includes self-reported brand spending from a separate panel. This inferred age is then used to investigate if advertisements personalised to inferred age will increase appeal. The results show that overall, after controlling for attitudes towards the neutral advertisements, participants who viewed advertisements that matched their inferred age expressed significantly more favourable attitudes towards the advertisements than those who viewed mismatched advertisements.

4.1 – Introduction

Marketing that is personalised to a consumer's characteristics is more persuasive (Cesario et al., 2008; Hauser et al., 2009; Hirsh et al., 2012). However, limiting the applicability of this insight is that marketers do not always know the characteristics of their customers. The effectiveness of personalised advertisements also relies heavily on the accuracy of consumer characteristics on which advertisers base their personalisation efforts. One way to overcome this would be to infer the characteristics of consumers from their behaviour. As digital marketing moved away from one-to-many communication towards highly personalised communication (Shah et al., 2006; Sheth et al., 2000), there is now an urgent need to understand how communication can be personalised to increase advertisement effectiveness.

One of the characteristics that strongly influences the behaviour of consumers is age (Phillips & Sternthal, 1977). From a child selecting their first toy in a store, to a retiree booking a cruise online; age is a defining feature of consumers. Given that age is commonly used in microtargeting advertisements (Bol, Strycharz, et al., 2020), it highlights the utility of this demographic variable in personalising advertisements. If the age of an audience is known, marketers can target audience segments with messages that more closely match these groups. For example, when tailoring advertisements, it is relatively straightforward to tailor the characteristics of an endorser, of which age is a salient characteristic that consumers can identify quickly. This study investigates the extent to which age inferred from a machine learning model developed in the previous study can be used to tailor advertisements and increase their appeal to viewers. This study empirically tests the hypothesis that participants who viewed advertisements matching their inferred age expressed more favourable attitudes towards the advertisements than those who viewed mismatched advertisements.

As more advertisers turn to social media for their ability to hypertargeting and segmentation (Alhabash et al., 2020), an increasing number of marketers are using demographic criteria for target-based segmentation. Despite the fact that techniques of personalised marketing have evolved into targeting consumers using psychographics and behavioural traits beyond demographics, demographics remain a fundamental part of consumer identity with which marketers use to personalise and target advertising (Lin, 2002). While some scholars have argued that psychological variables provide more value in understanding consumers compared to demographic variables, empirical evidence on the utility of demographic and psychological variables in market segmentation remains inconclusive (Kennedy & Ehrenberg, 2001; Novak & MacEvoy, 1990; Sandy et al., 2013). In fact, several studies have shown that demographics may be more important than personality variables in predicting consumer behaviour (Müllensiefen et al., 2018; Novak & MacEvoy, 1990; Sandy et al., 2013). At the very least, demographics form a crucial part of the information used in conjunction with psychographics (Keller, 1993; Levy, 1959) such that without demographic information a consumer's profile would be incomplete.

The Role of Age in Advertising

Age is one of the most common segmentation criteria for microtargeting (Bol, Strycharz, et al., 2020; Müllensiefen et al., 2018). Age reflects life-stage, cohort effects and often financial position, and consumers from different age groups have different interests, values, and spending patterns. Further, the multidimensional nature of the ageing process involves changes in different aspects of an individual, such as biology, psychology and social relationships (Ahmad, 2002). For instance, as people age, their motivations become less focused on development goals of growth and shift towards those concerning maintenance and regulation of loss (Baltes et al., 1999; Cole et al., 2008), which in turn influences the way they respond to communication messages and products (Wei et al., 2013). As a result of ageing-related changes, prior research shows that younger people differ from older people in terms of their preference in products (Hervé & Mullet, 2009), the way they process information on packaging labels (Piqueras-Fiszman et al., 2011), susceptibility towards certain messaging (Alhabash et al., 2020), as well as the types of media they consume (Bachmann et al., 2010). These differences can be exploited to create more relevant advertisements and target them to different age groups. In fact, age can be an effective demographic factor for targeting consumers, as demonstrated by a recent study which used multivariate testing of an advertisement campaign on Facebook and found that age-congruent advertisements personalised to specific age group demographics yielded significantly higher click-through rates compared to incongruent advertisements (Higgins et al., 2018).

Cues in ads, such as messaging frame, colours, and spokespersons, are essential in consumers' decision-making process, and each of these cues can be tailored for personalisation. Especially useful are the visual aspects of an advertisement, such as photographs, graphics, and human model depictions, as they are powerful tools for conveying important messages to consumers about the advertised products and serve as ways for consumers to identify with the portrayed images (Sung & Hennink-Kaminski, 2008). Among the variety of visual cues, the model depicted within an advertisement is one of the most salient aspects of an advertisement which readily draws a viewer's attention. Therefore, consumer goods marketers "often feature endorsers as the centrepiece of their advertising or promotions efforts" (Shimp et al., 2005; p. 4). Models in advertisements play a particularly significant role in the transfer of personality traits (Erdogan & Baker, 2000), and are used to broadcast a specific lifestyle (Chang, 2008), where their extrinsic attributes (i.e., ethnicity, age, and gender) activate the self-categorisation process whereby consumers evaluate the advertised product as "for-me" or "not-for-me" (Forehand & Deshpandé, 2001; Maldonado et al., 2003). For instance, a 60-year-old cisgender male seeing an ad featuring women in their twenties might automatically think the ad does not target him specifically. Furthermore, perceived congruence between the consumer's self-concepts and characteristics of an endorser model results in more favourable ad evaluations (e.g., Kamins, 1990; Wright, 2016) as consumers may find this match to be psychologically comfortable (Hong & Zinkhan, 1995). As a result, consumers are more likely to report more positive attitude toward the advertisement and purchase intention when there's a high congruence between consumer's self-concept and a celebrity endorser's image (Choi & Rifon, 2012).

Celebrity Endorsers

The mechanism underpinning the endorser-consumer congruence effect stems from the brand-user image associated with the brand which is invoked by the salient characteristics of an endorser. Brand-user image is a perception of the generalised or prototypical user of a particular brand (Johar & Sirgy, 1991; Sirgy, 1982). A brand's associations to certain demographics arise as a consumer experiences or interacts with a brand through a wide range of communication channels (e.g., other brand users, the customer service team, endorsers in an advertisement), therefore personalised advertisements can be an appropriate way to induce these perceptions (Aaker, 1997; Keller, 1993). As endorser characteristics are crucial in influencing how consumers evaluate a brand (Grewal, 1995), featuring an endorser with characteristics that are in line with a brand's target demographic is fundamental for increasing appeal to a product. Thus, congruence with endorser characteristics is expected to positively influence consumers' attitudes towards an advertisement.

One of the most prominent features of an endorser is their age. People are accurate judges of other's age and are able to discern facial variations indicative of age, even if the faces are unfamiliar to them (Burt & Perrett, 1995; George & Hole, 2000), making age perception one of the key cognitive processes when looking at an endorser's face in an advertisement. Age of endorsers can be transferred to products, as the age of the typical user signals the perceived age of the brand (Huber et al., 2013). This means that it is possible to manipulate an endorser's age in an effort to change consumers' brand age perceptions. Supporting this notion, prior research found that endorsers' age-related cues affect ad evaluations and purchase intentions (Chang, 2008; Day & Stafford, 1997; Pezzuti et al., 2015; Simcock & Lynn, 2006), and that the perceived match between endorsers' and consumers' ages positively influences self-brand affinity, self-referencing, and brand attitudes (Chang, 2008). Perceived congruence between consumer's and endorsers' age is associated with a higher degree of "for-me" perceptions (Chang, 2008), more positive ad evaluations (Roy et al., 2015) and greater click-through ratios (Higgins et al., 2018). Older people in particular are more likely to judge the extent to which they are similar to the model (Kozar & Lynn Damhorst, 2008; Nelson & Smith, 1988), showing that it is especially important to feature endorsers with whom older people will identify most (Kozar, 2010; Kozar & Lynn Damhorst, 2008). The age-congruence effect has also been found in younger samples. In two recent studies involving young participants, Alhabash et al. (2020) found that alcohol ads featuring models congruent in age to that of the participants' cohort membership exerted greater cognitive resource allocation (i.e., attention), elicited more favourable evaluations of the ads, and higher drinking intentions. In all, incorporating the age of an endorser appears to be an effective way to personalise advertising, when targeting consumers of different age groups.

The shift in advertising and marketing towards ad personalisation and microtargeting, as well as the potential to profile consumers at a scale using machine learning models calls for an investigation incorporating these two processes in microtargeting advertisements. The present study looks to address a lack of research directly linking the inference of consumer characteristics and microtargeting using inferred traits. The aim of this study is to investigate the extent to which inferred consumer characteristics from bank transactions can be used to effectively personalise advertising. This study empirically tests the extent to which chronological age inferred from the XGBoost machine learning model developed in the previous study using brand spending can be used to tailor advertisements by matching endorsers' and viewers' age, thereby increase their appeal to viewers. Study 1 established that it is possible to accurately predict chronological age from one's bank transactions. To further demonstrate the practical relevance of the findings, this study investigates the extent to which age predicted via the machine learning model in Study 1 can be used for tailoring advertisements to individuals to increase the appeal of these advertisements. In order to do this, a follow-up experiment is conducted to test the change in appeal to advertisement tailored to participants' age as predicted by the machine learning algorithm devised in Study 1. The endorser depicted in the advertisements is manipulated to test for the effects of personalisation on advertisement appeal. The objectives of this study are as follows. First, to test the extent to which, without knowing a participant's actual age, it is possible to reliably infer their age by applying the machine learning algorithm devised from bank transactions on their self-reported spending information. Second, to investigate whether advertisements featuring an endorser whose age is congruent with the participants' inferred age are more appealing than those featuring an endorser with age incongruent with participants' inferred age. I hypothesise that when participants are shown advertisements with endorsers whose age is congruent with their own, they are more likely to find these advertisements appealing.

4.2 – Method

Participants

192 participants were recruited from Prolific, an online panel. The participants were current residents of the United Kingdom, aged 18 to 75 (mean = 39.74 years, *SD* = 13.71). Of these, 112 were female (58.33%), and 80 male.

Measures

Self-reported spending

Participants were asked to report to the best of their ability the amount of money they spent on each of 652 brands (see Table S2 in supplementary materials) in pounds; the list of brands was taken from Study 1. For each of these brands, they were required to respond to the question "Please estimate how much you spend over a year for each of these brands, and then enter that number into the box. If the amount is 0, simply leave it blank."

Advertisement ratings

Previous research has found that the incorporation of older models could be effective for age-neutral products as well as products aimed at older people (Greco, 1989), so the age of the subject in the advertisements was manipulated to test the hypothesis. For the advertisements, four age-neutral products or services (i.e., healthcare, groceries, convenience store, furniture) were chosen for this study. Participants were asked to rate each advertisement on three scales which measured the extent to which they liked the advertisement they were shown, the degree to which they identify with the advertisement, as well as their likelihood of buying the product being shown in the advertisement. Three single-item questions were used. Rated on a 7-point Likert scale, "How much do you like this advertisement?" ranged from "Dislike a great deal" to "Like a great deal", while "To what extent do you agree with this statement… I identify strongly with this advertisement." ranged from "Strongly disagree" to "Strongly agree". The final question, "How likely would you be to buy what is being sold in this advert? Please indicate this below, from 0-100% likelihood of buying" was responded on a slider anchoring at 0 and 100. The scales were highly internally consistent (Cronbach alpha

= .88), so the mean of their z-standardised scores was taken to represent the level of advertising ratings. The ratings for each advertisement were also normally distributed (see Figure 4.1).

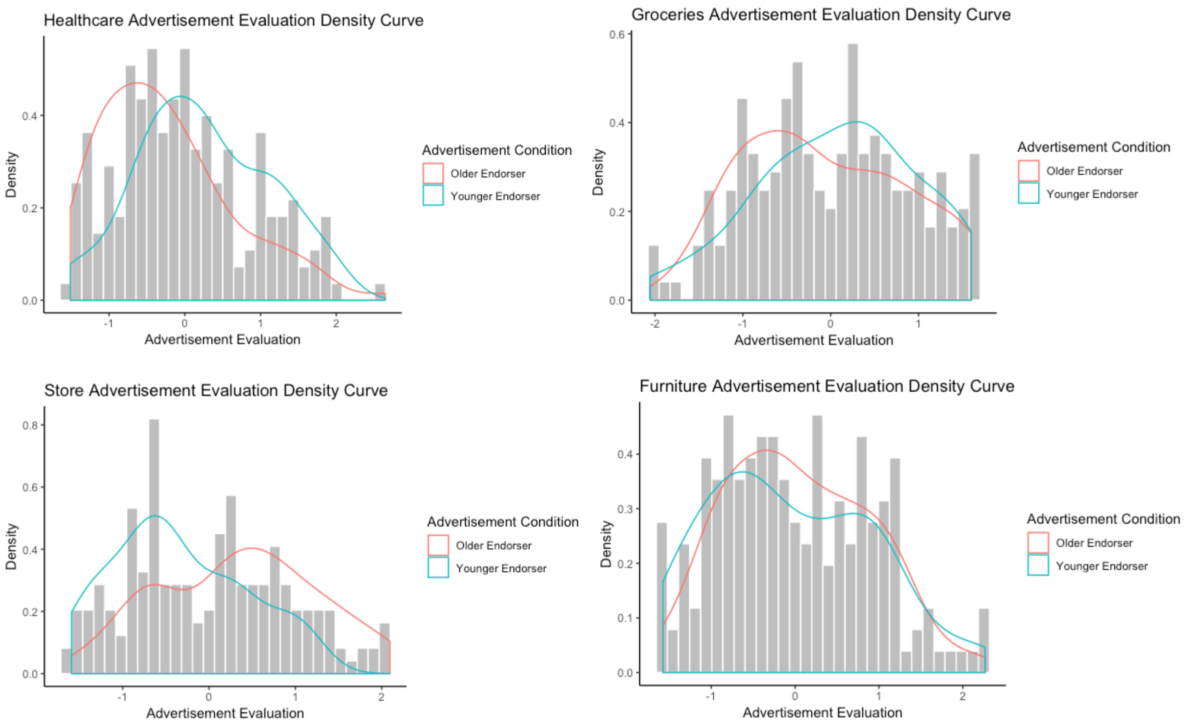

Figure 4.1 Histogram and density plots for the evaluations for each advertisement

Demographic questions

Participants responded to questions regarding their age in years, their gender, education level, and household income. Education level was measured with the question "What is the highest level of education you have completed?", selected from five options: Secondary School (e.g., GCSE's), Sixth Form education (e.g., A Levels), University degree (e.g., BA, BSc), Masters degree (e.g., MA, MSc), Doctoral degree (e.g., PhD). Household income was measured using the question "What is the annual income of your household, before taxes?", with the following options as answers: Less than £10,000, £10,001 to £15,000, £15,001 to £20,000, £20,001 to £30,000, £30,001 to £40,000, £40,001 to £50,000, £50,001 to £60,000, £60,001 to £80,000, £80,001 to £100,000, £100,001 to £120,000.

Procedure

Figure 4.2 shows the experimental procedures for the current study. The study utilised a between-subject design. Participants were randomly allocated into either an 'older' or 'younger' advertisement conditions. The model featured within the tailored versions of each of the four advertisement variation (i.e., healthcare, groceries, convenience store, furniture) are manipulated to be either older or younger (see S4 for the advertisements). Depending on which condition participant has been allocated to, they each saw four advertisements which were either tailored to appeal to older or younger people, as well as the neutral version of the four advertisements which do not feature an endorser. In total, participants saw eight advertisements: four with are manipulated with younger or older endorser, and four which do not feature an endorser. The advertisements were checked to ensure the subjects were presented in a way that was neutral to the context without positive or negative stereotypes to age to avoid confounds of the experiment. The order of the four advertisements was randomised, so participants saw the advertisements at random order. They were required to rate the advertisements on three metrics, the extent to which they liked and identified with the advertisement as well as their likelihood to buy the product. The experimental manipulation ended here. Following this, participants were given a brief introduction to the brand categories and were asked to report as accurately as they can the amount of money they have spent in each of 652 brands shown in 19 categories over the past 12 months, all shown in random order. Finally, participants completed a series of questions regarding their demographics, and were monetarily compensated for their time.

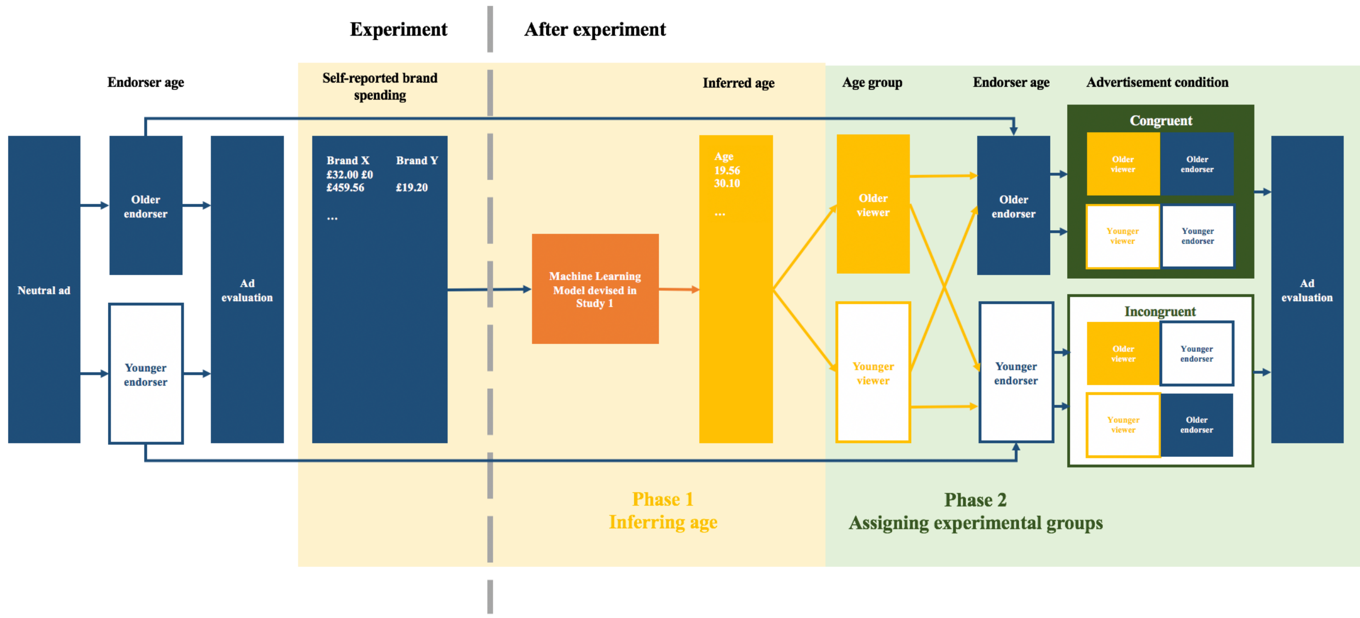

Figure 4.2 Summary of experimental procedures in Study 2

Note. The blue boxes indicate variables collected from participants, the rest were inferred and assigned post-experiment.

Data Analysis

After the experiment, an analytical procedure was conducted to infer age (highlighted in yellow) and to assign experimental groups (highlighted in green) for the analysis of ad evaluation (see Figure 4.2). Using self-reported brand spending collected in the panel of participants in this study as input, the XGBoost regressor was applied using the same hyperparameters derived in Study 1 to obtain a predicted age as an output for each participant in this study. Using predicted age, the participants were split into two groups: 'older' and 'younger' according to the median age. Participants were then assigned into congruent and incongruent groups based on whether there is a match between their age group (older, younger) and the adverts they were shown (showing an older, or a younger endorser). For instance, participants who were put into the older group were shown the adverts featuring old endorsers would be considered as belonging in the congruent group, while old participants shown the adverts with young endorsers would be included in the incongruent group.

A series of ANCOVA models were computed to determine the effect of endorser-viewer age matching on overall ad evaluation, controlling for the overall evaluation for the neutral advertisements as a covariate within the model. This is done to ensure there is no confounding effects of attractiveness of advertisement types, as it is possible that certain advertisements may be more appealing than others simply because the visual effect is more striking, or the product being advertised is more attractive.

4.3 – Results

Age Inference

Applying the XGBoost regressor devised in Study 1 on a completely new set of self-reported spending in the same brands, self-reported age was predicted with an accuracy of $r = .61$. This shows that the model built in Study 1 can be applied with reliable accuracy even to self-reported spending, indicating a level of similarity between self-reported and actual spending.

The median of the inferred age is 38.48, which was used to split the sample into two groups of Older and Younger participants (N for both groups = 96). The categorisation based on a match between inferred age group and advertisement condition resulted in 101 participants in the congruent group, and 91 participants in the incongruent group. A series of independent samples t-tests showed that there was no significant difference between the congruent and incongruent group in terms of actual and inferred age, gender, education level, or income levels ($p > .05$). As the two groups do not significantly differ in these demographic factors, they were not be controlled for in the subsequent analyses.

The Effect of Endorser Age Congruence on Ad Evaluation

A series of ANCOVAs were conducted to determine whether there is a significant effect of endorser age congruence on the evaluation for all adverts on average, as well as individual adverts. The overall and individual ratings for the neutral advertisements were controlled for as a covariate in the models. The adjusted means of the congruent and incongruent groups were also reported. The results showed a significant difference in overall advert and healthcare advert (see Table 4.1) where the congruent group reported significantly higher ratings for the adverts tailored to them compared to the incongruent group, who reported significantly lower ratings for the adverts mismatched to their inferred age. The covariates of ratings for the neutral advertisements were significant in all the models ($p < .001$). While the endorser age congruence did not reach statistical significance for the other advertisements, the adjusted means of ad evaluation revealed that participants in the congruent group were on average more likely to positively evaluate the advertisement, than those in the incongruent group.

Table 4.1 *A series of ANCOVAs to test for the significant effect of endorser age congruence on evaluation of advertisements*

Rating metric	F(1,189)	Adjusted R^2	*p*	η_p^2	Adjusted mean	
					Congruent	Incongruent
Overall	5.938	.604	.016	.030	.070	-.077
Healthcare	8.408	.328	.004	.043	.147	-.163
Groceries	2.939	.495	.088	.015	.076	-.085
Store	.213	.337	.645	.001	.024	-.026
Furniture	2.045	.494	.154	.011	.064	-.071

Figure 4.3 and Figure 4.4 present the interaction plots between inferred age group and the overall, as well as individual advertisement condition. In general, older participants were likely to rate the advertisement similarly whether or not the endorser's age was tailored to fit theirs. However, younger participants were more likely to show larger differences in how they rate the advertisements, particularly they showed more favourable attitudes toward advertisements that include an endorser who appears to be of similar age to them, while they showed more negative attitudes toward advertisements that portrayed an older endorser.

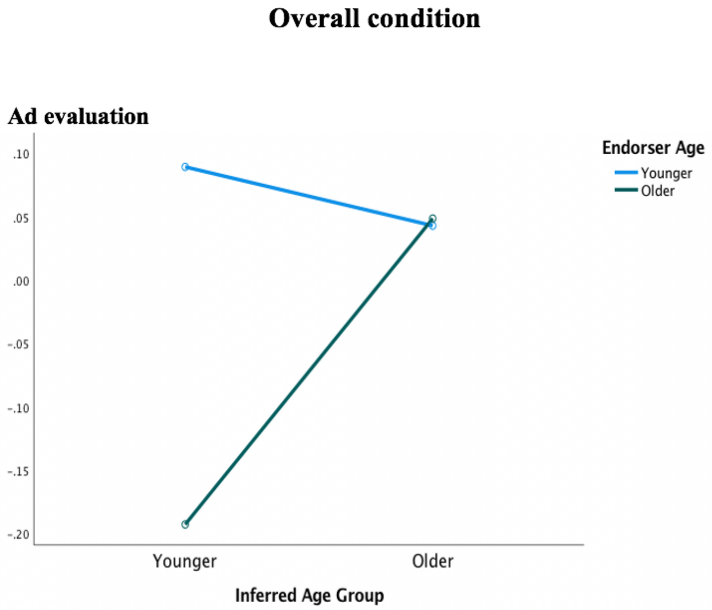

Figure 4.3 Interaction plot of overall advert condition and predicted age group on advertisement evaluation

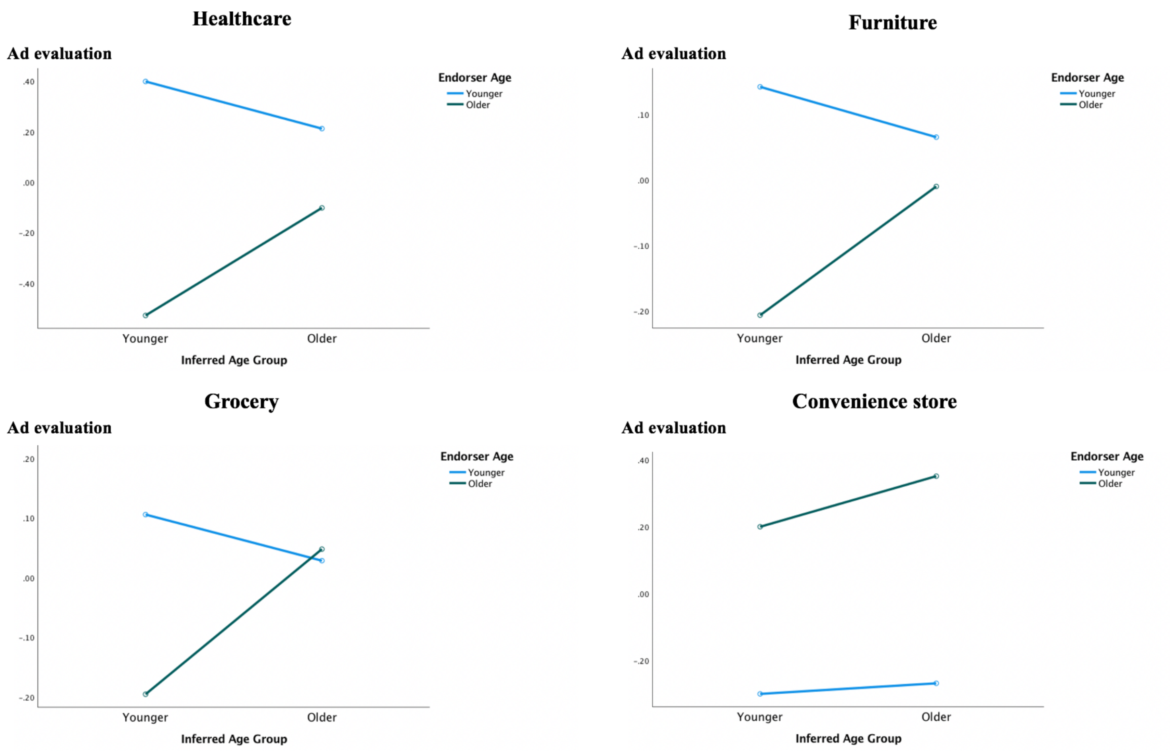

Figure 4.4 Interaction plots of individual advert conditions and predicted age group on advertisement evaluation

4.4 – Discussion

The aim of this study was twofold. First, it tested the extent to which it is possible to use the machine learning model devised in Study 1 to infer age in a different sample, using self-reported spending. Second, the degree to which inferred age be used to tailor advertisements to increase appeal was tested. The results showed that the machine learning algorithm developed using actual bank transactions as input could be applied to a completely different dataset which uses self-reported spending and achieve an out-of-sample accuracy of .61. It was hypothesised that participants would rate advertisements with age congruent with their own more favourably. This hypothesis was partially supported: in general, when consumers are shown advertisements that were matched to their inferred age, they were likely to give significantly more positive evaluations towards the advertisements, as indicated by their higher ratings for the advertisement, when matched compared to mismatched. This suggests that self-congruity in advertisements increases the appeal of these advertisements to the target consumers. However, when the four advertisements were inspected individually, only in the advertisement for a healthcare scenario was the effect significant.

The findings of this study corroborated those of past research that assessed the effects of self-congruence in marketing and psychology (Alhabash et al., 2020; Hirsh et al., 2012; Matz et al., 2016). In line with previous research showing that consumers exhibit positive reactions towards products or brands that are aligned to their identity, this study shows that this effect can also be extended to advertisement appeal. These findings show that participants who were shown advertisements in which the endorsers appeared to be congruent with their age were more likely to rate these advertisements more positively than those who were shown advertisements depicting endorsers who appeared incongruent with their age. Overall, the congruence effect is statistically significant (p = .016).

The mean ratings of congruent and incongruent advertisements clearly indicated that all congruent advertisements were rated more positively, and incongruent advertisements were rated more negatively (see Table S2). The effect was expected to be weak due to the inconsistent findings from previous studies, so an average evaluation of four adverts was used as a dependent variable. While the direction of the congruence effect was as hypothesised, it has reached statistical significance only in one of the advertisements: the one about healthcare. This may be due to the higher stake nature of the healthcare advertisements, as the consequences of choosing a less suitable healthcare professional or clinic may be more severe (i.e., illness, death). This may have led to the effect of congruence to be more pronounced in this advertisement than in the other advertisements included, which are lower stake, such as those about groceries, convenience store and furniture, where the consequences of purchasing from the wrong store may simply be financial loss. This suggests that the salience of endorser characteristics in personalised advertisements may be dependent on product type, possibly the extent to which a product is high- or low-stakes. The fact that the effect concentrated on the healthcare advertisement could also be due to the congruence with subject matter of the advertisement and the age of the endorser. For instance, a young endorser may make the advertisement appear to be less congruent as a subject matter as healthcare as a product may be more strongly associated with older people. Future research could benefit from exploring this. Echoing findings from Winter et al. (2021) suggesting inconsistent congruence effects, the results of the current study support the idea that the persuasive power of personalisation may depend on a complex relationship between a multitude of factors, including advertising quality, matching algorithms, the accuracy of inferred characteristics, and features of the media environment (Winter et al., 2021).

From the interaction plots (see Figure 4.3), it seems that when endorsers' age is incongruent with the viewer's age, advertisements depicting an older endorser are less attractive to young people, in contrast to older viewer's relatively more favourable attitude towards advertisements featuring a younger endorser. In other words, young people may be experiencing more strongly that an incongruent advertisement is 'not-for-me' than older people. It is possible that younger people may have stronger self-expressive needs as they are still exploring their identities (Harter, 2015), which means that their self-categorisation process may be more active, leading to more extreme evaluations. This suggests that personalising advertisement may be more important when targeting younger customers than it is when targeting older customers. This effect is the most apparent in the convenience store advertisement. It seems that younger and older participants both preferred the advertisement showing an older endorser over younger endorser, however the congruence in endorser age only seemed to increase the ratings for older participants, but not younger participants.

The findings of the current study provide partial support for the effectiveness of personalised advertising using inferred age. In relation to self-congruity in the context of advertising, the results are in line with previous studies showing that self-congruity leads to higher intention to purchase, and higher identification with, and more favourable attitudes towards, brands and products (Ericksen, 1997; Liu et al., 2012; Pradhan et al., 2016; Üner & Armutlu, 2012; Yu et al., 2013). Further, the results indicate that a demographic factor such as age is useful information for targeting consumers, supporting previous findings showing value in demographics (i.e., Sandy et al., 2013) in segmenting and microtargeting. This study has demonstrated that for marketers who are interested in increasing the effectiveness of their advertisements, it is possible to infer consumer age at scale using transactional data and target individual users with advertisements that fit with their inferred age.

In order to meaningfully contribute to existing literature of the effectiveness of personalised advertising, this study responded to criticisms relating to study design in prior research by making several significant changes to account for issues that have been raised such as the role of algorithm in distributing advertisements (Eckles et al., 2018) and the lack of a control group (Sharp et al., 2018). One of the criticisms of field studies such as Matz et al. (2017) was that they were prone to issues surrounding internal validity as it was not possible to control for Facebook algorithms, thus ensuring random distribution of participants to the experimental conditions (Eckles et al., 2018). It is possible that there was a confounding role of algorithm in distributing advertisements to those who are more likely to react more positively to certain advertisements that was potentially present in previous study (Matz et al., 2017), thereby inflating the effect of ad personalisation. This study has taken the potential confounding effects of the algorithm on social media into account and eliminated this possibility by presenting congruent and incongruent advertisements to randomly allocated groups of participants in an experimental setting. The results are in alignment with Zarouali et al. (2020), showing that not only would personalisation of advertising work in political ads when inferred personality traits are used, but it would also work in commercial advertisements using inferred demographic information such as age. In previous studies (e.g., Matz et al., 2017) where a control condition was not included, it was not possible to ascertain whether personalisation is better than no personalisation (Sharp et al., 2018). The study has also responded to this gap within the literature by including a neutral advertisement as a control. By doing this, the study has demonstrated that congruent advertisements are responded to more positively than incongruent advertisements even after evaluations of the neutral advertisements were accounted for in the ANCOVA model as a covariate.

Practical implications

The findings of this study show a direct link between the automatic inference of consumer characteristics and its use in a commercial context. The results align with previous studies in showing that personalising advertisements based on age can increase the appeal of advertisements. Importantly, this study has demonstrated the usefulness of automatic inference of consumer characteristics via machine learning by showing that the age inferred by a machine learning model devised from bank transactions is accurate, even when applied to self-reported data. This shows the value of the model devised in Study 1, further demonstrating its practical relevance in improving marketing efforts. It has shown that for marketers interested in increasing the effectiveness of their advertisements, they could apply a similar framework as shown in Study 1 and the current study. The inference of age from self-reported spending data indicates that there is potential to scale the process of inference and therefore personalise advertisement in a larger pool of consumers.

Personalisation of advertisements using inferred consumer characteristics from spending records could be applied in different marketing channels, such as email marketing and social media influencer marketing. For instance, marketers could activate social media influencers who have characteristics that are congruent with a focal trait of their target segments, which they are able to infer from their purchase behaviours on their platforms. Another application would be to personalise and target advertising to individual consumers on a brand's website who have not registered a customer account, which means that the brands will not receive information about the individual beyond those necessary for order fulfilment. Using machine learning, marketers are able to infer the consumers' age from their past purchases over a period of time, even when the consumers have not provided them with such information, and accordingly target advertising that will appeal to them via email.

Although the findings have demonstrated it is possible to use inferred age to target consumers of different age groups by tailoring the advertisements to represent them, evidence suggests that consumers are concerned about the implications to their privacy resulting from the use of their personal information in targeting them in personalised advertising (Goldfarb & Tucker, 2011; Okazaki et al., 2009; Turow et al., 2009). In fact, a large majority of consumers still do not want retailers to adjust advertisements to their online behaviours across websites (Turow et al., 2009). Van Doorn and Hoekstra (2013) demonstrated that a high fit of personalised adverts may lead to both higher purchase intentions as well as higher perceived intrusiveness levels. When consumers perceive advertisements to be intrusive, it increases usage of ad blockers (Mogaji & Danbury, 2017), which means that the gains of personalising advertisement may come at the cost of higher levels of intrusiveness, indicating a need to balance these factors to ensure optimal outcome.

Future research

Numerous questions remained unanswered which could be addressed in future research. This study opted for a salient age indicator in the tailoring of the advertisements, such as the use of an endorser who appears to be either older or younger. It would be interesting for future research to explore the use of other indicators of age in the advertisements which may respond to different dimensions of the ageing process (i.e., biological, psychological, or social). For instance, the following aspects of an advertisement could be manipulated: tone of voice by incorporating slangs that are more instantly recognisable by a generation than another, or creative concepts that evoke certain memories that resonate more with a cohort which has a collective memory of an event or subject. It would also be useful to directly compare the matching effects of other demographics factors and personality traits which could further inform marketers on the effectiveness of each of these factors in advertisement appeal. Another avenue of research that would further the current investigation is to test for the effects of congruence in personalised advertisements by measuring click-through rates or actual purchases, which may be stronger indicators of purchase intention than self-reported attitudes towards a product or a service.

Conclusion

In all, this study provided an empirical contribution to the discourse on the effects of personalised advertisements using inferred characteristics derived from purchasing behaviour. The results demonstrated that using age inferred from a machine learning model, consumers can be targeted with age-congruent advertisements to which they are more likely to respond to with significantly more positive evaluations. However, this effect appears to only be strong enough in a speculatively high-stake product, suggesting that the underlying mechanism may be less straightforward than has been previously suggested within the existing microtargeting literature. As most previous studies have chosen to focus on the Big Five personality dimensions, the current study contributed to the literature of personalising advertisements and self-congruity by showing that that advertisements tailored to demographic variable such as age, inferred automatically from machine learning model built with transaction records, can have direct consequences for increasing their appeal. By showing the direct practical utility of inferred attributes in personalised advertising, this study has successfully bridged the gap between the two processes necessary to enhance personalised advertising: accurate inference of consumer characteristics at scale, and customisation of advertisements based on inferred traits.

Chapter 5 – Detecting Feelings of Financial Distress

Chapter 5 Summary

As stated in Chapter 2, the existing body of research in attribute inference from digital footprints have been predominantly focused on predicting the Big Five personality traits. There is a lack of studies investigating the potential to predict more malleable traits using digital footprint. To address this gap, this study has opted to infer subjective feelings of financial distress. Predicting financial distress is important because feeling stressed about money contributes to poor mental health, including increased levels of depression and even risk of suicide (Glei et al., 2018; Kerr et al., 2017; Sweet et al., 2013). The adverse impact is exacerbated by the fact that individuals experiencing stress and anxiety over money often feel too ashamed to seek help (Starrin et al., 2009). The current research demonstrates the ability to predict subjective feelings of financial distress from individuals' bank transactions using data collected from 2,274 users of a money management mobile app. Applying a machine-learning model to a dataset combining more than one million spending records with survey responses, individuals experiencing financial distress could be identified with moderate accuracy (r = .43). The automatic detection of financial distress through spending records could provide a scalable policy solution to identifying and targeting support for those in financial need.

5.1 – Introduction

Transaction records offer a novel method to understand how consumer characteristics are related to their consumption patterns. One of the underexplored characteristics are those that are more malleable, and less stable. One of the characteristics that may be inferred from consumption patterns is the subjective feelings of financial distress. Perceptions of financial security are an important component of human well-being (O'Neill et al., 2005). It is therefore disturbing that feelings of financial distress are so widespread, with the majority of people in the United States reporting feeling stressed about money (Anderson et al., 2015). The mental toll of acute financial stress is detrimental to mental and physical health (Sweet et al., 2013), causing significant surge in cases of suicide during economic recessions (Kerr et al., 2017). It is even more alarming that individuals experiencing stress and anxiety over money often feel too ashamed to seek help due to the stigma attached to financial hardship (Starrin et al., 2009), hampering attempts at detection and intervention. There is therefore a need for tools to automatically detect financial distress. The rapid expansion of digital payment technologies coupled with advances in predictive modelling techniques presents a promising avenue for inferring financial distress automatically in the population.

People vary in how they perceive their financial situations; some people *feel* stressed about their finances, while others *feel* financially secure. These feelings are not simply a reflection of a person's payslip or bank balance: despite a positive relationship between objective and subjective measures of financial wellbeing (Carroll, 1997; Friedman, 2018; Karlsson et al., 2004, 2005), this relationship is often surprisingly weak (Glei et al., 2018; Johnson & Krueger, 2006). There are many definitions used to capture these subjective feelings, (e.g., financial well-being, perceived income adequacy, economic distress, economic insecurity). This study chooses to use financial distress, operationalised as the level of stress originating from individuals' personal financial conditions (Prawitz et al., 2006). Although a focus on objective measures of financial hardship (e.g., defined by a lack of income) is more prevalent in the economics literature, a subjective measure of financial distress offers rich information that the former lacks, particularly the depth of an individual's feelings or reactions to their financial situation. The subjective nature of financial distress means that individuals may experience high or low financial distress, independent from their objective financial status;

individuals on the same income level can have differing assessments of their financial distress depending on their personal preferences, consumption values and spending habits (Brüggen et al., 2017). In fact, about 50% of US citizens with incomes ranging from $20,000 to $80,000 have been concerned about their financial circumstances (Consumer Federation of America and Providian Financial Corp, 2003). Therefore, it is evident that financial distress is not the same as poverty (i.e., a lack of income); the subjective nature of financial distress means that individuals may feel financially deprived regardless of their objective financial position (Gasiorowska, 2014).

Consequences of Subjective Financial Distress

Critically, the social and health consequences of widening income inequality rely on subjective perceptions equally as much, if not more, than they do on objective economic indicators (Glei et al., 2018). Prior studies found that even after taking objective economic factors into account, subjective measures signalling financial distress remain predictive of a deterioration in mental well-being (Wilkinson, 2016), self-reported health status (Arber et al., 2014; Shippee et al., 2012), as well as increased rates of mortality (Szanton et al., 2008). Based on two waves of cross-sectional surveys conducted about 15 years apart, a recent study revealed that while changes were observed in objective measures of financial well-being indicated by reported economic and employment circumstances, they were much smaller compared to perceived economic distress which widened more than would have been expected (Glei et al., 2018), suggesting that subjective feelings of financial distress may not directly reflect objective economic circumstances. Indeed, perspectives from studies in resilience suggest that the identical life challenge when experienced by different people, may be internalised and handled in very different ways depending on the individuals' characteristics as well as the social context in which they are embedded (Bonanno, 2012; Pearlin, 1982; Pearlin et al., 1981, 2005). A person's perceptions of reality are not only heavily influenced by depression and other forms of mental ill-health, they can also pose serious risk to physical health (Glei et al., 2018). In fact, even after controlling for current income, perceived financial strain has been found to result in wide-ranging health issues, such as physical impairment, chronic conditions, and depressive symptoms (Glei et al., 2018).

Consumption Patterns Related to Financial Distress

While these subjective perceptions are not directly observable, past research suggests that specific financial behaviours may provide insights into an individual's levels of financial distress. For example, regardless of total income and consumption, financially prudent behaviours, such as a monthly pay-off of credit card bills, saving for the future, and positive cash management, are likely to be associated with stronger financial well-being (Gutter & Copur, 1990; Hayhoe et al., 2015; Joo & Grable, 2004; Shim et al., 2009; Xiao et al., 2006, 2009). Conversely, transactions such as bank interest charges will be indicative of greater financial distress (Anderloni et al., 2012). The emotional toll of financial distress might also instigate engagement in compensatory consumption to restore consumers' sense of well-being (Kim & Gal, 2014; Mandel et al., 2017), or similarly, excessive spending on status goods itself might lead to financial distress. These suggest that objective and measurable financial behaviours such as spending patterns could be related to subjective feelings of financial distress.

The symbols embedded in products make them central to identity creation, maintenance and expression (Dittmar, 2011; Elliott & Wattanasuwan, 1998; Gabriel & Lang, 2015; Oyserman, 2009; Shankar et al., 2009). The way that spending records relate to feelings of financial distress may also reflect an individual's attempt to combat the negative affect that accompanies financial distress, often through compensatory consumer behaviour. Compensatory consumption refers to the "consumer intentions and behavioural responses triggered by perceived deficits, needs and desires that cannot be fulfilled directly, hence compensated for via alternative means" (Koles et al., 2018, p. 98). These behavioural strategies are usually activated as a response to self-discrepancy – a divergence between individuals' perceptions of their ideal and actual selves (Higgins, 1987) – to alleviate the discomfort that arises (Lisjak et al., 2015; Woodruffe-Burton & Elliott, 2005). When opportunities to improve their financial position through material means are absent, financially distressed consumers might engage in compensatory consumption to reinstate their sense of well-being (Tesser et al., 1991). In general, consumers tend to spend less money when they experience financial deprivation (Karlsson et al., 2004). However, it is likely that these feelings of inadequacy stemming from financial distress could lead these individuals to selectively pursue resources that can help them mitigate the sense of deficiency (Sharma & Alter, 2012). Since money plays a significant role in influencing human behaviour (Lea & Webley, 2006), financial distress might similarly exert influence on consumption behaviour by prompting consumers to search for and purchase relevant products that symbolise financial success in an effort to mitigate the aversive psychological consequences of deprivation (Sharma & Alter, 2012) and enhance their sense of self. Of particular relevance in the context of financial distress, when consumers' self-concept is threatened, they are more likely to acquire material symbols (Koles et al., 2018) by spending more money on products that are self-affirming (Kim & Gal, 2014; Rucker et al., 2014; Wen et al., 2014) and signal desirable traits (Rucker et al., 2014), especially those related to power and status (Rucker & Galinsky, 2008).

Individuals who are financially distressed may also engage in another type of compensatory consumer behaviour, which is escapism. Escapism refers to any recreational or leisure activity that transports a person from their burdensome reality to a pleasurable world of fantasy (Evans, 2001). In the context of consumer behaviour, escapism can appear in the form of diverting one's attention to hedonic activities such as gaming (Jeng & Teng, 2008; Yee, 2006), eating (Heatherton & Baumeister, 1991; Polivy et al., 1994), watching television or films (Livingstone, 1988; Moskalenko & Heine, 2003), shopping (Arnold & Reynolds, 2003; Dharmesti et al., 2019), and gambling (Reid et al., 2011; Rockloff et al., 2011). In fact, escapism through consumption activities is so commonplace that it has been referred to as retail therapy (Lee & Böttger, 2017). By providing temporary fulfilment and satisfaction through imaginative scenarios (Evans, 2001), these activities have the potential, at least for the short-term, to lower the salience of self-discrepancy by means of temporary distraction. Hence, it is likely that financial distress could be detected from spending patterns which reflect escapism.

The Current Study

In sum, existing literature surrounding financial distress and spending behaviour suggests that subjective perceptions of one's financial situation although not directly observable, may be able to be detected from individuals' transaction records. Bearing in mind the detrimental consequences of perceived financial distress on physical and mental well-being, there is value in automatic identification of individuals experiencing financial distress. The current study used a machine learning model (XGBoost) to infer financial distress using basic summary spending records in the form of the proportion spent on a list of categories over a 12-month period.

5.2 – Method

Participants and Procedure

The same procedure described in Chapter 3 was used in this study (see Chapter 3.2 for details). The proportion people spent across a wide range of goods and services was calculated using a dataset containing 1 million spending records over a 12-month period matched with survey responses measuring financial distress. Participants were 2,274 anonymous users of a money management mobile app. The sample size was determined by the number of users who decided to take part in the study. As predictive modelling was performed in this study, power analysis is not possible. All debit transactions across each of a customer's bank accounts were automatically grouped into 268 categories by the app (e.g., clothes, flights). To compare spending across participants, the relative amount spent on a specific category was calculated by dividing the scores by the participant's overall spending. Relative, as opposed to raw amounts, was used to ensure the predictor variables are indicative of an individual's spending profile, rather than simply reflecting their overall income or wealth. These transactions were then matched to participants' self-reported ratings of financial distress, measured using the 5-item version of the Consumer Financial Protection Bureau Financial Well-Being Scale (Consumer Financial Protection Bureau, 2017).

Measures

Spending Categories

The transaction records attained from participants' banking data included detailed information of all debit transactions that spanned twelve months preceding the survey. The company automatically classified participants' spending records into 268 categories. Subsequently, the scores were divided by the participant's overall spending to provide the relative amount spent on a specific category. For instance, if participant X spent a total of £200 on interest charges, and £20,000 overall, the relative expenditure on interest charges for this person would be 1.0%, the same as for participant Y, who spent only £20 on interest charges and £2,000 overall.

Financial distress

Financial distress was measured using the 5-item abbreviated version of the Consumer Financial Protection Bureau (CFPB) Financial Well-Being Scale (Consumer Financial Protection Bureau, 2017), rated on a 7-point Likert Scale. Designed using cognitive interviews and established psychometrics procedures, the measure allows practitioners and researchers to quantify the extent to which an individual feels that their financial circumstances and the financial aptitude that they have developed allows them a degree of security and freedom of choice. The scale demonstrated high internal consistency (Cronbach's alpha = .78).

To demonstrate that the machine learning model is not specific to a single financial distress measure and that it is generalisable to an alternative measure assessing financial distress, an alternative measure of financial distress was computed from four items that are completely separate from the CFPB Financial Well-Being Scale, "I am satisfied with my financial situation", "I often lose sleep worrying about my finances", "Compared to the average person in the UK, I am well-off", "I feel wealthy right now". These four items also appeared to be reliable (Cronbach's alpha = .77).

Data analysis

Different machine learning models including linear regression, LASSO and XGBoost regressors were used to predict financial distress from proportion of spending in categories. Nested cross validation was applied in the analysis (see Chapter 3.2 for details). For the sake of comparison, correlations between predicted and actual financial distress scores were used to assess model accuracy.

5.3 – Results

Machine-learning models were implemented with financial distress as the dependent variable and the spending categories as independent variables. Three models were compared, and the best performing model was determined based on the Pearson correlation coefficient between predicted and actual outcome values, as well as Root Mean Squared Error (RMSE). The Linear Regression model had the poorest predictive accuracy (r = .11). The prediction accuracy of .43 by the best performing model, XGBoost Regressor, compares favourably with previous research using other forms of behaviour as inputs for predicting personality traits (r ranging from .29 to .40; Azucar et al., 2018). Results of the RMSE also indicated that XGBoost Regressor produced predictions with the smallest error units with a mean of .90, while linear regression produced much larger error units (mean RMSE = 1.89). As psychological traits are latent, they cannot be measured directly. It is only possible to measure their values approximately, for instance, by evaluating responses to questionnaires (Kosinski et al., 2013). However, as CFPB financial distress has not been tested for test-retest reliability, it was not possible to compare the correlation coefficients to such metric. Altogether, these results demonstrate that predictions of out-of-sample financial distress can be made with reasonable accuracy based purely on the proportion people spend on a range of goods and services.

The hyperparameters of the best performing XGBoost Regressor model was as follows. Max_depth = 4, learning_rate = 0.1, n_estimator = 150, base_score = 0.6, subsample = 0.9, colsample_bytree = 0.5, colsample_bylevel = 0.2, reg_lambda = 65, gamma = 0.0001, min_child_weight = 1, max_delta_step = 0, scale_pos_weight = 1, reg_alpha = 0, objective='reg:linear', booster='gbtree', n_jobs= -1.

Table 5.1 *The average Pearson's r and RMSE scores across 10 outer folds of the machine learning models predicting financial distress from amount spent in categories*

	Pearson's r		RMSE	
	Mean	*SD*	Mean	*SD*
Linear Regression	.11	.08	1.89	1.28

LASSO Regression	.29	.08	.96	.03
XGBoost Regressor	.43	.06	.90	.04

In order to ensure these results were not simply the result of using this specific measure of financial distress, a supplementary analysis was run using another measure constructed from four items (see Method). Applying XGBoost with the same parameters, it was possible to achieve a similar degree of predictive accuracy *r* = .40 (mean RMSE = .92). This shows that this method is robust to predicting financial distress measured using different inventories.

To understand which types of spending contributed most to the models' predictive accuracy, a feature importance score was calculated for each spending category in the model. Additionally, Pearson's correlation coefficients were calculated for each individual feature. Positive correlations indicate that higher spending in this category predicted greater financial distress, while negative correlations indicate spending in this category was linked to lower financial distress (Table 5.1).

Table 5.2 *The categories which best predicted financial distress based on feature importance (> .01)*

Category	Feature importance	*r*
Interest charges	.088	.104
Mobile	.053	.133
Food, groceries, household	.049	.177
Hotel B&B	.047	-.052
Takeaway food	.032	.123
Flights	.031	-.064
Credit card repayment	.029	-.110
Council tax	.028	-.017
Bank charges	.026	.039
Personal care	.026	.069
Home and garden	.024	-.055
Toiletries	.022	.073
Dining or going out	.022	.045
Current account	.020	-.057
TV movies package	.019	.043
Mobile app	.019	.067
Unsecured loan repayment	.018	.082
Vehicle insurance	.017	.061

Energy, gas, electricity	.017	.036
Clothes	.015	.057
Vehicle tax	.015	.097
Lifestyle Other	.015	.018
Cash	.015	.136
Gambling	.015	.027
Home electronics	.013	.032
Lunch or snacks	.012	.065
Media bundle	.012	.101
Donation to organisations	.011	-.049
DIY	.011	-.016

Note. The correlation coefficients were computed separately from the building of the model.

The feature importance list provides insights into why a person's spending can reveal their financial distress. First, signals of poor financial management (i.e., interest charges, bank charges, unsecured loan repayment) were strongly related to heightened financial distress, while good financial management behaviours (i.e., unsecured loan repayment, credit card repayment) were related to lower levels of financial distress. Second, individuals experiencing financial distress were also found to spend a greater share of their budget on necessities which are less income-sensitive and elastic, such as toiletries, public transport, food, groceries and household, energy, gas and electricity, mobile, fuel, vehicle tax, vehicle insurance. And third, the results reveal that high financial distress was linked to spending money on clothes, dining or going out, which are conspicuous and can be used to signal one's status (Belk et al., 1982).

Previous research indicates that financial distress is largely linked to income and wealth, however these findings suggest that spending patterns are more predictive of financial distress than income. As a comparison, Pearson's r was computed between financial distress and self-reported income, as well as objective salary. The results show significant, but relatively small negative correlations between financial distress and self-reported income (r = -.21, p < .001), and objective salary (r = -.15, p < .001). This suggests that people with relatively high income can still experience financial distress, depending on their life circumstances and attitudes. Furthermore, this correlation is also weaker than that predicted by spending patterns (r = .43).

5.4 – Discussion

Transaction records can be used to offer valuable insight into consumer psychology, particularly in the area of consumer profiling. Building upon the growing body of research in attribute inference from digital footprints, this study aimed to predict subjective financial distress from outgoing bank transactions over a period of 12 months. The study found that it is possible to predict financial distress at a moderate accuracy of .43, using the XGBoost Regressor model. The feature importance analysis showed that signals of poor financial management (i.e., interest charges, bank charges, unsecured loan repayment) are strongly related to heightened financial distress, while good financial management behaviours (i.e., investment, credit card repayment) were related to lower levels of financial distress, in line with previous research (Hayhoe et al., 2015; Joo & Grable, 2004; Kim & Gal, 2014; Xiao et al., 2009). Further, individuals experiencing financial distress were also found to spend more on necessities which are less income-sensitive and elastic, and to spend less compared on more elastic categories. These results suggest that spending a large proportion of expenditure in basic needs can signal financial distress, supporting previous findings (Bernini & Cracolici, 2016; Eugenio-Martin & Campos-Soria, 2011). Furthermore, these findings revealed that high financial distress was linked to spending money in conspicuous categories, such as clothes, dining or going out, which can be used as signals of status (Belk et al., 1982). This supports previous findings that suggest individuals who are financially distressed could be engaging more with compensatory consumption.

As the machine learning model was developed to predict subjective financial distress, rather than objective financial distress, the feature importance analysis reveals that subjective financial distress may encompass actual financial trouble (i.e., a lack of income) and perceived financial deprivation (i.e., not measuring up compared to others). Although signals of poor financial management may indicate someone is in financial trouble, signals of conspicuous consumption indicate that regardless of income, people who perceive themselves to be in financial distress are more likely to spend more conspicuously. The findings also show that signals of financial distress come in the form of larger proportions of expenditure on basic needs and income-inelastic spending categories, which indicates lower income or financial trouble. With rises in income, consumers' proportion of total expenditure for necessity goods declines (e.g., food, electricity, internet) as consumers will buy these products and services regardless of their income levels. On the other hand, consumers' proportion of total expenditure increases for luxury goods (e.g., premium cars, vacations) (Bernini & Cracolici, 2016; Eugenio-Martin & Campos-Soria, 2011; Fleischer & Rivlin, 2009). The findings thus align with previous research showing that those n financial distress spend a larger proportion of their expenditure on necessities, as opposed to more elastic categories.

The results also showed instances of impulsive spending amongst those experiencing financial distress, such as clothes, mobile apps, lunch or snacks, dining or going out, gambling and takeaway food. These spending categories are hedonic in nature but can often be inexpensive, which increases the chances that people would purchase them on a whim. Thus, they reflect instant rather than delayed gratification which are indicators of impulsivity and self-regulatory deficits (Khang et al., 2013; Wang et al., 2015; Wulfert et al., 2002). Aligning with previous findings, Fernandes et al. (2014) revealed that impulsive individuals were more likely to show a higher tendency for financial behaviours that contributed to credit and checking account fees, whereas their less impulsive counterparts tended to engage less in these behaviours. The findings are also supportive of the notion of escapism under financial distress. Compared to individuals who do not experience financial distress, those experiencing heightened levels of financial distress tended to spend a larger proportion of their money in consumption contexts that invoke escapism (Evans, 2001), such as TV movie packages, media bundles, cinema, mobile apps and mobile. This corroborates previous research indicating that people who are experiencing stress are more likely to engage in problematic Internet use for escapist motives (Khang et al., 2013; Wang et al., 2015).

Furthermore, the current findings revealed that high financial distress was linked to spending money on clothes, dining or going out, lunch or snacks which are conspicuous and can be used to signal one's status (Belk et al., 1982), possibly driven by a motivation to reconcile ideal and actual self-views regarding one's financial situation. These findings are in line with studies showing that materialism is related to high credit card debt, excessive borrowing, and the types of spending that are characterised by impulsivity and compulsivity, as well as lower current financial satisfaction (Richins, 2004, 2011; Watson, 2003). Engagement in compensatory consumption may also be taken as a way to lower self-discrepancy. Put simply, people who experience financial distress are more likely to spend money in categories which are conspicuous and can be used to signal their status in an effort to reduce their negative affect resulting from the disparity between their ideal and actual self-views. Although this may work for some people, at least momentarily, material culture is unable to offer a long-term solution for those suffering from chronic identity deficits, as it can only, at best, serve as tools for temporary management and restoration for these issues through consumption (Dittmar, 2011). It is precisely these functions of identity repair and mood management that are damaging to consumer well-being. Although signaling wealth through greater consumption may temporarily help those experiencing financial distress gain a sense of power (Rucker & Galinsky, 2008), conspicuous consumption may also perpetuate financial hardship. This may hence result in a vicious cycle whereby the consumer is constantly seeking out illusory solutions to mitigate their actual-ideal identity gap, which in turn reinforces their financial distress from poor money management and further exacerbates the incongruence in their actual and ideal identities. Therefore, this emphasises the importance of identifying individuals are exhibiting such behaviours and experiencing financial distress, and providing them with support to break this vicious cycle.

Based on these findings, it seems plausible that people who are financially distressed may not be spending in a way that allows them to express their actual self-concept. Financial distress may constrain an individual's ability to spend money on things that fit with other aspects of their actual self-concept such as their personality, possibly due to having a smaller budget allocated for such spending while spending more on basic necessities, financial charges and conspicuous consumption (see Table 5.2). It is also likely that discrepancy between their actual and ideal selves may propel individuals to spend in a way that focuses on aspects of their ideal selves that they perceive to be lacking (e.g., financial success) through compensatory consumption, thereby neglecting the types of spending that fulfill fundamental needs associated with their actual selves. It could be that when individuals are experiencing financial distress they may be driven to spend in such a way as to respond to this lack, be it perceived or actual, and are therefore unable to consume products or services that fulfill needs that are required by the other parts of their self-concept. However, as this study only looks at spending categories most predictive of financial distress, it is not possible to confidently infer this from the results. To disentangle these findings and gain more clarity into the relationship between financial distress and self-congruent spending, a matching coefficient will be computed and its correlation with financial distress will be tested in the next study. Inference of causality is not possible with the current study due to its cross-sectional nature. Future studies could utilise longitudinal data to detect feelings of financial distress from transactions prior to the development of these feelings.

Practical implications

The automatic prediction of financial distress has important applications in research and policy. Many people experience some financial stress (Anderson et al., 2015), but chronic financial stress can be harmful to health (Sweet et al., 2013). The shame associated with financial problems (Starrin et al., 2009) means people who experience financial distress are reluctant to seek help. By identifying those experiencing financial distress, this allows for targeted support. For example, financial service companies may be able to nudge people into healthier financial behaviours to increase people's well-being by tailoring messaging adjusted to each user's inferred financial situation. With regards to intervention, the findings of the current study suggest the possibility of more effectively helping financially distressed individuals by facilitating change in their spending behaviours. The weaker relationship between income and financial distress suggests that it is perhaps insufficient to simply provide them an allowance to aid their day-to-day living if their spending behaviours remain unchanged. By mapping the relationship between spending pattern and financial distress, this study has pinpointed targetable behaviours for adjustment. Future research could look into the relationships between specific spending behaviours and financial distress, and test the effectiveness of behavioural change by targeting these behaviours.

Similar to inferred age which could act as a proxy for detecting other vulnerabilities such as cognitive decline and financial literacy, inferred financial distress can also pose serious concerns for consumer privacy. As individuals experiencing financial distress are particularly vulnerable due to their heightened negative affect associated with their financial circumstances, such information has the potential to be abused if not regulated. Just as policymakers are able to target these individuals with interventions to help them improve their financial situations, fraudulent companies could target them for loans with high interest rates, or other harmful financial products of which they may be more susceptible due to their financial strain. Retail companies could also target the same individuals with conspicuous goods that perpetuate their compensatory consumption behaviour, in turn exacerbating their poor financial situation. Therefore, strict regulation around such profiling of individuals' vulnerabilities should be put in place in order to prevent these potential misuses.

Conclusion

The current study has shown that subjective feelings of financial distress can be predicted at a moderate accuracy based on only 12-month's worth of outgoing transactions. By drawing on the granular details contained within transaction data, the study demonstrated for the first time that records of spending can accurately predict an individual's financial distress. The analyses revealed clear consumption patterns which differentiate between those with high and low financial distress. These insights present potential opportunities for organisations to use them in a socially responsible way which may benefit people who are financially distressed. As the digital revolution in payment services continues, each day, billions of cards are swiped across check-outs worldwide. Thus, the increasing ubiquity of digital payment and continuous improvement of machine-learning algorithms suggest that this method to infer financial distress may become increasingly accurate over time. However, identifying financial distress from spending also raises concerns about ethics and privacy. The fact that people's intimate psychological traits can be predicted automatically from their behavior, makes it increasingly difficult for individuals to avoid being subjected to automatic psychological assessment in this form, even when they have not explicitly consented to such usage of their data.

Chapter 6 – Correlates of Self-Congruent Spending

Chapter 6 Summary

Another way in which basing research on transaction records can provide a meaningful contribution to the understanding of consumer psychology, is by measuring self-congruence in overall consumption patterns objectively (Matz et al., 2016). As consumption has been argued to be more useful than income in understanding how money is related to happiness (DeLeire & Kalil, 2010; Dunn et al., 2011), the use of transaction records offers a comprehensive view of one's purchases, and the extent to which an individual is consuming in a way that is self-congruent in relation to their overall consumption pattern. The positive impact of self-congruence in consumption on consumer well-being can potentially form the basis for interventions to improve consumer well-being. However, there is limited evidence on the potential correlates of the tendency to consume in a way that fits with one's personality. It is unclear what kind of consumers are more or less likely to spend in a way that is congruent. This study aims to explore the potential correlates of self-congruent consumption. Using two sets of data, a large-scale dataset of transaction records containing transactions across 1,876 participants grouped into 277 spending categories, and a separate dataset including Big Five personality ratings of the spending categories, this study looks at how personality match between a consumer and his or her overall consumption pattern is related to chronological age, materialism and financial distress. The study shows that financial distress and materialism are both negatively and significantly correlated with self-congruent spending. Dominance analysis reveals that financial distress is the most important predictor of self-congruent spending, followed by materialism. However, the effect sizes are very small.

6.1 – Introduction

Self and identity concerns are central to a person's pursuit of well-being (Sharma & Sharma, 2010). The crucial role of self-congruence in well-being has been firmly established in previous research. Self-congruence – the match between one's self-concept and behaviour – has been consistently found to increase life satisfaction and self-esteem (Assouline & Meir, 1987; Campbell, 1990; Lenton et al., 2016; Reich et al., 2008; Sheldon et al., 1997). Conversely, when an individual behaves in a way that is incongruent with his or her self-concept, they are more likely to experience higher stress levels, as well as a deterioration in physical and mental health (Festinger, 1957; Heppen & Ogilvie, 2003; Higgins, 1996; Palsane, 2005; Sirgy, 1986). It has been established that an individual's psychological well-being is at least to a certain extent attributed to positive perceptions of themselves as well as the possession of valued social identities (Thoits, 2006). Psychological disorders are associated with conflicts within identity functions, such as identity development issues, threats to perceptions of self or self-esteem and loss of identity (Thoits, 1999).

Self-congruence in many aspects of our life is often associated with well-being (Assouline & Meir, 1987), including the area of consumption (Hill & Howell, 2014; Matz et al., 2016; Petersen et al., 2018; Zhang et al., 2014). Self-congruence in consumption is found to increase happiness. In a recent study utilising transaction records (Matz et al., 2016), people who spend more on products that align with their own personality reported higher levels of life satisfaction. In addition, Hudders and Pandelaere (2012) found that luxury consumption leads to higher life satisfaction for materialistic consumers relative to less materialistic consumers, indicating that materialistic consumers not only have a higher tendency to consume luxury products than their less materialistic counterparts, but they are also more likely to reap benefit from them. Together with findings of self-congruence in other domains, these studies suggest that self-congruence in consumption is highly relevant to consumer well-being, necessitating investigation into the conditions that are more or less conducive to this type of spending.

Degrees of Self-congruence and Authenticity

A related concept to self-congruence is authenticity, which has been conceptualised as the extent to which individuals' behaviours are congruent with their psychological attributes, values, motives and beliefs (Kernis & Goldman, 2006; Sheldon et al., 1997; Wood et al., 2008). Much behaviour and emotion is predisposed to influences from implicit intrapersonal processes and environmental factors that prime their responses without people being consciously aware (Bargh & Chartrand, 1999; Kahneman, 2011; Wilson, 2003). Thus, people may be able to, but do not always, have direct access to their dispositions and personal standards which would guide them to intentionally behave in accordance with who they believe themselves to be, or ensure that their behaviours remain authentic (Jongman-Sereno & Leary, 2020). The concepts of trait and state authenticity (Kernis & Goldman, 2006; Sedikides et al., 2019) suggests that individuals can vary on a continuum with respect to how authentically they perceive their behaviour to be in accordance with their 'true' selves. Importantly, incongruities can occur when real, or imagined situational demands or external pressures do not facilitate the expression of one's dispositions, beliefs and values (Wood et al., 2008). As consumption is also another form of behaviour, it is likely that people may also vary in terms of the degree of self-congruence in the way they spend their money.

While it has been established that spending self-congruently may increase subjective well-being (Hill & Howell, 2014; Matz et al., 2016; Petersen et al., 2018; Zhang et al., 2014), it is unclear what consumer characteristics may be associated with this tendency to spend in alignment with one's personality. In general, previous studies have found that individuals tend to behave, or consume in a way that is congruent with their self-concepts (Higgins et al., 2003; Matz et al., 2016; Sirgy, 1982). However, these studies assume that people are able to, and are always attuned to their psychological needs when considering a purchase. It is possible that certain individual differences could predispose some consumers to purchases that are more or less aligned with their selves. Studies of authenticity has found that there are indeed factors that affect whether people perceive themselves to be behaving authentically, for instance, culture (Slabu et al., 2014), personality and neurobiological determinants (Martens, 2007). The key question this study explores is, what differentiates people who spend more congruently than those who do not? Clarification on the kind of consumers who are more or less likely to consume self-congruently will be useful to marketers and practitioners interested in nudging them into better purchases which are more likely to bring about happiness. Four plausible correlates are proposed: a demographic variable (age), a personality trait (self-control), a value orientation (materialism) and a malleable emotional state (subjective feelings of financial distress).

Chronological age

Self-congruence in consumption can change as people age, as some of consumers' most fundamental concerns include the discovery of one's true consumption preferences and the expression of one's identity through consumption (Escalas & Bettman, 2005) are subject to change over lifespan. While one perspective suggests that people are naturally authentic at a young age, but that this authenticity deteriorates over lifetime as people are imposed conditions of worth (Rogers, 1959). An alternative perspective suggests that as adolescents develop their identities, they adopt and switch between different personas across different situations and relational roles (Harter, 2015). It is likely that these experiences could lead adolescents to experience more frequent occurrences of state inauthenticity than older individuals do. Supporting this is a recent study which revealed that perceptions of authenticity increased over time and across lifespan (Seto & Schlegel, 2018). This suggests that as people perceive themselves to be more authentic, they may be more able to behave in line with their personality, which will lead to improved ability to spend in a way that better matches their personality. Furthermore, younger people tended to have fewer financial resources compared to older adults to express themselves through symbolic consumption. Altogether, it seems more plausible that age may be positively correlated with self-congruence in consumption (H1).

Self-control

Self-control refers to the "ability to override or change one's inner responses, as well as to interrupt undesired behavioural tendencies (such as impulses) and refrain from acting on them" (Tangney et al., 2018, p. 274). Extending this definition, the exertion of self-control is seen as deliberate, conscious, and effortful (Friese et al., 2017). In relation to consumption, people who are high on self-control may be less likely to purchase on impulse, and more likely to consider their purchases more thoughtfully so as to fit with their psychological preferences. There is limited evidence on the direct associations between self-control and self-congruent spending. However, there is some evidence to support the idea that self-congruence is associated with constructs or behaviours that arguably relate to self-control, such as impulsive buying. In a recent study, actual self-congruence was found to be negatively correlated with impulsive buying (Japutra et al., 2019). As impulsive buying is frequently associated with a lack of self-control, it is likely that there may be a positive correlation between self-control and self-congruence in consumption. It is plausible that low self-control may lead a consumer to purchasing on a whim, and less likely to result in spending that aligns with one's personality. It may require more deliberation and conscious decision making to spend in a way that better matches one's psychological preferences. Similarly, individuals who are more self-aware are more likely to rely on their preferences when making purchase decisions and are less likely to select compromise options (Goukens et al., 2009). While research into whether thoughtful, considered purchases are more psychologically aligned with one's personality is scant, this study aims to fill this gap by exploring the potential links between self-control and self-congruence in consumption. Based on the limited existing evidence, this study proposes that self-control is positively correlated with self-congruent spending (H2).

Materialism

Materialism is "the importance a consumer attaches to worldly possessions" (Belk, 1984, p. 291). Individuals who value materialism are characterised by their over-concern with possessions by pursuing material ownership and the accumulation of income and wealth (Richins & Dawson, 1992). Through a focus on having, materialism may bias an individual's consumption motives to one of self-enhancement and status and symbols, rather than their actual selves, which means that they could be less likely to engage in self-congruent spending. Materialism causes alienation and discontent; it also hampers individuals' potential for self-actualisation (Maslow, 1954). Importantly, materialistic people are less likely to take part in activities aimed primarily at pursuing intrinsic goals (e.g., self-actualisation), which have a more positive effect on subjective well-being than the those targeted at fulfilling extrinsic motives (Csikszentmihalyi & Halton, 1981; Kasser & Ryan, 1993; Richins, 1987). As self-congruence in consumption suggests the types of consumption that are more fulfilling to one's personality, deviation from behaviours that lead to self-actualisation may indicate the possibility that materialism may lead individuals away from spending that allows their personality to flourish.

Prior research has provided evidence from different areas demonstrating the tendency for materialism to exhibit a focus on extrinsic rewards. For instance, children with high materialism learn to serve performance goals as opposed to mastery goals (Ku et al., 2014). This indicates that when materialism is given too much priority and importance, two possible outcomes may ensue: intrinsic goals are deprioritised in order to prevent cognitive dissonance and value conflicts that may result in mental strain; intrinsic goals are "crowded out" or overlooked, since the individual's focus has shifted to improving their image and popularity, as well as signalling financial success (Burroughs & Rindfleisch, 2002; Kasser, 2016). This shows that when people are focused on fulfilling their material needs, they are less likely to attend to their intrinsic needs. In the context of consumption, this may look like a focus on outwardly conspicuous, or status-driven purchases, and a deprioritisation of self-congruent purchases. Focusing mainly on ideal-self purchase motivation, that is, when individuals buy products which enable them to become more like their ideal selves, (Dittmar, 2005) found that while materialism predicted compulsive buying tendencies, it was partially mediated via buying motivations aimed at fulfilling their ideal-self. These studies point to the possibility that people who are materialistic may be more likely to spend in a way that fulfils their self-enhancement needs rather than their self-consistency needs. Thus, H3 is that materialism is negatively correlated with self-congruent spending.

Financial distress

People who are financially distressed may be less likely to spend in a way that is consistent with their personality. In Chapter 5, it was apparent that the key categories that predicted financial distress was in maladaptive spending behaviours. While this finding was useful for understanding the financial behaviours that underpin financial distress, it is unclear, however, whether individuals who are financially distressed are more or less likely to spend in a way that fits with their personality. Further evidence alluding to the possibility that people who are financially distressed may be less likely to spend in a way that is congruent with their personality is provided by Gladstone et al. (2019), who found that in the prediction of somer personality traits (i.e., self-control and neuroticism) from transaction records, the strength of predictions was moderated by postcode-level deprivation. This means that people inhabiting poorer neighbourhoods may be less prone to having a large discretionary-spending budget reserved for self-congruent spending, as they might be using larger proportions of their resources for necessities. However, because the effects for total spending and income at the individual level did not reach statistical significance, these results could indicate that there are perhaps fewer opportunities for consumption which allow people to express their psychological preferences in deprived geographical areas (Gladstone et al., 2019).

From a cognitive perspective, two related psychological constructs related to financial distress have been linked with ideal-self congruence, and inauthenticity. First, higher levels of state authenticity are linked to high positive affect and low negative affect (Heppner et al., 2008; Lenton et al., 2013; Smallenbroek et al., 2017). As financial distress is characterised by negative affect (Glei et al., 2018), it is likely that people who are financially distressed may also behave in a way that is inauthentic to their selves, including in their consumption. Second, low self-esteem resulting from financial distress may trigger self-enhancement motives, leading to more spending which fits with their ideal self, rather than their actual self. According to the self-congruity theory, people may behave in a way that fits with either their actual selves or ideal selves. Driven by the social enhancement motive, individuals may spend in a way that reflects how they would like to be perceived by others (Hosany & Martin, 2012; Sirgy et al., 2017). As a consequence, consumers will act to leave a good impression, trying to earn approval from others (Sirgy et al., 2017). People who are experiencing financial distress are more likely to suffer from lower self-esteem (Kernis et al., 1991). Individuals who are low on self-esteem have been found to be more motivated to spend in a way that is congruent with their ideal selves (Sirgy, 1985), rather than actual selves. This greater allocation of attention to consumption with a goal of self-enhancement may mean that there may be a possible neglect of consumption geared towards self-consistency. Given the association between financial distress and self-esteem, it seems likely that financial distress may be negatively related to self-congruence in consumption (H4).

Transaction Records Reflect Self-congruence in Consumption

Self-reported measures of self-congruence are limited in a number of ways. In the research on authenticity, when asked to assess their own authenticity, these self-judgments of authenticity were found to be confounded with positivity (Jongman-Sereno & Leary, 2020). In the area of consumer research, traditional methods of measuring self-congruence in consumption largely focused on participants' self-reported personality and the personality of a single brand (see Kuenzel & Halliday, 2010; Pradhan et al., 2020; Sirgy, 1986). Not only does this limit the extent to which such congruence can be generalised to a larger number of brands and spending categories, it also prevents the interpretation of findings to be extended to the overall consumption pattern. In addition, these congruence effects were often examined in conjunction with self-reported measures of purchase intention rather than objective purchase behaviour, further reducing their external validity. To circumvent issues of positivity bias and limited generalisability, this study will use a more objective indicator of self-congruence in overall consumption pattern, calculated using transaction records, which are consumers' real-world purchasing data, a methodology previously used in (Matz et al., 2016). To measure congruence between a brand's personality and the purchaser's personality, a score is computed to indicate the match or discrepancy between these two personality scores (Sirgy, 1986). Crucially, transaction records allow a comprehensive view of a consumer's spending habits which can be directly linked to the extent of self-congruity in their purchases. This study will utilise this objective measure of self-congruence in a transaction dataset of a larger scale than that used in Matz et al. (2016), and extend the research question to investigate the potential correlates of self-congruence in overall consumption.

The current study

This study aims to explore the correlates of personality self-congruent spending. Given the benefits of self-congruent spending on subjective well-being, it is useful to identify individuals who are more, or less, likely to consume in such a way. Based on the existing literature, this study focuses on four main constructs: consumers' chronological age, self-control, materialism and subjective feelings of financial distress. The following hypotheses are proposed.

H1. Age is positively correlated with self-congruence in overall consumption.

H2. Self-control is positively correlated with self-congruence in overall consumption.

H3. Materialism is negatively correlated with self-congruence in overall consumption.

H4. Financial distress is negatively correlated with self-congruence in overall consumption.

6.2 – Method

Participants

In the final sample, 1,876 participants remained after eliminating those who did not complete the financial distress and materialism questionnaires, and who did not spend any money in any category. The participants were between the ages of 18 and 81 (median = 36, *SD* = 11.68), with a mean of 38.29 years. Information on gender was not collected, but participants' gender was derived by running their first names through a name database (see Participants in section 3.2). The participants are all based in the United Kingdom.

Measures

Spending categories

All of the participants' debit transactions across their bank accounts including checking accounts and credit cards over the span of 12 months prior to the survey were obtained. The purchases were automatically grouped by the mobile app into 277 categories, providing the raw amount of money spent in each category for each participant.

Personality traits of spending categories

A panel of 100 participants was recruited from Prolific to rate each spending category based on the dimensions of the Big Five personality model. Adapting a similar methodology to Matz et al. (2016), a 7-point scale was created for each Big Five personality trait. Each rater was shown 148 to 150 categories randomly selected from the pool of 277 categories. They were given the following instructions:

"On the following pages we are going to show you a number of categories that people can spend their money on (e.g., travel or entertainment). We would like you to think of each category as if it were a person. This may sound unusual, but think of the set of human characteristics associated with each spending category. We're interested in finding out which personality traits or human characteristics come to your mind when you think of a particular spending category. There are no wrong or right answers. Please indicate the extent you agree with the following statement for each spending category on a scale ranging from 1 = Strongly disagree to 7 = Strongly agree. If this 'spending category' were a person, it is extraverted and enthusiastic."

Ratings of each of the Big Five personality traits for each of the spending categories were combined across raters and converted into *z*-scores with higher scores indicating that the spending categories are being perceived as embodying high trait characteristics and lower scores indicating low trait characteristics. Table S3 in supplementary materials presents the mean scores of the Big Five personality trait for each of the 277 spending categories. Inter-rater agreement across all categories was excellent, as indicated by the intraclass correlation coefficients between .95 and .97 (Koo & Li, 2016).

Big Five Personality

The Big Five model (Costa & McCrae, 1992) is the most widely accepted model of personality, which proposes a taxonomy of five personality traits: Extraversion, Agreeableness, and Neuroticism, Conscientiousness, Openness-to-Experience. The 10-item Big Five Inventory (BFI-10), a short scale of the Big Five model (Rammstedt & John, 2007), was used to measure these traits. The Cronbach's alphas for each trait are as follows: Extraversion (.76), Agreeableness (.34), Conscientiousness (.57), Neuroticism (.64) and Openness to Experience (.32). The internal consistencies for the scales measuring each trait ranged from poor to high.

Age

Information about participants' age was gathered from the date of birth provided by users when registering with the service (mean = 38.29 years, median = 36, *SD* = 11.68, range = 18-81). The age distribution of this sample is provided in Figure S1 of the supplementary materials. The median age of the UK population was 40.6 (CIA, 2021), meaning the sample was comparable with, but younger than, the population overall.

Self-control

Self-control is defined as individuals' capacity to control their impulses in order to ensure their behaviours are aligned with their goals and standards (Mead et al., 2009). It was measured with a single item ("I am good at resisting temptation") from the Brief Self-Control Scale (Tangney et al., 2004). The decision to opt for the single-item measure was made in order to ensure the survey included only a minimal number of essential questions so as to avoid fatigue resulting from a long survey. While this is less than ideal, it is still able to provide a sensible estimate of self-control as a wider construct of (Gladstone et al., 2019).

Materialism

Materialism is defined as the extent to which a person places high importance on material possessions and physical comfort (Richins & Dawson, 1992). It was measured using three items taken from a widely used measure of materialism (Richins & Dawson, 1992): (a) "I admire people who own expensive homes, cars and clothes"; (b) "I like a lot of luxury in my life"; and (c) "I'd be happier if I could afford to buy more things." The scale showed acceptable internal consistency (Cronbach's alpha = .62).

Financial distress

Financial distress was measured using the 5-item abbreviated version of the Consumer Financial Protection Bureau (CFPB) Financial Well-Being Scale (Consumer Financial Protection Bureau, 2017), rated on a 7-point Likert Scale. The same measure was used in Chapter 5 (see Chapter 5 for details).

Procedure

A subset of the dataset from Study 3 was used here. The participants answered questionnaires regarding their financial distress, materialism, age and happiness and agreed to having their daily panels of all debit and credit transactions across all of their bank accounts matched to their survey responses. A separate panel was recruited on Prolific, requiring a group of 100 raters to rate each spending category following the instructions outlined in the previous section.

Data analysis

To measure self-congruence in overall consumption, a basket-participant match was calculated to indicate the extent to which a participants' shopping basket personality matched their Big Five personality. The same methodology was applied in a previous study, but with a different and smaller transaction dataset comprising of a smaller number of categories (Matz et al., 2016). First, the spending categories in which participants had not made a single purchase were removed. Informed by evidence suggesting that an accumulation of purchases with smaller amounts are more likely to lead to greater happiness, compared to a few larger ones (Dunn et al., 2011), all spending categories were assigned an equal weight rather than the amount spent. This means that for each participant, the personality scores of the spending categories in which they have spent money were averaged and standardised to produce five scores representing the average Big Five personality profile of their overall consumption pattern, in relation to other participants included in the study. For instance, the shopping basket of a participant who bought from more categories seen as being extraverted (e.g., dining or going out, holidays) or fewer categories seen as being introverted (e.g., vehicle tax, TV licence) would be considered to be high on trait Extraversion. The same applies to the rest of the Big Five personality traits. Following this, a score for the basket-participant match was computed using the Euclidean distance (Deza & Deza, 2009), which reflects the extent to which the overall personality profile of a participant *i* and that of their shopping basket *b* is similar, of which score was then subtracted from the mean (Matz et al., 2016).

$$\text{basket-participant match}_{i,b} = \\ \text{mean} - \sqrt{\left(z(\mathrm{O}_i) - z(\mathrm{O}_b)\right)^2 + \ldots + \left(z(\mathrm{N}_i) - z(\mathrm{N}_b)\right)^2}$$

Following this, correlation analyses were run between the four psychological constructs and the basket-participant match, which tested the hypotheses proposed in this study. A dominance analysis was then performed to determine the dominance of one variable over the others across all subsets of models (Azen & Budescu, 2006).

6.3 – Results

A correlation matrix was computed for all the variables used in this study (see Table 6.1). Upon inspection of Table 6.1, it appears that the constructs are all strongly correlated with one another. The results showed that there is a non-significant correlation between age and basket personality match, as well as a weak significant positive correlation between self-control and basket personality match ($p = .07$). This means that H1 and H2 are not supported. Moderate significant negative correlations were found between financial distress and basket personality match ($p < .01$), and between materialism and basket personality match ($p < .01$). The results confirm H3 and H4. While two of the hypotheses were not significant (H1 and H2), the relationships were in the direction proposed by the hypotheses set out in this study.

Table 6.1 *Correlations between age, self-control, materialism, financial distress and self-congruent spending*

		1	2	3	4	5
1	Age	-	.06**	-.22***	-.08***	.03
2	Self-control		-	-.20***	-.28***	.04†
3	Materialism			-	.34***	-.06**
4	Financial distress				-	-.07**
5	Self-congruent spending					-

Note. $^{\dagger}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$,

I chose to use dominance analysis instead of multiple regression models to test for the variance explained by each of the four constructs. Regression coefficients from a multiple regression analysis denote the amount of unique variance explained by an individual predictor. In cases where there is a correlation between predictors as is the case for this study (see Table 6.1), regression coefficients are not appropriate for representing a predictor's performance compared to all combinations of the other predictors (Azen & Budescu, 2003). As a solution, dominance analysis will be better-suited than multiple regression in addressing the research question, as it determines the importance of each predictor in the selected regression model. If a focal predictor accounts for more variance in the predictive model of the outcome variable than does the rest of the predictors included at a particular level of analysis, it is deemed more important than the other predictors included in the model (Azen & Budescu, 2003). The package ‘dominanceanalysis’ in R Studio was used to conduct dominance analysis.

The model including all four predictors explains 0.8% of basket personality match. The numbers included in each row of Table 6.2 presents the average change of R^2 of the focal predictor when it is added to regression models including different subsets of the other predictors. As can be seen in Table 6.2, financial distress provides the largest dominance value within each subset of models, as well as the largest general dominance value. Financial distress contributed to an average of 0.4% increase in the amount of variance explained across all subset models, rendering it the most important predictor of self-congruent spending. The second most important predictor is materialism, which added an average of a 0.2% increase in variance explained across all subset models.

Table 6.2 *Average R^2 across subsets of dominance analysis*

Number of predictors in model	Age	Self-control	Materialism	Financial distress
0	.001	.002	.004	.006
1	.001	.001	.003	.004
2	0	0	.002	.003
3	0	0	.001	.003
Average contribution	.001	.001	.002	.004
Percentage contribution	12.5%	12.5%	25%	50%

6.4 – Discussion

Transaction records offer an unprecedented opportunity to measure self-congruence in overall consumption as it allows a detailed view of a consumer's purchases. Exploiting this opportunity to further our understanding of self-congruent spending behaviour, this study aimed to explore the potential correlates of self-congruent spending. The correlates examined here are chronological age, self-control, materialism and financial distress. Out of the four proposed hypotheses, H1 and H2 were not confirmed, but H3 and H4 were confirmed (see Table 6.1). Age and self-control were not significantly correlated with self-congruent spending; materialism and financial distress were both significantly and negatively correlated with self-congruent spending. While the correlations did not reach statistical significance for H1 and H2, the direction of the effects were as proposed. The dominance analysis indicated that financial distress contributed to up to 50% of the variance explained in self-congruent spending, followed by materialism (25%). However, it is also important to note that the effect sizes were very small.

For the first time, this study has shown that people of different characteristics can differ in terms of their ability to spend in a way that is congruent with their personality. This is in line with previous studies showing people can vary in their trait and state authenticity (Kernis & Goldman, 2006; Sedikides et al., 2019), which means that they tend to behave more or less congruently to their beliefs and dispositions. While people generally tend to consume products and services that fit with their self-concepts, the finding that the extent to which individuals are able to do this can vary necessitates further investigation into the different factors and mechanisms at play which affect this. This study has opened up this line of inquiry by demonstrating a direct link between self-congruent spending and two constructs: financial distress and materialism.

Based on the low correlation between financial distress and basket personality match, it appears that individuals who are financially distressed are less likely to spend money in a way that fits with their personality. Seen in light of the findings of Chapter 5 which show that financially distressed individuals are more likely to engage in conspicuous consumption, the lower tendency for these individuals to spend congruently to their personality found in the current study confirms the proposition that financial distress may prevent people from spending congruently to their self-concept, which could be due to a shift of focus onto consumption that address their perceived or actual lack in their self-concept (Mandel et al., 2017), and away from that which fits with their personality. The lower tendency for financially distressed individuals to spend congruently to their personality also corroborates the findings of Gladstone et al. (2019) which suggests that people living in deprived areas may have fewer opportunities for the type of consumption that allows them to express their identity. However, the current study is unable to disentangle cognitive and environmental factors related to financial distress in its relationship with a self-congruent consumption pattern.

The results showed that materialism is significantly and negatively correlated with self-congruent spending, indicating that individuals who are highly materialistic are less likely to spend in a way that is congruent with their personality. With evidence suggesting materialism, in both forms as an individual trait and socio-cultural phenomena, are on the rise (Lim et al., 2012), the negative association between materialism and self-congruent spending could mean that people may also become increasingly less likely to consume products or services that lead to intrinsic rewards. With previous studies suggesting a likelihood for materialistic people to prioritise popularity, image or financial success (Burroughs & Rindfleisch, 2002; Kasser, 2016), and away from behaviours that contribute to self-actualisation (Ku et al., 2014), these findings indicate that the lower tendency for people high on materialism to consume in a way that is self-congruent could have implications to their mental health and sense of fulfilment. Although the current study is unable to confirm this, it could also be possible that individuals living in more materialistic cultures may also be less likely to spend more congruently. While the effect size observed in the current study is very small, when manifested in a large population the impact would still be meaningful at a national and global level.

The current findings that both materialism and financial distress are significantly related to a lower tendency to engage in self-congruent spending point to a possibility that it may be self-enhancement motives that underpin these relationships, steering individuals to consumptions with their ideal-self, rather than actual-self in mind (Sirgy, 1985). Materialism constitutes part of self-enhancement values (e.g., achievement and power) (Burroughs & Rindfleisch, 2002), whereas the sense of lack stemming from financial distress (Kernis et al., 1991) may activate self-enhancement motive for consumption. Although the paths that trigger the desire to augment one's sense of self may be different for materialism and financial distress, it is possible that self-enhancement may underlie the negative relationship between these constructs and self-congruent consumption patterns by prioritising spending to signal power and status, rather than spending to fulfil fundamental needs associated with one's personality. This proposition could be tested more explicitly in future work by investigating the potential mediating role of self-enhancement in how materialism and financial distress relate to self-congruence in overall consumption pattern.

Contrary to the proposed hypotheses, age was not significantly correlated with self-congruent spending. It is possible that changes in identity-related functions over lifespan may not be linear, hence its effect on self-congruence in consumption may not fit a linear trend which can be detected with a correlation. The case could also be that an age-related increase in perception of authenticity (Seto & Schlegel, 2018) may not translate into an increase in the tendency to engage in self-congruent spending. In addition, while young people may have lower purchasing power to purchase symbols in an effort to self-express, the effect of an age-related increase in self-congruent spending may be diluted by the fact that young people may have more self-expressive needs, compared to older adults (Harter, 2015). Future studies could directly test the relationship between different stages of identity development, individuals' self-expressive needs and self-congruent spending. While self-control was not significantly related to self-congruent spending, the effect was in the proposed direction and it was approaching significance. It is possible that self-control was a proxy of another psychological disposition which may be more directly related to self-congruent spending.This necessitates further investigation to confirm the findings of the current study.

Although two of the hypotheses were confirmed, the amount of variance explained by both constructs, financial distress and materialism, was very small (see Table 6.2). A few explanations may be offered for the small observed effects. First, the personality traits of the spending categories in this study were rated by a separate panel, rather than the participants whose spending records were being examined. It is possible that the way that a buyer perceives a product may be more important in their purchase decision, than the way most people perceive a product. However, the high inter-rater correlations for the ratings of the spending categories suggest that people tend to perceive these categories in a similar way. This means that even if the purchasers themselves rated the spending categories, the ratings are unlikely to differ dramatically. However, in order to determine the extent to which this may be true, future research could examine the potential differences in how buyers and non-buyers may perceive the personality of a product.

Second, self-congruence was measured in relation to overall consumption patterns. This is another marked distinction from previous studies examining self-congruity effects, which have predominantly measured self-congruence in relation to single brands (see Kuenzel & Halliday, 2010; Pradhan et al., 2020; Sirgy, 1986). The fact that this study had a larger sample size, and a single score was used to represent congruence across 277 categories, means that the effects can reasonably be expected to be smaller. In fact, the smaller effect size is consistent with previous studies showing that the effect sizes found with small sample sizes are often inflated and tend to vary greatly (Funder & Ozer, 2019), and that as sample size increases, effect size decreases (Yarkoni, 2009). Nevertheless, a very small effect should not be dismissed entirely, as in some circumstances, a very small effect size could accumulate into a larger one over time, situations, or individuals (Funder & Ozer, 2019; Ozer & Benet-Martínez, 2006). While Funder and Ozer (2019) uses r = .05 as a benchmark to indicate that a very small effect that can be consequential when accumulated over long-term, it is possible that an effect size of r = -.07 in the relationship between self-congruent spending and financial distress could lead to an accumulation of potential downstream effects in well-being in the long run. However, the current study does not allow for such examination. The potential cumulative effects of these psychological constructs on self-congruent spending will hopefully be clarified in future studies.

Future research

By showing that materialism and financial distress are related to the tendency to spend congruently, the exploratory findings suggest that there may be other factors at play which affect this behaviour. This opens up a path to future research in this line of inquiry. Considering the importance of self-congruence in consumer well-being, interventions could be implemented to steer individuals with high materialism and financial distress into more self-congruent consumption patterns, which may in turn lead them to gain more happiness. However, this study did not explicitly test for the moderating effect of these correlates, therefore these suggestions remain speculative. The following study will clarify this by testing for the extent to which the most dominant correlate of self-congruent spending, financial distress, moderates the relationship between self-congruence in consumption and happiness. Future research could also look into the mechanisms underlying congruent and incongruent spending behaviour. As the authenticity scale suggests, there are three components to authenticity (Wood et al., 2008): lack of self-alienation, authentic living and accepting external influence. It is likely that these mechanisms also apply to consumption behaviour to a certain extent. This line of investigation will potentially shed light onto the specific cognitive processes that an individual may be facing problems in which is preventing them from being able to consume in a way that aligns with their personality.

Limitations

This study has utilised transaction records to infer self-congruent spending, demonstrating the usefulness of this data type for creating variables for psychological inquiries. Differing from traditional self-congruence measures, this method is highly scalable and is more objective. However, self-congruence was measured in terms of personality, limiting the interpretation and generalisability of the findings to congruence solely in this domain. As self-concept is multifaceted, future studies could look at congruence in other psychological characteristics. The speculation that the role of self-enhancement in self-congruent spending underlies the links between materialism and financial distress could be clarified in future studies by directly measuring self-enhancement motives and investigate its potential mediating effect. The findings may inform interventions for alleviating distractions from self-congruent spending which are more beneficial for subjective well-being. While this study was motivated by how these constructs may affect people’s ability to spend more congruently to their personality, and in turn their ability to experience happiness, it did not test this explicitly. Thus, the next study will further clarify the extent to which the most important predictor in this study, financial distress, might moderate the relationship between self-congruent spending and happiness.

Conclusions

The current study demonstrated that materialism and financial distress are significant correlates of self-congruence in consumption, though the effect sizes were small, thus providing only partial support for the hypotheses. Individuals who are high with respect to materialism and financial distress are less likely to spend money in a way that fits with their personality. Dominance analysis suggests that among the four constructs investigated in this study, financial distress is the most important predictor of self-congruent spending. However, the amount of variance explained by the construct remained very small, so the findings should be interpreted with caution. Given that previous findings have suggested a link between self-congruent consumption and happiness, the next study will investigate the potential moderating effect of financial distress on the relationship between self-congruent spending and happiness.

Chapter 7 – Self-Congruent Spending and Happiness: Moderating Effect of Financial Distress

Chapter 7 Summary

Transaction records offer a way to measure self-congruence in individuals' overall consumption patterns in an objective way, which can be used to examine the links between self-congruity in consumption and consumer's subjective well-being. While it has been established that self-congruence in consumption can bring consumers happiness, there is however limited evidence on the potential moderators of this effect. As demonstrated in Chapter 6, financial distress was the most important predictor of self-congruent spending among the correlates included in the study. Specifically, people who are experiencing financial distress are less likely to spend in a way that matches with their personality. Considering the adverse impact of financial distress on people's mental health and overall well-being, this necessitates further inquiry into whether financial distress moderates the effect of self-congruent spending on happiness. This study looked at the moderating role of financial distress on the relationship between self-congruence in overall consumption patterns and subjective well-being. This effect is found to be significant, indicating that the increase in happiness related to self-congruence in spending is more pronounced for those who are experiencing financial distress.

7.1 – Introduction

Historically, marketing practitioners tend to give more consideration to the psychological processes resulting in the purchase of a product, but they are less concerned about post-consumption consequences (Donnelly et al., 2017; Trudel et al., 2016). Among the different consequences of consumption, one of the most crucial but under-explored areas is consumer well-being. This line of inquiry has the potential to offer key insights which may help consumers improve their decision-making processes and lead to more positive outcomes (e.g., higher satisfaction, happiness, need fulfilment), which may in turn strengthen consumer's relationship with brands. Chapter 4 looked at how self-congruity can lead to an increase in advertising appeal; this study is concerned with the links between self-congruity in consumption and subjective well-being. By exploring the potential correlates of self-congruent spending, it was found in Chapter 6 that financially distressed individuals may be less likely to spend in a way that is congruent with their personality. Considering the links between self-congruent spending and happiness, this study sets out to test the possibility that there might be differential effects between those who are experiencing higher or lower levels of financial distress in terms of how much happiness they may gain from spending more congruently to their personality.

Self-congruent Spending and Subjective Well-being

How money can bring about happiness has been a question of substantial interest amongst both researchers and general public. However, the fundamental proposition of economics that "more is better" has been challenged (Dutt & Radcliff, 2009). With mixed evidence in the relationship between income, consumption and happiness, recent research has painted a more nuanced picture of the relationship between these factors. As outlined in Chapter 2, people tend to act in ways that are in line with their self-concept, and self-congruence is also associated with higher levels of well-being and overall life satisfaction (Assouline & Meir, 1987; Jokela et al., 2015; Reich et al., 2008). In the context of consumption, self-congruence in consumption has been linked with improved well-being (Hill & Howell, 2014; Matz et al., 2016; Petersen et al., 2018; Zhang et al., 2014).

Most recently, using more than 76,000 bank transactions, Matz et al. (2016) revealed that not only are individuals more likely to spend more money on products that are congruent with their personality, those who engage with consumption activities that are better aligned with their personality are happier. A follow-up experiment showed that this effect is causal: spending congruent with one's personality led to an increase in positive affect. Highly extraverted and introverted individuals were given by random allocation, then instructed to spend within three days, either a high or low extraversion payment (voucher for use in a bar vs. a bookstore). The experiment revealed that participants who had engaged in personality-congruent consumption reported a significant increase in positive affect, whereas participants who engaged in personality-incongruent consumption reported a decrease in positive affect (Matz et al., 2016). In line with previous research in behavioural congruence and well-being, consumption that fits with one personality may be similarly satisfying fundamental psychological needs related to autonomy and competence (Maslow, 1954). The effect of self-congruence in spending on happiness had been shown consistently in both studies, which the current research will aim to replicate in a larger dataset of transaction records aggregated across bank accounts which include a larger number of spending categories.

Financial Distress and Subjective Well-being

Subjective well-being comprises a sense of well-being in different life domains; a key part of it concerns material and financial aspect of one's life (Sirgy, 2018b). Individuals' perception of their financial well-being is a key predictor of their overall well-being (Netemeyer et al., 2018). Notably, the magnitude of this effect is comparable to that of other life domains taken together (i.e., physical health assessment, relationship support and job satisfaction) (Netemeyer et al., 2018). Individuals who perceive themselves as being financial distressed experiences more negative emotions related to their financial situation. Given that financial position is strongly related to other domains of an individual's life, particularly in whether they spend or consume in a way that allows them to enrich their other life domains (e.g., family, social, leisure), people who are financially distressed are more likely to experience low subjective well-being, on the whole. A recent study found that financial worry is negatively related to life satisfaction (Tay et al., 2017), indicating that while financial distress is an indication of an individual's subjective feelings about their financial situation, well-being in this the focal domain can potentially spill over to multiple life domains. Using consumer financial narratives, large-scale surveys and experiments, Netemeyer et al. (2018) demonstrated that perceptions of financial well-being are significantly related to happiness and that this effect is robust across different research designs.

Individuals' subjective perceptions of their financial circumstances play a vital part in their experience of happiness, as studies show that people who perceive their financial situations in a negative light tend to report lower life satisfaction (Dolan et al., 2008). In fact, positive financial behaviours (e.g., budget-led spending, regular savings, maintaining emergency funds, contributing to investment or retirement accounts) improves financial satisfaction, which then leads to heightened life satisfaction (Xiao et al., 2009). It has been suggested that this may occur via a bottom-up spill-over process (Sirgy, 2018b). Financial behaviours can be seen as events within the domain of material life that influence the extent to which one experiences well-being in that particular domain. When an individual is dissatisfied in the material domain, the negative affect originating from these concrete financial events spills over to the overall life domain, which concerns the abstract conception of one's own life (Sirgy, 2018b). In sum, the evidence indicates that financial distress is intricately linked to overall life satisfaction. Thus, it is possible that altering one's financial habits to enhance the other life domains may increase one's overall life satisfaction; one way to do this is through increasing the frequency of self-congruent spending.

Benefits of Self-congruent Spending on Happiness for Financially Distressed

Evidence suggests that those who are more financial distressed are more at risk of mental health issues (Glei et al., 2018; Wilkinson, 2016), indicating that financial distress may be related to one's overall subjective well-being. As a remedy to lower subjective well-being caused by financial distress, a fruitful research avenue would be to investigate if the gain in levels of happiness may be more pronounced for those who are financially distressed. It is likely that financially distressed individuals are less capable of spending money in the 'right' way, choosing to spend money in categories that are maladaptive or to compensate for a sense of lack, as seen in Chapter 5. Confirming this notion, it was found in Chapter 6 that individuals experiencing financial distress are less likely to spend money in line with their personality. This may potentially be due to their need to pay off debts or spending on necessities may lead them to have less disposable income to spend on things that matches their personality. Further, the subjective feelings of worry about their financial situations may predispose them to spend money in order to give them short term relief to their immediate distress, rather than goods or services that are more fitting with their fundamental psychological needs and will more substantially increase their happiness. In addition, low self-esteem emanating from financial distress (Kernis et al., 1991) may trigger self-enhancement motives, resulting in a focus on spending to fit with one's ideal self, while potentially neglecting their actual self.

Altogether, these findings suggest that the reason why individuals experiencing financial distress are less happy may be because they have a lower tendency to engage in self-congruent spending. There may be forms of obstacles (e.g., cognitive, environmental) stemming from financial distress that may affect the extent to which an individual spends congruently, as well as their propensity to yield happiness from self-congruent spending. Further, the ability for people who are experiencing financial distress to gain happiness from self-congruent spending may be enhanced when they are able to consume in a way that fits with their personality, or when opportunities to do so are more readily available. Considering the detrimental effects financial distress may cause on individuals in physical and mental health (Glei et al., 2018; Kerr et al., 2017; Starrin et al., 2009), it is important to explore avenues for alleviating mental strain which may lead to these outcomes.

The current study

This study aims to investigate the moderating effect of financial distress on the relationship between self-congruence in consumption pattern and happiness. To this end, the investigation looks to clarify whether spending on consumption categories that match with consumers' personalities provide more of an increase in happiness for those who are more financially distressed. Further, the study also aims to investigate the extent to which inferred financial distress from a machine learning model devised in the previous study can be used in the moderation analysis. This study proposes that individuals who are experiencing financial distress may benefit from spending more congruently to their personality and gain more happiness. It is likely that subjective feelings of financial distress may limit an individual's ability to spend in a congruent way to their personality, thus leading to higher subjective well-being. By modifying their consumption patterns, it may be possible to soften the adverse impact of stress stemming from their financial situation from spilling over into their overall life satisfaction.

The objectives of the current study are as follows:

1. To replicate Matz et al. (2016)'s findings that basket personality match is positively and significantly associated with happiness.
2. To investigate the moderating effect of financial distress on the relationship between basket personality match and happiness.
3. To investigate the extent to which inferred financial distress can be used to obtain similar results to actual financial distress in its moderating effect.

7.2 – Method

Participants and procedure

The same sample and procedure in Chapter 6 were used in this study (see Chapter 6.2 for details).

Measures

Spending categories

The spending categories included here are the same as in Chapter 6 (see Chapter 6.2 for details).

Personality traits of spending categories

The spending categories were rated in the same way as in Chapter 6 (see Chapter 6.2 for details).

Big Five Personality

The 10-item version of the Big Five Inventory (BFI-10) (Rammstedt & John, 2007) was used to measure Big Five personality in this study (see Chapter 6.2 for details).

Happiness

Happiness was measured using the short 5-item Satisfaction with Life Scale (SWLS), which assesses individuals' judgments of satisfaction with their life as a whole (Diener et al., 1985). The scale demonstrated excellent internal consistency (Cronbach's alpha = .88).

Financial distress

Financial distress was measured using the 5-item abbreviated version of the Consumer Financial Protection Bureau (CFPB) Financial Well-Being Scale (Consumer Financial

Protection Bureau, 2017) (see Chapter 6.2 for details). In addition to the CFPB measure, this study also used the machine learning model devised in Chapter 5 to obtain a score of predicted financial distress for each participant.

Data Analysis

A basket-participant match was computed using the same method as Chapter 6 (see Section 6.2). In a hierarchical regression analyses, life satisfaction was regressed on the basket-participant match predictor in the first step. In the second step, the interaction of financial distress and basket-participant match was added. Finally, in the third step, total spending was controlled for to eliminate the potential confounding effect of income. To demonstrate the robustness of the effects, the same analysis was performed by replacing actual financial distress with predicted financial distress.

7.3 – Results

To examine the extent to which actual and predicted financial distress moderated the relationship between self-congruence in consumption pattern and subjective well-being, two separate models of moderated hierarchical regression were run using actual and predicted financial distress as moderators (see Table 7.1). The first step of the simultaneous regression showed that both the main effects of financial distress ($p < .001$) and self-congruence in consumption ($p < .01$) on subjective well-being were significant, for both models using actual financial distress, and predicted financial distress. The interaction between financial distress and self-congruence in consumption was also significant ($p < .01$), for both actual and predicted financial distress. In addition, for both actual and predicted financial distress regression models, the interaction remained significant ($p < .01$) even when total spending was added into the regression model in the final step.

Table 7.1 *Simultaneous regression models of interaction between financial distress (actual and predicted) and self-congruence in consumption on life satisfaction*

	Model 1	Model 2
Step 1		
Financial distress	-.43***	
Predicted financial distress		-.35***
Match	.07**	.07**
Adj R^2	.20	.13
$F(2, 1873)$	231.1***	140.1***
Step 2		
Financial distress		
Predicted financial distress		-.35***
Match	.07**	.07**
Interaction	.05**	.06**
Adj R^2	.20	.13
$F(3, 1872)$	156.7***	96.61***
Step 3		
Financial distress	-.41***	
Predicted financial distress		-.34***
Match	.05**	.07**
Interaction	.05**	.06**
Spending (log transformed)	.07**	.01
Adj R^2	.20	.13
$F(4, 1871)$	120.9***	72.48***

Note. * $p < .05$, ** $p < .01$, *** $p < .001$.

Figure 7.1 illustrates the moderation effect of actual and predicted financial distress on the relationship between self-congruence in consumption and subjective well-being. To visually present this interaction, financial distress was median-split into two groups: high and low. The relationship between self-congruence in consumption and happiness was plotted, while two lines represented high and low levels of financial distress. The figure indicated that subjective well-being increases as congruence between the personality of a buyer and his or her overall consumption pattern increases, however this effect is stronger amongst those with higher financial distress. This implies that those with higher financial distress may benefit more from spending in categories that fit with their personality. Further, predicted financial distress is almost as good as actual financial distress in demonstrating this moderation effect.

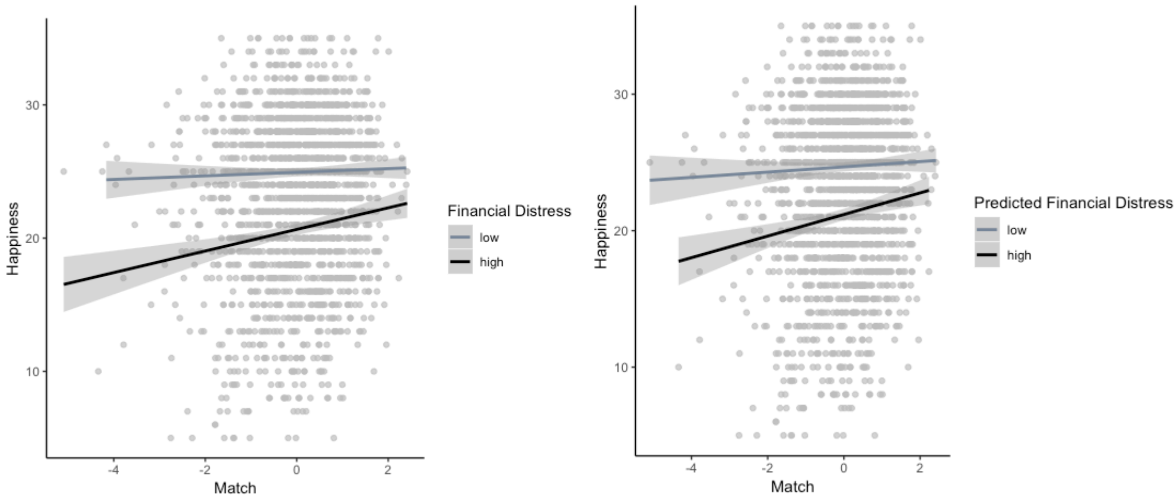

Figure 7.1 Actual and predicted financial distress as moderators to the relationship between self-congruence in consumption and subjective well-being

7.4 – Discussion

The findings replicate those of Matz et al. (2016), showing that there was a significant positive relationship between self-congruence in consumption and happiness. Further, there was a significant interaction between financial distress and self-congruence in consumption, such that the increase in happiness resulting from self-congruence in consumption pattern is greater for individuals who score higher on financial distress. This effect remained significant even when total spending was controlled for. Further, the moderation effect was of similar magnitude even when predicted financial distress was used, which indicates that inferred financial distress can be used to reliably identify individuals who are experiencing heightened financial distress. In all, the study shows that the strength of the match between the personality of buyers and their overall consumption pattern is related to higher life satisfaction; however, this effect is stronger amongst those with higher financial distress, implying that individuals with higher financial distress may benefit more from spending in categories that fit with their personality.

The significant positive main effect of self-congruent spending and subjective well-being is in line with the extant literature which has largely agreed that positive affect results from self-congruence (Assouline & Meir, 1987; Lenton et al., 2016; Matz et al., 2016; Sirgy, 2018a), and that psychological tension associated with cognitive dissonance results from behaviours and outcomes perceived to be inconsistent with one's actual self-image (Sirgy, 1982, 1985). Compared to the dataset used by Matz et al. (2016), the dataset in the current study contains three times as many participants. This study utilised more spending categories (277 vs. 59) and the transactions were also aggregated across all participants' bank accounts, rather than using transactions from a single bank account. This successful replication of the effect of personality congruent spending on subjective well-being suggests that the effect is robust, even in a completely new dataset with a larger sample. This is important especially in light of the reproducibility crisis in psychology research (Open Science Collaboration, 2015).

The main contribution of this study is in demonstrating that while self-congruent spending can increase happiness for all individuals in general, it has a more positive effect on the happiness of those experiencing financial distress. Together with the findings of the previous chapter showing that financially distressed individuals are less likely to spend in a way that is congruent with their personality, the current findings indicate that the association between financial distress and low subjective well-being (Netemeyer et al., 2018; Sirgy, 2018b) may be exacerbated by their generally lower tendency to spend in a way that is congruent with their personality. As can be seen in Figure 7.1, the increase of happiness associated with self-congruent spending is greater for those experiencing financial distress. When inspecting individuals high on financial distress, these individuals are happier when they spend money in a way that better matches their personality, while those equally financially distressed are less happy when their spending is less aligned to their personality. As the findings from Chapter 5 showed, individuals experiencing financially distress are more likely to spend larger proportions of their spending in financial charges, basic necessities, as well as conspicuous consumptions typically related to escapism and status signalling, which means that they may be allocating fewer resources on spending that allow them to express their personality. These findings suggest that due to consumption aimed at compensating for their lack or negative emotions related to financial distress, they may deprioritise spending that fits with their personality, leading to a greater sense of dissonance due to a lack of self-concept verification.

Managerial implications

This study clearly shows that while there is a benefit from self-congruent spending, the gain in happiness is larger for people who are experiencing financial distress to alter their consumption patterns into one which fits better with their personality. Thus for interventions aimed at improving well-being at a collective level, it appears that rather than targeting interventions at every individual to increase their happiness by facilitating self-congruent spending, policymakers may gain more from targeting a smaller group of financially distressed individuals who are in greater need and will benefit more from such interventions. Although the effect size found in this study is small, when applied on a large scale this change has the potential to result in meaningful impact. Considering the widespread phenomenon of financial distress, this small effect size could be consequential at a societal or national level, especially for communities or countries experiencing economic hardships.

As the findings reported in Chapters 5 and 6 suggest, there are several reasons for a lower tendency to spend more congruently among those who are experiencing financial distress. For instance, it could be an inability to budget well in order to allocate a proportion of their disposable income to express their personality, as indicated by their poor financial management skills, or compensatory consumption in order to respond to their perceived lack in comparison to others around them, as indicated by conspicuous spending categories which can be used to signal status. Together, this means that policymakers could potentially look into removing these obstacles to enable a basic degree of self-congruent spending which is able to ensure the average level of a community's or a nation's subjective well-being is at an acceptable standard. This could be through providing education on financial management in order to free up resources for spending on self-expression and raising awareness on how to consume in a way that contributes to long-term rather than short-term happiness. Beyond these measures, charities and government bodies may also consider allocating budgets to financially distressed individuals aimed at specific uses, such as necessities, and self-congruent consumption, rather than simply providing a lump sum. It may also be that alongside providing financial aid, policymakers could potentially implement nudges to encourage at least some purchases that are more aligned with these individuals' psychological profile.

Furthermore, by showing that inferred financial distress from machine learning model built in Chapter 5 reflects well in the moderation analysis in the current study, these findings indicate that it is possible for government bodies or charities to identify financially distressed individuals accurately and target them with potential interventions, as mentioned above. The study demonstrated that it is possible to use the machine learning model devised in Chapter 5 to infer subjective feelings of financial distress, which works just as well as actual questionnaire responses for investigating its effect on subjective well-being. As the use of machine learning means that individuals' levels of financial distress can be detected at scale, without relying on responses of self-reported questionnaires, it has great potential for improving the effectiveness of interventions as it allows these solutions to reach a larger number of individuals, even when they may not be seeking assistance due to the stigma attached to financial distress.

Limitations

This study is not without limitations. Due to the cross-sectional nature of the study, it is not possible to infer causality. It is not possible to ascertain whether financial distress leads to lower self-congruent spending, or whether lower self-congruent spending leads to financial distress. Previous findings show that happy people tend to behave differently in the financial domain; they differ with respect to their less happy counterparts in how much they save, spend, distribute their income over time, as well as the variety in their consumption (Frey & Stutzer, 2002; Kahn & Isen, 1993). With evidence suggesting links between income and frequent rather than intense happiness (Jachimowicz et al., 2020), future research could also look at how self-congruent spending may lead to different dynamics of happiness. Other future research avenues include investigating the causality of the relationship between financial distress and self-congruent spending, as well as the factors leading to a lower degree of self-congruent spending amongst those who are financially distressed. These will add to the current discourse on the relationship between money and happiness, and allow for a more targeted approach to intervention. An experiment could also be run to see if individuals who are financially distressed at a certain point in time will experience higher levels of happiness after having started spending in a way that fits more with their personality. This will help cement the benefit of an intervention involving the cultivation of self-congruent spending habits amongst those who are financially distressed.

Conclusion

Overall, this study showed that the increase in happiness gained from spending congruently to their personality is larger for individuals who experience higher financial distress than those who are less financially distressed. It also builds on recent work on self-congruence in overall consumption and happiness by showing the relevance of financial distress — an addition that opens up a line of inquiry into other potential moderators which may cause differentiation in strength of gain in happiness from self-congruent spending. Finally, these findings suggest that potential inequalities in happiness could be exacerbated by the inability of people to spend in a way that fits with their personality, particularly for those who are experiencing financial distress. To address such inequalities, future research could assess interventions for nudging and steering financially distressed individuals into the types of consumptions that are more congruent with their personality, which may potentially yield greater benefits for them.

Chapter 8 – General Discussion

Chapter 8 summary

This final chapter contains a discussion of the research presented in this thesis. It starts with a summary of the motivations for the thesis. The empirical research, as described in Chapters 3 to 7, is then critically evaluated in relation to the aims of the thesis proposed in Chapter 2. The extent to which this thesis has contributed to methodological, theoretical, practical and ethical discourse is discussed. The chapter ends with acknowledgement of limitations and suggestions for future research.

8.1 – Overview

This doctoral research was motivated by the recent developments in the methods for collection and analysis of human-centric data, particularly in the domain of consumption. Overall, the aim of this thesis was to understand the role of self-congruity in consumer preference through transaction records. To this end, the thesis employed novel methodologies for investigating self-congruity effects, specifically through machine learning models in the inference of consumer characteristics, and the measurement of self-congruence in overall consumption patterns, based on a large-scale transaction record dataset.

A critical review of literature concerning inference of individual differences from digital footprints and self-congruity theory was presented in Chapter 2. The chapter identified opportunities and gaps in the literature, both methodologically and theoretically. Firstly, there are long-standing issues of traditional methodologies such as low statistical power, representativeness and reliance on self-reported questionnaires. These are addressed in the empirical studies of Chapter 3 to 7 using transaction records as a basis, and a combination of traditional and big data methodologies. Secondly, a preoccupation with inferring Big Five personality traits, using social media data, was also identified. This thesis responded this gap in the literature to understand other facets of consumer self-concept such as demographics and more malleable traits by inferring consumers' chronological age (see Chapter 3) and subjective feelings of financial distress (see Chapter 4) using an underutilised data type, transaction records.

The lack of attempts to directly demonstrate the practical relevance of these inferences (particularly in linking attribute inference to personalised advertising) was addressed in Chapter 5. In the emerging area of research into self-congruence consumption and happiness, questions remain regarding the types of individuals who are more or less likely to spend in a way that fits with their personality. This thesis added to the nascent academic discourse by looking at the potential correlates of self-congruent spending, namely chronological age, self-control, materialism and financial distress (see Chapter 6). A key question which followed was, whether some individuals may benefit more, or less, in terms of happiness, from self-congruent spending. This was addressed in Chapter 7, which investigated the moderating role of financial distress on the effect of self-congruent spending on happiness.

The following sections of this chapter seek to evaluate the empirical research conducted in Chapter 3 to 7, alongside highlighting the key contribution this thesis makes to the academic literature. The results of this thesis may be summed up in three main points. Firstly, the thesis has clearly and successfully demonstrated the value of transaction records for generating consumer insights. Secondly, the inferences from machine learning models have practical relevance to marketers and researchers. Finally, the findings provided empirical evidence to the growing body of research in using self-congruity for understanding consumer preferences.

8.2 – Theoretical and Methodological Implications

This thesis made important theoretical and methodological contributions to the current approach to examine consumer phenomena. Most notable is the demonstration of the value of big data methodology in the research on consumer psychology. It was not the intention, nor was it possible for this thesis to solve the replicability crisis, but it modestly and realistically aimed to mitigate some of the methodological limitations associated with traditional psychology research that contribute to this crisis by opting for methods that are less prone to these issues. Contrary to traditional psychology and consumer research where the studies are often underpowered (Cohen, 1992; Matz & Netzer, 2017), parts of this thesis were able to garner high statistical power due to the large sample size (N = 2,274 in the transaction dataset) and use of powerful analytical methods (i.e., XGBoost model in Chapter 3 and 5). It has overcome one of the key limitations of traditional consumer research which relied predominantly on self-reported consumer behaviour by using an objective measure of consumer purchases through actual transaction records. Through this, the thesis offered valuable insights into real consumer behaviour associated with the characteristics investigated, namely chronological age and financial distress. The machine learning models employed in Chapter 3 and 5 which are able to sift through the large number of predictors and spot patterns previously impractical or impossible to identify enables us to gain new insights into the types of purchases that characterise people of different ages, and those who are experiencing differing levels of financial distress. These conclusions were also drawn with a lower risk of overfitting, due to the cross-validation technique employed in these studies. Importantly, the findings obtained after having been cross-validated are more robust and generalisable, which can also help counter the adverse impact of p-hacking (Simmons et al., 2011) and the replicability crisis (Open Science Collaboration, 2015).

Comparing linear regression with other machine learning models on predictive accuracy in Chapter 3 and 5, it was clear that more advanced machine learning models are able to provide more superior predictive power to that of linear regression often used by psychologists. With the increase in scale in the number of individuals in the sample, breadth of variables and granularity of data comes the challenge that traditional approaches of statistical analyses as well as the interpretation of results may no longer be viable (Adjerid & Kelley, 2018).

Chapter 3 and 5 demonstrated that one of the most universally used statistical approaches – multiple linear regression – in psychology is limited in its ability to create models of high complexity that comprise a large number of predictors such as the one used in this thesis (652 brands in Chapter 3, 268 categories in Chapter 5). In contrast, machine learning is better able to handle increasingly rich sets of variables and to discover patterns that might not be apparent in smaller samples with a smaller number of variables. It was clear in Chapter 3 and 5 that compared to linear regression, the ensemble methods (i.e., XGBoost) were better able to handle a large number of predictors. The insight into the extent to which age and financial distress could be inferred from transaction records including a large number of predictors and participants would not have been possible without the help of these machine learning techniques (specifically, XGBoost regressor and feature importance analysis). It is hoped that this thesis shows psychology researchers that machine learning can be incorporated into the existing statistical toolkit for studying psychological phenomena.

Beyond the high statistical power resulting from the larger sample size as well as more powerful analytical techniques used in this thesis, the incorporation of a cross validation technique in Chapter 3 and 5 which is absent from traditional methods (Koul et al., 2018) also allowed findings to be produced that account for one of the key issues contributing to the replicability crisis in psychology research (Open Science Collaboration, 2015), that is overfitting. Machine learning algorithms are more effective than traditional statistical approaches commonly used in psychology (e.g., small-sample ANOVA or multiple linear regression) in avoiding the capitalisation on chance through several different reasons (Oswald, 2020), with the key one being cross validation. Scholars have started to consider *p*-hacking a form of procedural overfitting that takes place before the stage of model estimation (Yarkoni & Westfall, 2017), which cross validation is able, to some degree, protect against (Oswald & Putka, 2017). On account of practical and methodological challenges, direct replications are often impractical or infeasible. Cross validation – a form of simulated replicability – can offer an alternative way for testing replicability of research findings (Koul et al., 2018) by imitating the benefits of an independent replication with the same number of observations, thereby increasing the confidence that the specific results will be replicated (Yarkoni & Westfall, 2017). Thus, it is hoped that, through the incorporation of machine learning methods, the findings of this thesis may stand a better chance of avoiding long-standing issues associated with the replicability crisis and therefore is able to contribute to consumer research by offering more rigorous, generalisable and replicable insights.

Furthermore, the application of machine learning models to test the predictions in the empirical studies of Chapter 3 and 5 have demonstrated that machine learning can be used to psychology researchers' advantage, maximising both the predictive accuracy and interpretability required to answer the research questions in mind. One of the main misconceptions of machine learning algorithms which have deterred psychologists from using the methods is that they are disparagingly labelled as 'black box' approaches that are able to produce high predictive accuracy but are difficult, and oftentimes impossible, to understand (Yarkoni & Westfall, 2017). While the models produced by many advanced machine learning approaches are not easily interpretable by human standards, this is often an artefact of specific approaches or implementations, rather than an inherent feature of machine learning approaches in general. Differing from traditional statistical methods, there are a larger variety of machine learning models to choose from to answer the same research question. Beyond considerations of a technique's complexity, and computing resources required, a key concern particularly relevant in the context of psychological research is the accuracy-and-explicitness trade-off. It posits that the most understandable explanations often lack predictive power while the most accurate predictions are not easily interpretable (Gilpin et al., 2018; Guidotti et al., 2019). In Chapters 3 and 5, machine learning models were applied to infer consumer characteristics, and feature importance analysis was used to complement the machine learning models to demonstrate that it was possible to achieve moderate to high predictive accuracy in predicting consumers' age from their brand spending, and at the same time expand our understanding of the types of spending that are the most strongly associated with consumers' characteristics. This clearly shows that machine learning models are in fact able to provide a level of interpretability that are compatible with the needs of psychologists in order to expand their knowledge of human behaviour, while overcoming other issues related to traditional statistical methods.

Through the application of computational methods in the analysis of the data utilised in the current investigation, this thesis has contributed to the scarce but growing research dialogue between researchers who study digital footprints, who are broadly in the field of computer science, or social science. As complex analytical techniques that large datasets require are often outside of the standard methodological toolbox of psychology researchers (Kosinski et al., 2016), this means that it is relatively rare among psychologists for research interest in examining digital footprints and the possession of the necessary skills for analysing this type of data to coincide. This has resulted in a phenomenon whereby research in this realm has largely been conducted by computer scientists, who are less well-versed in psychological theories and the ethical standard involved with the use of human subjects in research (Buchanan et al., 2011; Hall & Flynn, 2001). Due to the disparities in focus, methodologies, the way results are reported, as well as the terminologies used, these two fields tend to remain largely divided (Hinds & Joinson, 2019). Bearing this in mind, I have attempted in this thesis to bridge these gaps by incorporating both big data and traditional approaches in the investigation of self-congruity effect in consumer psychology, followed by an interpretation and communication of findings in a way that is valuable to both psychology and computer science researchers.

Through using machine learning models, the thesis has provided empirical evidence that it is possible to predict chronological age and financial distress from transaction records (see Chapter 3 and 5). Seen in light of the lower predictive accuracy of transaction records on the Big Five personality traits ($r = .15$, Gladstone et al., 2019), it appears that consumption patterns may be more indicative of chronological age and financial distress, compared to personality traits. It is possible that age is related to more self-concepts that can be effectively expressed through symbolic consumption, more so than the Big Five personality traits. In terms of financial distress, Chapter 5 revealed that the predictive accuracy was moderate, but still higher than for the Big Five personality traits. It could be that because financial distress is a domain specific construct, which is able to be more reliably reflected in purchase patterns.

While machine learning was appropriate for Chapter 3 and 5, Chapters 4, 6 and 7 were better suited to be answered through a mixture of old and new research designs and statistical methods. Specifically, Chapter 3 demonstrated that experimental design can be combined with large-scale behavioural field study to derive new insights. By leveraging the power of machine learning to infer consumer characteristics, and the high control in experimental settings, the findings of Chapter 3 were able to contribute meaningfully to the discourse of attribute inference by showing its practical relevance through the use of an online experiment. Altogether, the combination of methods used throughout the thesis has allowed each research question to be answered adequately and appropriately, further supporting the integration of big data methodologies in traditional psychology research design to create new insights.

The thesis also successfully demonstrated the relevance of attribute inference in practice and in research. Chapter 3 showed that inferred age was correlated to various financial outcomes at a similar strength to actual age, indicating that it can potentially be used to investigate other psychological phenomena related to age. In Chapter 7, inferred financial distress was used to test for the moderating effect of financial distress on the relationship between self-congruent spending and happiness. The regression models replacing actual financial distress with inferred financial distress produced very similar results, indicating that inferred traits can be successfully used in psychological research, potentially serving as an alternative way to increase sample sizes for when responses for traits are missing. Indeed, previous research studies have used similar methods to measure psychological attributes (i.e., computational personality assessment), rather than self-reported questionnaires (see Stachl et al., 2021). The results of Chapter 7 expand on this by showing that it is also possible for inferred characteristics from transactional records to be used in psychological research to obtain valid findings. Furthermore, Chapter 4 demonstrated that inferred attributes can be used for personalised advertisements to increase appeal. While the example used in Chapter 4 was personalised advertising, the findings suggest that inferred characteristics could also potentially be used in conjunction with other marketing techniques.

Although Chapters 6 and 7 did not strictly utilise machine learning, the way self-congruence in overall consumption pattern was computed was only possible through a dataset which captures a comprehensive view of consumers' transaction records classified under a large numbers of brands and categories. While this method for measuring self-congruence in consumption is not entirely new, the value this thesis added to the research of self-congruity and happiness is through applying this method in the pursuit of new research questions in this domain, using a larger transaction dataset aggregated across bank accounts. This is a clear indicator that bank transactions are rich in information which facilitates the creation of new variables for empirical investigation by combining datasets. Transaction records have opened up opportunities to investigate self-congruence in overall consumption, which is an indicator of a consumer's tendency to consume in a way that fits with their personality, seen across all their purchases rather than just one or a few specific brands. In contrast to the majority of previous studies which has measured self-congruity in relation to a small number of brands and relied on self-reported purchase intention rather than actual purchasing behaviour, in this thesis I measured self-congruity in terms of overall consumption patterns by utilising transaction records spanning a 12-month period which provided a comprehensive view of a consumer's overall consumption patterns. Hence, a new perspective on self-congruence in consumption through the measure of congruence in terms of overall consumption pattern, across a long period of time has been demonstrated.

The use of transaction records in the examination of the self-congruence effect has allowed the findings of Chapter 6 and 7 to contribute to this area of research by enabling insights to be drawn with regards to the possibility that certain psychological constructs may be related to the match between these consumers' *actual, overall consumption pattern* and their Big Five personality traits. The results obtained in Chapter 6 have shown that people differ from one another in their ability to spend in a way that is congruent with their personality, and that this ability is correlated with materialism and financial distress. It is also precisely this methodology which has allowed the investigation into the potential moderating effects of financial distress on the relationship between consumers' personality self-congruence in their overall consumption, and happiness. Chapter 7 successfully replicated the findings of Matz et al. (2016), further strengthening the notion that self-congruent spending can lead to happiness. The fact that a different set of transactional records aggregated across different banks, collected at a different time, which included more participants than in Matz et al. (2016) and more spending categories shows that the effect of self-congruent spending on happiness is robust. Furthermore, Chapter 7 extended the discourse around the concept of money buys happiness, by showing that financial distress is a significant moderator for the relationship between self-congruent spending and happiness. This is important because it shows that people who are financially distressed tended to experience a larger increase in their levels of happiness from spending more congruently, indicating that they are able to benefit from this more so than people who are low on financial distress. This has hopefully opened up research interest in exploring other potential correlates or moderators of self-congruent spending behaviour which may impact people's ability to experience happiness.

As the measure of self-congruent spending used in this thesis reflects self-congruity in overall consumption across a large number of spending categories, the effect sizes were much smaller in comparison to previous studies investigating self-congruity (see Aguirre-Rodriguez et al., 2012 for a meta-analysis). This is in line with previous studies which have observed that as sample sizes increase, effect sizes shrink (Ioannidis, 2008; Yarkoni, 2009), as well as the possibility that small-sample studies may be largely overfitted (Yarkoni & Westfall, 2017), both procedurally and analytically. While the effect sizes observed in the studies included in this thesis were small, when applied at scale the impact can be meaningful (Götz et al., 2020). Importantly, by incorporating a big data approach in the study of self-congruity effects, this thesis has provided a corrective to potentially overfitted past research that have exaggerated the intuitions and expectations of researchers in this area.

8.3 – Managerial and Ethical Implications

As Chapter 3 and 5 have demonstrated, transaction records offer marketers an opportunity to accurately profile consumers (r = .70 for chronological age, and r = .43 for financial distress). While the accuracy of predictions varies in terms of the target characteristics, seen in light of previous studies that have attempted to infer individual differences from various types of digital footprint, the studies in this thesis demonstrated the practical utility of transaction records for consumer profiling. Chapter 4 has shown that consumer characteristics inferred using machine learning (see Chapter 3 and 5) could be successfully implemented in personalised advertising to increase appeal. Importantly, there is value in knowing consumer's characteristics and targeting them based on these characteristics (i.e., trait-based personalisation) rather than just targeting them based on their shopping patterns (i.e., behavioural targeting). While general shopping patterns without insights regarding a consumer's psychology is difficult to be incorporated into advertisement content, these inferred characteristics are much more useful to marketers as they could be used in different forms of personalisation, including personalised email, newsletters, machine-mediated interactions as well as in-person customer throughout different stages of consumer life cycle.

The methods used in this thesis when applied in marketing practices makes it possible for tailored advertising to be scaled and automated. As Chapter 4 has shown, the machine learning model built using a sample is robust and can be used to predict age at a high accuracy in a completely different dataset. This means that marketers could employ a similar method to profile their consumers using a smaller pool of data, and apply the machine learning model onto a larger sample, thereby scaling the consumer profiling process. With this information, marketers can then present advertisements aimed at appealing to different groups of consumers based on their demographic and psychological attributes. Previously, different processes (e.g., consumer insight, content creation) within the advertising framework were divided across different teams. It is now possible to automate the generation of advertising messages with minimal or no human involvement (van Noort et al., 2020), and shifting the reliance of this process onto consumer behavioural data or trait-based data. Automated advertising in this way has the potential to improve the effectiveness of advertising efforts.

Consumer profiles could also be used to target consumers with products that would increase their well-being, which has important implications for environmental and consumer welfare, marketing managers and policymakers. As suggested in Chapter 7, self-congruent consumption is more beneficial for consumer well-being. In a way, consuming products that only fit with one's personality requires one to be more mindful, and when performed on a large-scale, could be beneficial to the collective issue of overconsumption. It is also beneficial for marketers and retailers to encourage self-congruent purchases which lead to higher levels of happiness, as consumers' experienced positive emotions can lead to more positive consumer judgments (Chitturi et al., 2008; Kim et al., 2010; Kwortnik & Ross, 2007; Mogilner et al., 2012; Pham et al., 2013) and customer loyalty (Homburg et al., 2006). Crucially, the findings of Chapter 7 also suggest that there is potential to help people experiencing financial distress to gain happiness by nudging them towards consumption that better match their personality. Therefore, in Chapters 5 and 7, I have provided useful techniques that are highly relevant to policymakers interested in targeting and nudging specific groups of consumers into making better choices that can help alleviate their negative affect associated with their financial distress.

However, personalised advertising can bring about both advantages and disadvantages to consumers. While it effectively reduces the number of irrelevant advertisements, the time spent on searching for the right products (Malheiros et al., 2012; McDonald & Cranor, 2010) and results in better deals (Strycharz et al., 2019; Treiblmaier & Pollach, 2007), microtargeting may also have serious negative individual and collective ramifications. Vold et al. (2019) highlighted several ways that microtargeting may cause harm at both individual and societal levels, the most notable being threat to privacy. As a large majority of consumers are not well-informed on the subject of online behavioural tracking and microtargeting, they might not realise the full extent to which they are targeted and being subjected to unsolicited influence or manipulation (Vold et al., 2019). As a result, consumers could be unknowingly influenced by disguised advertising messages into more preferences that appeal to their impulsivity (Costa & Halpern, 2019), or through misinformation steered towards benefitting the party performing the targeting (Susser et al., 2018). They might even hand over sensitive information without being aware of the potential threat to their privacy that this action may bring about. As discussed in Chapter 3, 4 and 5, when abused, targeted advertising can be used to exploit individuals who are especially vulnerable. For instance, a company could target older people with fraudulent financial products, or individuals experiencing financial distress with loans with high interest rates, which in turn exacerbate their already poor financial situations, in turn aggravating the deterioration of their well-being.

Altogether, microtargeting could lead to an imbalance in the power dynamic and has the potential to undermine consumers' autonomous decisions (Finn & Wadhwa, 2014). This has partly motivated the introduction of the General Data Protection Regulation (GDPR) in the countries within European Union, which requires that organisations which gather data about consumers inform them that data mining is taking place, the purpose for doing so, and if they are being profiled, the rationale and mechanism of automated profiling, as well as the potential consequences for consumers. However, some scholars have expressed concerns that the current data protection law may not be sufficient to safeguard individuals with respect to inferences made from data for the purpose of targeting are used (Wachter et al., 2017).

Beyond the commercial context, microtargeting online can be employed in political advertising, enabling political candidates to tailor their promotional messages by emphasising certain aspect of their campaign agenda to specific voter segments which appeal to their interests or concerns. This practice has been deemed a threat to privacy and has the potential to undermine democracy (Perloff, 2021), underlining the danger of how individual vulnerabilities could be identified and abused through microtargeting, potentially amounting to a large societal problem. Another way that microtargeting may undermine societal values is through discrimination. Ribeiro et al. (2019) drew distinctions between targeting opportunities to exclude certain groups (e.g., employment, housing, social support) and targeting socially divisive and polarising issues (e.g., race-based policing, immigration, abortion), with the former likely to result in explicit discrimination, while the latter may incite broader societal discord. It is apparent that microtargeting could magnify the threats of propaganda and misinformation (Walker et al., 2019), leading to the phenomena of echo chambers and the 'fragmentation of truth' (Boyd, 2019; Costa & Halpern, 2019), where different social networks of people whose lived realities become increasingly separate, whose versions of the truth are different and often difficult to be reconciled.

8.4 – Limitations and Future Outlook

Although in this thesis I have successfully demonstrated the value of transaction records for understanding the role of self-congruity in consumer preferences, the work is not without its limitations. While each study has already been critically evaluated and future research avenues have been highlighted accordingly, the following section revisits several issues that apply to the majority of the research presented in this thesis.

The most notable issue relates to the generalisability of the findings. First, individuals who use money management tools may constitute a specific group of the population that reflects a selection bias. Financial Techology users are found to be younger, higher-income city-dwellers, for example (Gulamhuseinwala et al., 2015). The sample used in this thesis contained a disproportionate number of younger consumers (see Figure S1), therefore future research should aim to use samples more representative of the overall population. Cultural differences may affect people's brand preferences and their respective symbolic meaning, which could in turn influence the reliability of predictions, the findings on which brands or spending categories are most predictive of age and financial distress, as well as the consumer characteristics that may act as stressors to people's ability to consume self-congruently. It is possible that the studies included in this thesis could have drawn different conclusions if the participants had been sampled from non-Western societies, an area worthy of exploration in future research. The cross-sectional and correlational nature of all five empirical studies does not allow any claims to be made about the causality of the observed effects, therefore the findings should be treated as exploratory, rather than confirmatory. This necessities future research which utilising longitudinal research designs to support the findings of the current thesis.

Another limitation of this thesis is the small number of psychological constructs included. In the investigation of the extent to which transaction records could be used to infer consumer characteristics, this thesis chose to focus on a demographic characteristic, chronological age (see Chapter 3) and a more malleable trait, subjective feelings of financial distress (see Chapter 5). It is beyond the scope of this thesis' ambition to investigate inferences of other psychological traits or characteristics which would have enabled a comparison of predictive accuracy between different constructs. Future research could expand on this discourse by looking at the predictive accuracy of transaction records on different psychological constructs. A similar point is also true for the study exploring the correlates of self-congruent spending (see Chapter 6). Future work could look at the other potential correlates of self-congruity effects using other personality traits, such as personal values or cognitive styles.

Limitation aside, another exciting avenue for future research lies in the investigation of other practical relevance and applications of attribute inferences in marketing, as well as policy. For attribute inferences to be useful to practitioners, more research of this type would strengthen the claims in previous studies of attribute inference which has alluded to the potential for attribute inference to be relevant to marketers and policymakers. For instance, it would be useful to look at how inferred attributes from transaction records can be successfully implemented in behavioural change interventions, identifying and nudging individuals towards consumption and financial behaviours which can positively impact their well-being. Not only are the potential uses of attribute inference worthy of future research, studies looking into the harm of such technology will also be instrumental in maintaining a balanced view of such technology. Investigations into both the uses and abuses of attribute inference and microtargeting will hopefully inform consumer protection regulations which are able to account for the benefits and the harms, as well as balance the tensions between the two.

8.5 – Conclusions

The advances in technology which have facilitated unprecedented amounts of data to be collected, stored and analysed have led to a surge of research using computational methods in psychological research. This PhD thesis sought to contribute towards this issue by integrating big data methodologies within a psychological research framework in the inquiry of self-congruity effects in consumer preferences. The findings have successfully demonstrated the value of transaction records and big data methodologies to understand the role of self-congruity in consumer preferences. This was achieved specifically through attribute inference using individuals' real-world purchasing data as input, as well as the use of an objective measurement of self-congruence in overall consumption pattern assessed through transactions in the investigation of self-congruity effects.

The findings of the thesis showed that chronological age and financial distress could be reliably predicted with a machine learning model built from transaction records. These inferred attributes were useful both in terms of marketing and research practice: inferred age could be used to personalise advertising to increase appeal, inferred financial distress has the potential to replace actual financial distress as a measure of the construct for psychology research. Transaction records also enabled measurement of self-congruence in consumers' overall consumption, leading to unique insights about the correlates of self-congruent spending behaviour, as well as the moderating effect of financial distress on the relationship between self-congruent spending and happiness.

To close, big data methodology can form a valuable addition of the existing toolkit of psychology researchers to garner insightful findings. It is hoped that the research presented in this thesis inspires further utilisation of transaction records and machine learning techniques in psychology research, which will build more robust models and generate more reliable results that account for the limitations of traditional research methods. The practical implications of this thesis would also hopefully help marketers to implement scalable consumer profiling and personalised advertising in a more effective way, while keeping in mind the potential benefit and adverse impact of such technology.

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Supplementary Material

Figure S1

A histogram of participants' age in the sample

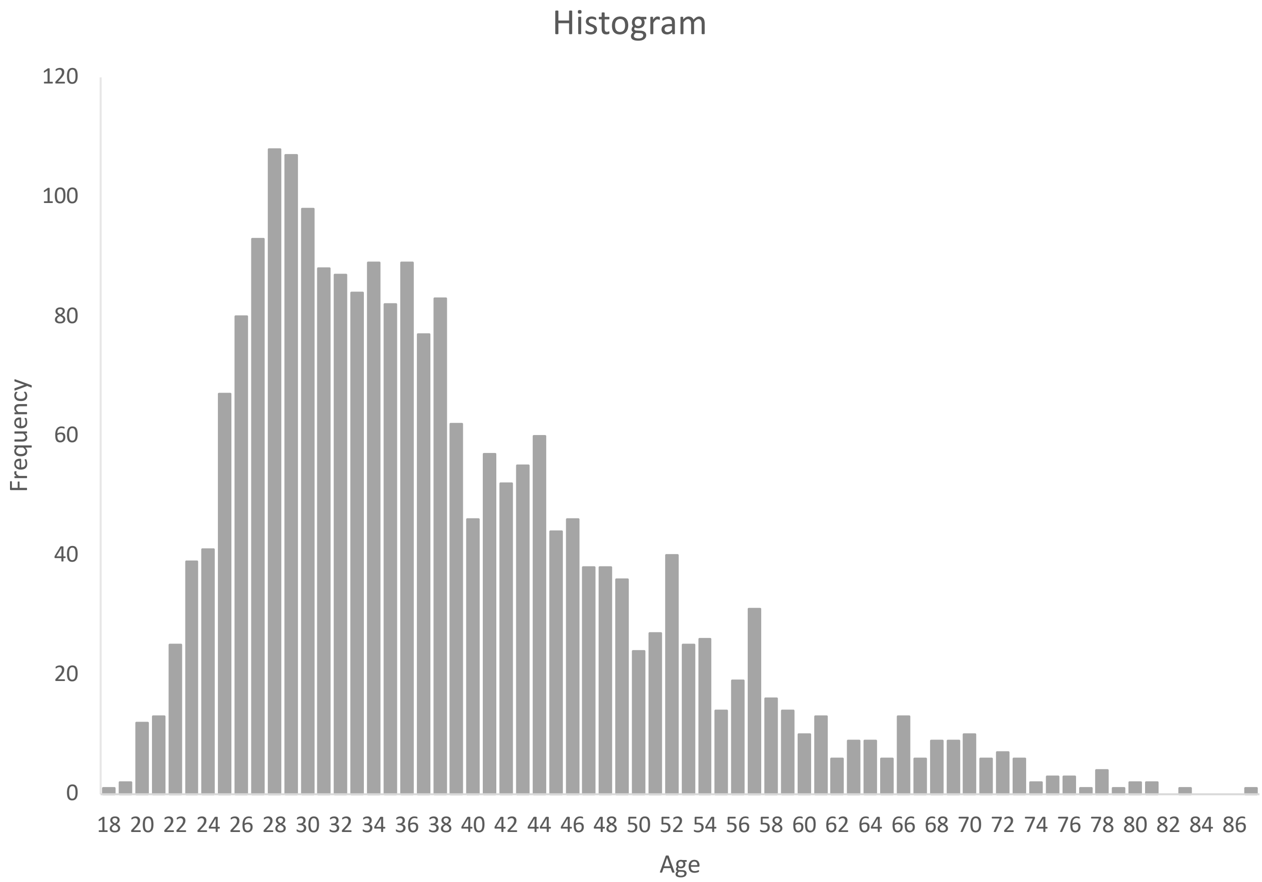


Table S2 *The list of brands for which participants were asked to report their spending*

Category	Brand	Category	Brand	Category	Brand
Clothing	Abercrombie And Fitch	Food and beverage	Chipotle Mexican	Books and stationery	WHSmith
Clothing	Adidas	Food and beverage	Chiquito	Books and stationery	Haymarket Publishing
Clothing	All Saints	Food and beverage	Costa	Books and stationery	Jessops
Clothing	Ann Summers	Food and beverage	Deliveroo	Digital services	Adobe
Clothing	Armani	Food and beverage	Dominos	Digital services	Dropbox
Clothing	ASOS	Food and beverage	Eat	Digital services	Fasthosts
Clothing	Banana Republic	Food and beverage	Frankie Benny’s	Digital services	GoDaddy
Clothing	Beaver Brooks	Food and beverage	Garfunkel’s	Digital services	Google
Clothing	Benetton	Food and beverage	Gaucho Grill	Digital services	Microsoft
Clothing	BHS	Food and beverage	Graze	Digital services	Paypal
Clothing	Blacks Outdoor Division	Food and beverage	Greggs	Digital services	Rackspace
Clothing	Boden	Food and beverage	Harvester	Digital services	Skype
Clothing	Boohoo	Food and beverage	Hotel Chocolat	Beauty	Crabtree Evelyn
Clothing	Brantano UK	Food and beverage	Hungry House	Beauty	Jo Malone
Clothing	Burton Menswear	Food and beverage	Itsu	Beauty	Lush
Clothing	Cartier	Food and beverage	Jamie’s Italian	Beauty	Space NK
Clothing	Claire's Accessories	Food and beverage	Just Eat	Beauty	Superdrug
Clothing	Clarks	Food and beverage	KFC	Beauty	The Body Shop
Clothing	Cotswold Outdoor	Food and beverage	Krispy Kreme	Beauty	The Fragrance Shop
Clothing	Cotton Traders	Food and beverage	LSG	Beauty	Toni & Guy
Clothing	Crew Amount in	Food and beverage	Mcdonald’s	Medical	Eyeplan
Clothing	Debenhams	Food and beverage	Morley’s	Medical	Lloyds Pharmacy

Clothing	Decathlon	Food and beverage	Nando's	Medical	Manor Pharmacy
Clothing	Dorothy Perkins	Food and beverage	Papa John's	Medical	NHS
Clothing	Dune	Food and beverage	Pasty Presto	Medical	Nuffield Health
Clothing	Dunnes Stores	Food and beverage	Pasty Shop	Medical	Optical Express
Clothing	Ernest Jones	Food and beverage	Patisserie Valerie	Medical	Simply Health
Clothing	Fatface	Food and beverage	Philpotts	Medical	Smiles Dentalcare
Clothing	Fenwick Ltd	Food and beverage	Pizza Express	Medical	Specsavers
Clothing	Fifty Plus	Food and beverage	Pizza Hut	Medical	Vision Express
Clothing	Fig Leaves	Food and beverage	Pod Food	Other	Envirofone
Clothing	Foot Locker UK	Food and beverage	Pret-A-Manger	Other	Equifax
Clothing	Freemans	Food and beverage	Prezzo	Other	Experian
Clothing	French Connection	Food and beverage	Pumpkin Cafe	Other	MCO
Clothing	Gap	Food and beverage	Revolution	Other	Freedom
Clothing	H Samuel	Food and beverage	Slurp	Other	Lifestyle Services Group
Clothing	H&M	Food and beverage	Starbucks	Other	Little Down Centre
Clothing	Hackett	Food and beverage	Strada	Other	Philip Williams And Company
Clothing	Harrods	Food and beverage	Subway	Other	Premium First Ltd
Clothing	High and Mighty	Food and beverage	Table Table	Other	Talk Me Through It
Clothing	Hollister	Food and beverage	Takeaway.com	Other	Cash Converters UK
Clothing	House pf Fraser	Food and beverage	TGIFriday	Family	Early Learning Centre
Clothing	Hugo Boss	Food and beverage	The Cornish Pasty Company	Family	Hobby Craft Group
Clothing	Jacamo	Food and beverage	The Works	Family	Mamas Papas
Clothing	Jaeger	Food and beverage	Thorntons	Family	Mother Care
Clothing	Jane Norman	Food and beverage	Toby Carvery	Family	Peacocks

Clothing	JD Sports	Food and beverage	Tortilla London	Family	The Entertainer
Clothing	JD Williams	Food and beverage	Upper Crust	Family	Toy Master
Clothing	Karen Millen	Food and beverage	Vital Ingredient	Family	Toys R Us
Clothing	Kitbag	Food and beverage	Wagamama	Family	Animal Health Care
Clothing	Kurt Geiger	Food and beverage	Wasabi	Family	Companion Care
Clothing	La Redoute	Food and beverage	Welcome Break	Family	Healthy Pets
Clothing	Laura Ashley	Food and beverage	Wetherspoon	Family	Pet Plan
Clothing	Levi Strauss UK	Food and beverage	Yo Sushi	Family	Pet Protect
Clothing	Links of London	Food and beverage	You Me Sushi	Family	Pets At
Clothing	Little Woods	Food and beverage	Zizzi	Transport	Addison Lee
Clothing	Long Tall Sally	Home	AO World	Transport	APCOA
Clothing	Louis Vuitton	Home	Argos	Transport	Arriva
Clothing	Lyle And Scott	Home	B&Q	Transport	BP
Clothing	M And M Direct	Home	Barratts	Transport	British Airways
Clothing	Mappin Web	Home	Bath Store	Transport	C2C
Clothing	Matalan	Home	Bensons For Beds	Transport	Cab Card
Clothing	Millets	Home	Bright House	Transport	Chiltern Railways
Clothing	Monsoon	Home	Carpet Right	Transport	City Link
Clothing	Moss Bros	Home	Conran Shop Holdings	Transport	Cross Country
Clothing	Muji	Home	Crocus	Transport	Docklands Light Railway
Clothing	Net-A-Porter	Home	DFS	Transport	East Coast Trains
Clothing	New Look	Home	Divertimenti	Transport	East Midland Trains
Clothing	Next	Home	Dixons	Transport	easyJet
Clothing	Notonthehighstreet.Com	Home	Dobbies	Transport	Eurostar

Clothing	Oasis	Home	Dreams	Transport	Flybe
Clothing	Pandora	Home	Dulux	Transport	Gatwick Express
Clothing	Primark	Home	Dunelm	Transport	Great Western Railway
Clothing	Reiss	Home	Ebay.co.uk	Transport	Greater Anglia
Clothing	River Island	Home	Ebuyer	Transport	Hailo
Clothing	Samuel Windsor	Home	Feather Black	Transport	Heathrow Express
Clothing	Schuh	Home	Firebox	Transport	Keolis
Clothing	Selfridges	Home	Frosts	Transport	London Midland
Clothing	Shoe Zone	Home	FTB Lawson	Transport	London Overground
Clothing	Simply Be	Home	Futon Company	Transport	Lothian Buses
Clothing	Slater Menswear	Home	Green Thumb	Transport	Mersey Rail
Clothing	Sports Direct	Home	Habitat	Transport	Metrolink
Clothing	Superdry	Home	Bargains	Transport	National Express
Clothing	Swarovski	Home	Homebase	Transport	National Rail
Clothing	Sweatshop	Home	HomeServe	Transport	Northern Rail
Clothing	Ted Baker	Home	Hopetoun Garden Centre	Transport	Red Spotted Hanky
Clothing	The Officers Club	Home	Ikea	Transport	RingGo
Clothing	The White Company UK	Home	Lakeland	Transport	Ryanair
Clothing	Thomas Pink	Home	Magnet	Transport	Scot Rail
Clothing	Timberland	Home	Maplin	Transport	South Eastern Trains
Clothing	TK Maxx	Home	Oldrids	Transport	Southwest Trains
Clothing	TM Lewin	Home	Pixmania UK	Transport	Southern Rail
Clothing	Topshop	Home	Plum Base	Transport	Stagecoach
Clothing	Urban Outfitters	Home	Richer Sounds	Transport	Streetcar

Clothing	USC	Home	Robert Dyas	Transport	TFL
Clothing	Vert Baudet	Home	Screwfix	Transport	Thameslink
Clothing	White Stuff	Home	The Garden Centre	Transport	Trainline.com
Clothing	Woolworths.co.uk	Home	The Range	Transport	Uber
Clothing	Zalando	Home	Timpson	Transport	Virgin Trains
Clothing	Zara	Home	Topps Tiles	Transport	Wessex Group
Financial product	Hargreaves Lansdown	Home	Wayfair	Transport	West Coast Trains
Financial product	Wage Day Advance	Home	Wickes	Transport	Zipcar
Financial product	AA	Home	Wilkinson	Transport	Action Bikes
Financial product	Admiral Insurance	Home	Gordale Garden Centre	Transport	BMW Finance
Financial product	Adrian Flux	Home	Wallpaper Direct	Transport	Driving Standards Agency
Financial product	Aegon	Home	Brandon Hire	Transport	DVLA
Financial product	Ageas Insurance	Home	HSS Hire	Transport	EMaC
Financial product	Allianz	Home	Jewson	Transport	Empark
Financial product	Avidia Ltd	Home	Tool Station	Transport	Esso
Financial product	Aviva	Home	Travis Perkins	Transport	Ford Credit
Financial product	AXA	Home	Fired Earth	Transport	M6to
Financial product	Bennetts Insurance	Bills	Affinity Water	Transport	Kwikfit
Financial product	BHSF	Bills	Anglian Water	Transport	Texaco
Financial product	Books Braith Waite	Bills	Boiler Juice	Retail	Nespresso
Financial product	Bupa	Bills	Bristol Wessex Water	Retail	Abel Cole
Financial product	Cia Insurance	Bills	British Gas	Retail	AF Blakemore
Financial product	Ciren Friendly	Bills	BT	Retail	Aldi
Financial product	Corgi	Bills	Cambridge Water	Retail	Amazon

Financial product	Dencover	Bills	EOn	Retail	Asda
Financial product	Denplan	Bills	EDF Energy	Retail	BM
Financial product	Dentists Provident	Bills	Edinburgh Council	Retail	Bargain Booze
Financial product	Direct Line	Bills	EE	Retail	Barnham Trading Post
Financial product	Divemaster Insurance	Bills	Essex Suffolk Water	Retail	Bean Bag Natural Health Witney
Financial product	Domestic General	Bills	First Utility	Retail	Boots
Financial product	End Sleigh	Bills	Giffgaff	Retail	Co-op
Financial product	Engage Mutual	Bills	Hutchison 3G	Retail	Costco
Financial product	Esure	Bills	Northumbrian Water	Retail	Cost Cutter
Financial product	Fresh Insurance	Bills	Npower	Retail	Dairy Crest
Financial product	Friends Life	Bills	O2	Retail	Farm Foods
Financial product	Halifax Insurance	Bills	Phones 4 U	Retail	Hello Fresh
Financial product	Hastings Insurance	Bills	Plusnet	Retail	Holland Barrett
Financial product	Hepburns Insurance	Bills	Portsmouth Water	Retail	Iceland
Financial product	Hiscox Insurance	Bills	Scottish Power	Retail	Inter Flora
Financial product	Protect	Bills	Severn Trent Water	Retail	John Lewis
Financial product	Hughes Insurance	Bills	Sky	Retail	Laith Waites
Financial product	Just Landlords	Bills	Southeast Water	Retail	Lidl
Financial product	Kwikfit Insurance	Bills	South Staffordshire Water	Retail	Majestic Wine
Financial product	Legal General	Bills	Southwest Water	Retail	Marks and Spencer
Financial product	Lets Cover Insurance	Bills	Southern Electric	Retail	McColl’s
Financial product	Lexham Insurance	Bills	Southern Water	Retail	Mcqueens Dairies
Financial product	Loyal Insurance	Bills	Talk Mobile	Retail	Morrisons
Financial product	MCE Insurance	Bills	TalkTalk	Retail	Myprotein.Com

Financial product	Mondial Assistance	Bills	Thames Water	Retail	Naked Wines
Financial product	Moneysuperma rket.com Ltd	Bills	United Utilities	Retail	Ocado
Financial product	More Than	Bills	Utility Warehouse	Retail	Odd Bins
Financial product	My Essentials Amex	Bills	Virgin Media	Retail	Peters Yard
Financial product	NFU Mutual	Bills	Virgin Mobile	Retail	Poundland
Financial product	One Call Insurance Services	Bills	Vodafone	Retail	Pound Stretcher
Financial product	Payment Shield	Bills	Welsh Water	Retail	Riverford
Financial product	Phoenix Life	Bills	Yorkshire Water	Retail	Sainsbury's
Financial product	Pier Insurance	Bills	Zen	Retail	Snax24
Financial product	Premium Credit	Bills	Carphone Warehouse	Retail	Spar
Financial product	Protect Your Bubble	Bills	Sutton And East Surrey Water	Retail	Spirited Wines
Financial product	Prudential Plc	Bills	Parcel2go	Retail	Tesco
Financial product	RAC	Bills	Parcel Force	Retail	The Whisky Shop
Financial product	Rampdale	Bills	Post Office	Retail	The Wine Society
Financial product	Royal Sun Alliance	Bills	Yodel	Retail	Waitrose
Financial product	Scottish Equitable	Bills	Companies House	Retail	Whittard Of Chelsea
Financial product	Scottish Provident	Bills	Metropolitan Police	Retail	Wholefoods Market
Financial product	Sky Protect	Entertainment	ABC Music	Retail	Wholegoods
Financial product	Square Trade	Entertainment	Alligator Music	Retail	Wine Cellar
Financial product	The Policy Shop	Entertainment	American Golf Discount Centre	Retail	Wine Rack
Financial product	Trent Services	Entertainment	Apple	Retail	World Duty Free Europe
Financial product	Uinsure Limited	Entertainment	Audible	Retail	Wyndham House
Financial product	Weslayan	Entertainment	Blizzard	Retail	Mightydeals.co .uk
Financial product	World Nomads	Entertainment	Build A Bear	Retail	Pounds To Pocket

Financial product	Worldwide Internet Insurance	Entertainment	Cineworld	Retail	Very
Financial product	WPA	Entertainment	Disney Store	Retail	W Boyes Co
Financial product	Zurich Insurance Group	Entertainment	Fair Deal Music	Retail	Quidco
Financial product	Supercover Insurance	Entertainment	Game	Retail	Which
Financial product	Britannia	Entertainment	Games Workshop	Holiday	Booking.com
Financial product	Clerical Medical	Entertainment	Hamley's	Holiday	Center Parcs
Financial product	Fidelity	Entertainment	HMV	Holiday	Expedia
Financial product	Hong Leong Asset Management	Entertainment	Humble Bundle	Holiday	Hilton
Financial product	Interactive Investor	Entertainment	Love Film	Holiday	Inn
Financial product	Northern Rock	Entertainment	Music Dynamics	Holiday	Lastminute.com
Financial product	Standard Life	Entertainment	Music Magpie	Holiday	Premier Inn
Financial product	Th March Co Limited	Entertainment	Netflix	Holiday	Thomas Cook
Financial product	Misco.co.uk	Entertainment	Now TV	Holiday	Travelodge
Donations	Action Aid	Entertainment	Odeon	Sports and fitness	Evans Cycles
Donations	Amnesty International	Entertainment	Play.com	Sports and fitness	Fitness First
Donations	British Red Cross	Entertainment	Rough Trade	Sports and fitness	Halfords
Donations	Cancer Research	Entertainment	Spotify	Sports and fitness	Holmes Place
Donations	Compassion	Entertainment	Steam	Sports and fitness	Bannatyne Fitness
Donations	Dogs Trust	Entertainment	Ticket Master	Sports and fitness	David Lloyd
Donations	Friends of The Earth	Entertainment	Ticket Web	Sports and fitness	DC Leisure
Donations	Just Giving	Entertainment	Tv Licensing	Sports and fitness	DW Sports
Donations	Médecins Sans Frontières	Entertainment	Vue	Sports and fitness	Virgin Active
Donations	Movember	Entertainment	Bet365	Sports and fitness	Wiggle
Donations	NSPCC	Entertainment	Betfair	Sports and fitness	Greenwich Leisure

Donations	Oxfam	Entertainment	Betfred	Sports and fitness	Lululemon Athletica
Donations	Plan	Entertainment	Camelot	Sports and fitness	Mountain Warehouse
Donations	RNLI	Entertainment	Gala Coral	Sports and fitness	West Lothian Leisure
Donations	RSPB	Entertainment	Ladbrokes	Bank and credit card	American Express
Donations	RSPCA	Entertainment	Paddy Power	Bank and credit card	Aqua
Donations	Save The Children	Entertainment	Sky Bet	Bank and credit card	Bank of Scotland
Donations	Shelter	Entertainment	William Hill	Bank and credit card	Barclay Card
Donations	Unicef	Books and stationery	Card Factory	Bank and credit card	Barclays
Donations	Water Aid	Books and stationery	Cards Galore	Bank and credit card	Capital One
Donations	World Vision	Books and stationery	Clinton Cards	Bank and credit card	First Direct
Donations	WWF	Books and stationery	Dennis Publishing	Bank and credit card	HSBC
Donations	Labour Party	Books and stationery	Funky Pigeon	Bank and credit card	Lloyds
Donations	United Patients	Books and stationery	Future Publishing	Bank and credit card	MBNA
Food and beverage	All Bar One	Books and stationery	Imagine Publishing	Bank and credit card	Nationwide
Food and beverage	AMT Coffee	Books and stationery	Independent	Bank and credit card	NatWest
Food and beverage	Beefeater	Books and stationery	Kelsey Publishing	Bank and credit card	RBS
Food and beverage	Bella Italia	Books and stationery	Moonpig	Bank and credit card	Sygma
Food and beverage	Benugo	Books and stationery	Nuts	Bank and credit card	Vanquis
Food and beverage	Black Horse	Books and stationery	Paper Chase	Bank and credit card	Hitachi Capital
Food and beverage	BrewDog	Books and stationery	Photobox	Bank and credit card	Loan Direct
Food and beverage	Brewers Fayre	Books and stationery	Ryman	Bank and credit card	Money Way
Food and beverage	Budgens	Books and stationery	Staples	Bank and credit card	Payday UK
Food and beverage	Burger King	Books and stationery	The Book People	Bank and credit card	Quick Quid
Food and beverage	Café Bar	Books and stationery	The Economist	Bank and credit card	Student Loans f

Food and beverage	Café Rouge	Books and stationery	The Times	Bank and credit card	Wonga
Food and beverage	Caffe Nero	Books and stationery	Viking Direct	Bank and credit card	Zopa
Food and beverage	Carluccio	Books and stationery	WG Foyle	Bank and credit card	Ellis Brigham
Food and beverage	Chicken Cottage	Books and stationery	Waterstones		

Table S3 *Means of Big Five personality traits for each spending category*

Category	Agreeableness	Conscientiousness	Extraversion	Neuroticism	Openness
Accessories	4.18	3.65	5.25	3.69	4.60
Administration other	3.07	4.06	2.69	4.50	3.41
Advertising	3.06	3.40	4.19	3.71	4.06
Alcohol	4.24	3.07	5.21	3.31	4.07
Antiques	4.06	4.17	4.56	3.73	3.80
Appearance	4.88	4.80	4.79	4.57	5.00
Appliances or Electrical	4.07	4.94	4.27	4.50	4.24
Art	4.81	3.87	5.63	3.94	5.14
Art, Antiques or Other	4.47	4.21	4.18	4.27	5.44
Art Supplies	4.88	3.80	4.71	4.38	5.31
Bank charges	3.00	2.73	2.80	3.75	3.40
Banking Charges	2.47	3.38	2.56	3.06	2.69
Beauty products	4.71	3.73	5.18	4.53	5.06
Beauty treatments	4.75	3.57	5.59	4.60	5.63
Bills	2.50	4.67	3.06	4.63	3.88
Birthday present	6.18	5.00	6.19	4.33	4.73
Books, Course Materials	3.75	5.59	4.00	4.81	4.47
Books, Magazines, Newspapers	4.13	4.14	4.88	4.82	5.00
Breakdown cover	3.47	5.19	2.94	4.71	3.67
Broadband	4.17	4.50	4.07	4.29	4.35
Business Accommodation	3.06	4.57	2.60	4.38	3.41

Business Expenses	2.82	4.63	3.24	3.25	3.41
Caravan Camping	3.88	3.64	4.83	4.31	4.71
Car fund	3.25	4.82	4.33	4.64	3.59
Car savings	4.75	5.29	3.31	5.33	3.60
Cash	4.59	5.06	5.00	5.00	5.53
Charity other	5.47	4.59	4.14	4.63	4.00
Childcare Fees	4.25	4.69	3.18	4.31	3.53
Child Clothes	5.06	4.87	4.00	4.71	4.44
Child Everyday or Childcare	4.81	5.18	4.00	4.67	4.33
Children other	5.60	5.18	4.29	4.63	4.27
Children's Club fees	3.93	4.50	3.61	4.19	3.80
Child support	3.69	5.31	2.88	5.00	3.06
Child Toys, Clubs or Other	5.33	3.76	5.35	4.46	5.18
Christmas present	5.87	5.27	5.35	4.64	5.36
Cinema	5.38	4.06	5.69	4.27	5.38
Clothes	5.38	4.35	5.00	4.82	4.80
Clothes Designer or Other	4.63	3.36	5.50	4.14	5.29
Clothes Everyday or Work	4.59	5.00	3.93	5.20	5.88
Clothes other	5.00	3.71	5.36	4.75	5.19
Clothing hire	3.69	3.73	3.82	3.93	4.88
Coal, Oil, LPG other	3.27	4.06	3.07	3.88	3.63
Concert Theatre	5.33	4.24	5.57	4.29	6.06
Contents or Other Insurance	3.69	4.47	2.56	4.73	3.00
Council Tax	2.38	4.73	1.94	4.25	3.00
Course and Tuition Fees	4.13	5.06	3.69	4.27	5.14
Credit Card	3.06	4.81	3.50	3.53	3.93
Credit card cash advance	3.25	2.79	3.57	3.14	3.89
Credit card payment	3.24	5.25	2.57	4.33	3.63
Credit card repayment	2.63	4.27	2.79	4.00	3.25
Current account	3.81	5.53	3.80	5.24	4.19
Cycling	3.88	4.53	4.06	4.47	5.44

Dental insurance	3.38	4.75	3.44	4.81	4.00
Dental treatment	3.13	4.73	2.86	4.00	3.93
Designer clothes	3.50	3.40	6.17	4.57	5.71
Device rental	3.94	4.11	4.73	3.59	4.93
Dining and drinking	5.67	3.79	5.88	4.00	5.94
Dining or Going Out	5.29	4.07	6.07	4.94	5.71
Dividend	4.00	4.33	3.81	3.94	3.60
Divorce settlement	1.81	3.18	2.13	4.06	3.56
DIY	4.43	5.00	4.00	4.67	5.24
Domestic supplies	4.47	4.53	3.38	4.71	4.06
Donation to organisation	5.47	4.59	3.73	4.56	4.67
Driving Lessons	4.06	4.79	4.57	4.50	4.94
Dry cleaning and laundry	3.44	4.65	3.20	4.56	3.25
Education other	4.38	5.20	4.12	5.31	4.94
Electrical equipment	3.80	4.94	4.00	4.67	4.47
Electrical fund	3.89	4.41	2.81	3.80	3.79
Electricity	3.64	5.12	3.21	4.47	3.75
Employment other	4.07	5.07	3.73	4.76	4.25
Energy Gas Elec Other	3.43	5.06	3.81	4.75	4.50
Enjoyment	6.07	4.25	6.06	5.88	5.88
Entertainment TV Media	5.56	4.58	5.73	4.94	5.60
Expenses	2.86	4.81	3.73	3.63	3.81
Eyecare	4.20	5.14	3.86	5.38	3.13
Family	6.67	4.88	5.75	5.82	5.82
Family benefits	4.86	5.25	3.76	4.56	4.59
Financial other	3.44	5.00	3.25	4.47	4.07
Fines	2.62	3.93	2.93	2.75	2.00
Flights	4.41	4.18	5.81	4.19	5.69
Flowers	5.86	2.75	5.14	4.56	4.81
Food Groceries Household	4.87	5.69	4.44	5.53	4.47
Fuel	3.67	4.75	3.44	4.80	4.13

Furniture	4.80	5.00	4.36	5.21	4.50
Furniture Furnishing Gardens	4.44	4.00	5.47	4.73	4.31
Gambling	1.93	1.83	5.56	1.75	4.56
Gambling account	2.63	1.78	4.38	1.79	3.56
Games and gaming	3.94	4.00	4.31	4.50	5.38
Garden	5.19	4.82	4.06	5.47	4.59
Gas	4.07	4.68	3.71	4.33	3.50
Ga sand electricity	3.00	5.40	3.69	5.13	3.38
General savings	5.19	4.81	4.50	5.40	4.27
Gift	5.59	3.93	4.88	4.87	5.50
Gifts or Presents	5.69	4.73	5.47	5.25	5.07
Gifts other	5.94	4.38	5.19	4.67	5.50
Going out other	5.00	3.93	5.38	3.71	5.33
Groceries	4.75	5.40	4.18	4.94	4.06
Ground Rentor Service Charge	3.07	5.00	2.75	3.93	3.35
Gym Equipment	3.94	4.38	4.76	3.87	4.63
Gym Membership	4.31	4.07	5.29	4.53	4.94
Hairdressing	4.14	3.69	5.50	4.29	5.20
Hairdressing Health Other	4.47	4.31	4.88	4.53	5.31
Health insurance	4.06	4.82	2.50	4.47	3.88
Hire Purchase	2.73	4.53	3.69	3.71	3.25
Hobbies or Activities	6.07	4.88	5.44	5.67	6.54
Hobbies other	5.33	4.47	5.00	5.25	5.06
Hobby Club Membership	5.19	4.18	4.53	4.93	4.93
Hobby Supplies	5.43	4.67	4.54	5.06	5.20
Holiday	5.13	4.44	5.94	5.06	5.56
Holiday fund	5.38	5.00	5.36	4.44	5.56
Holidays	5.46	4.13	6.43	5.27	6.38
Holiday savings	5.44	5.27	4.94	5.20	5.50
Home	6.20	5.33	4.75	5.00	4.43
Home and garden other	4.69	4.67	4.88	4.79	5.20

Home appliance insurance	3.53	4.00	2.65	4.35	2.50
Home DIY or Repairs	4.25	5.47	3.60	4.14	4.93
Home electronics	4.67	4.69	4.75	4.44	4.82
Home insurance	4.14	5.13	2.75	4.77	2.75
Hotel BB	4.67	4.43	4.87	4.50	5.36
Household other	4.18	5.15	4.62	4.81	4.08
Income	4.21	5.56	4.67	5.12	4.81
Income insurance	3.00	5.00	3.71	4.69	3.29
Inheritance	5.07	4.65	4.19	5.12	4.31
Insurance	3.38	5.53	3.56	4.53	3.24
Insurance other	3.93	4.69	3.21	5.13	3.18
Interest charges	2.40	4.44	2.81	4.13	3.58
Interest income	4.12	5.38	3.71	5.18	3.79
Investment income other	3.63	4.57	3.76	5.06	4.63
Investment other	3.47	5.00	3.93	4.88	5.00
Investments or Shares	3.71	5.13	4.25	4.94	4.47
Irregular Income or Gifts	4.67	3.93	4.80	3.63	4.88
ISA	3.93	5.00	3.93	4.67	4.65
Jewellery	4.81	4.00	5.77	4.73	4.13
Kitchen Household Appliances	4.60	4.50	4.31	4.73	4.73
Legal	2.81	4.56	3.19	4.82	3.13
Life insurance	3.75	5.69	3.06	4.69	3.47
Life style other	5.19	4.13	5.07	4.63	5.75
Lighting	4.36	4.57	4.36	5.27	3.73
Loan or Credit Income	2.88	4.13	3.94	3.88	3.19
Lumpsum	4.19	5.21	4.13	3.44	3.88
Lunch or Snacks	4.79	4.43	4.60	5.33	4.60
Media bundle	5.06	4.19	4.88	4.81	4.47
Medical Dental Eye Care	3.94	5.41	3.87	5.27	3.71
Medical treatment	4.43	5.92	3.31	5.13	3.44
Medication	3.93	5.50	2.56	5.17	4.00

Memberships	4.47	4.73	4.81	4.82	4.80
Miscellaneous income other	4.79	4.81	4.06	3.47	4.13
Mobile	4.13	4.56	4.65	4.07	4.31
Mobile app	3.59	3.80	4.50	3.73	4.67
Mobile phone insurance	3.63	4.36	2.77	4.07	3.25
Mortgage or Rent	4.07	6.06	2.94	5.00	3.38
Mortgage payment	3.31	5.27	2.81	5.88	3.81
MOT	3.38	4.94	3.00	4.93	3.56
Motorbike Insurance	3.38	4.29	3.25	3.88	3.50
Museum exhibition	4.94	3.78	4.07	4.93	5.73
Music	5.40	4.00	5.79	4.50	4.92
Musical Equipment	4.56	4.06	5.13	3.92	5.40
No Tag	3.47	3.40	3.08	3.79	3.44
Nursery Fees	4.75	4.93	3.00	4.69	3.81
Office Supplies	3.47	4.35	2.94	4.36	4.00
One-off or Other	4.00	3.71	4.73	3.93	4.31
One-off or Other Payment	3.71	4.20	4.19	3.88	3.63
Other account	3.56	3.69	3.27	4.13	3.64
Other fund	4.20	4.27	3.63	4.65	4.13
Other goal savings	4.59	5.40	4.53	4.53	4.53
Other Repayment	3.19	4.57	2.86	4.13	3.47
Overtime	4.73	5.41	3.71	4.29	4.24
Parking	2.59	4.25	2.88	4.00	3.00
Parking or Tolls	2.69	4.38	2.33	3.64	3.38
Payday Loan	1.93	2.76	3.07	3.07	3.29
Payday loan funds	2.87	3.19	2.81	3.00	3.11
Payment Protection Insurance	3.38	2.60	2.50	3.44	3.50
Paypal account	3.75	4.71	4.33	4.75	4.33
Penalty charges	3.07	3.00	2.47	2.82	3.13
Pension	4.40	5.81	3.00	5.19	3.94
Pensionor Investments	4.27	5.69	3.73	5.69	3.88

Pension other	4.80	5.50	2.53	4.60	3.53
Personal Care Other	4.80	4.29	4.27	5.06	4.50
Personal Electronics	3.80	5.06	5.13	4.29	4.64
Personal Loan	3.25	4.20	2.41	4.00	4.27
Personal Training	4.07	4.87	5.06	4.50	5.41
Pet Everyday or Food	5.80	4.86	4.77	5.07	4.53
Petfood	5.21	4.79	3.71	4.81	4.00
Pet housing care	5.00	5.25	3.81	4.76	3.93
Pet Insurance	4.53	4.88	3.72	4.43	3.27
Pets other	5.44	4.50	5.23	4.60	5.71
Pet toys	4.60	3.88	4.44	3.53	4.19
Pet Toys Training Other	4.57	4.67	4.27	4.31	4.88
Pet training	5.38	5.06	4.39	4.00	4.60
Phone landline	3.79	3.79	3.50	4.93	3.60
Phone or Internet	4.44	4.38	4.25	4.81	4.79
Photography	4.60	3.73	4.73	4.60	5.67
Physiotherapy	4.57	4.53	3.63	4.35	4.25
Postage Shipping	3.87	4.65	2.79	3.81	2.80
Printing	3.50	4.00	2.87	3.60	4.07
Property	5.46	5.81	5.33	4.82	4.69
Property fund	3.88	5.14	4.00	4.82	3.38
Property other	4.44	5.13	4.50	4.63	4.62
Property savings	4.00	5.08	3.43	5.21	3.76
Public Transport	3.88	4.00	2.85	4.31	4.38
Rainy day fund	5.35	5.60	3.94	5.65	4.75
Rainy day savings	5.40	6.00	4.43	4.79	4.67
Refunded purchase	3.79	4.88	4.13	4.13	3.40
Religious Celebration	4.67	3.93	4.06	4.31	2.87
Religious Donation	4.00	4.06	2.76	3.27	3.41
Rent	3.67	5.18	2.25	4.77	3.67
Rental Income	3.69	5.00	3.69	4.80	4.38

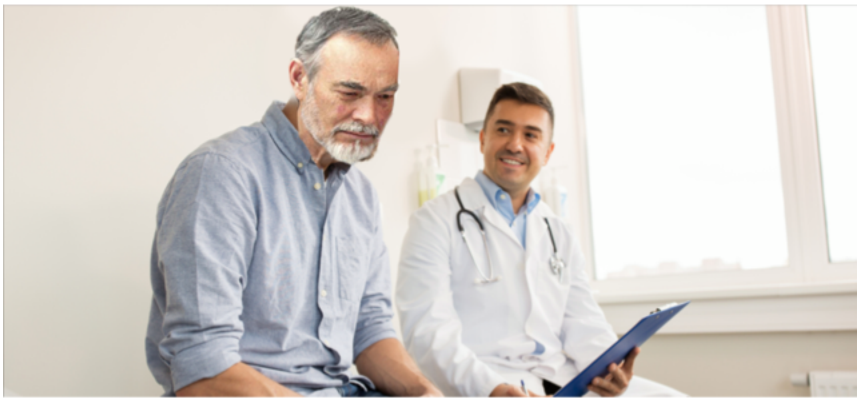
Rental income whole property	3.87	5.18	3.88	5.12	3.75
Repayments	3.25	5.75	3.00	4.88	3.44
Rewards cashback	5.27	4.94	4.56	4.88	4.93
Road charges	3.07	3.93	2.50	3.40	2.88
Road traffic fines	3.00	3.07	2.89	3.06	2.94
Salary or Wages Main	4.44	5.56	3.94	5.50	3.64
Salary or Wages Other	4.20	5.81	4.53	5.20	3.73
Salary secondary	4.28	5.13	4.64	4.06	4.31
Sale other	3.87	4.19	4.82	3.71	4.06
Saving for a rainy day	5.06	5.33	3.59	5.08	4.83
Saving for car	4.00	4.78	4.06	5.44	4.19
Saving for electrical item	4.13	4.38	3.38	4.87	3.88
Saving for holiday	5.44	4.86	5.00	5.25	4.47
Saving for other goal	5.13	5.94	3.87	5.13	5.07
Saving for property	4.75	5.41	4.13	5.71	4.67
Saving for wedding	5.00	4.81	5.13	4.75	4.12
Saving general	4.47	5.50	3.21	5.40	3.71
Savings general	4.81	5.94	3.94	5.80	4.50
School fees	3.06	4.15	3.56	4.31	4.00
Secured loan funds	3.50	4.13	3.29	4.00	4.00
Secured loan repayment	3.53	4.47	2.82	4.24	3.63
Service Parts Repairs	3.38	4.47	2.73	4.59	3.40
Share dealing account	3.21	3.80	3.47	4.00	3.94
Shoes	5.19	5.13	5.31	4.47	5.00
Social club	4.25	3.69	5.33	4.13	5.06
Soft furnishings	5.47	4.27	4.79	5.00	4.41
Software	3.78	5.06	3.47	4.21	4.93
Spa	5.38	4.19	5.44	4.93	4.53
Sponsorship	4.53	4.63	4.61	3.77	4.21
Sports Club Membership	3.81	4.15	5.50	4.44	4.60
Sports Equipment	3.88	4.53	5.44	3.81	5.29

Sports event	3.93	4.00	4.93	4.20	4.93
Staff costs	2.94	4.94	3.20	4.73	3.56
State pension	4.00	5.00	3.25	4.76	3.65
Stationery	4.20	4.33	3.94	4.69	3.75
Stationery consumables	4.11	3.59	3.73	4.76	4.60
Storecard repayment	2.87	4.07	2.94	3.67	3.18
Student Loan funds	3.00	5.38	3.47	4.47	3.31
Student loan repayment	3.44	4.29	2.47	4.53	4.18
Supermarket	4.13	5.07	4.67	4.94	4.38
Takeaway	4.25	3.19	4.59	3.47	4.50
Taxi	4.13	3.67	3.87	4.00	4.14
Taxisor Vehicle Hire	3.56	3.87	3.88	4.13	4.47
Tax Payment	2.94	4.44	2.73	3.94	3.27
Tobacco	3.07	2.50	3.53	2.61	3.00
Toiletries	4.43	5.13	3.75	4.76	3.73
Toys	5.29	3.25	5.40	4.06	4.36
Tradesmen fees	2.82	4.31	3.13	4.00	3.00
Transfers	3.38	4.19	2.93	4.65	3.94
Transport	4.27	5.07	4.38	4.73	4.20
Transport other	3.47	3.94	3.67	4.00	4.63
TV Licence	3.44	4.19	2.87	4.94	3.93
TV Movies Package	4.50	3.33	5.38	4.33	5.60
Unsecured loanfunds	2.13	2.94	3.94	3.38	4.13
Unsecured loan repayment	2.21	3.67	2.93	2.88	2.67
Vehicle	4.13	4.88	4.19	4.93	5.06
Vehicle hire	2.82	4.20	3.63	3.88	4.41
Vehicle insurance	3.19	5.33	3.18	4.53	3.82
Vehicle purchase	4.06	4.63	4.88	3.94	4.33
Vehicle Running Costs	3.56	4.75	2.82	3.53	3.40
Vehicle tax	3.20	4.44	2.31	3.47	2.93
Vet	5.19	4.93	3.25	4.25	4.53

Water	3.87	5.18	3.31	5.38	3.57
Web hosting	3.06	3.76	4.13	4.27	4.19
Wedding fund	5.00	4.93	3.93	4.65	4.40
Wedding savings	5.13	5.19	5.29	3.93	4.88
Winnings	4.75	3.56	6.07	3.88	5.50
Work pension	3.75	6.06	3.53	5.12	3.47
Workwear	3.20	4.78	4.06	4.81	3.64
Zoo theme park	5.33	3.81	5.56	4.93	5.31

S4

Advertisements used in Study 3, Chapter 4.







ABERTO
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Sofa Kings.


Sofa Kings.


Sofa Kings.