Segmentation Informs the Gamification of Sustainable Food Consumption

by

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○ Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

○ Abstract

Food systems activities produce around 30% of global anthropogenic greenhouse gas (GHG) emissions and are responsible for numerous environmental issues which could ultimately harm our ability to grow food reliably. One way to reduce the food system's impacts is to transition to a more sustainable diet composed of low impact foods. The objective of this study is to identify consumers demonstrating an intention to consume sustainably produced foods, and to identify their characteristics to inform the design of targeted gamified interventions that would promote sustainable food purchasing. A survey incorporating variables from the theory of planned behaviour (e.g. attitude), socio-demographic information (e.g. age), gamification profiling variables (e.g. player typology), as well as preferred mobile applications, was developed in this study and distributed via a market survey company. Statistical analysis in the form of hierarchical clustering was used to segment and identify target markets, while contingency analysis assessed the most effective means of promoting sustainable diets. A total of four hundred and ninety surveys were distributed and three hundred and seventy-six of them were validated because they agreed to participate, were not detected as potential AI powered responses, and their responses from the theory of planned behaviour were completed. Linear regression was used to assess the significance of all variables on the intent to consume a sustainable diet. Cluster analysis identified 3 potential target segments, and contingency analysis was used to detect their unique features. Two consumer segments were identified as having high potential as a target market. Individuals in this market intended to consume a sustainable diet but lacked follow through. Strong evidence towards the effectiveness of gamification of interventions was not observed due to low and medium frequency in gaming behaviours for the two target segments. Interventions distributed through mobile applications would be most effective if they were delivered through social media and included game design elements associated with Philanthropist and Free Spirit user types. The survey was confined to Ontario, therefore it may not be generalizable to other regions. Nevertheless, this study is unique in its assessment of the profiles of consumers with high intention to purchase sustainably sourced foods through a combination of the theory of planned behaviour, socio-demographic factors, gamification player types and game behaviours, as well as preferred mobile application usage.

KEYWORDS:

Sustainable, Food, Segmentation, Healthy, Diet, Gamification, Behaviour change, Intervention.

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○ List of Abbreviations

ABC: Alphabet theory includes attitude, behaviours, and context

FTNC: Theory of Normative Conduct

GFT: Goal Framing Theory

GHG: Green House Gas.

GUTHS: Gamification User Types Hexad Scale

HBM: Health Belief Model

PBGA: Pirate Bri's Grocery Adventure

NAT: Norm Activation Theory

SCT: Social Cognitive Theory

TNSB: Theory of Normative Social Behaviour

TPB: Theory of Planned Behaviour

TRA: Theory of Reasoned Action

TTM: Transtheoretical Model

VBN: Value Belief Norm (Theory)

Chapter 1 : Introduction

1.1 Background

There is an urgent need to globally transition towards an environmentally sustainable model of development that can preserve the Earth's limited natural resources because human activities are destabilizing the Earth's biosphere and are accelerating an upcoming and irreversible set of tipping points for the planet (Goodland et al. 1993; Steffen et al. 2015). In other words, if the planet' environmental threshold is crossed, a sustained warming of the earth would become irreparable (Barnosky et al. 2012; Steffen et al. 2015; Steffen et al. 2018). Regardless of their differences in scale and diversity, food systems activities (i.e. the production, preparation, processing, packaging, distribution, intake, and disposal of food products) produces around 30% of global anthropogenic greenhouse gas (GHG) emissions (Fanzo, 2019; Garnett et al. 2015; Vermeulen et al. 2012; Crippa et al. 2021). Food systems generate numerous environmental issues which could ultimately harm our ability to grow food reliably (e.g. global warming, species extinction, as well as land and water degradation) (Schmidhuber and Tubiello, 2007; Vermeulen et al. 2012; Behrens et al. 2017; Heller et al. 2018). Therefore, due to their impact current agri-food systems are threatening human survival on Earth (Chao and Feng, 2018; O'Neill et al. 2017). Apart from their environmental impact, food systems also involve multiple social concerns that are interconnected, including: health issues, gender equality, and insufficient wages (Dania et al. 2018).

Environmental crises (e.g. resource depletion, ecosystem destruction) as well as social crises (e.g. equal opportunity, health pandemic) are all linked to how we produce and consume goods and services including how we consume food (Bengtsson et al. 2018). The Food and Agriculture Organization (FAO) of the United Nations defines a sustainable food system as one that "delivers food security and nutrition for all in such a way that the economic, social, cultural, and environmental bases to generate food security and nutrition for future generations are not compromised" (FAO, nd, np). Regrettably, the environmental, social, and economic effects of food production, distribution, and consumption make it challenging for agri-food systems to achieve the sustainable development objectives established by the United Nations (Nemarumane and Mbohwa, 2013). For instance, food systems can damage the wellbeing of the labor force and customers, it can do so by creating difficulty for local producers to maintain price competitiveness due to the influence applied by other industrial sectors and consumers (Buttel, 2003; Fluck, 2014). Furthermore, research has shown that the foods that improve human health are the same foods that have the lowest impact on our planet. This true for all foods apart from two exceptions: 1) fish was found to have a medium impact on the environment while being extremely healthy for humans, and 2) sodas are quite unhealthy to humans but have a minimal impact on the environment (Clark et al. 2019). Another study measuring the environmental impact of four groups of foods (red meat, vegetables/beans, seeds/nuts, and fruits) confirmed that moving away from red meat consumption and towards more plant-based diets produces significant benefits for the environment (Bahn et al. 2019). Which is why a healthy diet composed largely of plant-based foods is deemed equivalent to a sustainable diet (Springmann et al. 2018; Lindgren et al. 2018). A healthy diet is a sustainable diet because it would have the lowest negative impact on both human and planetary health. There is therefore a need to understand how to influence food systems to make them produce more plant-based foods, and therefore become more sustainable.

Food systems are constantly evolving and adapting to supply and demand drivers (von Braun et al. 2021). The demand-side drivers that alter food systems comprise the following factors: increased population and income, shifting consumption trends, as well as food industry marketing (Vermeulen et al. 2012; Kearney, 2010). For instance, food systems will have to adapt to a rapidly rising global population and produce around 70% more food by 2050 to satisfy the needs of an exponentially increasing population that is estimated to reach 9.1 billion people (Davies et al. 2009; Alexandratos and Bruinsma, 2012). Moreover, as average wealth increases rapidly around the world, so does the demand for animal products (Campbell et al. 2017; Godfray et al. 2010) which greatly contributes to the unsustainability of our food consumption (Reisch et al. 2013) and threatens humanity's ability to grow food since it accelerates the struggle for more land, water, and energy (Godfray et al. 2010). A rapid change in population and its dietary preferences could therefore prevent feeding the world population in a healthy manner without creating ecological, economic, and social consequences (Lindgren et al. 2018). It was found that the eating habits of consumers affect the unsustainability of our food consumption to a greater extent than the business practices, policies, and regulations of the food market (Steier, 2011; Reisch et al. 2013). Because diets are both the outcomes and the drivers of the state of our food systems (Meybeck and Gitz, 2017) consumers have the power to minimize the negative effects of existing food systems by purchasing lower impact foods (Joshi and Rahman, 2015; Redman and Redman, 2014; Helms, 2004; Hartmann and Siegrist, 2017; Berger et al. 2020). Hence, changing people's current eating habits to adopt diets with low environmental impact has become more crucial than ever (Magrini et al. 2018; Heller et al. 2018; Hedin et al. 2019). According to the descriptions of what constitutes a sustainable diet provided by the United Nations (WHO and FAO, 2019) and Von Koerber et al. 2017) this thesis defines sustainable foods as: organic foods, plant-based proteins, and local foods. Local food is defined as food produced in the same province in which it is sold, or food sold across borders within 150 kilometres of the production site. Plant-based protein is defined as any dietary source of protein which is found in plants. Organic food is defined here as food with no genetically modified organisms, no artificial flavours, no artificial colours, no artificial preservatives, and no synthetic fertilisers.

Several approaches were identified to shift current food consumption standards towards healthier and sustainable options. They include incentivizing specific food choice through fiscal measures (e.g. taxes and subsidies), and changing the governance surrounding the production and consumption of food (e.g. macroeconomic policies and regulations) (Borthwick and Garnett, 2015). So far, government regulations have been found inadequate and inefficient at managing the negative externalities created by food systems (Thompson et al. 2007; Steier, 2011). Moreover, a recent review of food policies concerning human and planetary health found that there were almost no examples of policies aiming to lower the consumption of animal-based food, and that the few policies that combined health and sustainability were mostly informative in nature (Temme et al. 2020). Other approaches to modifying individual food consumption are to apply behaviour change interventions such as Nudge theory, and to promote sustainable diets through media and education (Borthwick and Garnett, 2015).

Modifying food consumption can also be approached by applying behaviour change interventions such as nudge theory in store layouts (i.e. changing the choice architecture of food by changing how it is physically displayed) (Borthwick and Garnett, 2015). The consumption of any food items in school cafeterias could potentially be increased or decreased by up to 25 percent when using nudge theory (Thaler and Sunstein, 2008). Moreover, a meta-analysis found that over eighty percent of the nudge interventions promoting healthy eating reported positive outcomes (Vecchio and Cavallo, 2019). While nudge theory shows great potential in efficiently influencing food behaviours, it also has significant limitations (e.g. practical, and also ethical constraints regarding the free will of participants) and was found to work best when combined with other procedures to tackle major and sustained dietary behaviour change (Trafford & De la Hunty, 2021). Apart from Nudge theory, other approaches to modifying individual food consumption via behaviour change interventions comprise the promotion of sustainable diets through medias and education (Borthwick and Garnett, 2015). However, solely educating consumers about the unsustainability of food is not enough to change their behaviours.

Sustainability education must not simply rely on delivering information but become more grounded in behaviour change theories in order to understand what truly motivates and constraints sustainable actions (Redman and Larson, 2011; Redman, 2013; Kaiser et al. 2003). Education is essential to behaviour change, however not enough on its own to change behaviours. Education was established as a necessary yet insufficient part of behaviour change concerning healthy behaviours (Arlinghaus and Johnston, 2017) as well as sustainable in food behaviours (Redman and Redman, 2014). In the past sustainable programs typically deployed information directed campaigns, however since this strategy was found to be inefficient to promote eco-friendly behaviours, environmental organisations began adopting behaviour change tools (McKenzie-Mohr and Schultz, 2014; Schultz and Kaiser, 2012). Past educational and environmental programs have not been efficient enough in creating behaviour change because there has been a constant gap between an individual's environmental thinking and their actions (Kollmuss and Agyeman 2002; Padel and Foster, 2005). In other words, there is a discrepancy between what consumers say about their growing concern regarding the environment, and what they truly do to help sustain the environment (ElHaffar et al. 2020). This is especially true in consumption behaviours where there can be a significant inconsistency between the values, beliefs, and attitudes someone holds towards buying certain products, and the products the same person buys (Carrington et al. 2014; Bauer and Reisch, 2019; Cornish et al. 2019). For example, many consumers were found to show a positive attitude towards purchases of organic food products (67%), but only a small number of consumers (4%) purchase those products (Joshi and Rahman, 2015). This conflicts with the fact that environmental attitudes and intentions were previously established as being strongly correlated to one another, as well as being two powerful predictors of ecological behaviours (Kaiser et al. 1999). The terms "attitude-behavior gap", "intention-behavior gap", "attitude-intention-behaviour gap" or even "value -action gap" all refer to and accurately describe the discrepancy between one's intentions and ability to act in line with them (Tomkins et al. 2018; ElHaffar et al. 2020). In the context of environmentally friendly behaviors, this phenomenon has been referred to as “the green gap” (ElHaffar et al. 2020).

The green gap is linked to the theory of planned behavior (TPB) (Ajzen, 1991), which assumes that attitude, along with subjective norms and perceived behavioral control, is a major influencer of behavior, and that the relationship between attitude and behavior is mediated by intentions. Strong evidence demonstrates that there is an important and persistent green gap to bridge between food consumers' expressed values, beliefs, attitudes, intentions to buy low impact foods and their actual purchasing behaviour (Vermeir and Verbeke, 2006; Davari and Strutton, 2014; Carrington et al. 2014; Joshi and Rahman, 2015; Yamoah and Acquaye, 2019; Vermeir et al. 2020; (ElHaffar et al. 2020). Common barriers to sustainable purchasing are cost, availability, mistrust of labels, insufficient marketing, and lack of knowledge about what makes a product sustainable (Mäkiniemi and Vainio, 2014; von Meyer-Höfer et al. 2015; Aertsens et al. 2009; Hughner et al. 2007). Even though consumers are increasingly more aware of the consequences of high impacts foods, they seem to still be lacking specific product knowledge, motivation, and/or capability to make such changes (Stubbs et al. 2018). To help close the green gap, Tomkins et al (2018) decided to remedy the lack of accessible and credible information on product sustainability by producing a statistical framework that provides product recommendation to consumers digitally. The framework identifies and match the preferences of sustainably minded customers with sustainable products to efficiently predict future purchases. Digital technologies have become widely used as the customary medium for behaviour change interventions since they provide a secure way to reach more people at a low cost (Glanz and Bishop, 2010; Michie et al. 2017; Murray et al. 2016). Furthermore, the digital environment can increase the odds of success of the behaviour change intervention by tailoring the content to the users’ desires and specific situations (e.g. social and environmental context) (Sucala et al. 2019; Fogg, 2003; Wendel, 2013).

A segmentation study should be employed to identify sustainably minded food consumers and tailor the intervention to their needs, wants and constraints regarding food purchasing. Engaging the public to alter their behaviours to combat climate change is a challenging task for climate change communicators such as scientists and policy makers because people have different beliefs, concerns, and motivations (Hine et al. 2014; Detenber et al. 2016; Hine et al. 2016). Which is why audience segmentation has been increasingly employed as a marketing tool to increase the effectiveness of climate change communication including eco-friendly consumption (Steg and

Vlek, 2009; Bostrom et al. 2013; Detenber and Rosenthal, 2020; Davari and Strutton, 2014). Segmentation consists of dividing a population into subgroups sharing common characteristics (e.g. values, motivations, beliefs, attitudes), which can then be used to target and tailor communications based on how each subgroup thinks and feels (Hine et al. 2014; Detenber and Rosenthal, 2020; Hine et al. 2016). Furthermore, a recent review concluded that it is essential to align a behaviour change strategy with the type of consumer being targeted, and that consumer segmentations based on the green gap can help design more effective interventions (ElHaffar et al. 2020). Reviews on best practices for sustainable behaviour change interventions recommend selecting a behaviour having a significant negative environmental impact (e.g. food consumption), segmenting a population based on behaviour change theories which can be used to detect and target which group(s) should be targeted by the intervention, or even assess whether to implement different types of intervention for different groups. Finally, segmentation research should inform which personalized tools (e.g. commitment, goal implementation, nudge, social diffusion, feedback, prompt, incentive) and persuasive technologies (e.g. smartphone application and games) would be most adequate for the targeted behaviour and group (Steg and Vlek, 2009; McKenzie-Mohr and Schultz, 2014; Klöckner, 2015; Klaniecki et al. 2018).

Gamification, "the use of game design elements in non-game context" (Deterding et al. 2011, p 10) is a behaviour change concept that has shown great potential in promoting nutritional behaviours (Chow et al. 2020; Ezezika et al. 2018; Yoshida et al. 2020; Jones et al. 2014), health behaviours (King et al. 2013; Edwards et al. 2018), and various environmentally-friendly behaviours (Ro et al. 2017; Kronisch, 2019), including sustainable food purchasing (Lounis et al. 2013; Berger, 2019). However, a review of gamification interventions demonstrated that the success rate of gamified interventions is immensely dependent on both the context being gamified, and on the user types' individual profile (Hamari et al. 2014). Concerning the gamification of sustainable food consumption specifically, interviews with participants demonstrated that people react very differently to the same aspects of gamification within the same gamified shopping context aimed at promoting eco-friendly purchases (Lounis et al. 2013). More recently, after experimenting with social norm-based feedback in a gamified online shopping environment, Berger (2019) stated on p 673 of her paper that future studies investigating how to promote sustainable food purchase should consider "elaborate, phase specific, target group specific gamification interventions". A user segmentation is therefore relevant in the context of sustainable food purchasing. The design of a gamified intervention for promoting and facilitating sustainable food procurement should be based on a segmentation and in-depth analysis of its potential users within the context of sustainable food purchasing.

1.2 Rationale

Market segmentation is one of the most efficient tools to both understand consumers' motivations and behaviours and to define target markets (a target market is a group within a greater population that share common characteristics, such as similar needs or behaviours, that are of high interest to marketers) (Arli, 2017). Market segmentation consists of dividing a population into subgroups (i.e. segments) which are determined by identifying similar responses, behaviours, or characteristics shared among numerous research participants. Understanding that multiple users fit into the same general category is useful for marketers to identify which segment(s) they should focus their efforts on (i.e. target market). Businesses can then tailor their communications and programs to be more relevant to the type of people composing the target market (Todorova, 2015). It was found that segmentations informing pro-environmental behaviour change would benefit to measure the population's current level of practice regarding the selected behaviour (i.e. penetration rate) to identify a target market and whether target-group specific interventions would be valuable (Steg and Vlek, 2009). The reason for this is because knowing if an individual is already acting on the desired behaviour or not is relevant to identify a prime target for behaviour change interventions and behaviour change tools. According to the Transtheoretical Model (TTM) there are different levels of intention to change a given behaviour: pre-contemplation, contemplation, preparation, action, and maintenance (Prochaska and DiClemente, 1983). The TTM is one of the most applied behaviour change theories (Hashemzadeh et al. 2019) and was validated as a useful model to study behaviours related to nutrition (Nakabayashi et al. 2020; Vaz de Melo Ribeiro et al. 2020; Carvalho et al. 2021). The Theory of Planned Behaviour (TPB) (Ajzen, 1991), which was established as being one of the chief theories of behaviour change that can reliably measure consumer intentions and behaviours in numerous contexts surrounding food choice (Nardi et al. 2019), confirms the importance of intention since it states that it is the chief determinant of behaviour and the theory suggests that the higher the intent to adopt a behaviour, the more likely it is to occur. Because behaviour change interventions are more effective on individuals who accept to participate of their own volition (Wendel, 2013), sustainable behaviour change interventions ought to identify which populations are most likely to modify their selected behaviour(s) and target them with behaviour change tools (Klöckner, 2015; Klaniecki et al. 2018).

More specifically, it is recommended for sustainable food marketers to target and satisfy the needs of the "convinced sustainable food consumer" segment (i.e. compared to conventional shoppers segment) because it is recognized as the sustainable food marketer' most relevant segment (von Meyer-Höfer et al. 2015). The variables significantly affecting the behaviour intention gap must therefore be examined to understand why the people who intend to change their behaviour fail to do so, and thus be able to understand how to alter those variables efficiently to help those individuals bridge the intention-behaviour gap so they can acquire the sustainable diet they wish to adopt. Therefore, sustainable behaviour change interventions should use segmentation to first identify and target the population most receptive to change the chosen behaviours(s) and then identify the adequate customizable behaviour change tools and medium (e.g. nudging, feedbacks, prompts, smartphone applications, and games) with which to target them (Klaniecki et al. 2018), which is why user segmentation was established to be relevant in the context of gamifying sustainable food purchasing (Lounis et al. 2013; Berger, 2019), and more precisely to inform the design of phase specific (i.e. pre-contemplation, contemplation, preparation, action, and maintenance of behaviour) and target group specific gamification interventions (Berger, 2019). To promote, facilitate, and maintain sustainable food purchasing, consumers with a high level of intention to shift their current purchasing behaviour towards a sustainable diet must be studied and targeted appropriately in order to design an efficient gamified intervention that can bridge the intention to behaviour gap. This study therefore should explore ways to identify and inform how to efficiently target individuals who are intending to shift their food habits towards consuming more sustainable foods but fail to translate this intention into action.

1.3 Objectives

The purpose of this study is to inform the design of targeted gamified interventions that would promote, facilitate, and maintain sustainable food purchasing, by identifying the characteristics and determinants of consumers who demonstrate an intention-behaviour gap associated with purchasing sustainable foods.

The specific objectives of this study are:

1) Identifying the framework variables (i.e., variables adapted from social psychology theories and socio-demographic categories) that significantly predict the intention to purchase sustainable foods using backward stepwise linear regression,
2) Segmenting the sample based on the framework variables using hierarchical cluster analysis,
3) Identifying the segments that have a gap between their intention to consume a sustainable diet and their actual consumption behaviour (i.e., the target segments, who have a high intention of consuming sustainable foods but are currently engaging in significantly less sustainable food consumption behaviour)
4) Identifying the characteristics (i.e., player types, gaming behaviours, and mobile application preferences) of these target segments,
5) Finally, informing about how to tailor gamification elements for interventions to increase sustainable food consumption, and the mobile applications via which these interventions are delivered, based on the characteristics of each target segment so that individuals in these segments would engage in higher sustainable food consumption behaviour (i.e., closing the intention - behaviour gap).

1.4 Contributions

There is a critical need to transition our current food consumption patterns to those that are more sustainable for human and environmental health; however, it is extremely difficult to change human food consumption behaviours. Gamified interventions hold promise for behaviour change, but previous studies have found that the gamification design must be adapted to the specific characteristics of both the targeted context (i.e. specific context in which the behaviour being targeted by the intervention takes place) as well as the people that would use the gamified intervention in order to be effective (Deterding, 2015).

This study will contribute to furthering previous research investigating how gamification can efficiently promote sustainable food purchases (Berger, 2019; Lounis et al. 2013). Specifically, this empirical study will provide new insights into what psychological variables determine the intention of an individual to purchase certain types of sustainable foods (and possibly other sustainable goods). Furthermore, this research advances the field of gamification research by investigating and identifying ways that gamification frameworks, such as the Gamification User Types Hexad Scale (GUTHS) (Marczewski, 2015), could be implemented into specific contexts for targeting specific consumer groups. Moreover, this could lead to an improved understanding of whether these frameworks are relevant in the context of sustainable food purchases. In practice, the results may also be of interest for designing and implementing food literacy programs more effectively. To the best of my knowledge, no previous research has ever segmented a population to inform the design of gamified interventions aimed at promoting sustainable food purchasing.

1.5 Structure

This thesis has the following structure: Following this introductory chapter, the second chapter will cover all relevant background information within the existing literature regarding concepts such as sustainable production and consumption, the interventions aiming to alter multiple behaviours concerning the areas of food, health, and environmental behaviours, as well as gamification interventions. The third chapter will cover the methodology of the survey of over 400 participants living in Ontario, Canada in March 2021 and outline the statistical methods used to analyse the survey responses. Then, chapter four discusses the results and their implications as well as their limitations. Finally, chapter five will make recommendations and concluding observations to future research for academics, practitioners, and policy makers.

Chapter 2 : Literature Review

The literature review covers the factors that can regulate environmentally sustainable behaviours, behaviour change tools used to modify food consumption, and the determinants of efficient gamification interventions. This literature review will also discuss the reasons why gamification can have inconsistent results and finally review what can be done to circumvent this issue.

2.1 Determinants of Sustainable Behaviours

Behaviour change theories play a crucial role explaining specific consumer environmental behaviour, those models encompass various concepts including motivational, contextual, and normative factors (Farrow et al. 2017; Klaniecki et al. 2018). Such theories are composed of concepts such as behavioural intentions, value norms, and motivation, which are recognized as fundamental for predicting actual sustainable behaviour (Klöckner, 2015; Klaniecki et al. 2018; ElHaffar et al. 2020). A review of various studies based on each of the theories will cover the concepts of motivational, normative, and contextual factors as determinants of environmentally sustainable behaviours.

2.1.1 Motivational Factors

The first determinant of environmentally sustainable behaviour change is the motivational factor. The concept of motivation in behaviour change is concerned with people's interest in activating the behaviour change. For instance, the Theory of Planned Behavior (TPB) which is a development of the Theory of Reasoned Action (TRA), states that an individual 's personal attitudes, perceived behavioural control, and subjective norm predict the degree to which a person intends to adopt a behaviour (Ajzen, 1991). Intentions are linked to motivational factors that influence behaviour, meaning that the greater the intention (i.e. desire to engage in a behaviour), the more likely the behaviour is to occur (Ajzen, 2020). TPB was utilized and validated as a model that can effectively predict the consumption of environmentally friendly products (Paul et al. 2016) and explain consumers' motivations to buy sustainable fashion products (Saricam and Okur, 2019). The TPB was also used to understand sustainable consumption at an online shopping festival (Yang et al. 2018) to investigate the purchasing behaviours related to four different environmentally sustainable products (Kumar, 2012), and to research sustainable housing purchases (Judge et al. 2019). Achieving environmentally sustainable behaviour is dependent on factors including both the intention and ability to adopt a behaviour (Klöckner and Blobaum, 2010). Therefore, identifying individuals with the motivation (intention) and behavioural control (ability) to achieve effective results are relevant concepts and tools for achieving environmental sustainability.

The goal framing theory (GFT) (Lindenberg, 2008; Lindenberg and Steg, 2013) also suggests that people would process information based on the motivation to accomplish their goals. According to goal framing theory, three goals are essential for achieving behavioural sustainability (i.e. the hedonic goal, the gain goal, and the normative goals), these objectives are used to frame how people process information (Westin et al. 2020). Feeling better right now is part of the hedonic plan, the normative goal entails acting appropriately, and the main goal entails "protecting and improving one's resources" (Lindenberg, 2008). It was found that while the three distinct concepts of the GFT affect consumers' environmentally friendly purchasing behaviours, the direct effect of normative motivations was much more significant than the other two types of motivations comprised within the GFT model (Yang et al. 2020; Hameed and Khan, 2020). Both the TPB and GFT models indicate that behaviour change is triggered and fuelled by an underlying motivation. Moreover, findings indicate that normative motivation plays a substantial role when individuals are purchasing low environmental impact products. The motivational power of normative factors to achieve sustainable behaviour change should therefore be further explored.

2.1.2 Normative Factors

Normative factors contribute to the formation of environmentally sustainable behaviour change patterns. Normative behaviour is the behaviour that follows the expected norms within the society. Several psychosocial theories emphasize the role of norm in influencing our environmental behaviours including the norm activation theory (NAT) (Schwartz, 1977), which specifies that personal norms are influenced by situational activators (e.g. efficacy, ability, awareness of consequences, and denial of responsibility), and that personal norms in turn predict behaviour. The NAT theory was used to explain pro-environmental behaviours (Harland et al. 2007; Onwezen et al. 2013) including recycling behaviour (Park and Ha, 2014). The Value Belief Norm Theory (VBN) (Stern et al. 1999) builds on core concepts from the NAT to suggest that behaviours related to social movements (i.e. activism supporting causes that aim to change the policies and behaviours related to environmental and/or social problems) can be activated if certain conditions are respected. The VBN was confirmed to be highly predictive of private (i.e. personal) pro-environmental practices (Gkargkavouzi et al. 2019), sustainable travel modes in urban areas (Lind et al. 2015), pro-environmental purchasing intentions (Davis, 2014), and actual environmentally sustainable product purchases (Kang and Moreno, 2020). For instance, the theory proposes that a person must first embrace altruistic values and reject egoistic and traditional values, as well as holding ecological worldviews (i.e. one believes that the environment is threatened and that their individual actions can help remedy the situation), in order to become predisposed to adopt pro-environmental behaviours (Steg and Nordlund, 2018). Normative factors can thus activate environmentally friendly behaviours under certain conditions, but what exactly can be defined as a norm?

The Theory of Normative Conduct (FTNC) (Cialdini et al. 1990), specifies the aspect of the norm that has more than one meaning. As a result, when discussing the normative influence on behaviour, it is critical to distinguish between social norms' injunctive and descriptive meanings because they point to distinct sources of human motivation. While descriptive norms describe what is a typically employed behaviour within society, injunctive norms describe beliefs or rules that include morally acceptable and unacceptable behaviour (Rimal and Real, 2005). A study using the Theory of Normative Social Behaviour (TNSB), which is an evolved version of the FTNC (Kang and Moreno, 2020), investigated the role of social norm in consuming four different single-use plastic products (i.e. bags, straws, coffee cups, and take-away containers) and found that descriptive norms were the strongest predictor of plastic avoidance (Borg et al. 2020). In general, descriptive norms are specific to what is done, while injunctive norms communicate what should be done. However, another study using FTNC found that although the influence of injunctive norms was an extremely important predictor of pro-environmental grocery shopping, descriptive norms were not a significant predictor of green (i.e. pro-environmental) grocery shopping (Weir, 2012). This was explained by the fact that descriptive norms do not seem to be salient (i.e. noticeable, or prominent) in this particular ‘green’ grocery shopping setting. Therefore, while injunctive and descriptive norms influence behaviour in various contexts, they can each affect behaviour to varying degrees depending on how noticeable they are in a particular circumstance.

2.1.3 Contextual Factors

Contextual factors similarly have a say in the development of environmentally sustainable behaviours. One of the models that explains the contextual factor of behaviour is the ABC model. The ABC theory (also known as the alphabet theory) is an acronym for three items that represent attitude, behaviours, and context. Context can come in many forms (e.g. community expectations, advertising, financial incentives and costs, physical capabilities, and constraints, as well as wide-ranging social, economic and political contexts such as the price of oil) (Stern, 2000). These three items relate to how external elements in our environment are involved with the behaviour change process and can also affect our internal factors (i.e. attitudes). This theory was validated in a study examining the variables influencing curb-side recycling (Guagnano et al. 1995). It was also applied in the context of organic food (Taghikhah et al. 2020), local food consumption behaviours (Zepeda and Deal, 2009), as well as purchasing wine with sustainability characteristics (Schäufele and Hamm, 2017). The model posits that the more important the influence of a particular contextual factor is (e.g. how incentivized you are to act a certain way), the less significant the attitudinal factor becomes (Stern, 2000). This model maintains that external and environmental stimuli have an immense impact on an individual's behaviour and must be taken into consideration when investigating the possible determinant of a certain behaviour. Moreover, research findings confirmed the influence of contextual factors specifically regarding ecological food purchasing, stating that certain contextual conditions (i.e. differences in household size and grocery store feature) can obstruct some ecological food purchasing behaviours while stimulating others (Tanner et al. 2004).

2.1.4 Habitual Factors

The majority of behaviours are determined by habits (i.e. frequently repeated behaviours). Even though habits were rarely considered as determinants of behaviour at all (Stern, 2000), there is a growing amount of evidence that habits are a major predictor for many environmental behaviours (Gkargkavouzi et al. 2019), eating behaviours (Riet et al. 2011; Flaherty et al. 2018; Cornelis et al. 2017; Conner et al. 2002), and food purchasing behaviours (Machín et al. 2020). Habitual behaviours have proven difficult to change even when contradicted by an individual’s intention to modify the habitual behaviour (Lally and Gardner, 2013). This phenomenon in part explains why studies on lower impact purchasing report a disparity between what consumers intend to consume and what they actually consume (Joshi and Rahman, 2015; Tanner and Kast, 2003). This discrepancy exists because when an individual frequently engages in a behaviour that has consistently rewarding consequences, he learns to recognize the situational cues linked to the rewarding behaviour, then the reactions to those cues become less conscious and more automatic each time (Riet et al. 2011; Lally and Gardner, 2013). The individual thus becomes less attentive and receptive to new information that may help alter the individual's behaviour (Verplanken and Aarts, 2011; Kurz et al. 2015). Therefore, to change a habit, it is recommended that one must interrupt the automatic routine by delivering immediate feedback to the individual based on the specific behaviour (Heimlich and Ardoin, 2008; Wendel, 2013). This recommendation explains why interventions focused on changing habitual behaviours primarily through education are not considered effective (Aarts et al. 1997; Rothman et al. 2009).

The Health Belief Model (HBM) behaviour change theory (Rosenstock, 1974), which was originally created to explain and prevent unhealthy behaviours, includes 'cues to action' as a variable influencing efficient behaviour change. The HBM was validated and applied in multiple contexts surrounding pro-environmental behaviours such as analysing the farmer's potential use of eco-friendly pesticides (Ataei et al. 2021), promoting the adoption of eco-friendly automatic vehicles (Yuen et al. 2021), and the adoption of sustainable water management (Aliabadi et al. 2020). Since the formation and maintenance of habits primarily depends on the situational cues found within the environment where the behaviour occurs (Riet et al. 2011), to create behaviour change, one must disrupt the usual pattern of action of a targeted individual with a new attention seizing situational cue (Wendel, 2013) displayed within the individual's environment, also known as a behavioural trigger (Fogg, 2003). This led to the finding that although behaviour change theories are useful in helping to predict and modify sustainable behaviours, they need to consider the specific context (e.g. specific environment) and the type of sustainable behaviour that are being targeted to correctly inform the attitude - intention - behaviour gap (Maki and Rothman, 2017). For this reason, this paper will now concentrate on the review of food consumption behaviour.

Food behaviours are determined by a broad variety of circumstances including social, economic, psychological, and environmental factors (Bublitz et al. 2010; Pollard et al. 2002; Renner et al. 2012), but they are mainly predicted by habits (Conner et al. 2002; Cornelis et al., 2017; Riet et al. 2011). For example, it was found that food purchases at the supermarket are mostly influenced by habits (Machín et al. 2020). Moreover, consumers are unaware of how powerful habits affect their purchasing behaviours when it comes to buying low impact foods. While people perceived ‘price’ to be the main barrier preventing lower impact food choices, the two most important barriers actually preventing climate-friendly food purchase were: habits (i.e. wanting to eat the same way as before), and the belief that food choices have little to no effect on climate change (Mäkiniemi and Vainio, 2014). The HBM was implemented to explain food consumption contexts, including increasing knowledge and consumption of folate-rich foods (LaBrosse and Albrecht, 2013), providing nutritional education (Diddana et al. 2018), and assessing the effect of a nutritional mobile application promoting healthy food (Samoggia and Riedel, 2020). The findings related to the determinants of sustainable behaviour are in accordance with a review of best practices for sustainable behaviour change interventions which states that once an adequate sustainable behaviour (i.e. behaviour having a large environmental impact, incorporating many individuals willing to change their behaviour) has been identified and analysed, segmentation studies grounded in behaviour change theories should identify the individuals within the population that are most receptive to change, and then inform how to target them with personalized behaviour changes tools (e.g. Feedback, Goal Setting, Nudge, Persuasive Technologies such as mobile application and games) (Klöckner, 2015; Klaniecki et al. 2018). Therefore, after summarizing the literature on influencing sustainable behaviours, this paper must examine the existing literature related to the behaviour change theories and tools used in the context of changing food consumption.

2.2 Conventional Methods to Influence Food Behaviours

This section will cover the conventional methods previously used to influence food behaviours. Those methods include social norm approach, where one can implement behaviour change cues by modifying someone’s perception of what is considered the social norm of food consumption. This section will also cover the typical strategies employed by food marketers. Finally, this section will cover the effect of the behavioural economics concept named Nudge Theory on food consumption.

2.2.1 Social Norm Approach

The situational cues that influence food behaviours are found within social environments. Findings from field experiments demonstrate that our perception of social norms concerning what and how much others eat has a strong effect on our personal food behaviours (Mollen et al. 2013;

Higgs and Thomas, 2016) even though we may not be consciously aware of this external influence (Robinson and Field, 2015). This phenomenon could be explained by the social cognitive theory (SCT), which proposes that learning occurs in a social context with a dynamic and reciprocal relationship of the person, environment, and behaviour (Bandura, 1986). The SCT was found to be a functional and useful framework to generalize and predict nutritional behaviours, especially the ones of adolescents (Tavassoli et al. 2014; Lubans et al. 2012; Ahmadi et al. 2018). A systematic review also revealed that SCT was the behaviour change theory most applied in dietetics practice in primary health care interventions (Rigby et al. 2020). The SCT was also validated and applied to the context of improving the diet of college students (Macchi and Coccia, 2021), improving childhood obesity (Koo et al. 2019; Zacarías et al. 2019), and developing an elementary school educational program about nutrition (Hall et al. 2015). Experiments showed that both adults and children are more likely to eat a larger amount of food when eating with someone who eats giant portions and eat less when eating with someone who eats little portions (Herman, 2015; Robinson et al. 2013a). Our perception of social norms related to food affect our behaviour by informing us of what is the most appropriate behaviour to adopt in each environment and situation (Herman et al. 2003) and we tend to feel emotionally rewarded when adopting these norms (Higgs, 2015). Those findings demonstrate that cues found within the social environment can significantly affect food consumption behaviours. Therefore, there is a need to understand how to use social norms surrounding food behaviours to design interventions that can efficiently promote and facilitate sustainable food behaviours.

Cues in the form of social norm messaging can be used to promote healthy eating. The use of food social norms messaging (e.g. displaying posters and flyers in a school cafeteria containing data information about the fruit and vegetable eating norms of other students belonging to the same university) has proven efficient at changing food behaviours (Robinson et al. 2013b; Higgs, 2015; Berger, 2019; Higgs and Ruddock, 2020). For example, in a field experiment, it was demonstrated that participants were more likely to select healthy foods after they were exposed to a message stating: "Every day more than 150 (name of university) students have a tossed salad for lunch here", indicating that most people chose the healthy foods because of the social influence of peers (Mollen et al. 2013). However, the effectiveness of social norm messaging on healthy eating is limited by the effect of other variables. For instance, a study found that while mass media nutritional campaigns highlighting the positive social norms surrounding healthy eating could increase daily fruit and vegetables intake, the results are highly dependent on the socio demographic characteristics (i.e. gender, education) of the neighbourhood being targeted (Li et al. 2016). Moreover, findings show that self-identity (e.g. the extent to which one identifies as a healthy eater) and social comparison (i.e. the extent to which you want to be compared to the person(s) displaying the eating social norm) factors act as moderators of the effect social norms has on the intention to eat a healthy diet (Yun and Silk, 2011). More experimental research confirms the effect of social comparison, since the effect of the social norm message is mediated by how much an individual wants to identify with the norm referent group (i.e. the effect of being exposed to a poster displaying the eating norms of the students of one's university would be augmented if the individual wants to be identified as part of the university group) (Robinson et al. 2013b). Finally, other findings revealed that while the effect of social norm on vegetable intake is affected by a self-identification factor, the social norm effect is also mediated by the attitude and behavioural control variables related to the consumption of vegetables (Stok et al. 2014). Therefore, cues within the social environment affect food behaviours indirectly by first influencing variables such as self-identity, social comparison, attitude, and behavioural control, which are determinants of the motivation (i.e. the intention) to change one's food consumption based on behaviour change theories.

Cues from our social environment influences our motivation to change our food behaviours. For example, social pressure from peers explained the gap between attitudes towards sustainable food and their consumption because social pressure influenced the intention to buy sustainable food (Vermeir and Verbeke, 2006). Behaviour change theories commonly used to research and understand different nutritional contexts (i.e. the TPB and the Theory of Self-Determination) propose that social influences only affect behaviour indirectly by impacting our motivation to change first (Ryan and Deci, 2000b; Ajzen, 1991). The TPB was established as being one of the chief theories of behaviour change that can reliably measure consumer intentions and behaviours in numerous contexts surrounding food choice (Nardi et al. 2019). It was used to help design healthy eating campaigns (Kazbare et al. 2010), predict healthy eating (Brouwer and Mosack, 2015; Malek et al. 2017), and determine factors influencing processed food consumption (Seo et al. 2014). The TPB was also used to predict and understand consumer's intention to buy organic foods (Arvola et al. 2008; Al Swidi et al. 2014; Donahue, 2017; Qi and Ploeger, 2019). The TPB proposes that what we perceive to be the current social norm surrounding a behaviour only influences our behaviour indirectly, because social norms first impact our attitudes, and then attitude impacts our intention to adopt the new behaviour (Ajzen, 1991).

The construct of the TPB confirms the findings from another behaviour change theory commonly used for food behaviour intervention, which is the Transtheoretical Model (TTM) (Prochaska & Velicer, 1997). The TTM is also known as the Stages of Change theory and is one of the most applied behaviour change theories (Hashemzadeh et al. 2019). The theory proposes that there are different levels of intention to change a given behaviour, the model is composed of five chronological levels of behaviour change (i.e. pre-contemplation, contemplation, preparation, action, and maintenance) (Prochaska and DiClemente, 1983). There is strong evidence of the efficiency of the TTM to be successfully applied in nutritional interventions aiming to change dietary intake (Nakabayashi et al. 2020; Vaz de Melo Ribeiro et al. 2020). The TTM was validated in multiple nutritional contexts, which include increasing fruit and vegetable intake (Carvalho et al. 2021), reducing intake of foods high in calories and fat (Menezes et al. 2015), explaining the intention to reduce red and processed meat intake (Wolstenholme et al. 2021), examining the purchase of packaged foods (Durán Agúero et al. 2020), and developing tailored nutrition information delivered through smartphones to prevent obesity (Lee et al. 2017). The TTM categorizes individuals based on their willingness to change in order to tailor the behaviour change intervention tools to motivate individuals adequately based on their current stages of change (i.e. pre-contemplation, contemplation, preparation, action, and maintenance). Those findings agree with the previously established best practices surrounding environmentally sustainable behaviour change interventions, which recommend identifying the individuals within the population that are most receptive to change (Steg and Vlek, 2009; Klaniecki et al. 2018). Therefore, there is a need to use segmentation research to first identify the individuals within the population that are most receptive to changing their food purchasing to adopt a sustainable diet, and also to inform how to target them with personalized behaviour changes tools (e.g. Feedback, Goal Setting, Nudge, Persuasive Technologies such as mobile application and games) (Klaniecki et al. 2018).

Audience segmentation and targeted messaging can be important tools for improving the effectiveness of climate change communication (Hine et al. 2014), changing dietary intentions by designing tailored messages (Verain et al. 2017), increasing the knowledge on food ingredients and artificial additives (Spitz et al. 2018), as well as designing healthy food promotional campaigns (Kazbare et al. 2010). Moreover, a review of the studies aiming to close the attitude-intention behaviour gap in pro-environmental consumption using behavioural interventions concluded that segmentation would help design more efficient interventions (El Haffar et al. 2020). Segmentation research is widely recognized as the first fundamental step of successful marketing strategy (Palmer and Millier, 2004; Dibb, 1998; 2017).

2.2.2 Food Marketing

Studies have found that food marketing can successfully influence food attitudes (Lazard et al. 2018), preferences, and consumption by children (Smith et al. 2019; Coates et al. 2019), adolescents (Qutteina et al. 2019), and adults (Folkvord and Hermans, 2020; Harris and Fleming-Milici, 2019). It has been shown that food advertisers can manipulate a consumer's perception of how healthy a food looks and even manipulate the intention to purchase them (Lazard et al. 2018). For instance, food marketing techniques include "social media marketing, celebrity endorsements, sports and music sponsorships, and influencer marketing" (Harris and Fleming-Milici, 2019). While one of the goals of food advertising is to make potential consumers have positive feelings towards a particular food product, the other is to educate consumers about the product characteristics (Folkvord, 2019). Food advertising is increasingly integrated in the entertaining content of media messages (e.g. advergames, social media advertising, product placement), thus increasing the effect of the food advertisement (Folkvord and Hermans, 2020).

Unfortunately, because most food promotion techniques focus on the rewarding aspects of appetizing, energy dense food products (i.e. high in fat, salt, and sugar) (Folkvord, 2019), most techniques used for marketing unhealthy food would be more difficult to replicate for the promotion of healthy foods (apart from education, using social media and sponsoring). Energy dense foods are likely to be more appealing than low energy ones. Moreover, the palatability of energy dense foods is likely to increase with repeated intake (Anguah et al. 2017) explaining why unhealthy food marketing leads to increased saliva secretion and the uptake of appetite-related hormones like ghrelin and insulin (Folkvord et al. 2016). Unhealthy food marketing techniques targeting the biological reward system triggered by energy dense foods can thus be difficult to be utilized for the marketing of healthy foods since healthy foods tend to be much less energy dense than unhealthy foods (Evans et al. 2018). Furthermore, repeated exposure to healthy food does not necessarily increase their perceived palatability (Anguah et al. 2017). Food marketing would thus be less efficient at employing techniques emphasizing the appealing and palatable aspects of foods when marketing healthy foods.

It has also been shown that the marketing of unhealthy foods affects thoughts and motivations related to food intake (Folkvord, 2019), and as previously established in this thesis, there is a persistent gap between the food consumers' expressed motivation to buy low impact foods and their actual purchasing behaviour (Vermeir and Verbeke, 2006; Davari and Strutton, 2014; Carrington et al. 2014; Joshi and Rahman, 2015; Vermeir et al. 2020). Promoting healthy food consumption is a particularly complex task due to individuals requiring a strong capability to self-control and to delay gratification when resisting the temptation of higher density, more palatable foods (Pelletier et al. 2004). Therefore, it can be hypothesized that conventional food marketing techniques (affecting thoughts and motivation via the human reward system triggered by energy dense foods) would not be efficient for marketing healthy foods.

Although a lot is already known about the effectiveness of food marketing in encouraging and maintaining energy dense food consumption in people of all ages (Folkvord, 2019), there is a prominent research gap when it comes to understanding how marketing could be used to promote healthy food on both children and adults which is why innovative methods and new research are desperately needed in the field of healthy food promotion (Folkvord and Hermans, 2020). On the other hand, a concept called Nudge Theory, which is based in behavioural economics, shows great promise in making food consumption healthier.

2.2.3 Nudge Theory

Nudge theory is a concept that was created by Thaler and Sunstein in 2008. The theory posits that there exists a choice architecture that involves outside forces which subtly guide an individual’s decisions (Thaler and Sunstein, 2008; Arno & Thomas, 2016). The theory also maintains that a choice architect exists which is in the form of an individual or collection of persons who design the environment to make a certain option more likely to be chosen. These outside environmental forces, which are referred to as nudges, are meant to influence people’s choices while maintaining their freedom of choice (Arno & Thomas, 2016). It has been established that the formation and maintenance of habits primarily depends on the situational cues found within the environment where the behaviour occurs (Riet et al. 2011), behaviour change interventions therefore need to disrupt the usual pattern of action of a targeted individual with a new attention seizing situational cue (Wendel, 2013), also known as a behavioural trigger (Fogg, 2003), which is why it was suggested that modifying food consumption could be achieved by applying nudge theory in store layouts (i.e. changing the choice architecture of food by changing how it is physically displayed) (Borthwick and Garnett, 2015).

The efficacy of the Nudge theory in changing consumers' food behaviours has been proved by several academic findings. Thaler and Sunstein (2008) discuss the example of nudging being used to either increase or decrease the consumption of any food items in cafeterias by placing them more prominently amongst the food selection. Arno and Thomas (2016) conducted a systematic review of several studies conducted in wealthy nations on the efficacy of nudges. They observed that nudges resulted in a more than fifteen percent increase in healthier nutritional or dietary choices and as such were the most preferred public health strategies for combating endemic lifestyle diseases (Arno and Thomas, 2016). After conducting a meta-analysis of several field experiments on the efficacy of seven healthy eating nudges, Cadario and Chandon (2019) found that in general, nudge interventions, especially the ones that are predominantly behaviourally oriented, are effective in reducing unhealthy eating (Figure 2-1). Vecchio and Cavallo (2019) conducted another systematic review of thirty-six articles that reported reviews of empirical studies performed between 2016 and 2018 on nudge interventions to promote healthy eating. They found out that over 80% of the reviewed empirical research reported positive outcomes on nudge interventions. These academic findings among others provide solid proof that nudge interventions are effective and as such, should be embraced.

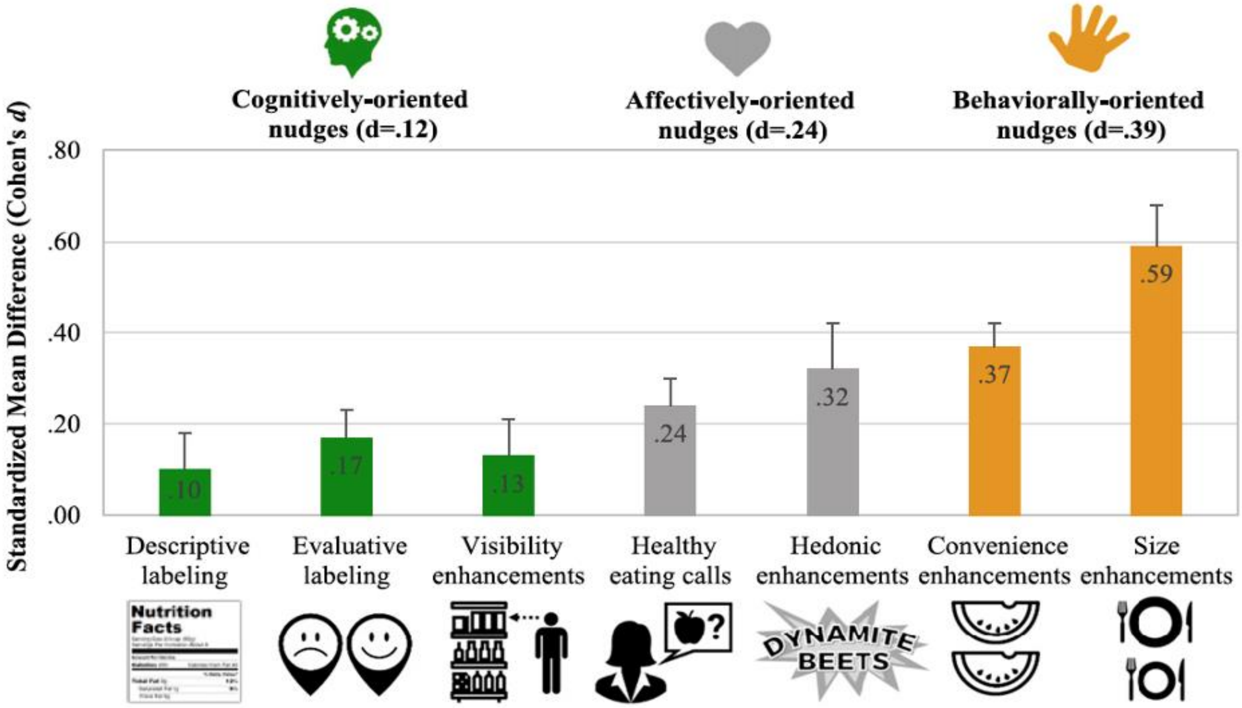


Figure 2-1: Bar chart from the meta-analysis study conducted by Cadario and Chandon (2019). Effect size by seven different Nudge types demonstrating that behaviourally oriented nudges (i.e. size enhancement, and convenience enhancement) were by far the most effective at promoting healthy eating. Error bars represent standard error of the mean.

This figure depicts the Nudges maintain individuals' freedom of choice while influencing their behaviour through cues and sidestepping their reasoning capabilities (Ensaff, 2021). Nudges are increasingly being implemented in the health sector as they are perceived as less invasive ways of steering consumers towards healthier behaviours without altering their economic incentives (Hoenink et al. 2020). The nudge intervention entails making the target choice easier for the consumer to access in a non-obtrusive and automatic way (Ensaff, 2021). This is achieved by among other methods, placement manipulations where the location of food is put closer to the consumer such as at eye level or near the till. Placement manipulation also entails the order of food options being adjusted by being put first in the menu or a buffet as well as emphasizing healthy food more than their competing unhealthy options. Another strategy entails changing the presentation or format of food such as plate size and the size of serving tongs to make people eat healthy portions (Ensaff, 2021).

Despite the Nudge theory being effective in changing consumer food behaviours, it has several limitations. First, Nudges in general may fail because they do not necessarily have long term effects, may be confusing, and can generate compensating behaviour, thereby nullifying the initial effect of the nudge (Sunstein, 2016). Next, there are opponents of Nudge Theory who rebel against it because part of the population considers nudging as a manipulative and exploitative practice, thereby creating an ethical dilemma regarding the implementation of nudge theory (Engelen, 2019; Schmidt and Engelen, 2020). Regarding Nudging for healthy food choice in food retail, meta-analysis shows that its effectiveness varies from weak to moderate depending on the study, on the specific nudge strategy being applied, as well depending as the characteristics of the population being nudged (Ensaff, 2021; Cadario and Chandon, 2019; Trafford and De la Hunty, 2021). For instance, a study reported that while nudge intervention increased the healthy food consumption of people who typically do not eat healthy, it also decreased the healthy food consumption of the previously habitual healthy consumers (Gonçalves et al. 2021). It was also found that nudges were more efficient at reducing the consumption of unhealthy foods than increasing healthy food consumption (i.e. "it is easier to make people eat less chocolate than to make them eat more broccoli") (Cadario and Chandon, 2019).

Besides the unreliability of its results, and the ethical issues it may create, the implementation of effective nudges for influencing food consumption are entirely dependent on the decision of retail business management (such as grocery stores, cafeterias, and restaurants) and not on the individual consumer. The ethical consideration and lack of voluntary participation by the individual consumer transgress the previously established assumption that behaviour change is more efficient when targeting individuals who voluntarily accept to participate in the behaviour change intervention (Wendel, 2013; Klaniecki et al. 2018). Finally, to tackle major and sustained dietary behaviour change, the effect of Nudge theory was found to increase when combined with other procedures (Trafford & De la Hunty, 2021). While influencing food purchasing behaviour in physical environments (i.e. grocery stores, cafeterias and restaurants) has several limitations, digital environments on the other hand (e.g. E-commerce, food and groceries subscriptions, and delivery service mobile platforms) provide promising path for digital nudging to promote ecologically sustainable food choices (Berger et al. 2020). Furthermore, Berger (2019) found that social norm-based gamification within a digital food store is efficient at promoting sustainable food purchasing. It could therefore be hypothesized that online food stores could not only implement gamification elements but could also implement Nudge theory to promote healthy food purchase more efficiently than their physical counterparts.

Digital technologies have become widely used as the customary medium for behaviour change interventions (Glanz and Bishop, 2010; Michie et al. 2017) since they provide a secure way to reach more people at a low cost (Murray et al. 2016). Moreover, digital environments and computer technologies provide an unprecedented way to use instantaneous data to tailor and send rapid behavioural feedback (i.e. situational cues) and help turn new behaviours into habits (Fogg, 2003; Wendel, 2013; Hermsen et al. 2016). Finally, internet technologies have made online food purchasing easier than ever, and packaged food online purchasing was found to have grown significantly since the Covid 19 pandemic started (Bhatti et al. 2020). For instance, daily downloads of grocery apps doubled during the first week following the World Health Organization official declaration of Covid-19 as a pandemic (Kim, 2020). Brick and mortar grocery stores are increasingly adopting the digitalization of commerce (Erdmann and Ponzoa, 2021). The Covid-19 pandemic may have thus transformed the entire market structure forever (Kim, 2020). The Covid-19 crisis and the accelerated digitalization of food purchasing it generated may provide opportunities for the promotion of sustainable consumption.

2.3 Gamification

Early research in the psychological field of games distinguished several player types (i.e. Achiever, Killer, Explorer, Socialisers) (Bartle, 1996) based on each player's motivation and play style within a game. Gamification, which can be defined as "using game-design elements in any non-game system context to increase users' intrinsic and extrinsic motivation, help them to process information, help them to better achieve goals, and/or help them to change their behaviour" (Treiblmaier et al. 2018) became a worldwide trend around 2010 (Dicheva et al. 2015) and has since then been established as an effective instrument for engagement and behaviour change (Johnson et al. 2016).

2.3.1 Digital Medium

Effective sustainable food consumption interventions should provide social norm messages digitally (i.e. through websites, mobile applications, wearable devices). Systematic reviews demonstrated that dietary mobile applications (i.e. computer program or software application designed to run on a mobile device such as a phone, tablet, or watch) are effective tools to improve nutritional behaviours (Paramastri et al. 2020; Fakih El Khoury et al. 2019). Furthermore, digital technologies have become the customary medium for behaviour change interventions since they provide a secure way to reach more people at a low cost (Murray et al. 2016). Because of the rise of digital technology, the use of digital interventions aimed at changing and maintaining behaviour change has become increasingly widespread (Michie et al. 2017). Digital technologies (e.g. internet, wireless technology, smartphones) offer efficient ways to apply behavioural interventions and have expanded the range of theory-based strategies available for effective behaviour change (Glanz and Bishop, 2010). Regarding food behaviours specifically, smartphone applications were established as a cost effective and innovative medium to deliver tailored food consumption behaviour change directly to users (Lee et al. 2017). Numerous digital behaviour-change interventions aiming to increase sustainable food consumption use a form of feedback grounded in social theories (e.g. social support and disapproval, social comparison, social incentives, restructuring the social environment) to change nutritional behaviours (Hedin et al. 2019). However, a common challenge restricting the effectiveness of all digital behaviour change interventions was poor continuing user engagement (i.e. a large percentage of users stop using the intervention) (Sucala et al. 2019; Kelders et al. 2012; Eysenbach, 2005). Therefore, there is a need to understand why, despite their best intentions, individuals stop engaging with mobile applications aimed at helping them change their behaviours.

2.3.2 Rewarding Behaviour

The reason explaining why numerous users stop engaging with digital applications aimed at helping them change their behaviours is that repeating a new behaviour enough times to turn it into a habit is more likely to fail when the new behaviour is not rewarding enough, at least in the early stages of adoption (Verplanken and Aarts, 2011). Previous findings showed that when a behaviour is particularly rewarding, it is more likely to be repeated (Lally and Gardner, 2013; Skinner, 1938; Postman, 1947) and therefore more likely to be maintained over time and become habitual. For example, people were found more likely to keep low impact behaviours, such as buying environmentally friendly washing products, when the new behaviour provides visible rewarding experiences (Kurz et al. 2015). In other words, when the benefits or rewards of the newly implemented behaviour are not immediate, but instead emerge later in time (e.g. such as changing your diet to achieve a certain weight goal), or the presence of reward is simply non-existent, it becomes more likely that the individual stops trying to change and decides to return to the previous habit (Verplanken and Aarts, 2011). Behavioural interventions must come to terms with the fact that most of the behaviour change process is gradual, and that maintenance of such change typically entails continued and focused efforts (Glanz and Bishop, 2010). Therefore, there is a need to understand how to reward users appropriately to design digital interventions that can efficiently promote, facilitate, and maintain sustainable food purchases.

However, rewarding a new behaviour to turn it into a habit can have the opposite effect for several reasons. For instance, it was shown that people with different personality types tend to favour different types of rewards (Nienaber et al. 2011). There is also a distinction between extrinsic rewards (i.e. tangible, external rewards such as financial incentives) and intrinsic rewards (i.e. intangible, innately pleasurable or enjoyable feelings created from performing an interesting activity) (Ryan and Deci, 2000a; Deci and Ryan, 2012). Moreover, it was found that giving external rewards (e.g. money) to someone for completing a given task could decrease their intrinsic motivation to engage with the task (Klaniecki et al. 2018; Deci, 1971). Therefore, understanding how to reward users adequately to keep them engaged with a dietary mobile application in order to promote, facilitate and maintain sustainable food purchase is needed. Combining multiple intervention tools is recommended when there are both contextual and motivational barriers to the behaviour being executed (Klaniecki et al. 2018), which is the case for sustainable food behaviours. Thus, I propose that an effective digital intervention promoting sustainable food purchase should combine social norm feedback with gamification techniques to reward users adequately and keep them engaged long enough to produce the desired habitual behaviour.

Gamification is a proven technique in the field of Human Computer Interaction (Rapp et al. 2019) widely used in numerous and diverse areas (Sardi et al. 2017), such as education (e.g. to foster the engagement of students) (Dreimane, 2019; Barata et al. 2013), human resource management (e.g. to increase employees' productivity) (Prasad and Vaidya, 2019; Aziz et al. 2017) digital marketing (e.g. increase customers loyalty and engagement (Noorbehbahani et al. 2019), health (e.g. to increase physical activity) (Guarneri and Andreoni, 2014; Hagberg et al. 2009; Lindberg et al. 2016), crowdsourcing systems (e.g. to increase participation and the quality of the crowdsourced work) (Morschheuser et al. 2017a), and also environmental sustainability (e.g. to help people conserve more energy and water) (Albertarelli et al. 2018; Ro et al. 2017). However, the application of the gamification concept seems to have drawbacks since its outcomes can be inconsistent.

2.3.3 Inconsistent Gamification Results

The various results of gamification interventions show that its effectiveness is inconclusive for reasons outlined in the following section. Even though gamification has positive effects such as increasing user engagement and motivation (Dicheva et al. 2015), the results about its effectiveness can be quite inconsistent (Seaborn and Fels, 2015; Koivisto and Hamari, 2019). On one hand, a paper reviewing whether gamification is effective to increase engagement in online programs found that gamification had substantial positive impacts. More specifically, the online educational programs that used gamification had more visits, more participation in quizzes and discussions, and more time spent by participants on the gamified programs than their non-gamified counterparts (Looyestyn et al. 2017). On the other hand, while the implementation in education is still fast-growing, there is also a rising number of studies revealing inconclusive and even negative results from implementing gamification in education (Dicheva and Dichev, 2015). For example, a 16-week longitudinal study that divided 71 students in two groups (one gamified class and one non-gamified), demonstrated that students in the gamified course ended up less motivated, which caused them to have lower final exam grade than the non-gamified students (Hanus and Fox, 2015). So how can gamification be so successful and such a counterproductive tool within the same context?

In 2012 the research and consulting company Gartner famously predicted that by 2014, 80% of all gamification interventions will fail to meet their objective largely due to inadequate design (Santhanam et al. 2016). Game systems are so intricate that the slightest flaw or tiniest change in design can have enormous repercussions on the overall experience of the user (Hunicke et al. 2004). For example, a gamified task manager named ‘Habitica’ that aims to help its users be more productive and feel more motivated has been found to have the reverse effect due to an inappropriate design of the reward system (Diefenbach and Müssig, 2018). One of the reasons ‘Habitica’ failed in its gamification design is the same reason many gamification interventions also fail to have consistent results: they did not understand how to satisfy their users’ psychological needs within the context of a task management application (van Roy and Zaman, 2017). This helps explain why the effectiveness of behavioural interventions can be enhanced by studying the potential audience and contextual factors (Glanz and Bishop, 2010). There is therefore a need to understand the targeted population's psychological profile within the targeted behavioural context to learn how to design an effective gamification intervention.

2.3.4 Gamification Design Guidelines

A review of gamification interventions demonstrated that the success rate of gamified interventions is immensely dependent on the context being gamified and the user (Hamari et al. 2014). It was found by multiple academics and researchers that not all contexts are equally fit to be efficiently gamified (Nacke and Deterding, 2017). For example, gamifying an academic or public library experience (e.g. "Providing level-up experience for library users, some status and powers associated with library use that can be admired, library currency to accumulate and spend, and show the progress bar in library catalog") was found to be potentially too focused on educational aspects to be enjoyable, thus public and academic libraries may not be the ideal contexts to be gamified (Kim, 2012). Moreover, personality types (e.g. introvert vs extrovert) influenced each individual's learning style and gaming preferences differently (Codish and Ravid, 2014). Jia et al (2016) found that "extraverts tend to be motivated by Points, Levels, and Leader boards; and people with high levels of imagination/openness are less likely to be motivated by Avatars". So not only are certain surroundings more suited to efficient gamification interventions than others (e.g. online classrooms vs physical libraries), but also the impact of a certain gamification element will differ based on the personality types of the participants. Therefore, there is a need to search for gamification design guidelines that can be used throughout all contexts and users.

There are agreements amongst gamification experts and existing studies on what an effective gamification framework must include to be effective. For instance, a systematic review on gamification design frameworks used in higher education recognized that despite existing differences amongst all existing gamification frameworks, there is a growing consensus on three guidelines:

1) The targeted behaviour (e.g. increased purchases of sustainable foods) must be clearly defined.

2) It is important to analyse the target users and identify player types (e.g. socialisers, killers, achiever, explorers) (Bartle, 1996).
3) It must employ the appropriate game design principles based on the player types of the users (Mora et al. 2017).

For example, a framework for guiding gamification design, called “activity-challenge-motivation triplets” (Deterding, 2015) has been extensively cited in numerous studies investigating how to apply gamification effectively and systematically for behaviour change (Hansen, 2017; Knutas et al. 2019; Morschheuser et al. 2017b; Li, 2017). Deterding’s personalized gamification model focuses on combining the examination of both the user and the context being gamified together (Deterding, 2015). Therefore, there is a need to determine a specific context that would fit to gamification design implementation.

2.3.5 Gamification Interventions Increasing Healthy Food Consumption

Gamification has been previously used successfully in the context of altering nutritional behaviours. For instance, it has been used to decrease the intake of unhealthy foods (Majumdar et al. 2013; 2015), teach food literacy while shopping in a grocery store and reducing impulse purchase (Bomfim and Wallace, 2018; Bomfim et al. 2020), promote fruits and vegetables intake in adolescents (Yoshida et al. 2020), and promote healthy breakfasts (Luhanga et al. 2016). Immersive and enjoyable gaming experience that used avatars have been found to influence behavioural intention towards a sustainable healthy lifestyle (Wang et al. 2020). Gamification is perfectly adapted to change food behaviours because games typically have feedback and social comparison as part of their core features (Webb, 2013). It has been previously established in this paper that food behaviours are habitual (Cornelis et al. 2017) as is food purchase behaviour at supermarkets (Machín et al. 2020). Therefore, those behaviours require immediate feedback based on the specific situation (Wendel, 2013). It has also been established that food behaviours can be efficiently influenced by manipulating signals found in the social environment (Higgs, 2015). Digital gamification therefore has the potential to increase low impact food consumption in part because it can use the power of social interactions to promote behaviour change (Hamari and Koivisto, 2013; Koivisto and Hamari, 2019; Hamari and Koivisto, 2015) through game design elements (e.g. points, badges, leader-boards, narratives, customization tools, levels, avatars, notifications, progress bars, and time constraints). What makes those elements a powerful tool for behaviour change is that they can be communicated instantaneously, therefore providing immediate feedback based on certain activities (McGonigal, 2011).

The effective gamification of food behaviours can be successfully implemented within a digital and mobile application environment. For instance, informative digital video games have been researched and designed to educate children about nutrition and increase their healthy foods consumption (Hswen et al. 2013; Dunwell et al. 2015; Ledoux et al. 2016; Saad et al. 2018). Similar digital games have also been designed for adult use as well (Grimes et al. 2010; Orji et al. 2013a; Belogianni et al. 2018). Moreover, it was found that the level of bonding players experience with their digital avatar influences their intention to consume healthy food as well as their intention to exercise (Wang et al. 2020). For example, Pollak et al. (2010), Byrne et al. (2012), and Hswen et al. 2013 researched and developed the use of mobile games that motivate adolescents to eat more healthy breakfasts by providing them with instant feedback through virtual pets (see Figure 2-2 for an example). Studies have shown that not only do people get emotionally attached to their virtual pets (Donath, 2004), but this bond to a virtual pet can also be used to successfully implement behaviour change interventions such as motivating physical activity (Pokemon Go is a more recent example of this phenomenon) (Lin et al. 2006) and promote ecologically friendly behaviour (Dillahunt et al. 2008).

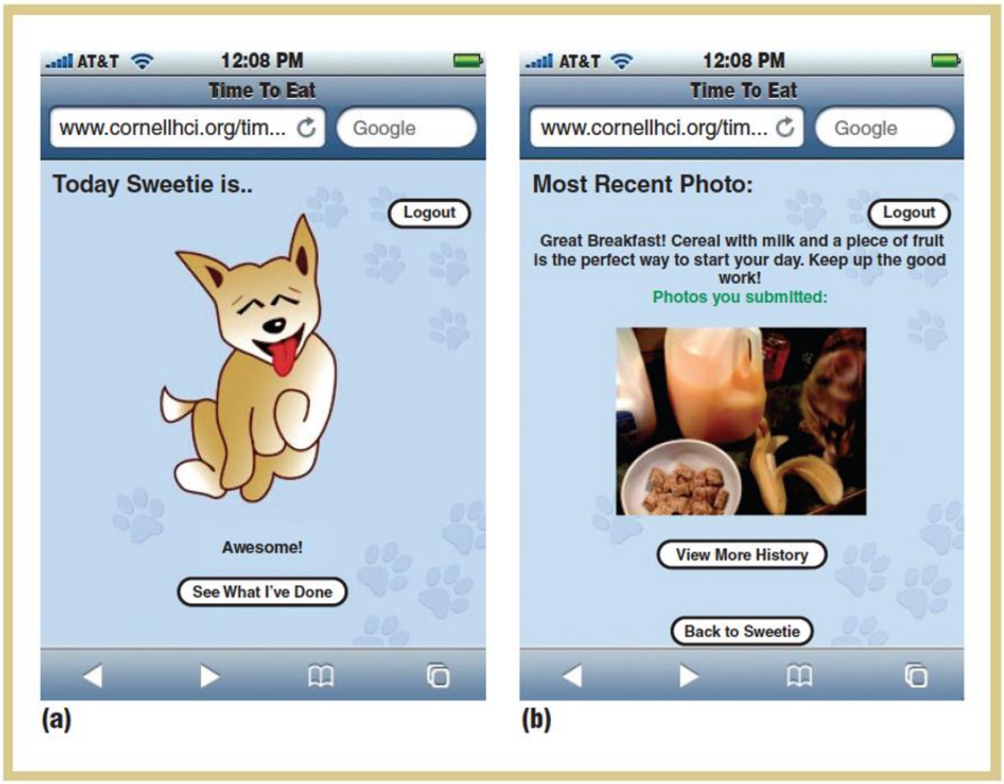


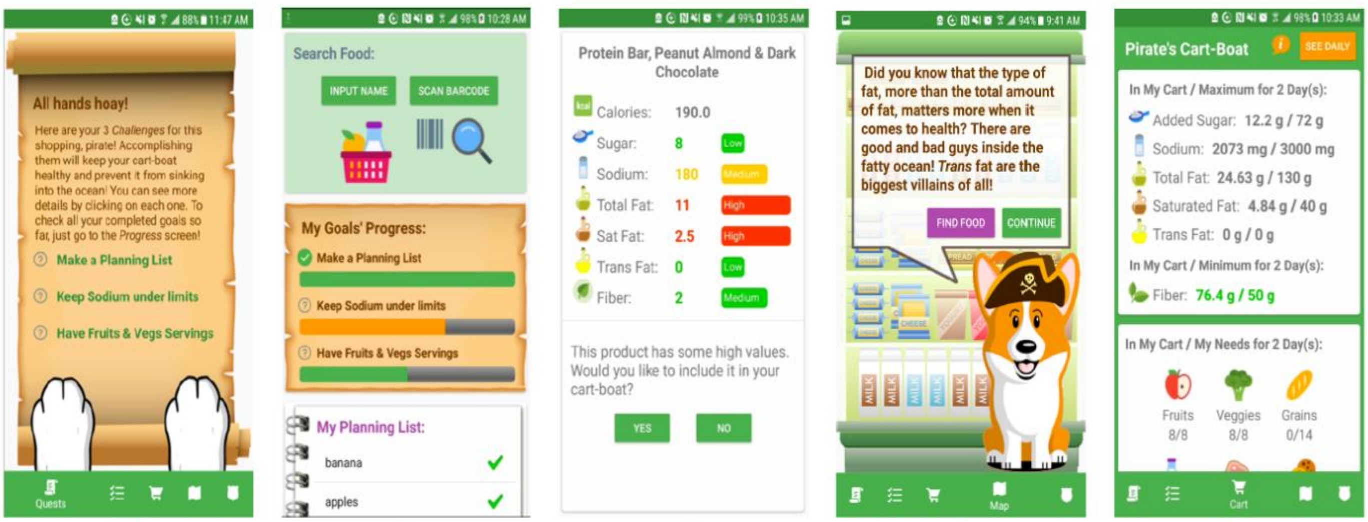
Figure 2-2: The Time to Eat user interface. (a) the home screen, depicting the pet's current emotional state and (b) the feedback screen with the corresponding food photo. The pet's emotional state reflects the quality of meals the player has recently eaten and submitted. Example from (Pollak et al. 2010).

Another example of a gamified digital environment is a computer based educational game named "Quest to Lava Mountain" designed for children to play at school. It was shown to help decrease sugar consumption and also increased positive attitudes towards physical activity (Beasley et al. 2012; Sharma et al. 2015) (see Figure 2-3). Digitally gamified interventions also had success in increasing the time participants were engaged in interventions designed to promote sustainable behaviours, like reducing energy use (Oppong-Tawiah et al. 2020) and increasing sustainable travel (Wells et al. 2014).

Figure 2-3: Visual Example of Quest of lava Mountain - Gameplay picture. The avatar has to learn about food, make conscious purchase decisions about which ones to eat (i.e. healthy or unhealthy) based on limited currency in order to survive and move forward in the game. Screenshot from youtube video published by cchaosmedia. (10 mai 2011). The Quest to Lava Mountain [Youtube.https://www.youtube.com/watch?app=desktop&v=QnY7Y_EuUo4&ab_channel=cchaosmedia].

The digital gamification of food behaviours can be implemented in situated interventions, which are applied when and where a behaviour occurs, such as when purchasing foods. For example, a three-week field experiment used a gamified mobile application named 'Pirate Bri's

Grocery Adventure'(PBGA) (see Figure 2-4) to influence purchasing behaviours at the grocery store (Bomfim et al. 2020). PBGA successfully increased its user's food literacy (i.e. combination of knowledge, skills and behaviours that help people make informed food choice), motivated them to eat a more balanced diet composed of healthier foods, and helped them moderate their purchasing of foods containing high amounts of sugar, fat and sodium.



(a) (b) (c) (d) (e)

Figure 2-4: (a) Brigitte, the Pirate Dog Nutritionist, presents the 3 Food Literacy challenges to be completed in the current shopping trip. (b) As players put food in their cart, they visualize the progress feedback towards each goal (challenge). (c) Players can make meaningful choices of which products to buy, by visualizing each item's nutrients using colours that highlight low, moderate, or high amount. (d) As players enter each section, they learn from Brigitte about the types of food they will encounter there. (e) Pirate's Cart-Boat shows a summary of personalized nutrients and servings for each food group in the cart versus how much is needed for the total trip.

The potential of gamification has also been identified specifically for the promotion of sustainable nutritional behaviours (Berger et al. 2014; Berger and Schrader, 2016; Kronisch, 2019; Vermeir et al. 2020) and even more specifically in promoting eco-friendly shopping (Lounis et al. 2013). Berger (2019) conducted an experiment in which an online shop was designed to resemble a physical shopping environment. She found that using social norm feedback with gamification elements (by providing a green meter that indicated the level of eco-friendliness of products accompanied by social norm information) was effective at increasing the number of eco-friendly foods the participants would place in their online baskets. Finally, Lounis et al (2013) conducted a series of interviews with consumers and found that, while gamification has the potential to shift consumers shopping practices towards more sustainable ones, it needs to be customizable and personalized depending on the consumer to be efficient.

2.3.6 Personalized Gamification Model

The personalized gamification model requires a user analysis that involves defining the target users by examining relevant information such as socio-demographics information, as well as the needs, motivations and hurdles the users have within a specific context (Deterding, 2015; Morschheuser et al. 2017b). For example, a meta-analysis review of 54 games for health concluded that personalization should be used according to the behaviour change needs and demographics of the users (DeSmet et al. 2014). Multiple gamification researchers suggest that to reach a maximum level of efficiency, a gamified system should be personalized based on who the user is (Hakulinen et al. 2015; Carreño, 2018; Mora et al. 2018; Monterrat et al. 2015). Different frameworks such as Personas, or Player types are then typically used to categorize the target users into different groups, segments, or clusters in order to inform the design of the personalized gamification (Morschheuser et al. 2017b; Knutas et al. 2019; Monterrat et al. 2015; Orji et al. 2018). There is a need to segment and personalize the gamification design based on the users within a certain context because it was demonstrated that different users understand and react differently to the same game element (i.e. badges) and that the context in which the badge is presented influences how user interpret the meaning of the badge (Antin and Churchill, 2011). Essentially, gamification researchers have learnt that a game that motivates a given individual can discourage another one (Dale, 2014; Monterrat et al. 2014; Orji et al. 2013b). Therefore, the design of a gamified intervention promoting and facilitating sustainable food procurement should be based on a segmentation and in-depth analysis of its potential users within the context of sustainable food purchase.

Theoretical framework must be utilized to provide information on what the psychology of a particular user is within a given context. For instance, motivational psychology frameworks must be incorporated so that both the user’s context and their psychological needs are addressed into a user centred gamification design (Conway, 2014). The motivation and behaviours of players has been researched to a great extent amongst studies attempting to establish player typologies within the in-game environment (Tuunanenand and Hamari, 2012). Bartle's player type framework (Bartle, 1996) was the first framework to distinguish and categorize different types of players (i.e. Achiever, Killer, Explorer, Socialisers) based on each player's motivation and play style within a game. More recently, the Gamification User Types Hexad Scale (GUTHS) (Marczewski, 2015), also referred to as the Hexad player type scale (HPTS) (see Figure 2-5), has built upon Bartle's Four player typology (Bartle, 1996) and incorporated the Self-Determination Theory (SDT) (Deci and Ryan, 2012) in its foundation because the SDT focuses on intrinsic motivation. The Hexad scale is composed of six player types (i.e. Free Spirit, Socializer, Disruptor, Player, Achiever, and Philanthropist) and was designed to match each user's personality to specific game elements, for the purpose of tailoring personalized behaviour change applications (Mora et al. 2017; Zhao et al. 2020).

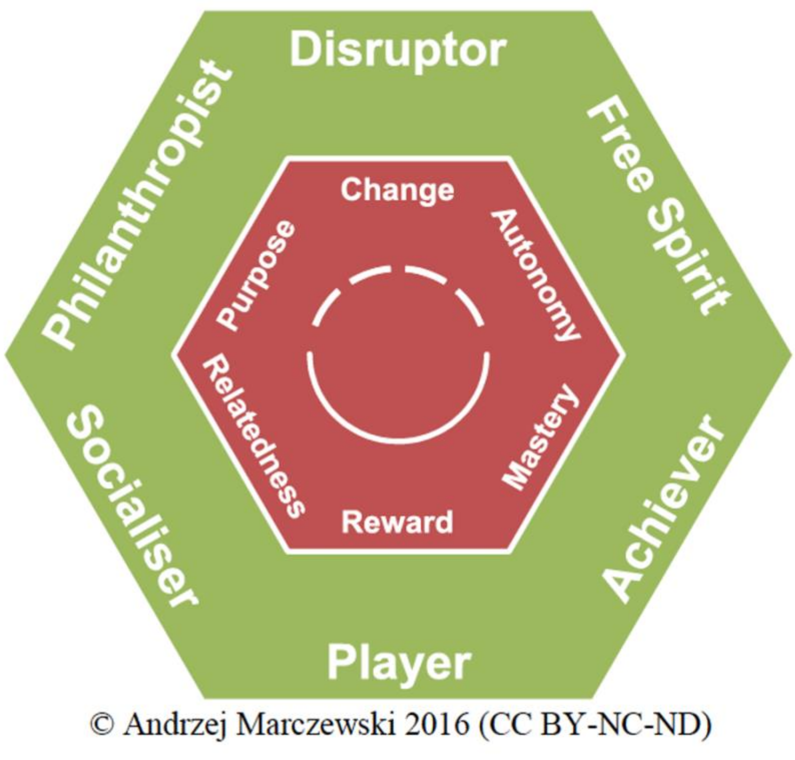


Figure 2-5: HEXAD player type scale, page 6 (Marczewski, 2015).

The HPTS (i.e. GUTHS) can match a player's personality to the appropriate game elements because it was found to be correlated to the Big 5 personality traits (Tondello et al. 2016), thus indicating the user's preferences towards different game design elements guidelines (Orji et al. 2013b). The Big Five personality dimensions (i.e. Extraversion, Emotional Stability, Agreeableness, Conscientiousness, and Openness to Experience) is a psychological tool widely used in academia to predict all sorts of human characteristics such as: learning styles and academic achievement (Komarraju et al. 2011), job performance (Mount and Barrick, 2006), social network usage (Huang, 2019) and even one's level of loneliness (Buecker et al. 2020). Motivational theories and frameworks should therefore be used to examine and segment potential users based on their psychology in each circumstance to inform a gamified behaviour change intervention.

Previous studies researching how to understand and change sustainable food choice stated that future researchers should segment the consumers. For example, based on the findings of their survey investigating the influences of environmentally friendly product choice, Dahlstrand and Biel (1997) suggested a behavioural change model that would segment users by the strength of their behavioural habits. Next, after reviewing 53 empirical articles that studied what influences consumers purchasing environmentally friendly products, Joshi & Rahman (2015) asked future researchers to consider consumer segmentation. Moreover, after studying what determines organic food consumption, Aertsens et al. (2009) indicated that future research should analyse the motivations and barriers of different user segments based on their organic food behaviours (e.g. non-, light-, medium- and heavy organic food users). This is because an intervention application that can adapt to the user specific situation (e.g. social, and environmental context) can improve the effectiveness of the digital intervention (Sucala et al. 2019). Professor B.J. Fogg at Stanford University explains in his book 'Persuasive technology' (2003) how new technology offers behaviour change proponents the advantage of tailoring content towards individual needs, interests, personality characteristics, and contexts. Therefore, the design of a gamified intervention promoting and facilitating sustainable food procurement should be based on a segmentation of its potential users and adapted to the context of sustainable food purchase.

Regarding low-impact foods, previous studies researching how to understand and change food behaviours using gamification techniques state that future research should segment the users as well. A systematic review of gamification interventions promoting fruits and vegetables intake (Yoshida et al. 2020) asks future researchers to adapt game design elements according to population subgroups (i.e. segments). More recently, after experimenting with social norm-based feedback in a gamified online shopping environment, Berger (2019) stated that future studies should consider “elaborate, phase specific, target group specific gamification interventions”. User segmentation is therefore relevant in the context of sustainable food purchasing since interviews with participants demonstrated that people react very differently to the same aspects of gamification within the same gamified shopping context aimed at promoting eco-friendly purchases (Lounis et al. 2013).

Consequently, the purpose of this study is to conduct a consumer segmentation aimed at informing the design of an effective digital intervention promoting and facilitating sustainable food behaviours. To the best of my knowledge, no previous research has ever segmented a population to inform the design of gamified interventions aimed at promoting sustainable food purchasing.

2.4 Objectives

The current study aims to expand the understanding of the link between behaviour change and gamification, and thus to contribute to the current literature. Overall, it is intended to provide novel information on i) the variables that significantly predict the intention to consume a sustainable diet, ii) the characteristics of the population segments that would respond to interventions for increasing sustainable food consumption the most, and iii) how to tailor elements of gamification to maximise the success of such interventions. Accordingly, the specific objectives of the study are as follows:

1. Identifying the framework variables (i.e., variables adapted from social psychology theories and socio-demographic categories) that significantly predict the intention to purchase sustainable foods using backward stepwise linear regression,
2. Segmenting the sample based on the framework variables using hierarchical cluster analysis,
3. Identifying the segments that have a gap between their intention to consume a sustainable diet and their actual consumption behaviour (i.e., the target segments, who have a high intention of consuming sustainable foods but are currently engaging in significantly less sustainable food consumption behaviour)
4. Identifying the characteristics (i.e., player types, gaming behaviours, and mobile application preferences) of these target segments,

5. Finally, informing about how to tailor gamification elements for interventions to increase sustainable food consumption, and the mobile applications via which these interventions are delivered, based on the characteristics of each target segment so that individuals in these segments would engage in higher sustainable food consumption behaviour (i.e., closing the intention - behaviour gap).

Chapter 3 : Methodology

To meet the study objectives detailed above, firstly, a survey was designed by the author. The survey consisted of items aimed at collecting data on a range of variables, including socio-demographic characteristics and variables identified based on the Theory of Planned Behaviour (TPB), such as gamification profiles and preferred mobile applications. This process is detailed below. Subsequently, the data collected via this survey were analysed using appropriate empirical methods, which are also detailed in the following sections. The analysis aimed to identify the variables that significantly predicted the intention to purchase sustainable foods, execute the segmentation of the sample, and identify the target segments along with their characteristics, all of which in turn inform the interventions to increase sustainable food consumption.

3.1 Rationale for Methodology

To meet the objectives, the survey was designed based on the previous literature and novel aspects were also included by the author, as explained in detail in the following section. Then, to meet the first objective, the constructs measured (i.e., demographics and TPB categories) were empirically examined to ensure their validity and relevance in significantly predicting participants' intent to purchase sustainable foods. This was done to verify the variables within the framework were not redundant and that they indeed served the purpose of measuring the intent to purchase sustainable foods, as intended.

Followingly, given the main objective of the current study is to identify and profile a target market in relation to the intent to consume sustainable food, a segmentation study was conducted (i.e., addressing the second objective). This is because behaviour change interventions were found to be more effective when they were tailored to homogeneous target groups (Schwarzer and Fleig, 2014) and segmentation studies are especially useful when studying behaviour change, given all individuals are different in terms of their capabilities and motivations to change (Heimlich and Ardoin, 2008). Psychographic (i.e., lifestyle data such as activities, interests, and opinions) and demographic data (e.g., age, gender) are relevant to segmentation strategy for nutritional products (Della et al. 2008) and should be combined with the theories that predict the targeted behaviour most accurately to generate insights to healthy eating campaigns (Kazbare et al. 2010). This will improve the relevance of the behaviour change intervention content and thus enhance the efficiency of the intervention.

The goal of a segmentation study is to create clusters in a way that while each cluster contains individuals that are as similar to each other as possible based on certain criteria or characteristics, the clusters themselves are as different from each other as possible, meaning that there should be distinct differences between the clusters in terms of the identified criteria or characteristics. Through this approach, meaningful and distinct groups can be created, which in turn can inform personalised gamified interventions tailored to each cluster. There are two general approaches to customer segmentation: a-priori and post-hoc. A-priori segmentation methods require segments to be established before the data is collected, while post-hoc methods identify segments empirically through data analysis (Cooil et al. 2007). According to a study that took a descriptive approach grounded in the TPB and compared a-priori and post-hoc segmentation methods, 'post-hoc solutions' were found to lend more insights into whom and how to target to promote healthy eating practices (Kazbare et al. 2010). Thus, the current study also makes use of a post-hoc segmentation method. The method employed by the current study (i.e., hierarchical cluster analysis) is also a model belonging to predictive clustering methods family, which were previously found to be one of the most powerful, flexible, and general approaches to customer segmentation (Cooil et al. 2007) and were established as more effective than descriptive methods for the segmentation of healthy eating consumers (Kazbare et al. 2010). While descriptive methods solely focus on summarising and describing the characteristics of the data at hand (Dillon & Goldstein, 2020), the predictive statistical methods examine whether the dependent variable can be explained or predicted by the independent variables, establishing such relationships by coefficient estimates and evaluating the predictive power of the models (Tabachnick & Fidell, 2019). This type of methodology involves planning the study first, collecting the data, and then exploring the data to find patterns to determine the different market segments (Kılıç and Akdamar, 2020).

Subsequently, the segments identified by the hierarchical cluster analysis were examined and the segments that had the largest gap between their intention to consume a sustainable diet and their actual consumption behaviour were identified as the target segments, given these are considered to be the segments that would respond the interventions the most (i.e., addressing the third objective). Then, the characteristics of these target segments were closely examined and the differences between these segments and the others were identified (i.e., addressing the fourth objective). Finally, what the identified characteristics of the target segments mean and what this information suggests in terms of tailoring the gamification elements for interventions to increase sustainable food consumption, and the mobile applications used to deliver these interventions, was discussed in detail (i.e., addressing the fifth objective).

3.2 Data Collection

Survey Distribution

The study received ethics clearance from the University of Waterloo ethics committee on the 1st of March 2021 (ORE #42144). A copy of the survey questionnaire can be found in the Appendix (see B1). The distribution list was determined by Quest MindShare, which is a market research organization that assists in online data collection. It was aimed to select the study sample to be as representative of the Ontario population in 2020 as possible in terms of the distribution of sex and age groups.

The Qualtrics questionnaire was distributed online through Quest Mindshare between March 9ths 2021 and March 12th, 2021. The current study did not receive any funding, thus the service Quest Mindshare provided was entirely self-funded by the author. Quest MindShare also managed the distribution of the incentives to the participants. Quest MindShare's participant recruitment pricing is based on the nicheness of the sample (i.e., the difficulty of reaching the required participant type), which country the participants reside in, the length of the survey, and the required responses. For this study, the remuneration for each participant was $1, which is, according to Quest Mindshare, in line with the industry standards for surveys and participants similar to those of the current study. The participants did not need to provide personally identifiable information to get the incentive.

Survey Design

The questionnaires included items taken from relevant previous literature examining the sociodemographic and psychosocial variables that determine sustainable food consumption. Novel items (i.e., number of people in the household, game(s) behaviour frequencies, and usage preferences in types of mobile application) were also devised and included by the author to offer practical information on the gamification design of intervention(s) aimed to increase sustainable food consumption.

The survey included a total of 103 questions, the majority of which were ranked on a 5-item Likert scale (e.g., Strongly agree= 5, Somewhat agree = 4, Neither agree nor disagree= 3, Somewhat disagree= 2, Strongly disagree = 1). Other questions asked the respondents to rank items in the order of their choosing and to select the demographic categories they belonged to.

The survey also included three open-ended questions prompting the respondents to write down any other barriers to consumption they could think of if these were not already included in the survey (e.g., "Can you think of another reason why it is difficult for you to buy **local foods**? (If yes, please specify what it is)". The analyses and results obtained from the data collected through these open-ended questions were later determined to be excluded from the main study and were instead included in the Appendix C.

The first three questions of the survey were screening questions (i.e., aimed to filter out individuals deemed unsuitable to participate in the study). These were: (1) Whether the person wishes to participate in the study, (2) Their age bracket, and (3) Whether they were currently living in Ontario. If the participants answered "no" to questions 1 and/or 3, and/or indicated that they were younger than 18 years old, they were excluded from the study. Participants under 18 years of age were excluded because authorisation from parents or legal guardians is required by the Ethics Committee of the University of Waterloo for these participants. Only participants residing within Ontario were included because they shared some specific geographical and cultural characteristics. In addition, Ontario is the most populated province of Canada and is therefore more representative of the overall Canadian population than any other province. After answering the screening questions, participants were provided with definitions and examples of sustainable diet and foods and proceeded to answer the following questions in the survey.

A total of 490 participants participated in the survey through Qualtrics. The time to complete the survey for these 490 participants ranged from 4 to 59455 seconds (i.e., from less than a minute to up to ~ 991 minutes), with a mean of 1235 seconds (~ 21 minutes). The participants who took significantly longer than others to send their responses (e.g., 991 minutes) may have been engaged in another activity while responding the survey at the same time, or they may have stopped responding the survey for a while and gone back to it later. After removing duplicate responses and potential bots (i.e., AI powered responses arising from computer software algorithms used to mimic human responses to questionnaires) detected by Qualtrics, 445 participants remained. For instance, the 4 second survey response was detected as a potential bot by Qualtrics, and thus excluded from the study.

Amongst the 445 participants left, 23 selected “I do not wish to participate” and were therefore excluded from the study. Additionally, 4 participants indicated that they were younger than 18 years, and 1 person responded that they were currently not living in Ontario, thus these participants were also removed from the study. Finally, 41 out of the 417 remaining participants did not provide an answer for all TPB-related questions that measure the intent to consume a sustainable diet and/or the questions that measure the player types. Upon exclusion of these participants for the reasons detailed above (i.e., not fitting the study criteria, duplicate responses and potential bots, and not giving or being able to consent to participate in the study), a total of 376 participants, who also provided an answer for all TPB and Hexad related questions, remained. These 376 participants were included in the analyses, thus forming the analytical sample of the study. For these 376 participants, the time to complete the survey ranged from 166 to 59455 seconds with a mean of 1420 seconds (~24 minutes). Based on latitude and longitude data collected through Qualtrics, the majority of the study participants were from the Greater Toronto area and a much smaller cluster was from around the Greater Ottawa region (see appendix A1).

3.3 Measures

3.3.1 Segmentation Variables

In this section, the theoretical background of the questionnaire design is explained, and the selection of the specific questionnaire items are detailed, as well as providing example items for each questionnaire.

3.3.1.1 Personal Determinants of Sustainable Food Consumption

This study used an integrated framework on personal determinants of organic food consumption to guide the theoretical background of the questionnaire design (see Figure 3-2). The framework used for guiding the questionnaire development was adapted from the Theory of Planned behaviour (TPB; Ajzen, 1985), based on previous literature on sustainable food consumption in general and literature on successful applications of measuring and understanding the personal predictors of organic food consumption in particular (Aertsens et al., 2009). In addition to the components of the TPB depicted in orange in Figure 3-2 below (i.e., intention, attitude, personal moral norm, behavioural control and subjective norm, abilities, and barriers), the framework also included the values and beliefs components from the Values Theory, which are depicted in green in Figure 3-2, as these variables influence the TPB variables. Furthermore, the framework included an emotions/concerns variable, which are depicted in pink in Figure 3-2. This variable is affected by the subjective norm and also influences three of the TPB variables determining the intention to act on a selected behaviour. Finally, the food buying experience, which is depicted in blue in Figure 3-2, is also a variable affecting attitude and personal moral norm related to a selected behaviour. Lastly, socio-demographic variables (e.g., age and gender) and macro levels factors (e.g., culture, technology, culture) were also included in the framework because the literature concerning the consumption of sustainable food indicates that these variables influence the relationship between attitude, intention, and behaviours (Aertsens et al., 2009).

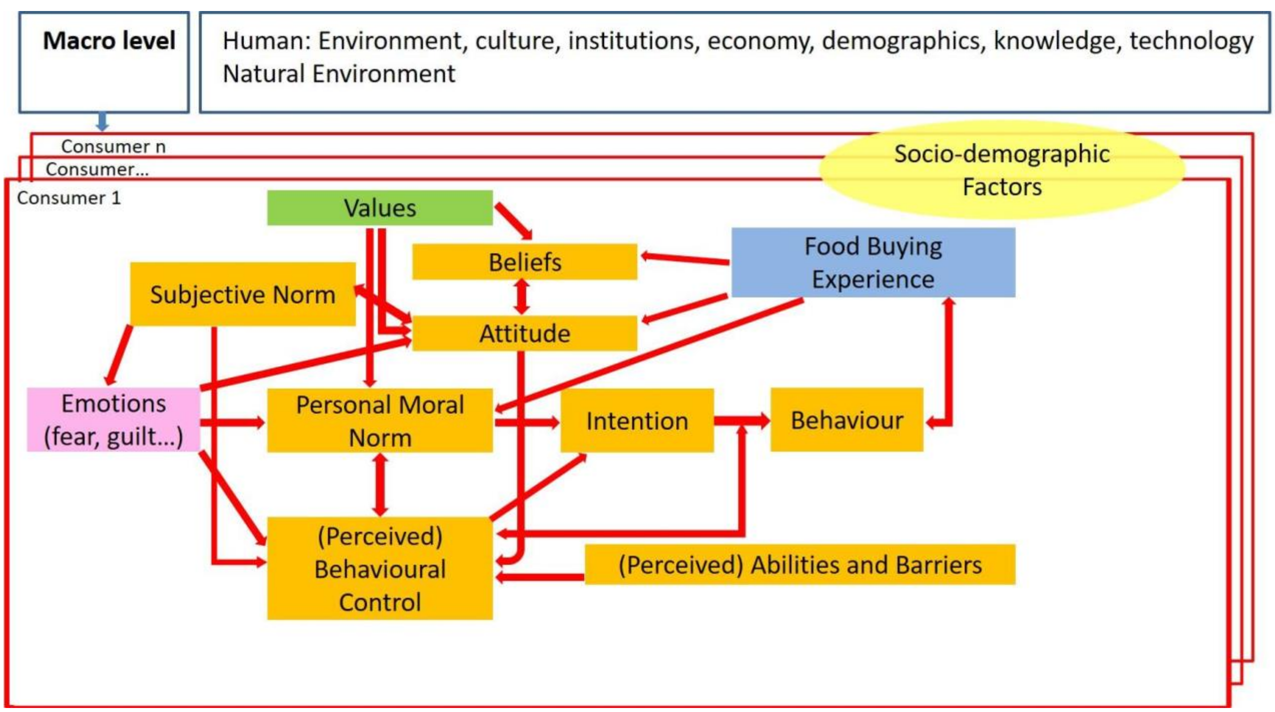


Figure 3-2: *Integrated Framework on personal determinants of sustainable food consumption based on Aertsens et al. (2009)'s framework on personal determinants of organic food consumption (see appendix A2).*

TPB (Ajzen, 1985) was used in this study to understand the target users' current food purchasing practices (i.e., food behaviour experiences), motivations, challenges, and goals regarding the purchase of different types of sustainable food (e.g., local foods, organic foods, plant-based proteins). The TPB model was selected given it is the most used theory in behaviour change interventions of sustainable behaviours (Klaniecki et al., 2018), as well as being able to reliably measure consumer intentions and behaviours in numerous contexts regarding food choice (Nardi et al., 2019).

The online questionnaire incorporated all variables from the integrated framework on personal determinants of organic food consumption (Aertsens et al. 2009) except the Values Theory components. Values Theory components were excluded because these originally required a Portrait Value Questionnaire (PVQ) of 56 items measuring 10 motivationally distinct types of values (e.g., power, security, stimulation; Schwartz, 1994). Even though shorter versions of the PVQ, which contain between 20-40 items, have been developed, these variables only indirectly influence the intention and behaviour variables via affecting the TPB variables. Therefore, incorporating these variables into the study would have yielded limited value while significantly extending the survey completion time, potentially discouraging participants from completing the survey. For these reasons, the Values Theory variables were excluded from the online survey and therefore not included in this study.

The design of the questions measuring the segmenting variables based on the TPB was inspired by the available questionnaires the relevant previous studies had administered, which measured at least one of the variables included in the framework (Figure 3-2). These studies measured organic food behaviours (Tarkiainen et al., 2005; Verhoef, 2005; Al Swidi et al., 2014; Bagher et al., 2018; Wang et al., 2019), food waste behaviours (Stancu et al., 2017), climate change actions (Kwon et al., 2019), sustainable food behaviours (Redman and Redman, 2014), green consumer profiles (Mintz, 2011), and even characteristics of sustainable food consumers (von Meyer-Höfer et al., 2015). The items in the questionnaires used in these studies were adapted to the context of sustainable food consumption for the current study. Moreover, because findings have shown the importance of taking product category differences into account in studying consumer food motivations and intentions (Verain et al. 2017), the survey addressed several food types that comprise a sustainable diet. Each question category related to Aertsens' framework (2009) (Figure 3-2) was designed to inquire about the three sustainable food types defined at the beginning of the survey (i.e., plant-based protein, organic food, and local food), given the current study characterises a sustainable diet to be a combination of these three types of food. The scores for each question within these categories were thus summed to provide an overall score for the given category to measure the determinants of sustainable food consumption accurately.

The categories taken from the Integrated Framework on personal determinants of organic food consumption (Aertsens et al., 2009), the example questions from each category section of the survey, and which types of Likert scales were used for each category are summarised in Table 3-1 directly below.

Table 3-1: Summary of the variables from the Integrated Framework on personal determinants of organic food consumption (Aertsens et al. 2009) used in this study.

Variable	Example Question	Questions Adapted From	Five-point Likert Scale Type
Intention to consume sustainable foods	Indicate to what extent you agree or disagree with the following statements: I intend to buy more local foods soon	Tarkiainen et al. (2005), Wang et al. (2019) and Stancu et al. (2017)	Agreement: Strongly Agree = 5/ Strongly Disagree = 1
Food buying practice[1]	When buying food, indicate how often you buy the following: Food at a local farmer's market	Redman and Redman (2014)	Frequency: Always = 5/ Never =1
Food abilities	Indicate your skill level in the following activities: Reading and understanding food labels (Nutrition facts table, ingredient lists, certifications, etc.)	Bagher et al. (2018) and Redman and Redman (2014)	Skills: Extremely skilled = 5 stars/ Not at all skilled = 5 stars
Subjective norm	Indicate to what extent you agree or disagree with the following	Al Swidi et al. (2014)	Agreement: Strongly Agree = 5/

	statements: I have noticed that many people around me are buying plant-based protein		Strongly Disagree = 1
Personal moral norm	Indicate to what extent you agree or disagree with the following statements: I feel a sense of responsibility to do something about climate change issues for future generations	Kwon et al. (2019) and Mintz (2011)	Agreement: Strongly Agree = 5/ Strongly Disagree = 1
Perceived behavioural control	Indicate your level of agreement with the following statements: I can handle any challenges (money, time, information related, etc.) associated with buying: Organic foods	Al Swidi et al. (2014)	Agreement: Strongly Agree = 5/ Strongly Disagree = 1
Perceived barriers	Indicate your level of agreement with the following statements: It is difficult to buy organic foods because: They are not available where I shop	von Meyer-Höfer et al. (2015) and Aertsens et al. (2009)	Agreement: Strongly Agree = 5/ Strongly Disagree = 1
Emotion/ concern	Indicate your level of agreement with the following statements: I choose food that: Is produced in a way that does not cause animals to experience emotional or physical pain	Verhoef, (2005), Wang et al (2019) and Batson et al. (1987)	Agreement: Strongly Agree = 5/ Strongly Disagree = 1
Attitude	Indicate how important it is for you to buy the following foods: Plant based proteins	Meyer-Höfer et al. (2015)	Likelihood: Extremely Likely = 5/ Extremely Unlikely = 1

Notes:

- The variable referred to as behaviour 'Experience' within the Integrated Framework on personal determinants of organic food consumption (Aertsens et al., 2009) was renamed to be 'Food buying practice' in this study to reflect its meaning more accurately.

Moreover, the Likert scale scores of two of the questions measuring the food buying practice of the participants (i.e., items 9 and 12 in the survey; see B1) were reverse coded because these items measure the opposites of the behaviours of interest in this study.

3.3.1.2 Socio-demographic Variables

Socio-demographic variables are included as part of the Integrated Framework on personal determinants of organic food consumption (Aertsens et al. 2009). Thus, these variables are also included as the variables used to segment the study sample, given they can predict and lend insights into an individual's intention to consume sustainable foods. Alongside screening questions regarding age category and residence in Ontario, five additional socio-demographic variables were incorporated: Total household income, marital status, highest level of formal education achieved, number of people living in the household, and gender. The possible response options to these items were given by the survey (B1). The inclusion of these variables is supported by relevant literature that explores the influence of sociodemographic factors on sustainable consumption, such as green, eco-friendly, and organic consumption (Mintz, 2011; von Meyer-Höfer et al., 2015; Aertsens et al., 2009; Padel & Foster, 2005). Socio-demographic variables are commonly assessed in various types of research (Nardi, 2018) and have been utilised in segmentation studies (Sarti et al., 2018). Therefore, the socio-demographic variables utilised in this study were adapted from the multiple sources, including the aforementioned studies above.

There were several reasons for including the “Number of people living in the household” item. Firstly, this variable was deemed important due to the influential role of social norms and contexts on individual food behaviours (Higgs, 2015; Robinson et al., 2013a; Higgs and Thomas, 2016; Higgs and Ruddock, 2020). Also, social and reference groups, particularly peers and individuals in close proximity, have been found to exert a strong influence on green purchase decisions (Salazar et al., 2013). Thus, by considering the number of people residing in a participant's household, it was aimed to identify individuals who, when targeted with behaviour change strategies, could potentially have a ripple effect on the sustainable food consumption of others in their immediate vicinity. Secondly, including the "Number of people living in the household" socio-demographic variable provided valuable insights into the overall household income. Lastly, the inclusion of household size was motivated by previous findings that highlighted its significant influence on ecological food purchasing (Tanner et al., 2004).

3.3.2 Profiling Variables

Profiling variables included user player types measured by an adapted version of the Hexad scale questionnaire, various game(s) behaviour frequencies, ranking of mobile applications' usage preferences, as well as ranking of the three food types (i.e., organic foods, plant-based proteins, and local foods) in terms of sustainability. However, because this study defines a sustainable diet as a combination of the three food types, as outlined in section 3.2.1.1. of this thesis, it became clear after the data collection phase that assessing how respondents rank the individual sustainability of these food types is not relevant for profiling the target market. Thus, the ranking of food types in terms of sustainability was excluded from the profiling variables.

Similarly, scores for each individual item related to a particular food type have been found to have no practical use to inform the gamification design for sustainable food consumption. The individual items were thus combined into a sum-score for each category in order to measure the determinants of sustainable food consumption accurately.

3.3.2.1 HEXAD

The Gamification User Types Hexad Scale (GUTHS) was expressly designed for gamification purposes (Hallifax et al. 2020). It is a widely used Player typology that incorporates domains of psychology (i.e., personality and motivation; Hallifax et al., 2020; Ferro, 2021) and was found to be the most appropriate player typology for tailoring gamification interventions when compared to other two user typologies (i.e., the BrainHex player typology and the Big five factor; Hallifax et al., 2019). The GUTHS' purpose is to match each user's personality to specific game design elements in order to provide tailored behaviour change applications (Mora et al., 2017; Zhao et al., 2020) because personalised interactive systems are shown to be more effective in motivating users than standardised (i.e., one size fits all) strategies (Tondello et al., 2016).

The Hexad scale is based on Bartle's player type framework (Bartle, 1996) and the Self-Determination Theory (SDT; Ryan and Deci, 2000b). The SDT is the most used behavioural model for gamification interventions (Mora et al. 2017) in part due to its emphasis on the distinction between intrinsic motivation (e.g., purpose) and extrinsic motivation (e.g., reward). Intrinsic motivation occurs when a task is enjoyable in and of itself without the need for external factors (e.g., financial rewards) to motivate an individual to do a given task (Deci and Ryan, 2012). The four intrinsically motivating factors in the Hexad model are based on the three types of intrinsic motivation from the SDT (i.e., relatedness, competence, and autonomy; Ryan and Deci, 2000b; Deci et al., 1994) as well as a fourth intrinsic motivating factor (i.e., purpose) identified by Pink's Drive Theory (Pink, 2009). The two types of extrinsic motivation, on the other hand, are change and reward (see Figure 2-5).

The GUTHS was found to be correlated to the Big 5 personality traits (i.e., extraversion, agreeableness, openness, conscientiousness, and neuroticism; Cobb-Clark et al., 2011; Tondello et al., 2016; see appendix B2). Furthermore, the reliability of the GUTHS in predicting user's preferences of the game design elements has been empirically validated (see appendix B3) and confirmed to be useful in tailoring gamification applications according to user's preferences (Tondello et al. 2016). Therefore, this study will use the TPB (Ajzen, 1991) in conjunction with Marczewski's Gamification User Types Hexad Scale (GUTHS; 2015) as a combined framework to inform the design of targeted gamified interventions that would promote, facilitate, and maintain sustainable food purchasing.

Player Types were measured using the HEXAD Scale questionnaire published by Tondello et al. (2016; see appendix B2). This study adapted Tondello and colleagues' Hexad scale questionnaire (2016) by removing the item that had the lowest subscale correlation coefficient (r) per player type. In other words, the item that was the least correlated with the other three items measuring each user type was removed to increase the efficiency of the questionnaire and ensure that the respondents could finish answering all survey items within a reasonable amount of time. The questions measuring the Hexad scale were randomised to minimize participants' awareness of the specific intent behind measuring the HEXAD Player types (i.e., Achiever, Philanthropist, Player, Free Spirit, Disruptor, and Socializer). By presenting similar items in a randomised manner, the study aimed to reduce any potential bias in participants' response patterns.

3.3.2.2 Mobile application(s) Usage Preferences

Macro level factors as defined by Aertsens and colleagues (2009; i.e., cultural differences, knowledge, and technological factors) were adapted to fit the purpose of gamification design and also included as profiling variables. As discussed in the literature review, digital and mobile technologies are recommended as a behaviour change medium. Thus, the current study examines which mobile application(s) the target market prefers to use to inform the design of the gamification of sustainable food consumption. The author researched previously gamified mobile applications and included 12 types of such applications in the study.

Mobile application(s) usage preferences were assessed by presenting the participants with the following item: "Which of the following categories of mobile applications are you most likely to use? Rank at least 3 categories in the order of which ones you are most likely to use (most likely to use item as #1, and least likely to use item as #12)." The possible response options are given in the survey (see B1).

3.3.2.3 Game(s) Behaviour Type Frequency

Finally, given the literature suggests gamification studies should concentrate on the relationships between "game dynamics, gamification contexts, gaming personalities or preferences, dynamic gaming engagement styles etc." (Tu et al. 2015), the survey established each participant's previous behaviour frequency for different genres of games. Moreover, it was previously found that participants with a high amount of experience in playing games benefit more from gamification compared to those with less experience (Landers and Armstrong, 2017). Therefore, measuring various types of game(s) (i.e., game genre) behaviour in terms of how frequently the participant engages with those types of game(s) is relevant to inform the gamification design of an intervention aimed to promote, facilitate, and maintain sustainable food consumption. Thus, a variety of game genres were included in the survey. The selection of these genres was based on the author's research on the taxonomy of game genres. Participants were asked to indicate their frequency of playing games from these selected genres in their leisure time. Please refer to B1 for the surveyed gaming options in the appendix.

3.4 Analytical Procedure

3.4.1 Objectives and Hypotheses

To empirically address the study objectives specified previously, five hypotheses (i.e., one hypothesis per each study objective) were generated as discussed below. Followingly, each of these hypotheses were tested using appropriate empirical methods as detailed in the following section. These hypotheses are specified to be:

Hypothesis 1*: The sociodemographic (i.e., age, gender, marital status) and framework variables (i.e., attitudes, behavioural control, social norm, personal moral norm, emotions) measured by the survey predict the intent to consume sustainable foods score.*

Hypothesis 2*: The study sample can be successfully segmented based on the sociodemographic and framework variables.*

Hypothesis 3*: Target segments for gamified interventions to increase sustainable food consumption can be identified based on having a high intention to consume sustainable foods but lower engagement in sustainable food consumption behaviour (i.e., having a behaviour gap).*

Hypothesis 4*: The characteristics (i.e., player types, gaming behaviours, and mobile application preferences) of these target segments differs from the rest of the segments.*

Hypothesis 5*: Customisation of gamified interventions to increase sustainable food consumption, and the mobile applications via which these interventions are delivered, can be informed based on the identified target segment characteristics.*

3.4.2 Statistical Methods

As per the reasons explained in the above section in detail, the data were analysed to ensure whether the variables significantly predict the intention to purchase sustainable foods, segment the study sample, identify the target market, and finally to profile the target market based on several variables related to behaviour change theory, gamification, and mobile application usage. All statistical analyses were performed using IBM SPSS (Statistical Package for the Social Sciences) version 23 and JMP 15 (SAS, Cary, NC, USA).

The statistical methods used in this study and their purposes are summarised in Table 3-2 below. The variables, most of which were measured by Likert scales, were treated as continuous given the ample evidence from the literature suggesting this was appropriate to do so for Likert scales with 5 or more response levels (Norman, 2010; Johnson and Creech, 1983).

Table 3-2: Statistical methods and their purposes used in this study.

Part 1: Analyses for the socio-demographic and TPB variables	
Analysis	**Purpose and Information Gained**
Descriptive statistics	• To understand how representative the study sample was of the general Ontario population in terms of sociodemographic variables. This informs about the generalisability of the study results. • To check whether the data were normally distributed. This helps with determining the appropriate statistical tests to employ for the analyses (i.e., parametric versus non-parametric testing).
Bivariate analyses	• To assess the relationships between sociodemographic variables and the intent to consume a sustainable diet. This serves as an initial step to gain information on the relationship between the sociodemographic variables and the intent to consume a sustainable diet.
Correlations and heatmaps	• To identify correlations between continuous variables presented as heatmaps This serves to lend initial insights into the relationships between the variables at a glance.
Linear regression	• To predict the intent to consume a sustainable diet using the study variables (i.e., demographic variables and TPB categories). This facilitates the process of verifying that all included variables significantly predicts the intention to consume a sustainable diet and identifying the variables that exhibit the strongest predictive power for the intention to consume.
Hierarchical Cluster	• To segment the study sample into clusters.

Analysis	This was done to achieve the segmentation of the study sample.
Part 2:	**Analyses for the gamification and preferred mobile application variables**
Bivariate analyses	• To understand which gamification player types were associated the most with having a high intent to consume a sustainable diet This informs about the associations between the gamification player types and the intention to consume a sustainable diet.
Contingency analysis	• To determine which preferred mobile applications and specific game behaviours were associated the most with having a high intent to consume a sustainable diet This informs about the associations between the preferred mobile applications and the intention to consume a sustainable diet, as well as the associations between the specific game behaviours and the intention to consume a sustainable diet.

Firstly, simple descriptive statistics and the normality of the data were evaluated, to gain initial insights regarding the data and to decide whether parametric or non-parametric tests were going to be used for the next steps.

Next, bivariate analyses were performed between the sociodemographic variables and the intent to consume a sustainable diet to evaluate the relationships between them. Then, this was followed by a scatterplot matrix/heat map displaying all bivariate relationships between the continuous variables. Multivariate linear regression was used to predict the intent to consume a sustainable diet using the summed scores from the different categories of the TPB variables and the sociodemographic variables as predictors. A backward stepwise regression procedure (i.e., backward elimination regression) was employed until only predictors significant at the 90% confidence level remained. This procedure allowed identification of the predictor variables that were the most significant and the elimination of any redundant variables in terms of predicting the intent to consume a sustainable diet.

Followingly, the hierarchical cluster analysis was performed. Clustering is a multivariate method that groups together observations with similar values across several variables. Typically, observations are not scattered evenly through n-dimensional space, where n is the number of variables. More often, the observations localise into clusters and identifying these clusters can provide further insights into the data. Clustering is a recognised statistical tool commonly used to distinguish and establish relevant market segments (Dolnicar, 2002). There are two common types of clustering algorithms: hierarchical and k-means. Hierarchical agglomerative cluster analysis is "the most common for grouping cases" (Banks and Fienberg, 2003). This method was used to examine associations between the continuous category scores (i.e., the sum-scores for each TPB category) and the categorical socio-demographic variables. This method first lets each observation to form its own cluster. Then, the distances between all pairs of clusters are calculated and the two closest clusters are combined together. This process continues until all observations are grouped in one cluster. However, the question remains: how can the optimal clustering solution can be achieved? Among the various methods available, one widely used approach is Ward's method, as described by Kılıç and Akdamar (2020). Ward's method is conceptually similar to an analysis of variance (ANOVA) and computes the linkage function by evaluating the increase in the "error of the sum of squares" (ESS) when merging two clusters into one. The primary objective of Ward's Method is to minimise the increment in the ESS at each clustering step. This is similar to evaluating a linear model, where the ideal scenario is that all data points perfectly align with the regression line. However, if they deviate, the ESS becomes larger, indicating a poorer model fit. The clustering process is visualised using a dendrogram, which represents a tree-like structure. Determining the optimal number of clusters is a subjective task, as there is no universally established method (Banks and Fienberg, 2003; Dolnicar, 2002). Many researchers make practical decisions regarding the optimal number of clusters by examining the shape of the dendrogram (Banks and Fienberg, 2003). Alternatively, a distance or scree plot, which illustrates the distances between clusters after each clustering step, can be employed (e.g., Yim and Ramdeen, 2015). By observing when the distances between clusters no longer exhibit significant differences, a knee in the distance plot can be identified, which indicates the appropriate number of clusters to choose. Thus, the author also used this method and identified the knee to decide on the number of clusters for the study data. In the current study, categorical data is handled in the following manner during the above-mentioned process :

- If the data is ordinal, the clustering value is derived from the index of the ordered category and treated as continuous data. These values are standardised as if they were continuous.
- If the data is nominal, the distance between two observations is zero if their categories match. If the categories differ, the distance is set to one.

Alternative multivariate statistical methods were also examined; however, these did not yield any substantial insights. One of the main reasons for this outcome is that the model framework incorporates categorical demographic data, which is not compatible with these other multivariate analyses that are designed for continuous numeric data. Specifically, factor analysis identified three categories characterised by high factor loadings: (1) high intent to consume, food buying practice, and attitude; (2) perceived barriers to plant-based proteins, organic, and local foods; and (3) emotions and concerns. On the other hand, k-means clustering consistently determined that the optimal number of clusters was two. However, because hierarchical cluster analysis aligns more effectively with the nature of the data and the research objectives of the current study, the market segmentation undertaken in the current study was based on the outcomes of the hierarchical cluster analysis. Therefore, only the clusters identified by the hierarchical cluster analysis are discussed throughout the rest of the thesis.

3.4.3 Analytical Limitations

There were a few limitations to the study's data collection approach. First, most of the participants were from the Greater Toronto area where the availability of sustainable foods is different compared to other, smaller cities and more rural areas in Canada. Secondly, the completion of the entire survey (i.e., sections for both consumption and buying patterns of sustainable food and gaming behaviour) required a considerable amount of time. On average, respondents spent over 20 minutes to complete the survey. This lengthy duration raises concerns that a shorter survey could have gathered more data, as participants may have experienced "survey exhaustion" and opted to skip optional text responses for certain questions. Additionally, it is important to acknowledge the limitations of online survey methodology. While online surveys offer advantages such as cost-effectiveness and wide reach, they are susceptible to self-selection biases, wherein individuals with specific biases may choose to participate. Furthermore, participants may provide incorrect responses intentionally or unintentionally, potentially influenced by factors such as a desire to expedite the survey completion process.

Chapter 4 : Results

4.1. Validating the Framework

4.1.1. Reliability of the questionnaires

The analytical sample consisted of a total of 376 participants, given these participants had provided an answer for all of the questions in the TPB and player type related questionnaires. Cronbach's alpha coefficients were calculated to ensure the reliability of the questionnaires. The Cronbach's alpha coefficient for the TBP questionnaire consisted of 49 questions was found to be 0.82. This was 0.79 for the gamification behaviour questionnaire consisted of 23 questions. Therefore, both questionnaires were deemed to be reliable given Cronbach's alpha coefficient values between 0.7 and .95 are considered to indicate the questionnaires are reliable, while values over 0.9 are considered to indicate collinearity (Tavakol and Dennick, 2011).

4.1.2. Distribution of the socio-demographic variables

A summary of the descriptive statistics is provided in Table 4-1. Of the 376 participants, 62.8% were female, 36.7% were male, and 0.5% self-identified as Other Gender. 9% of the participants were between 18 and 24 years, 40.4% were between 25 and 44 years, 37.5 % were between 45 and 64 years, and finally 13% were over 65 years of age. However, the gender distribution of the sample had a significantly higher ratio of female participants (~ 63%) compared to the Ontario population in 2020 (~ 53%). Upon investigation and inquiry with QuestMindshare, it was discovered that despite their efforts to achieve a sample distribution closely resembling the Ontario population, they encountered challenges in achieving an exact match. The predominant participation of females in the online survey led to a difference between the study sample and the Ontario population. Therefore, it is important to acknowledge that the gender distribution in the sample may introduce bias into the study findings.

Table 4-1: Socio-demographic distribution of the participants.

		Frequency	Percent
Gender	Female	236	62.8%
	Male	138	36.7%
	Other	2	0.5%
	Total	376	100%
Age	18-24	34	9%
	25-44	152	40.4%
	45-64	141	37.5%
	65- (+)	49	13%
	Total	376	100.0%
Number of people living in the household	1	68	18.1%
	2	130	34.6%
	3	88	23.4%
	4	64	17%
	5 (+)	26	6.9%
	Total	376	100.0%
Highest level of education	Grade School	12	3.2%
	High school diploma	82	21.8%
	College diploma or trade apprenticeship	110	29.3%
	Bachelor's degree	116	30.9%
	Master's degree	39	10.4%
	Ph.D.	12	3.2%
	I prefer not to say	5	1.3%
	Total	376	100.0%
Marital status	Married	187	49.7%
	Widowed	9	2.4%
	Divorced	34	9%
	Separated	18	4.8%
	Never Married	119	31.6%
	I prefer not to say	9	2.4%
	Total	376	100.0%
Total household income (after taxes)	(-) 25 000	46	12.2%
	25 000 – 35 000	25	6.6%
	35 001 – 50 000	45	12%
	50 001 – 75 000	79	21%
	75 001 – 100 000	75	19.9%
	100 001 – 150 000	58	15.4%
	(+) 150 000	31	8.2%
	I prefer not to say	17	4.5%
	Total	376	100%

4.1.3. Distribution of the continuous variables

The normality of the data was assessed to guide the selection of the statistical methods to be used in the next steps. B4 in the appendix shows the distributions for the TPB variables depicted as histograms with fitted normal curves where the X-axis is the sum of the Likert scale scores for all questions in that category. The skewness and kurtosis values are also provided. A value of zero for both the skewness and kurtosis calculated by the JMP software indicates normal distribution. For all the food related categories, a reasonably good fit of a normal distribution curve was observed, as well as low skewness and kurtosis values. The Food Abilities and Personal Moral Norm categories had the greatest departure from normality and were better characterised by a Weibull distribution. In the gamification categories, only Gaming Frequency Behaviour and Philanthropist user type were found to have somewhat higher skewness and kurtosis values (see appendix B5). In summary, since most of the data was found to be normally distributed, it was decided to employ parametric tests in this study where appropriate.

4.1.4. The association between the sociodemographic variables and the intention to consume sustainable foods

The detailed results of the bivariate analyses, examining the relationship between intention to consume sustainable foods and various demographic variables, can be found in the appendix A3. The statistical tests employed for the analysis include a Student's t-test for comparing the effect of gender and a Tukey HSD test for comparing multiple pairs of variables.

The analysis revealed no significant differences based on age groups the participants belonged to. However, a significant difference was observed in terms of gender, indicating that females had higher scores on intention to consume sustainable foods ($p = .0078$). The number of people living in the household did not emerge as a significant predictor of high intent to consume sustainable foods. On the other hand, married individuals were significantly more likely to have higher intent to consume sustainable foods compared to divorced couples ($p = .0072$). Household income did not show significant predictive power for intention to consume sustainable foods. However, the highest level of education attained was found to be a factor in certain situations.

Specifically, individuals with master's degrees or bachelor's degrees were significantly more likely to have the intention to consume sustainable foods compared to those with high school diplomas ($p = .0008$ and $.0251$, respectively).

Based on these findings, the bivariate analyses provide initial insights into the population with a high intent to consume sustainable foods, which includes educated, married females.

4.1.5. The relationship between framework variables and the intention to purchase sustainable foods

Multivariate scatterplot matrices and heat maps illustrating food-related category sum-scores, as well as the discussion of these results, can be found in the appendix A4.

4.1.6. Significant predictors of the intention to consume sustainable foods (i.e., objective-1)

The backward stepwise linear regression model results are presented in Table 4-2 below. The regression coefficients in the form of a standardised beta and their significance in the form of p-values, as well as their upper and lower confidence intervals are included in the table. Additionally, the variance inflation factor (VIF), which indicates potential multicollinearity issues in the model is also presented in the table. The standardised beta coefficients are of utmost interest in the current study as they signify the relative predictive value of each predictor for the intent to consume sustainable foods, as well as the direction of the relationship. These standardised coefficients are also useful because they transform the variables with different units into a common unit. This allows for a meaningful comparison of the strength of the coefficients across variables, as they are measured on the same scale.

The R-squared value for the regression model was found to be 0.64. The R-squared value is a statistical measure of how well the data fits the linear model. This value indicates the percentage of the variation in the predicted variable (i.e., the intent to consume sustainable foods) explained by the predictor variables in the linear regression model. This value ranges between 0 and 1, 1 indicating a perfect model fit (i.e., no deviation from the regression line; Rights and Sterba, 2019). Thus the R-squared value for the current model, 0.64, indicates a reasonably good fit, though not perfect.

The mathematical expression of the model can also be found in the appendix A5.

Table 4-2: Results from backward stepwise linear regression model to predict the intent to consume sustainable foods.

Term	Estimate	Prob>|t|	Lower 95%	Upper 95%	Std Beta	VIF
Intercept	12.75	<.0001	9.36	16.13	0	.
What is your age? [18 - 24]	-1.50	0.0140	-2.69	-0.30	-0.11	1.91
What is your age? [25 - 44]	1.19	0.0009	0.49	1.88	0.12	1.37
What is your age? [45 - 64]	0.70	0.0562	-0.02	1.43	0.07	1.43
What is your current marital status? [Divorced]	-1.91	0.0066	-3.14	-0.54	-0.10	1.29
Food buying practice	0.30	0.0004	0.13	0.46	0.15	1.73
Personal Moral Norm	0.43	<.0001	0.25	0.61	0.18	1.33
Perceived Behavioural Control	0.35	0.0003	0.16	0.54	0.14	1.42
Perceived barriers to buying Plant based foods	-0.22	<.0001	-0.30	-0.14	-0.19	1.15
Emotions/Concerns	0.16	0.0980	-0.03	0.35	0.06	1.49
Attitude	0.95	<.0001	0.73	1.16	0.39	2.02

As can be seen from the above table, among the framework variables, the "Attitude" category sum-score emerged as the strongest positive predictor of the intent to consume sustainable foods. It was closely followed by the sum-scores for the "Personal Moral Norm", "Food Buying Practice", and "Perceived Behavioural Control" categories. The results also showed that participants between 25 and 44 years of age were the most likely to have a high intent to consume sustainable foods.

On the other hand, the “Perceived barriers to buying plant-based foods” category sum-score was found to be the strongest negative predictor of the intent to consume sustainable foods. Similarly, participants between 18 and 24 years of age and participants who were divorced were found to be the least likely to have a high intent to consume sustainable foods.

All VIFs in the current study were found to be smaller than 2.5, indicating the absence of multicollinearity. It is worth noting that previous studies have reported VIF values as high as 10 without considering them problematic (Johnston et al., 2018). Therefore, the current study adopts a conservative threshold for VIFs, and it can be concluded that multicollinearity was not a concern in the backward stepwise linear regression model used.

4.2. Segmenting the study sample (i.e., objective 2)

The dendrogram and distance plot obtained from the hierarchical cluster analysis can be found in the appendix A6. By examining the curve of the distance plot and identifying the point of inflection or "knee" as the cut-off, six distinct clusters were determined. The resulting clusters are described in the Table 4-3 below, which also includes the number of participants in each cluster and their relative percentages. Notably, Cluster 1 comprises the largest proportion of the participants among all clusters.

Table 4-3: Number and percentage of participants in each cluster obtained from the hierarchical cluster analysis.

Cluster	**n**	**%**
1	124	33.2
2	50	13.4
3	43	11.5
4	70	18.7
5	48	12.8
6	39	10.4

4.3. Identifying the target segments (i.e., objective 3)

The cluster means for each category sum-score were converted into percentages to indicate the proximity of each cluster's mean score to the highest possible score in that category. These mean scores expressed as percentages are presented in Figure 4-1 below. Cluster 5 is found to have the highest intent to consume score (89.54%), followed by clusters 6 and 4, which have very similar intent to consume scores (i.e., 80.40% and 79.65%, respectively). Therefore, these clusters were identified as the target markets in the current study.

		Hierarchical cluster					
		1	2	3	4	5	6
N		124	50	43	70	48	39
Food buying practice (%)	Mean	44.89	46.20	48.14	51.86	61.25	59.83
Food Abilities (%)	Mean	80.81	58.67	80.62	81.14	91.67	82.91
Subjective Norm (%)	Mean	56.40	56.53	58.14	68.38	65.28	75.38
Personal Moral Norm (%)	Mean	70.91	60.27	68.22	80.67	89.44	88.21
Perceived Behavioual Control (%)	Mean	69.03	55.87	60.93	78.10	85.56	79.32
Perceived barriers - plant based foods (%)	Mean	60.44	62.74	60.13	48.73	34.76	75.02
Perceived barriers - organic foods (%)	Mean	54.84	61.71	57.21	46.20	33.81	71.94
Perceived barriers - local foods (%)	Mean	43.80	56.29	52.82	40.24	31.43	62.78
Emotions/Concerns (%)	Mean	46.53	42.00	50.47	57.93	63.02	64.62
Attitude (%)	Mean	48.66	51.60	48.68	64.76	80.14	72.99
Intention to Consume (%)	Mean	64.55	57.82	66.10	79.65	89.54	80.40

Figure 4-1: The cluster means for each category expressed as percentages.

4.4. Identifying the characteristics of the target segments (i.e., objective 4)

Given the Clusters 5, 6, and 4 are identified as the target segments, the characteristics of the participants of these clusters were identified and compared in in Figures 4-2 to 4-7 and are summarised in Table 4-4 below.

What is your gender? By Hierarchical cluster

	Freq / Share	Hierarchical cluster 1	2	3	4	5	6
What is your gender?	Male	46 37.1%	18 36.0%	20 46.5%	23 32.9%	12 25.0%	19 48.7%
	Female	78 62.9%	32 64.0%	23 53.5%	47 67.1%	36 75.0%	20 51.3%
	Total Responses	124	50	43	70	48	39

Figure 4-2: Gender distribution within each cluster.

What is your age? By Hierarchical cluster

	Freq / Share	Hierarchical cluster 1	2	3	4	5	6
What is your age?	18 - 24	0 0.0%	14 28.0%	1 2.3%	10 14.3%	4 8.3%	4 10.3%
	25 - 44	37 29.8%	24 48.0%	24 55.8%	28 40.0%	20 41.7%	18 46.2%
	45 - 64	61 49.2%	9 18.0%	16 37.2%	28 40.0%	17 35.4%	10 25.6%
	65+	26 21.0%	3 6.0%	2 4.7%	4 5.7%	7 14.6%	7 17.9%
	Total Responses	124	50	43	70	48	39

Figure 4-3: Distribution of ages within each cluster.

How many people live in household? By Hierarchical cluster

How many people live in household?	Freq / Share	Hierarchical cluster 1	2	3	4	5	6
1	Freq	14	8	25	0	16	5
	Share	11.3%	16.0%	58.1%	0.0%	33.3%	12.8%
2	Freq	54	10	16	20	15	14
	Share	43.5%	20.0%	37.2%	28.6%	31.3%	35.9%
3	Freq	38	16	2	17	6	8
	Share	30.6%	32.0%	4.7%	24.3%	12.5%	20.5%
4	Freq	14	12	0	22	7	9
	Share	11.3%	24.0%	0.0%	31.4%	14.6%	23.1%
5+	Freq	4	4	0	11	4	3
	Share	3.2%	8.0%	0.0%	15.7%	8.3%	7.7%
Total Responses		124	50	43	70	48	39

Figure 4-4: Distribution of number of members of the household within each cluster.

What is your current marital status? By Hierarchical cluster

What is your current marital status?	Freq / Share	Hierarchical cluster 1	2	3	4	5	6
Married	Freq	90	7	2	49	18	21
	Share	72.6%	14.0%	4.7%	70.0%	37.5%	53.8%
Widowed	Freq	3	2	1	1	1	1
	Share	2.4%	4.0%	2.3%	1.4%	2.1%	2.6%
Divorced	Freq	19	4	4	0	2	5
	Share	15.3%	8.0%	9.3%	0.0%	4.2%	12.8%
Separated	Freq	5	1	2	2	6	1
	Share	4.0%	2.0%	4.7%	2.9%	12.5%	2.6%
Not married	Freq	6	33	32	15	21	11
	Share	4.8%	66.0%	74.4%	21.4%	43.8%	28.2%
Prefer not to say	Freq	1	3	2	3	0	0
	Share	0.8%	6.0%	4.7%	4.3%	0.0%	0.0%
Total Responses		124	50	43	70	48	39

Figure 4-5: Distribution of marital status within each cluster.

Total household income By Hierarchical cluster

Total household income	Freq / Share	1	2	3	4	5	6
< 25k	Freq	3	10	14	3	10	6
	Share	2.4%	20.0%	32.6%	4.3%	20.8%	15.4%
25k-35k	Freq	7	3	6	3	2	4
	Share	5.6%	6.0%	14.0%	4.3%	4.2%	10.3%
35k-50k	Freq	15	6	9	4	6	3
	Share	12.1%	12.0%	20.9%	5.7%	12.5%	7.7%
50k-75k	Freq	34	9	11	9	8	8
	Share	27.4%	18.0%	25.6%	12.9%	16.7%	20.5%
75k-100k	Freq	29	6	3	20	8	9
	Share	23.4%	12.0%	7.0%	28.6%	16.7%	23.1%
100k-150k	Freq	19	6	0	16	10	7
	Share	15.3%	12.0%	0.0%	22.9%	20.8%	17.9%
> 150k	Freq	13	1	0	12	3	2
	Share	10.5%	2.0%	0.0%	17.1%	6.3%	5.1%
Prefer not to say	Freq	4	9	0	3	1	0
	Share	3.2%	18.0%	0.0%	4.3%	2.1%	0.0%
Total Responses		124	50	43	70	48	39

Figure 4-6: Distribution of total household income within each cluster.

Highest level of education? By Hierarchical cluster

Highest level of education?	Freq / Share	1	2	3	4	5	6
Grade School	Freq	2	3	2	0	1	3
	Share	1.6%	6.0%	4.7%	0.0%	2.1%	7.7%
High School	Freq	26	21	11	9	8	7
	Share	21.0%	42.0%	25.6%	12.9%	16.7%	17.9%
College Diploma	Freq	39	11	14	21	12	12
	Share	31.5%	22.0%	32.6%	30.0%	25.0%	30.8%
B.A.	Freq	38	14	15	25	15	9
	Share	30.6%	28.0%	34.9%	35.7%	31.3%	23.1%
M.A.	Freq	11	0	1	12	10	5
	Share	8.9%	0.0%	2.3%	17.1%	20.8%	12.8%
Ph.D.	Freq	5	1	0	1	2	3
	Share	4.0%	2.0%	0.0%	1.4%	4.2%	7.7%
Prefer not to say	Freq	3	0	0	2	0	0
	Share	2.4%	0.0%	0.0%	2.9%	0.0%	0.0%
Total Responses		124	50	43	70	48	39

Figure 4-7: Distribution of education level within each cluster.

Table 4-4: Characteristics of the clusters with the highest intent to consume (i.e., the target markets).

Cluster 5 (Highest intent to consume)	Cluster 6 (2nd highest intent to consume)	Cluster 4 (3rd highest intent to consume)
● Low perceived barriers to buying plant-based proteins, organic, and local foods ● High Attitude, Food abilities, Personal moral norm, and Perceived behavioural control, Food buying practice, and Emotions/Concerns ● 75% female ● Highest percentage of members with a bachelor's or postgraduate degree ● Highest percentage of members earning 75k and more ● Highest behaviour to intention gap among all other segments	● High Food abilities, Personal moral norm, Subjective norm, Attitude, Perceived behavioural control, Food buying practice, and Emotions/Concerns ● High perceived barriers to buying local foods, especially for plant-based proteins and organic foods ● Highest percentage of PhDs ● 3rd highest behaviour to intention gap among all other segments	● Scored highest in number of members in household ● Also highest in total household income ● Along with cluster 5, highest percentage of members with a bachelor's or postgraduate degree. ● Lower food buying practice than the other two higher intent segments ● Lower perceived barriers to consume all three sustainable food types ● 2nd highest behaviour to intention gap among all other segments

Clusters 5 and 6 share similar characteristics, but they differ in terms of perceived barriers to buying plant-based, local, and organic foods. Additionally, Cluster 5 consists of individuals who are more highly educated and more likely to be women. Both clusters have high scores in food buying practice, indicating a significant level of sustainable diet purchases. However, Cluster 4 has a considerably lower food buying practice score compared to Clusters 5 and 6. This suggests that individuals in Cluster 4, despite their high intent to consume sustainably, are not translating that intention into actual purchases as much as the other two segments.

The "behaviour gap" can be defined as the difference between intention to consume and food buying practice. For Cluster 5, this gap is approximately 28.29%, similar to Cluster 4's gap of 27.79%. Cluster 6, on the other hand, has a lower behaviour gap of 20.57%. Based on this definition, the market segments that would benefit most from targeted interventions are clusters 4 and 5. Cluster 4 consists of individuals with medium scores in all variables but stands out in terms of socio-demographics, with larger households and higher total incomes. Cluster 5 is primarily composed of highly educated females. Although both clusters have potential as target markets due to their behaviour gaps, Cluster 5, with its higher level of intention and larger behaviour gap, should be considered the prime target market.

Cluster 1 is the largest cluster, but it has the second-lowest intention to consume, as well as the lowest attitude, subjective norm, and food buying practice scores. The majority of Cluster 1 members are married and fall into the age brackets of 45-64 and over 65. This cluster can be described as "older." While it presents a large market segment, considerable effort may be required to convince its members to adopt a sustainable diet.

Lastly, Cluster 2 has the lowest intent to consume a sustainable diet. It ranks lowest on all TPB variables and consists of younger, predominantly unmarried individuals.

It is worth noting that the Clusters 4, 5, and 6 score the highest on the category sum-scores that most strongly positively predict the intent to consume sustainable foods (i.e., Attitude, Personal Moral Norm, Food Buying Practice). This convergence of results from different statistical methods adds to the reproducibility and validity of the analysis.

4.5. Identifying the relationships between gamification elements, mobile applications, and the target markets (i.e., objective 5)

4.5.1. Mobile application rankings and the target markets

Figure 4-8 below presents the rankings of mobile application types in terms of preferred usage among the target markets (i.e., Clusters 4, 5, and 6) as well as the largest cluster (i.e., Cluster 1) identified in the current study. The figure uses colour coding to group the rankings: apps ranked 1st or 2nd are shown in red, apps ranked as 3rd-6th are shown in green, and apps ranked as 7th-12th are shown in blue. The highly ranked apps that have a significant share within Clusters 4, 5, 6, and 1 are of special interest given the study objectives.

The results reveal that social media apps are highly ranked by the participants in Clusters 4, 5, and 6. This suggests that a social media marketing campaign would be an excellent starting point to persuade these clusters to engage in sustainable purchasing practices. Moreover, members of Cluster 5 show a strong preference for personal fitness and wellness apps, with Clusters 6 and 4 also ranking these apps as the second and third most favoured choices. Hence, targeting these clusters with personal fitness and wellness apps could be an effective strategy too.

It is unsurprising to find that personal finance or banking apps are widely used across all clusters, likely driven by necessity rather than a specific interest in sustainability. Cooking and recipe instruction apps also emerge as good candidates for a marketing campaign, especially for Cluster 1 and to a slightly lesser extent Cluster 6. Thus, a potential approach could involve providing recipes that incorporate sustainably produced ingredients. Cluster 6 also exhibits a high ranking for food delivery service apps. However, it remains unclear whether this usage primarily pertains to sustainable food delivery services or standard takeaway and fast-food deliveries, which typically offer mostly unsustainable food. If the usage predominantly relates to sustainable food delivery, a marketing campaign in this area may be successful.

Overall, the findings suggests that a social media marketing campaign targeting Clusters 4, 5, and 6 would be beneficial in promoting sustainable food consumption. Additionally, personal fitness and wellness apps, cooking and recipe instruction apps, and potentially sustainable food delivery services are areas that could be considered for targeted marketing efforts. The contingency table for the preferences of mobile apps as a function of cluster membership can be found in appendix B6.

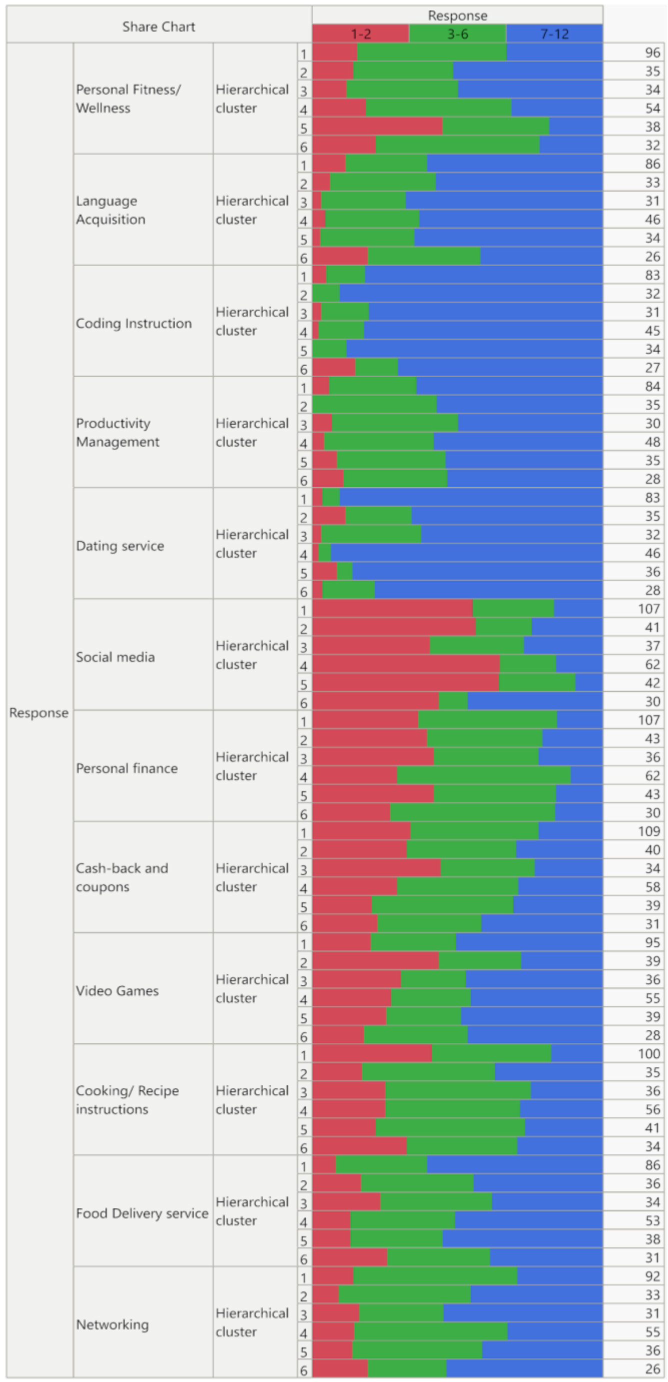
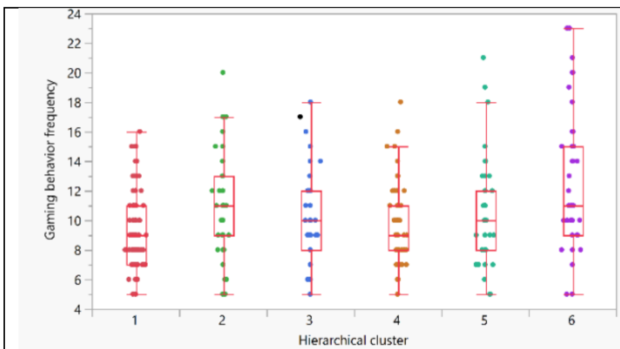


Figure 4-8: Bar chart showing app usage as a function of hierarchical cluster membership. Apps ranked 1st or 2nd are grouped together and shown in red, apps ranked between 3-6 in green, and apps ranked between 7-12 in blue.

4.5.2. Gamification elements and the target markets

The Tukey HSD test was conducted to examine significant differences between the clusters' scores for gaming variables. Clusters 4 and 5, which showed high intention to consume but also a behaviour gap, were of particular interest. Cluster 6, characterised by high intention and favourable food buying practices, on the other hand, still perceived barriers to sustainable diet purchases. Targeted marketing campaigns may help address these concerns. Cluster 1, despite its large size, requires significant effort to increase their intention to consume. Figures 4-9 to 4-15 below present the results for gaming behaviour frequency and player types.

Clusters 4 and 5 ranked 5th and 3rd, respectively, in gaming behaviour frequency (Figure 4-9). They scored significantly lower than cluster 6 ($p < .0001$ for Cluster 6 vs cluster 4, and $p = .0280$ for Cluster 6 versus cluster 5), which was the highest scoring cluster. Cluster 1 had the lowest gaming behaviour frequency score, which did not significantly differ from those of Cluster 4 ($p = .9626$) or Cluster 5 ($p = .1267$), but was significantly lower than that of Cluster 6 ($p < .0001$). Thus, it can be concluded that a marketing campaign based on gamification would be more successful for participants in Cluster 6, while its impact may be relatively lower for those in Clusters 4, 5 and 1.



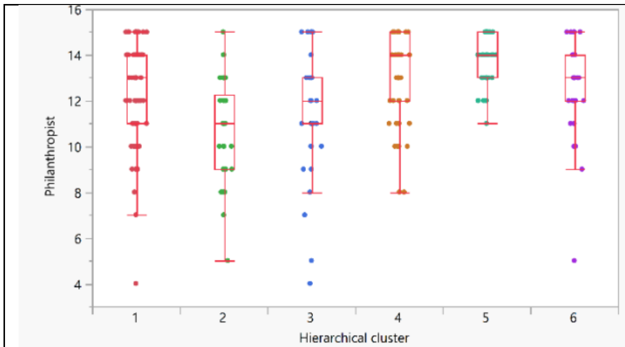
Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean	Lower 90%	Upper 90%
1	124	9.23	2.47	0.22	8.86	9.59
2	50	10.78	3.45	0.49	9.96	11.60
3	43	9.98	3.16	0.48	9.17	10.79
4	70	9.61	2.71	0.32	9.07	10.15
5	48	10.56	3.38	0.49	9.74	11.38
6	39	12.64	4.72	0.76	11.37	13.91

Figure 4-9: Gaming behaviour frequency scores as a function of cluster membership.

Members of Cluster 4 and 5 showed the highest scores in the Philanthropist player type (Figure 4-10). Cluster 5 had the highest score, although not significantly higher than Cluster 4 ($p = .1860$).

However, Cluster 5 did score significantly higher than Cluster 6 (p = .0083) and Cluster 1 (p < .0001). Based on these results, marketing campaigns targeting the Philanthropist player type could be successful.

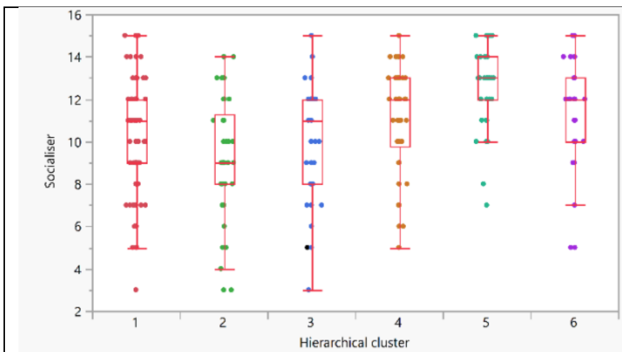


Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean	Lower 90%	Upper 90%
1	124	12.43	1.95	0.17	12.14	12.72
2	50	10.68	2.22	0.31	10.15	11.21
3	43	11.79	2.49	0.38	11.15	12.43
4	70	13.16	1.74	0.21	12.81	13.50
5	48	14.00	1.11	0.16	13.73	14.27
6	39	12.56	1.92	0.31	12.05	13.08

Figure 4-10: Philanthropist user type scores as a function of cluster membership.

Cluster 5 ranked the highest for the Socialiser player type (Figure 4-11), while Cluster 4 ranked third. There was a significant difference in scores between Cluster 5 and Cluster 4 (p = .0095). Cluster 6 ranked second, but the differences were not significant compared to Cluster 5 (p = .2380) or Cluster 4 (p = .9645). Thus, sustainable food buying practice campaigns targeting Socialiser player types may also prove effective.

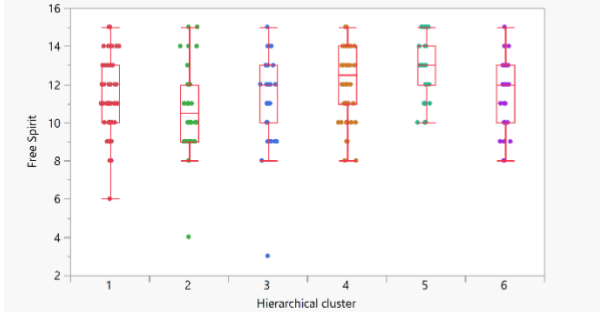


Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean	Lower 90%	Upper 90%
1	124	10.33	2.64	0.24	9.94	10.72
2	50	9.30	2.70	0.38	8.66	9.94
3	43	10.14	2.62	0.40	9.47	10.81
4	70	11.16	2.45	0.29	10.67	11.64
5	48	12.75	1.84	0.27	12.30	13.20
6	39	11.56	2.38	0.38	10.92	12.21

Figure 4-11: Socialiser user type scores as a function of cluster membership.

Cluster 5 ranked the highest in the Free Spirit player type (Figure 4-12), followed closely by Cluster 4 in the second position. The scores for these two clusters were not significantly different (p = .1863). Cluster 6 had the third highest score, which was significantly lower than Cluster 5 (p = .0109), but not significantly different from Cluster 4 (p = .6967). Therefore, targeting Free Spirit player types may be an effective strategy for interventions.

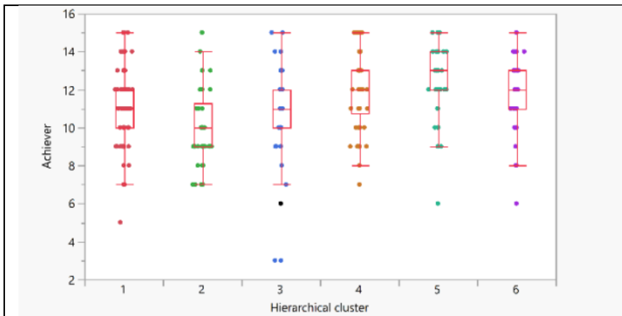


Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean	Lower 90%	Upper 90%
1	124	11.53	1.74	0.16	11.27	11.79
2	50	10.72	2.08	0.29	10.23	11.21
3	43	11.28	2.16	0.33	10.72	11.83
4	70	12.21	1.70	0.20	11.88	12.55
5	48	13.00	1.44	0.21	12.65	13.35
6	39	11.69	1.75	0.28	11.22	12.16

Figure 4-12: Free Spirit user type scores as a function of cluster membership.

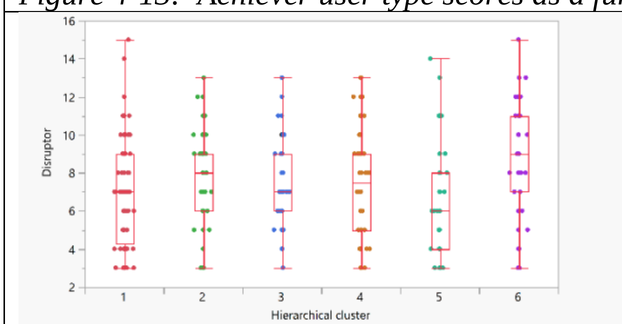
For the Achiever player type (Figure 4-13), Cluster 5 was again the top performer, followed by Clusters 6 and 4. However, these scores did not differ significantly (p > at least .1714). In the Disruptor player type (Figure 4-14), Cluster 6 scored the highest, while Cluster 4 ranked fourth, with a weakly significant difference compared to Cluster 6 (p = .0664). Cluster 5 had the lowest score among all clusters, significantly lower than Cluster 6 (p = .0002), but not significantly lower than Cluster 4 (p = .2955). Therefore, interventions targeting Disruptor player types may be less effective compared to other player types discussed thus far.



Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean	Lower 90%	Upper 90%
1	124	11.27	1.89	0.17	10.99	11.55
2	50	10.10	1.96	0.28	9.63	10.57
3	43	10.84	2.60	0.40	10.17	11.50
4	70	11.74	1.96	0.23	11.35	12.13
5	48	12.65	1.99	0.29	12.16	13.13
6	39	11.79	2.08	0.33	11.23	12.36

Figure 4-13: Achiever user type scores as a function of cluster membership.

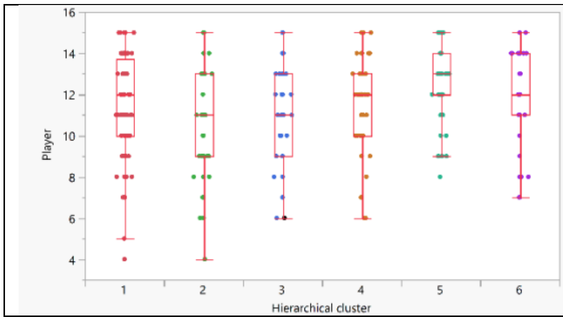


Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean	Lower 90%	Upper 90%
1	124	6.81	2.65	0.24	6.42	7.21
2	50	7.88	2.37	0.34	7.32	8.44
3	43	7.56	2.40	0.37	6.94	8.17
4	70	7.46	2.66	0.32	6.93	7.99
5	48	6.42	2.91	0.42	5.71	7.12
6	39	8.92	2.97	0.48	8.12	9.72

Figure 4-14: Disruptor user type scores as a function of cluster membership.

For Player user type (Figure 4-15) Cluster 5 ranked the highest, with Clusters 6 and 4 following closely. However, there were no significant differences between the scores of these clusters (p > at least .2577). Thus, Player type would also make an effective target for an intervention campaign.



Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean	Lower 90%	Upper 90%
1	124	11.60	2.32	0.21	11.25	11.94
2	50	10.50	2.54	0.36	9.90	11.10
3	43	11.21	2.43	0.37	10.59	11.83
4	70	11.67	2.22	0.27	11.23	12.11
5	48	12.60	1.95	0.28	12.13	13.08
6	39	11.82	2.30	0.37	11.20	12.44

Figure 4-15: Player user type scores as a function of cluster membership.

Overall, the comparisons between the target segments based on player types did not yield significant insights for tailoring intervention campaigns to increase sustainable food consumption. The lack of significant differences in player type scores among the target segments suggests that player types may not be a reliable indicator for designing effective intervention strategies. Additionally, the low gaming behaviour frequencies in the target segments make it challenging to specifically target a market segment based on player types. However, avoiding the targeting of the Disruptor player type can be recommended based on the study results. Alternative approaches are needed to effectively engage and target these market segments in interventions promoting sustainable food consumption.

4.5.3. Specific gaming behaviour and the target markets

Despite not finding significant differences between the target markets in overall gaming behaviour, it is worth exploring the relationships between the target markets and the frequency of playing specific types of games. By examining the relationship between each Likert-scale question and the target market, the data is treated as categorical rather than continuous numeric.

The bar chart in Figure 4-16 directly below visualises these relationships, and detailed contingency tables can be found in the appendix B7.

Figure 4-16: Specific game playing frequencies as a function of hierarchical cluster membership.

Examining the "Most of the time" (Orange) and "Always" (Turquoise) responses for Clusters 4, 5, and 6, for example, it can be observed that Cluster 6 has the highest proportion of frequent players in categories such as board games, casino games, and games without equipment. In contrast, Cluster 5, representing individuals with the most frequent food buying practices, has the highest share of individuals who never play casino games and video games, as indicated by the absence of Turquoise bars. Cluster 4, on the other hand, shows limited engagement with these game types, as evidenced by the absence of Turquoise bars in the board games, casino games, and games without equipment categories. These results suggest that a gamification-based marketing approach is unlikely to be effective for individuals in Cluster 4.

4.6. Text Analysis

Text analysis was performed on the open-ended question responses collected by the study survey. This was intended to identify whether the participants could name any other barriers to purchasing the different types of sustainable foods that were not already listed in the questionnaire. However, because the results are not directly relevant to the current study's objectives, the details regarding this text analysis and its results have been presented in Appendix C.

Chapter 5: Discussion and Conclusions

5.1 Discussion

A very small portion of the world population consumes a sustainable diet, which creates significant environmental problems. Thus, increasing sustainable food consumption is of utmost importance. However, the literature suggests that a marketing approach purely based on information and facts would be inefficacious in promoting sustainable food consumption. The evidence from the literature suggests that the persistent sustainable behaviour gap should be tackled by targeting people having a high intent to adopt the sustainable behaviour with behaviour change tools (Meyer-Höfer et al., 2015; Klöckner, 2015; Klaniecki et al., 2018). Gamification (i.e., the use of game elements in a non-game context) was established as a promising behaviour change vehicle in a wide variety of behaviours, including sustainable food consumption. Even though the success of interventions based on gamification can be inconsistent depending on the specific context and persons being targeted, the literature revealed that successful applications of gamification for interventions to change food behaviours also exist, thus suggesting sustainable food consumption is an appropriate context to implement gamified interventions. Segmentation can be used to understand what motivates and prevents a consumer group from implementing the sustainable behaviour in their lives as well as to determine whether gamification could be a good fit depending on the types of sustainably minded consumer clusters.

Therefore, the objectives of the current study were i) to identify variables that significantly predict the intention to purchase sustainable foods, ii) to segment the study sample based on sociodemographic variables and characteristics that were previous found to be relevant to sustainable food consumption (i.e., the TPB variables), iii) to identify target segments with a gap between intention and actual consumption behaviour, indicating high intention but low engagement in sustainable food consumption, iv) to examine the traits of these target segments, including player types, gaming behaviours, and mobile application preferences, and finally v) to inform the tailoring of gamified interventions and mobile applications to increase sustainable food consumption in the target segments based on their traits.

The preliminary results, obtained through descriptive statistics and bivariate analyses, indicated that university-educated, married females exhibited a significant intention to adopt a sustainable diet overall. These results are consistent with the existing literature on sustainable food consumption and provide the first clues into the characteristics of the target segments the current study aims to identify. However, due to the potential confounding effects of the numerous variables included in the study and the possibility of redundancy among them, a backward stepwise linear regression model was utilised to identify any such variables, as well as to identify the strongest predictors of the intent to consume sustainable foods (i.e., study objective-1). The results suggested the strongest predictors of the intent to consume a sustainable diet were the sum-scores for the TPB categories of "Attitude", "Personal Moral Norm", "Food Buying Practice" and "Perceived Behavioural control." These findings were, too, consistent with the current literature on sustainable food consumption. Additionally, the analysis revealed that participants in the age range of 25-44 years exhibited the highest likelihood of having a strong intent to consume sustainable foods. On the other hand, the results revealed that the sum-score for the TPB category of "Perceived barriers to buying plant-based foods", and being in the 18-24 age range and being divorced negatively predicted the intent to consume a sustainable diet.

Next, hierarchical cluster analysis was employed to segment the study sample based on sociodemographic and TBP variables (i.e., study objective-2). Hierarchical cluster analysis was chosen as the statistical method to segment the study sample, given the study includes a mix of categorical and numerical variables, which means employing k-means clustering was not possible. Followingly, target segments, who have a high intent to consume sustainable foods, but exhibit an intention - behaviour gap that prevents them from doing so on a regular basis, were identified (i.e., study objective-3). Using hierarchical clustering, two clusters (Clusters 4 and 5) were identified to have a high intention to consume sustainably, but scored rather poorly in the TPB "Food buying practice" category sum-score. These two clusters exhibited the intention - behaviour gap previously discussed and were identified as the target segments for the current study.
Followingly, the characteristics of these target segments were examined (i.e., study objective-4) and how to best tailor gamified interventions for these target segments were discussed (i.e., study objective-5). Cluster 4, was found to have the highest number of members in the household, which means persons belonging to this cluster could potentially impact the food consumption of many other individuals not directly targeted by the intervention. Members of the Cluster 4 also had the highest total incomes and were well-educated. These are likely larger families where both parents are likely to be professionally employed. This group represented 18.7% of the study sample.

However, when gaming behaviour frequency of these target segments was analysed, Cluster 4 scored second lowest out of the all six segments identified in the current study. This casts doubt on the effectiveness of gamified interventions for the intention - behaviour gap of this particular segment since game experience greatly influences the success of such interventions. Nonetheless, if a gamification intervention was to be designed for Cluster 4, the results indicate targeting the Philanthropist, Free Spirit, or Achiever player types would be the best strategy. Despite concerns regarding the effectiveness of gamification interventions due to the low frequency of game behaviours among this target segment, it is noteworthy that Cluster 4 showed the highest usage of social media apps compared to other target segments. Therefore, an intervention campaign with a strong presence on social media platforms would have the greatest potential for effectiveness.

Cluster 5, on the other hand, demonstrated the highest behaviour to intention gap (slightly higher than Cluster 4), as well as the highest level of intention out of all segments. Thus, Cluster 5 can be considered the primary target segment/market based on the sustainable behaviour change literature previously discussed. Cluster 5 represents 12.8% of the study sample, scored highest in positive attitude towards sustainable food consumption, and is mainly composed of female members (75%). This cluster was ranked the 3rd highest in game behaviour frequency, which suggests they have a medium game behaviour frequency. Cluster 5 is also the most likely to be a Philanthropist player type, and second most likely to play board games. This target segment is also very likely to use social media. Finally, this segment is the most likely to be both a Philanthropist and Socialiser player type. The Cluster 5 is the most likely to use personal fitness/wellness apps. The results of the current study suggest that online food stores (e.g., Amazon, grocery stores' online platforms, etc.) might not be suitable to implement gamification elements, as the gaming behaviour frequency scores were low and medium for the target markets (i.e., Clusters 4 and 5, respectively).

A third segment that was identified as potentially being of interest was Cluster 6. It represented the smallest percentage of the study sample (10.4%) but was of interest given they exhibited somewhat of a disconnect in consumer behaviour. These participants had the second highest intent to consume a sustainable diet, the second highest food buying practice, and the third biggest intent - behaviour gap. Yet, they also, by a large margin, perceived the highest barriers to purchasing local, organic, and plant-based foods out of all segments.

It is puzzling therefore, how one can have these perceptions of barriers yet still rank highly in food buying practice. It may be related to the individual differences in the perceptions of the barriers. Some people may perceive the higher prices of sustainable foods as a barrier, while others may think about how little time they have to shop for and cook those foods. The Cluster 6 tends to had a high household income, however also ranked food delivery, language acquisition, and networking mobile applications higher than any other segments. These participants may have a busy lifestyle requiring the need to travel internationally on a regular basis and therefore struggle to find the time necessary to consume a sustainable diet. This group may believe that having to make special trips to local markets or health food stores, rather than a single visit to a grocery store, is a barrier to sustainable food consumption. Moreover, out of all the clusters, Cluster 6 had the most frequent players of board games, casino games, games without equipment, and card games. This suggests that Cluster 4 may be more receptive to a gamified marketing campaign promoting sustainable food purchases, increasing the likelihood of successful engagement with this segment.

Each of the player types have their own specific psychological needs and are motivated by different sorts of design elements (Marczewski, 2015). Certain game design elements associated with the fulfilment of those needs were therefore established as useful to appeal to and motivate each player type (Marczewski, 2015; Gil et al., 2015; Tondello et al., 2016). An examination of the player type scores as a function of the different socio-demographic variables was also carried out (see appendix A7 through A12) including only the respondents with a high intent to consume (Clusters 4, 5 and 6). If certain socio-demographic variables were common to clusters with high intent to consume and to certain player types, this information would also drive a gamified marketing strategy. There was no difference in any of the player type scores based on age, number of members living in the household, or marital status. Females were significantly more likely to score higher as Philanthropist player types than males ($p = .0154$) and less likely to be Disruptors ($p = .0010$) and Achievers ($p = .0124$). In terms of household income, those that preferred not to disclose what their incomes scored weakly significantly to very significantly lower than all other income categories ($p = .1247$ to $.0147$) in the Achiever player type. In terms of education, there was some indication that more educated people scored higher in the Free spirit and Achiever player types (Master's degree versus high school diploma), but this general statement was not consistent as there was no difference in these player scores between participants with a PhD and a high school diploma. These results do suggest, however, that by designing a gamification strategy that appeals to Philanthropists, this would more likely appeal to women who also make up more than 75% of the members of Cluster 5 (Table 5) that have the highest intent to consume, as well as the highest behaviour to intention gap. Another way of interpreting this is to say that there is no particular advantage of targeting a specific player type, but to ensure that the Disruptor player type is avoided.

Because of the target segments' (Clusters 4 and 5) scores in the User type category, it is recommended to avoid using game design element associated with Disruptor user type, but instead to favour the ones associated with Philanthropist and Free Spirit user types when designing the intervention. For instance, Philanthropists are altruistic, they are motivated by purpose and meaning. They want to give to others without expecting rewards. The game design elements associated with this player type are Collection and Trading, Gifting, Knowledge sharing, and Administrative roles. Free Spirits are independent thinkers. They are motivated by autonomy and self-expression; they want to create and explore. The game design elements associated with this player type are: Exploratory tasks, Nonlinear gameplay, Easter eggs, Unlockable or rare content, Creativity tools, and Customisation. The gamification elements associated with the Disruptor type must be avoided. The disruptor player type is motivated by change. The game design elements associated with this player type are Innovation Platforms, Development tools, Anonymity and Voting mechanisms.

Interventions delivered via mobile applications would be most effective if they were delivered through social media and included game design elements associated with Philanthropist and Free Spirit user types in order to change the behaviours of the target markets (i.e., Clusters 4 and 5). When examining how to target the clusters with the highest intent (i.e., Clusters 4,5, and 6), the results suggest that besides social media, they also all enjoy personal fitness & wellness applications. In fact, the higher the cluster's intent to consume low impact foods, the more they prefer to use this type of applications. When making designs to influence the behaviours of those three clusters combined (4,5, and 6), design elements associated with Cash Back and Coupons applications should be avoided. Regarding game behaviours, while Cluster 4 favours video games, the Clusters 5 and 6 both enjoy board games.

There are other market segments that might be of interest, but not because they show a significant intention - behaviour gap regarding the consumption of a sustainable diet. One could argue that behaviour change interventions should also target the group that do not have a high intent to change. This could be hypothetically done by attempting to affect the most significant factors of the intention to adopt a sustainable diet (i.e., attitude, personal moral norm, etc.). Increasing their intention using behaviour change tools and thus increasing the likelihood that they will consume more sustainable foods may close the intent – behaviour gap. For instance, paying attention to Cluster 1 is particularly relevant due to its significant size, accounting for 33.2% of the study sample. This cluster had a very low intent to consume and poor scores for food buying practice, and thus a great deal of effort would be necessary to convince them to purchase and consume a sustainable diet. However, even if only a small percentage could be convinced, the impact could be significant. This cluster also scored low on gaming behaviour frequency, so again the effectiveness of the gamification of interventions is questionable, and they do not identify strongly with any of the gamification player types. However, they did rank usage of cooking and recipe instruction mobile applications higher than any other segment, thus, attempting to appeal to them through these mobile applications may be a first step in their conversion to a sustainable diet, perhaps by sharing recipes that use predominantly or even exclusively sustainable ingredients.

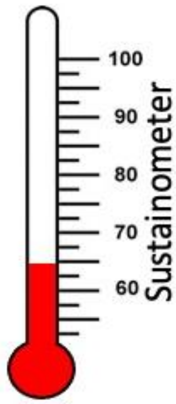
It is also insightful to look at the results of this study in the light of Aertsens and colleagues' review (2009) of the personal determinants of organic food consumption, where the authors state that they could not quantify the relationships between all variables in their integrated framework. The current study, on the other hand, takes a significant step in that direction. They note that attitude, subjective and personal moral norms, as well as perceived behaviour control influence consumption of organic foods. The results of the current study do not only support these assertions but also quantifies these relationships. Aertsens and colleagues (2009) also point out a need for future research focusing on a more detailed description of the values, attitude, involvement, and motivations and barriers of different user segments. The current study provides information on these factors as well, as sum-scores representing these categories were created and included in the analyses. Future studies may analyse the relationship between the specific components that made up these sum-scores and provide more detail on these relationships.

An interesting point that Aertsens and colleagues (2009) mention that several authors found that household income was significantly positively correlated with organic food purchases in

Europe, Canada, and Australia. The current study results, however, did not indicate such a relationship. There was no significant correlation between the household income and the intent to consume a low impact diet as defined in this study. Aertsens and colleagues (2009) also pointed out that socio-demographics played a limited role, though there are suggestions that a higher proportion of women have a much higher intent to purchase organic foods compared to men, and that families with children are more likely to purchase organic products. The results of this study also supports these findings.

5.2 User Personas

User personas are used in the marketing and user experience design fields. Those personas are representative of the data collected on archetypical users whose goals and characteristics represent the needs of a larger group of users. They are meant to provide a deep understanding of a target audience (i.e., to understand the expectations, concerns, and motivations of target users) in order to design a product that will satisfy users' needs and therefore be successful.



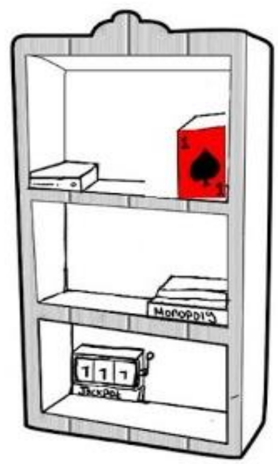
Cluster/Persona #1: Donna

Age: 52
Education: College Diploma
Family: Married
Household: Living with her partner
Income: 60k

About games:
"I usually don't play games at all, and no one dislikes board games and games like charades as much as I do, but if I did play, I would tolerate card games."

About Food:
"I do not consider buying low impact foods. I do love to cook and enjoy using my recipe apps and sometimes even coupon apps on my phone. I do not intent to eat sustainably even if I am capable to do so. I don't see my social circle and I eat such diet.

My phone and game shelf



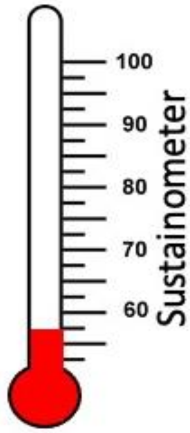
Sustainable food consumption and sociodemographic characteristics

- 45-64 years of age
- Female
- College diploma/University graduate
- Married
- Income 50-75k
- Amongst least likely to consume sustainably
- High food abilities
- No major perceived barriers to consuming sustainably, but a poor attitude towards it
- Represents the largest fraction of the population

Game and application related characteristics

- Least likely to play any kind of games
- Will tolerate card games
- Next to Philanthropist player type, best described as Player player type
- Most likely to use cooking/ recipes apps
- Likely to use cash back/coupon apps
- Least likely to use a food delivery service

Figure 5-1 : User Persona Cluster #1



Cluster/Persona #2 Melissa

Age: 26
Education: High School Diploma
Family: Not married
Household: Living with a couple of friends
Income: < 25k

About games:

"My friends and I play a lot of video games, both on our computers and on our phones. We have made a lot of on-line friends that way. Otherwise, we don't really play cards or board games or anything like that much at all."

About Food:

"I don't consider buying low impact foods. I don't know how to cook well so I rely a lot on pre-packaged food. I'm not all that concerned about the environment at the moment"

My phone and game shelf

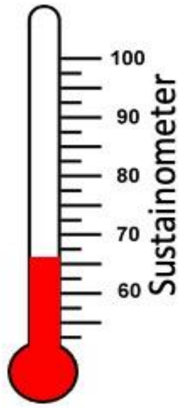
Sustainable food consumption and sociodemographic characteristics

- 25-44 years of age
- Female
- Not married
- High school diploma
- Income < 25k
- Least likely to consume sustainably
- Lowest food abilities and perceived behavioural control.
- Lowest personal moral norm (regarding climate change).

Game and application related characteristics

- High gaming behaviour frequency overall
- Most frequent video game player
- Best described as Free Spirit player type.
- Her favorite apps are video games, and she dislikes cooking/ recipe apps
- Most likely to use dating apps

Figure 5-2 : User Persona Cluster #2



Cluster/Persona #3 Brad

Age: 28
Education: College Diploma/University Graduate
Family: Not married
Household: Living by himself
Income: < 25k

About games:

"I'm currently between jobs and finding it hard. I enjoy going to the casino and playing games there, always hoping I will strike it rich! Otherwise, I'm not really into games all that much though will play a few on my phone from time to time. "

About Food:

"I think I am a reasonably good cook and use my coupon app to help save a bit of money at the grocery store. I would not say I never think about the impact my food choices has on our environment; but it does creep into my mind from time to time. I could exercise more control over what I eat, because I am somewhat concerned about the impact of my diet. However, consuming sustainably is not important to me.

My phone and game shelf

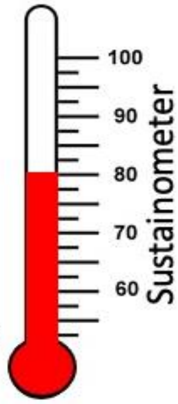
Sustainable food consumption and sociodemographic characteristics

- 25-44 years of age
- Male
- Not married
- College Diploma/University Graduate
- Income < 25k
- Not very likely to consume sustainably
- Generally poor perceived behavioural control and attitude towards buying low impact foods.

Game and application related characteristics

- Not a big gamer but enjoys playing casino games the most.
- After Philanthropist, best described as a Socializer player type.
- Biggest user of cash back and coupons apps.
- Could use either a recipe app or a food delivery app

Figure 5-3 : User Persona Cluster #3



Cluster/Persona #4 Melanie

Age: 43
Education: University Graduate
Family: Married
Household: Living with her partner and two children
Income: 85k

About games:

"With both my partner and I working and between talking the kids to all their various activities, we don't have much time for games. But occasionally, we will join in and play video games with the kids. We are no good, but it is worth a good laugh"

About Food:

"I enjoy cooking when I find the time and do try to buy sustainable foods when I can, but I know I can do better. Some people think it is difficult to get good local sustainably farmed food, but I don't see the problem as much as others, just need to do it more. I would say I am concerned about and feel responsible of our environment, however I am so busy balancing work and family that having a sustainable diet is not my biggest priority"

Sustainable food consumption and sociodemographic characteristics

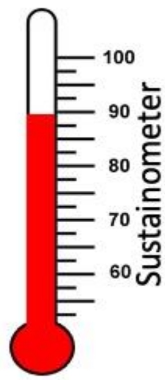
- 25-64 years of age
- Female
- Married with kids
- University Graduate
- Income 75-100k
- Tries to consume sustainably and has good intentions to do so despite an average attitude
- High subjective norm, low perceived barriers for low impact foods

My phone and game shelf

Game and application related characteristics

- Not a big gamer but her favorite type of game are video games
- After Philanthropist, best described as a Free Spirit player type
- Social media apps are quite important to her
- Least likely to use a dating app

Figure 5-4 : User Persona Cluster #4



Cluster/Persona #5 Liz

Age: 36
Education: University Post-Graduate
Family: Not married
Household: Living with her partner
Income: 100-150k

About games:

"When I am not working, I enjoy playing board games. I like that they require more thought and that they tend to be more sociable than video games. When I am not doing that, I use my fitness to work out and compare my results with my friends on social medias. Have to stay in shape you know!"

About Food:

"We have about 50 cookbooks, and I like to think I am an excellent cook. All the recipes work best with fresh sustainable foods, and they are no problem to find around here. And buying them helps our environment which is why we have a battery powered car as well. But I know I can still do more to prevent climate change."

Sustainable food consumption and sociodemographic characteristics

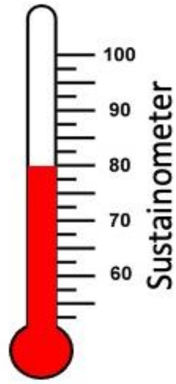
- 25-44 years of age
- Female
- Married
- University, Post-Graduate
- Income 100-150k
- Very high intention to consume sustainably, with an excellent attitude and with high concerns towards the environment
- High food abilities, personal moral norm and perceived behavioural control.
- Lowest barriers to eat sustainably
- Highest behaviour to intention gap

My phone and game shelf

Game and application related characteristics

- Enjoys playing board games the most
- Ranked Highest as a Philanthropist, after which she is best described as a Free Spirit player type
- Least likely to be a disruptor player type
- Most likely to use personal fitness
- Social media apps are important to her
- Likely to use a personal finance app

Figure 5-5 : User Persona Cluster #5



Cluster/Persona #6 Barry

Age: 41
Education: College diploma/University graduate
Family: Married
Household: Living with partner
Income: 75-100k

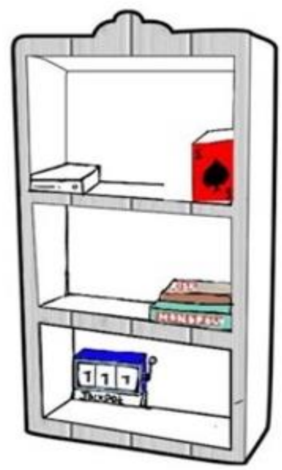
About games:

"I love to play games, particularly card games or casino kinds of games. I travel quite a bit with my wife and like going to fancy casinos just to play a bit and people watch. It's even more fun if you try to speak the local language so I use Duolingo a lot to try to prepare before we leave. And we always bring our cards. They are small and easy to pack, but they can bring my competitive side."

About Food:

"I enjoy cooking, but a problem I face is that it is so hard to get sustainable foods when I want to. I feel concerned and obligated to do my part to be more ecological, but it's not always convenient. I believe that the people around me are really trying to adopt a sustainable diet as well"

My phone and game shelf



Sustainable food consumption and sociodemographic characteristics

- 25-44 years of age
- Female
- Married
- College diploma/University graduate
- Income 75-100k
- High intention to consume sustainably, has an excellent attitude and highest concerns towards the environment
- High food abilities, personal moral norm, perceived behavioural control and the highest subjective norm
- High perceived barriers to all forms of sustainable foods

Game and application related characteristics

- Enjoys playing card, board games and casino games the most.
- After Philanthropist, is best described as either an Achiever or Player player type.
- Most likely to use apps to learn new languages
- Most likely to use food delivery apps
- Likely to use a personal fitness app

Figure 5-6 : User Persona Cluster #6

5.3 Limitations

This study does have a few limitations that should be noted. We do not know the extent of which intentions to consume sustainable foods are under- or over reported. There is certainly self-bias involved in answering these questions. The generalizability of the research findings in the Canadian context may be suspect, as the survey strategy is confined with the most populated territory of Canada. There will certainly be other factors that will influence responses from other regions in Canada, where local agriculture and fisheries are important, and thus availability of local and organic foods may be more prevalent, or at least have fewer barriers. Also, Canada is a highly multicultural country and cultural beliefs, and practices will also be a determinant of food consumption (Wright, 2001; Aertsens et al. 2009). In terms of gamifications the survey did not include any type of sport, as there were far too many to list. As a minor point, no questions were asked pertaining to consumption of insects as a source of protein. However, this practice, at least in Canada, is still in its infancy so likely would not have affected the results significantly.

Other factors that may have affected the generalizability of the results include that the survey started being distributed when regions of Ontario (i.e. Toronto and Peel) were barely coming out of COVID-induced stay at home orders which were lifted on March 5, 2021. The survey started being distributed on the 9th of March 2021. For instance, e-commerce grew significantly since the Covid-19 pandemic started, including the growth of packaged food online purchasing (Bhatti et al. 2020). Because online food purchasing has become easier thanks to Internet technologies, and since Covid has created restrictions and concerns concerning physical food purchasing, Covid 19 has effectively made people reassess their purchasing behaviours, including food purchasing (Öztürk and Öçlü, 2020). For instance, the impact of Covid-19 induced stay at home orders increased the score of healthy eating significantly (Flanagan et al. 2021). As the impact of Covid-19 will transform the future of geopolitical and socio-economic norms (Rowan and Galanakis, 2020) it also provides behaviour change opportunities (Gunner et al. 2020) that could be used to reform unsustainable behaviours to accelerate the transition towards more sustainable transitions (Cohen, 2020; Ranjbari et al. 2021; Sarkis et al. 2020).

Strengths of the study include a relatively high number of fully completed responses, the breadth of the survey to include additional questions on gaming behaviour and app usage and the fact that it was distributed by Quest MindShare to people they thought best addressed the target survey audience. Similar studies are often carried out by polling shoppers at 1 or 2 different store locations, so a bias is introduced in that manner. In this case, the respondents will likely shop at a variety of different store types (large chain, smaller family owned, online only, specialty foods etc.) better representing the breadth of store types where sustainable foods are available.

5.4 Future Studies

This work paves the way for future studies including a broader and larger survey to include respondents from across the country, thereby making the results much more generalizable to the whole of Canada and eliminating some of the biases previously mentioned. Such studies should also include, where possible, assessments of the impacts of any interventions or marketing campaigns towards sustainable diets that may have been implemented. Further work may also include more targeted surveys into specific components of the TPB framework such that they may be better understood, particularly those that are associated with a high intent to consume a sustainable diet. For example, rather than asking 3-6 questions to quantify a response, more questions pertaining to that category might be able to probe intricacies within the category with more precision and further help to understand and define target markets. Finally, future studies should replicate similar segmentation studies but only analysing the personal determinants to consume each of the sustainable food type (i.e. Organic foods, Plant-based proteins, and local foods) separately. Future studies should also investigate the specific barriers to consuming sustainable foods each segment having a significant intention- behaviour gap experiences for each of the sustainable food type. The data from the text analysis also supports previous findings citing that Cost, Availability, Mistrust of claims and Health concerns are amongst the main perceived barriers to consuming sustainable foods.

5.5 Conclusions

The main conclusions derived based on the current study results can be summarised as follows:

1) A novel modified socio-demographic/TPB model framework developed by the author and measured by an online survey can successfully help segment the participants and identify the target markets to increase sustainable food consumption.

2) Elements of gamification and mobile application usage can help optimise the interventions to close the intention - behaviour gap observed in individuals who have a high intention to consume sustainable foods but are not yet exhibiting that practice. To the best of the author's knowledge the current study is the first to adopt and test such an approach.

3) Multivariate backward linear regression and hierarchical clustering were found to be powerful statistical methods to help identify those socio-demographic and TPB category sum-scores that significantly positively predicted the intent to consume a sustainable diet and segment consumers to identify a target market(s).

4) Two consumer segments (Clusters 4 and 5) stood out as target segments given they had a high intent to consume a sustainable diet, but did not put their intent into practice, hence, displaying a significant intention - behaviour gap.

5) Strong evidence towards the effectiveness of gamified interventions was not observed because the target markets (i.e., Clusters 4 and 5) ranked low and in the middle (i..e, fifth and third out of the six clusters respectively) in gaming behaviour frequencies averages.

6) Sustainable food consumption interventions delivered via mobile applications would be the most effective and have the highest probability of reaching the target market if these were delivered via social media platforms and incorporated game design elements associated with the Philanthropist and Free spirit user types.

7) Interventions aiming at the target markets (i.e., Clusters 4 and 5) should be delivered via social media mobile applications and include game design elements associated with the Philanthropist and Free Spirit user types.

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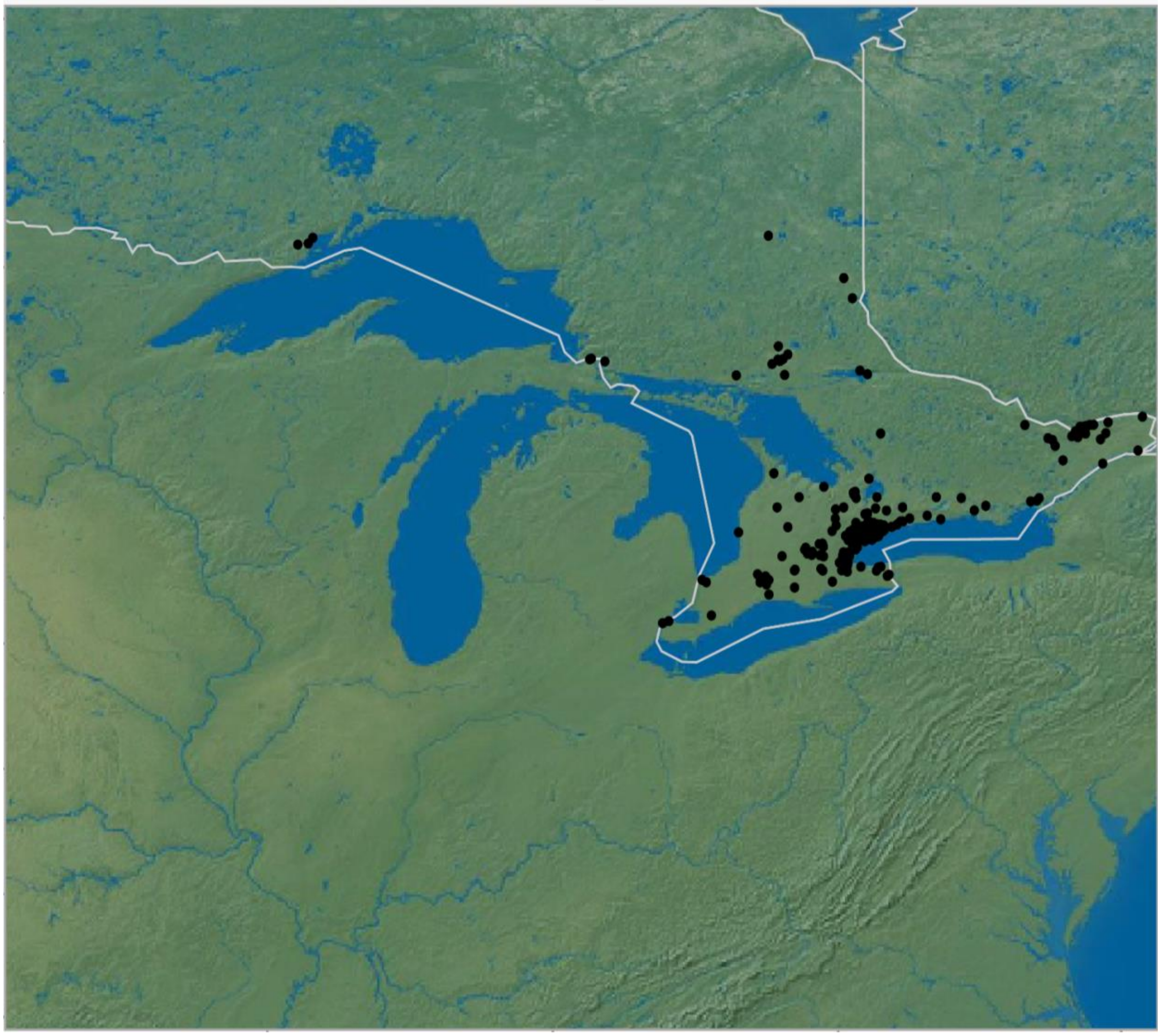
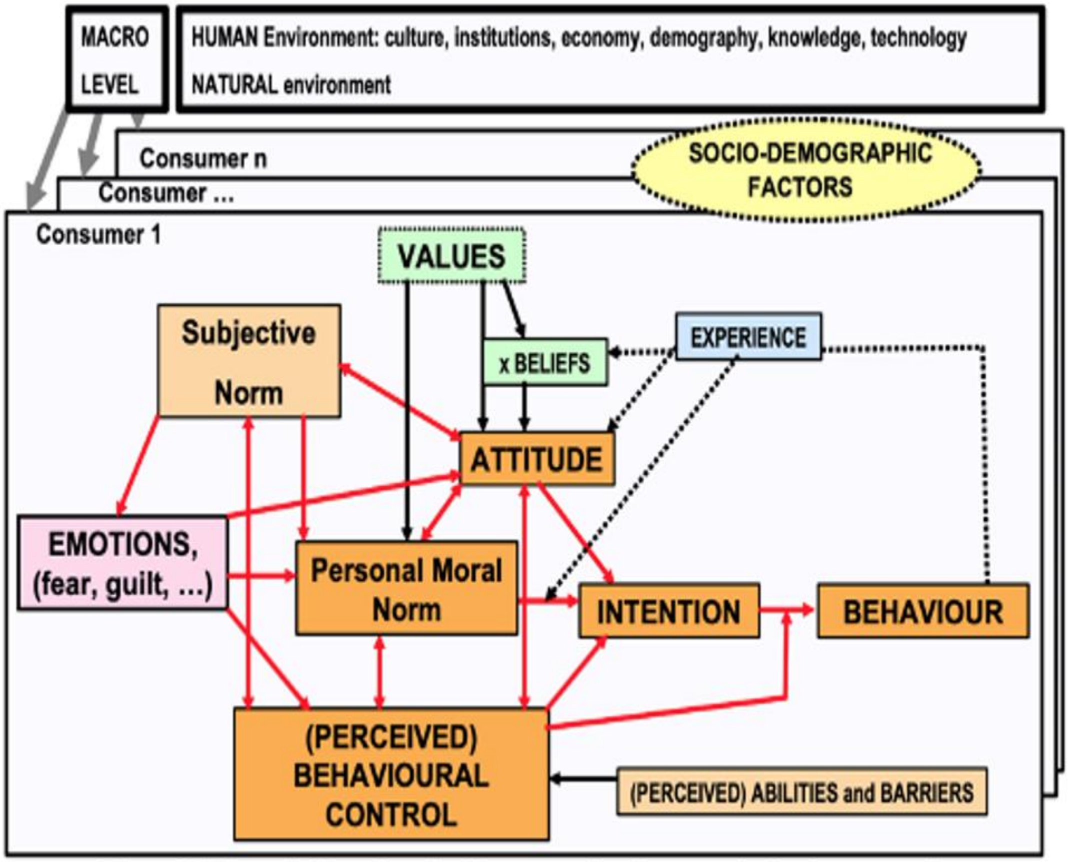
Appendix A: Figures

A1: Location within Ontario of final 376 respondents according to Qualtrics latitude/longitude data.



A2: Aertsens et al. (2009) framework on personal determinants of organic food consumption.

Figure 1: Integrated Framework on personal determinants of organic food consumption

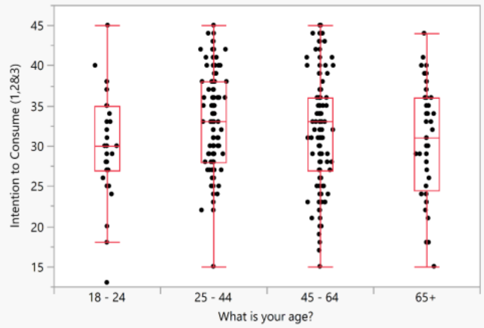


Source: Adapted TPB-model based on the literature related to organic food consumption

A3: Bivariate analysis of socio-demographic variables against intent to consume sustainable diet.

Oneway Analysis of Intention to Consume (1,2&3) By What is your age?

Q1Screener



Means Comparisons

Comparisons for all pairs using Tukey-Kramer HSD

Connecting Letters Report

Level		Mean
25 - 44	A	33.039474
45 - 64	A	32.141844
65+	A	30.653061
18 - 24	A	30.500000

Levels not connected by same letter are significantly different.

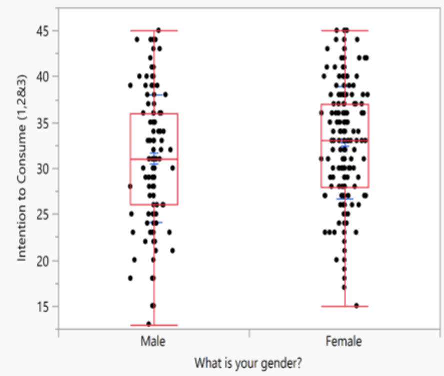
Ordered Differences Report

Level	- Level	Difference	p-Value
25 - 44	18 - 24	2.539474	0.1610
25 - 44	65+	2.386412	0.1096
45 - 64	18 - 24	1.641844	0.5403
45 - 64	65+	1.488783	0.5025
25 - 44	45 - 64	0.897630	0.6311
65+	18 - 24	0.153061	0.9996

A3-1: Bivariate analysis of intent to consume by age bracket.

Oneway Analysis of Intention to Consume (1,2&3) By What is your gender?

Q2Gender What is your gender? - Selected Choice



Means and Std Deviations

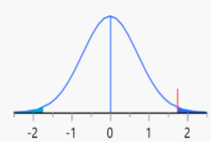
Level	Number	Mean	Std Dev	Std Err Mean	Lower 90%	Upper 90%
Male	138	31.086957	6.9434402	0.5910649	30.108122	32.065791
Female	236	32.822034	6.1223433	0.3985306	32.163915	33.480153

t Test

Female-Male

Assuming unequal variances

Difference	1.73508	t Ratio	2.433931
Std Err Dif	0.71287	DF	258.7103
Upper CL Dif	2.91186	Prob > |t|	0.0156*
Lower CL Dif	0.55830	Prob > t	0.0078*
Confidence	0.9	Prob < t	0.9922

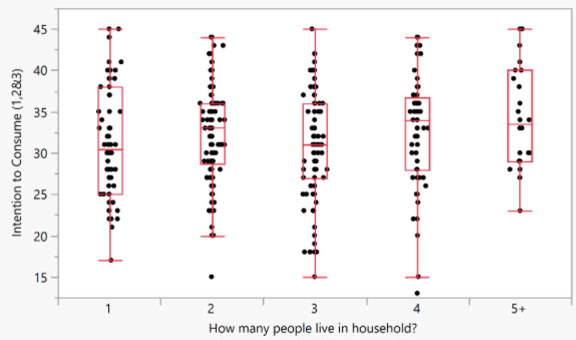


Missing Rows 2

A3-2: Bivariate analysis of intent to consume by gender.

Oneway Analysis of Intention to Consume (1,2&3) By How many people live in household?

Q3HouseMemberNumber How many people currently live in your household?



Means Comparisons

Comparisons for all pairs using Tukey-Kramer HSD

Connecting Letters Report

Level		Mean
5+	A	34.115385
4	A	32.875000
2	A	32.392308
1	A	31.382353
3	A	31.329545

Levels not connected by same letter are significantly different.

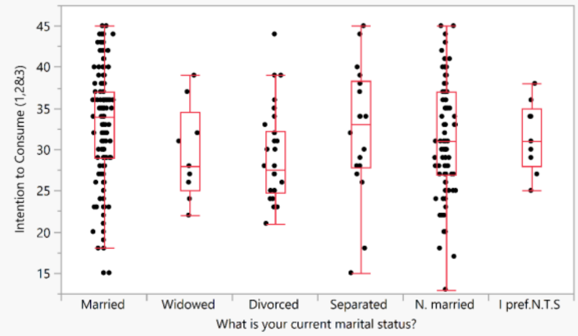
Ordered Differences Report

Level	- Level	Difference	p-Value
5+	3	2.785839	0.3016
5+	1	2.733032	0.3544
5+	2	1.723077	0.7265
4	3	1.545455	0.5910
4	1	1.492647	0.6742
5+	4	1.240385	0.9224
2	3	1.062762	0.7557
2	1	1.009955	0.8340
4	2	0.482692	0.9883
1	3	0.052807	1.0000

A3-3: Bivariate analysis of intent to consume by number of people in household.

Oneway Analysis of Intention to Consume (1,2&3) By What is your current marital status?

Q25MaritalStatus



Means Comparisons

Comparisons for all pairs using Tukey-Kramer HSD

Connecting Letters Report

Level			Mean
Married	A		33.096257
Separated	A	B	32.111111
N. married	A	B	31.865546
I pref.N.T.S	A	B	31.555556
Widowed	A	B	29.555556
Divorced		B	28.941176

Levels not connected by same letter are significantly different.

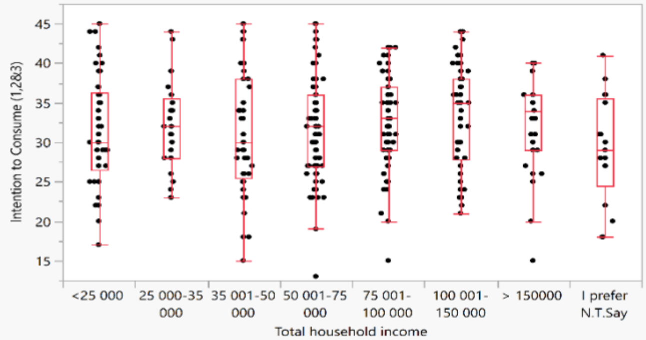
Ordered Differences Report

Level	- Level	Difference	p-Value
Married	Divorced	4.155080	0.0072*
Married	Widowed	3.540701	0.5835
Separated	Divorced	3.169935	0.5316
N. married	Divorced	2.924370	0.1759
I pref.N.T.S	Divorced	2.614379	0.8847
Separated	Widowed	2.555556	0.9243
N. married	Widowed	2.309991	0.9021
I pref.N.T.S	Widowed	2.000000	0.9857
Married	I pref.N.T.S	1.540701	0.9811
Married	N. married	1.230710	0.5711
Married	Separated	0.985146	0.9892
Widowed	Divorced	0.614379	0.9998
Separated	I pref.N.T.S	0.555556	0.9999
N. married	I pref.N.T.S	0.309991	1.0000
Separated	N. married	0.245565	1.0000

A3-4: Bivariate analysis of intent to consume by marital status.

Oneway Analysis of Intention to Consume (1,2&3) By Total household income

Q23Income Which of these groups describes your total household income (after taxe) last year?



Means Comparisons

Comparisons for all pairs using Tukey-Kramer HSD

Connecting Letters Report

Level		Mean
100 001-150 000	A	33.465517
75 001-100 000	A	32.813333
> 150000	A	32.516129
50 001-75 000	A	32.037975
25 000-35 000	A	31.920000
35 001-50 000	A	31.444444
<25 000	A	31.391304
I prefer N.T.Say	A	29.117647

Levels not connected by same letter are significantly different.

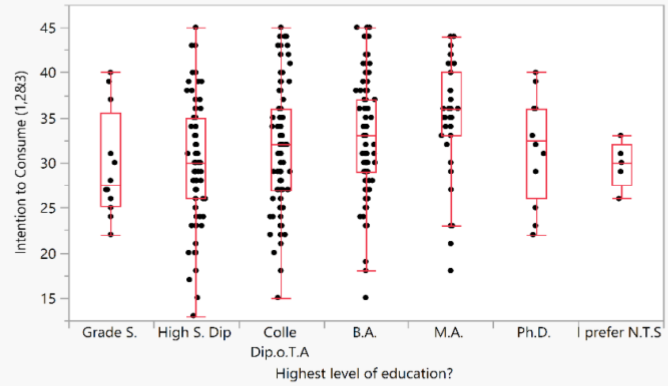
Ordered Differences Report

Level	- Level	Difference	p-Value
100 001-150 000	I prefer N.T.Say	4.347870	0.2252
75 001-100 000	I prefer N.T.Say	3.695686	0.3978
> 150000	I prefer N.T.Say	3.398482	0.6589
50 001-75 000	I prefer N.T.Say	2.920328	0.6933
25 000-35 000	I prefer N.T.Say	2.802353	0.8660
35 001-50 000	I prefer N.T.Say	2.326797	0.9110
<25 000	I prefer N.T.Say	2.273657	0.9194
100 001-150 000	<25 000	2.074213	0.7342
100 001-150 000	35 001-50 000	2.021073	0.7651
100 001-150 000	25 000-35 000	1.545517	0.9743
100 001-150 000	50 001-75 000	1.427543	0.9066
75 001-100 000	<25 000	1.422029	0.9385
75 001-100 000	35 001-50 000	1.368889	0.9514
> 150000	<25 000	1.124825	0.9954
> 150000	35 001-50 000	1.071685	0.9967
100 001-150 000	> 150000	0.949388	0.9979
75 001-100 000	25 000-35 000	0.893333	0.9989
75 001-100 000	50 001-75 000	0.775359	0.9955
100 001-150 000	75 001-100 000	0.652184	0.9991
50 001-75 000	<25 000	0.646670	0.9994
> 150000	25 000-35 000	0.596129	1.0000
50 001-75 000	35 001-50 000	0.593530	0.9997
25 000-35 000	<25 000	0.528696	1.0000
> 150000	50 001-75 000	0.478154	1.0000
25 000-35 000	35 001-50 000	0.475556	1.0000
75 001-100 000	> 150000	0.297204	1.0000
50 001-75 000	25 000-35 000	0.117975	1.0000
35 001-50 000	<25 000	0.053140	1.0000

A3-5: Bivariate analysis of intent to consume by income level.

Oneway Analysis of Intention to Consume (1,2&3) By Highest level of education?

Q24Education What is the highest level of formal education that you have completed?



Means Comparisons

Comparisons for all pairs using Tukey-Kramer HSD

Connecting Letters Report

Level				Mean
M.A.	A			35.307692
B.A.	A	B		33.103448
Colle Dip.o.T.A		B	C	31.945455
Ph.D.	A	B	C	31.833333
High S. Dip			C	30.182927
I prefer N.T.S	A	B	C	29.800000
Grade S.	A	B	C	29.666667

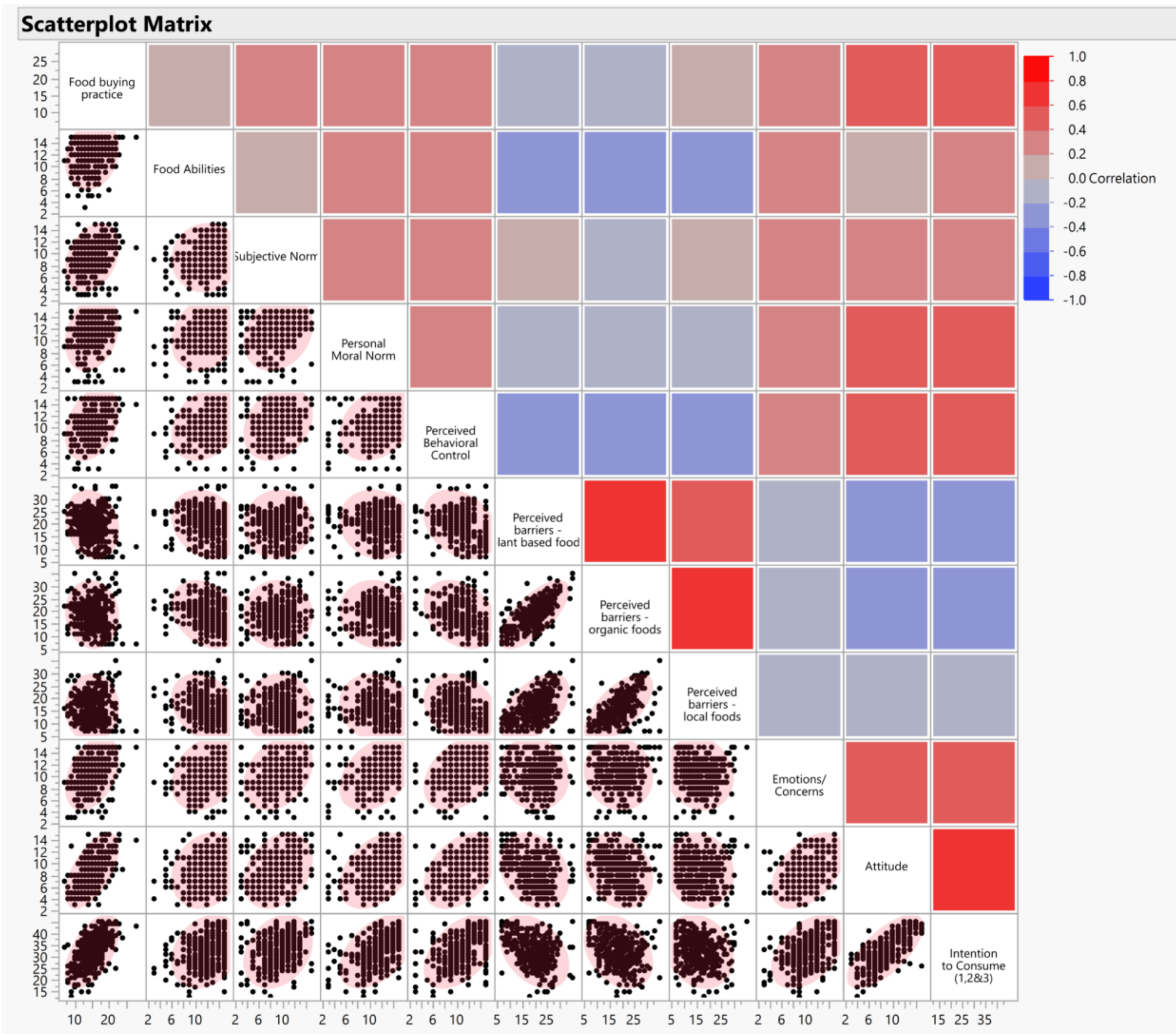
Levels not connected by same letter are significantly different.

Ordered Differences Report

Level	- Level	Difference	p-Value
M.A.	Grade S.	5.641026	0.1012
M.A.	I prefer N.T.S	5.507692	0.5274
M.A.	High S. Dip	5.124765	0.0008*
M.A.	Ph.D.	3.474359	0.6414
B.A.	Grade S.	3.436782	0.5553
M.A.	Colle Dip.o.T.A	3.362238	0.0685
B.A.	I prefer N.T.S	3.303448	0.9144
B.A.	High S. Dip	2.920521	0.0251*
Colle Dip.o.T.A	Grade S.	2.278788	0.8999
M.A.	B.A.	2.204244	0.4940
Ph.D.	Grade S.	2.166667	0.9807
Colle Dip.o.T.A	I prefer N.T.S	2.145455	0.9899
Ph.D.	I prefer N.T.S	2.033333	0.9967
Colle Dip.o.T.A	High S. Dip	1.762528	0.4759
Ph.D.	High S. Dip	1.650407	0.9801
B.A.	Ph.D.	1.270115	0.9945
B.A.	Colle Dip.o.T.A	1.157994	0.8151
High S. Dip	Grade S.	0.516260	1.0000
High S. Dip	I prefer N.T.S	0.382927	1.0000
I prefer N.T.S	Grade S.	0.133333	1.0000
Colle Dip.o.T.A	Ph.D.	0.112121	1.0000

A3-6: Bivariate analysis of intent to consume by education level.

A4: Scatterplot matrix and heat map depicting correlations between TPB variables and intention to consume sustainable diet.



Discussion of the heat map results

The side axes of the matrix represent the scores for each sum-score, however, these are not particularly crucial in this context. Instead, the current study's focus is on the distribution of data points contained within narrow shaded ellipses, indicating strong correlations between variables. The heat map can also be examined, where squares in darker red indicate positive correlations between variables and squares in darker blue indicate negative correlations.

For instance, the variable "Intention to Consume" is located in the bottom right corner. As one moves up the column, one immediately observes a dark red square corresponding to the category "Attitude," indicating a strong positive correlation between "Attitude" and "Intent to Consume." Positive correlations are also observed between "Intent to Consume" and "Food buying practice," "Personal Moral Normal," "Perceived Behavioural Control," and "Emotions/Concerns." On the other hand, negative correlations are found with "Perceived barriers to buying plant-based foods" and "Perceived barriers to buying organic foods."

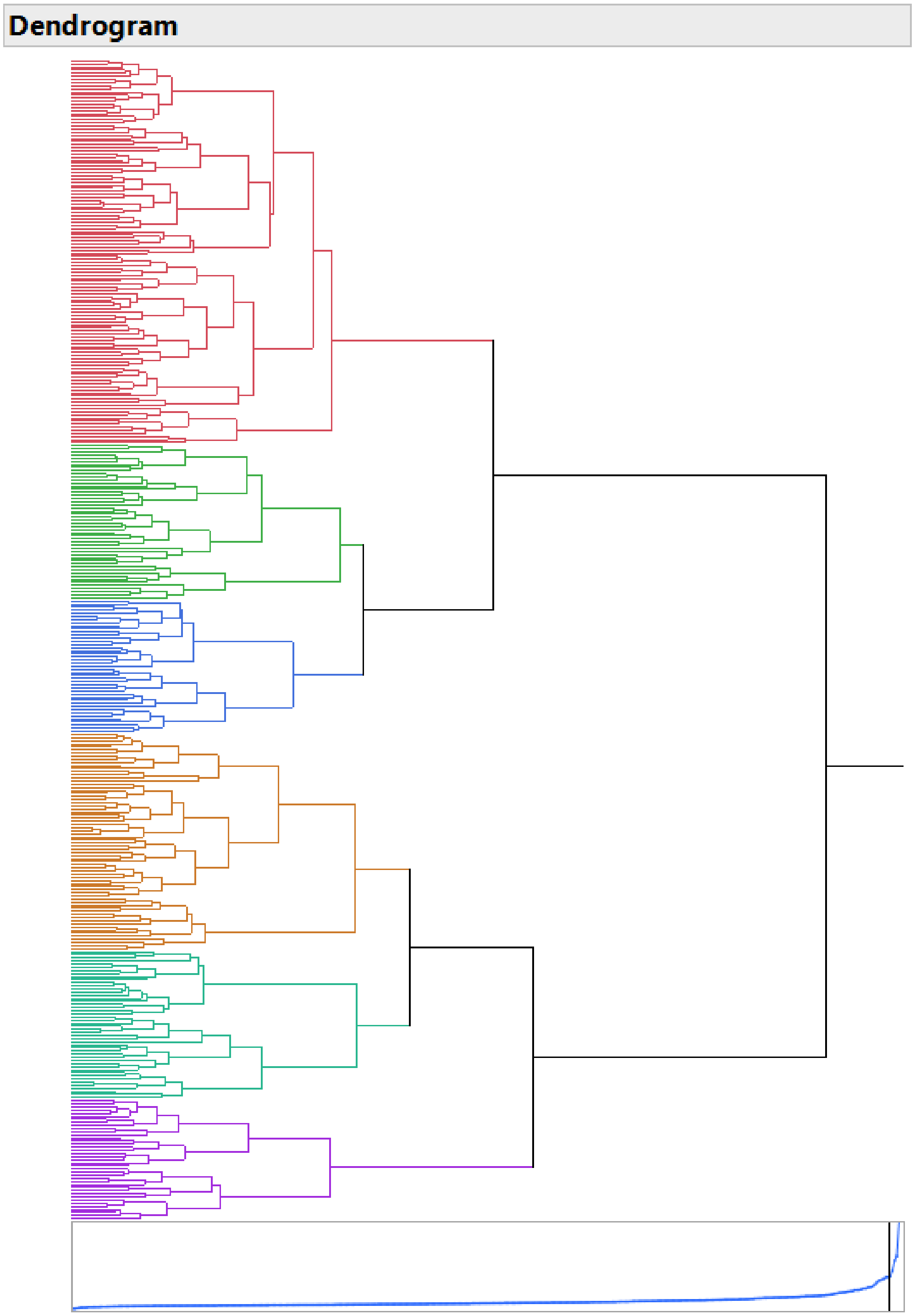
In summary, a strong positive correlation between intention to consume and variables such as Attitude, Food buying practice, Personal moral norm, Perceived behavioural control, and Emotions/Concerns can be observed here.

A5: Prediction equation for intent to consume sustainable diet obtained from linear regression analysis. Codes for age: 1 = 18-24; 2 = 25-44, 3 = 45-64, 4 = 65+. Codes for marital status: 1 = Married, 2 = Widowed, 3 = Divorced, 4 = Separated, 5 = Not married, 6 = Prefer not to say

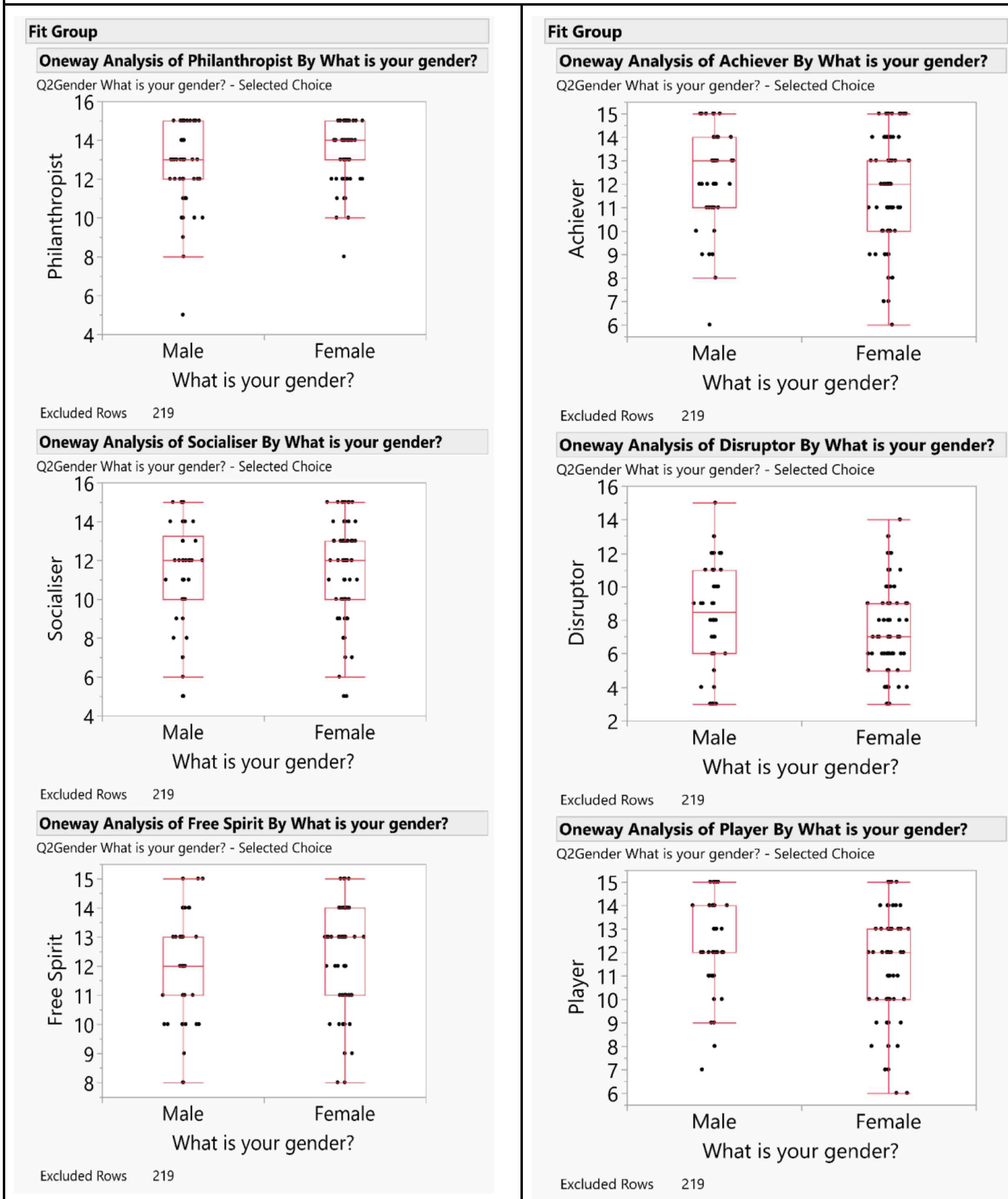
Prediction Expression

$$
\begin{aligned}
&12.748635559 \\
&+\mathrm{Match}\left(\text{What is your age?}\right)\begin{pmatrix} \text{"1"} \Rightarrow -1.495311763 \\ \text{"2"} \Rightarrow 1.1863713218 \\ \text{"3"} \Rightarrow 0.7034539829 \\ \text{"4"} \Rightarrow -0.394513542 \\ \text{else} \Rightarrow . \end{pmatrix} \\
&+\mathrm{Match}\left(\text{What is your current marital status?}\right)\begin{pmatrix} \text{"3"} \Rightarrow -1.918262058 \\ \text{"6"} \Rightarrow 1.6442632131 \\ \text{"1"} \Rightarrow 0.4928688021 \\ \text{"5"} \Rightarrow 0.057201222 \\ \text{"4"} \Rightarrow -0.289018036 \\ \text{"2"} \Rightarrow 0.0129468565 \\ \text{else} \Rightarrow . \end{pmatrix} \\
&+0.295820031 \cdot \text{Food behavior Experience} \\
&+0.4311214529 \cdot \text{Personal Moral Norm} \\
&+0.3503169861 \cdot \text{Perceived Behavioral Control} \\
&+-0.21919646 \cdot \text{Perceived barriers - plant based foods} \\
&+0.1616398243 \cdot \text{Emotions/Concerns} \\
&+0.9466289418 \cdot \text{Attitude}
\end{aligned}
$$

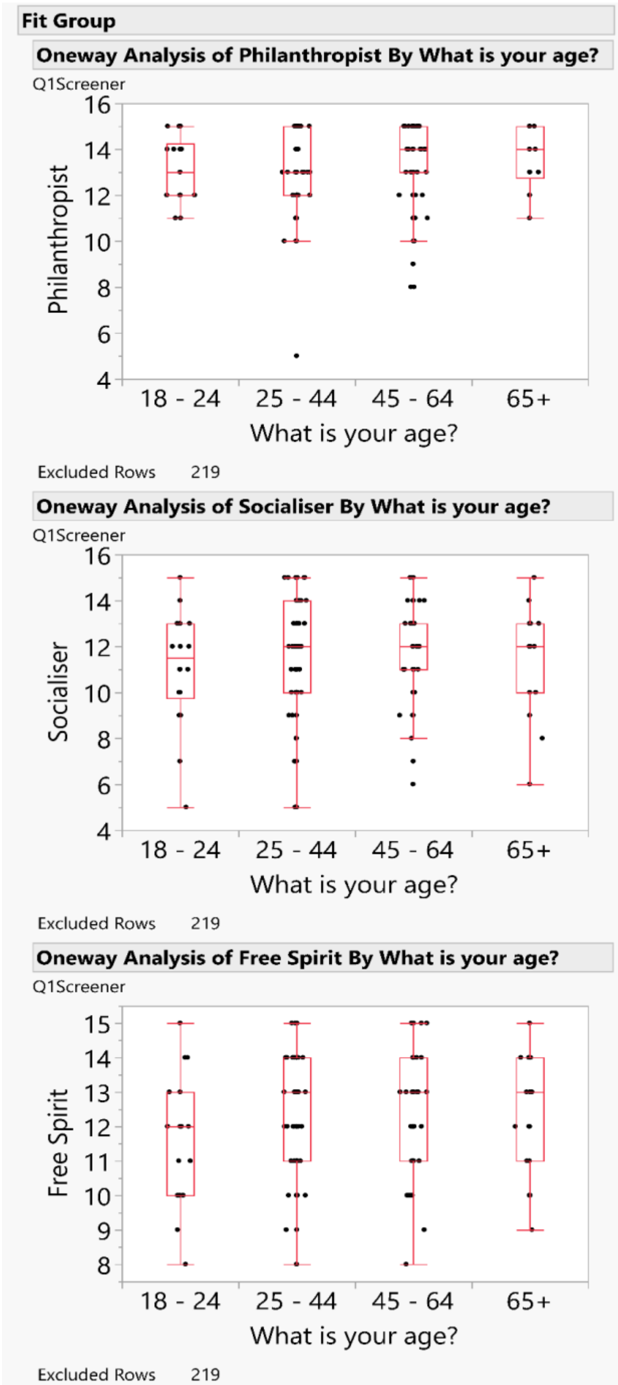
A6: Dendogram and distance plot from hierarchical cluster analysis.

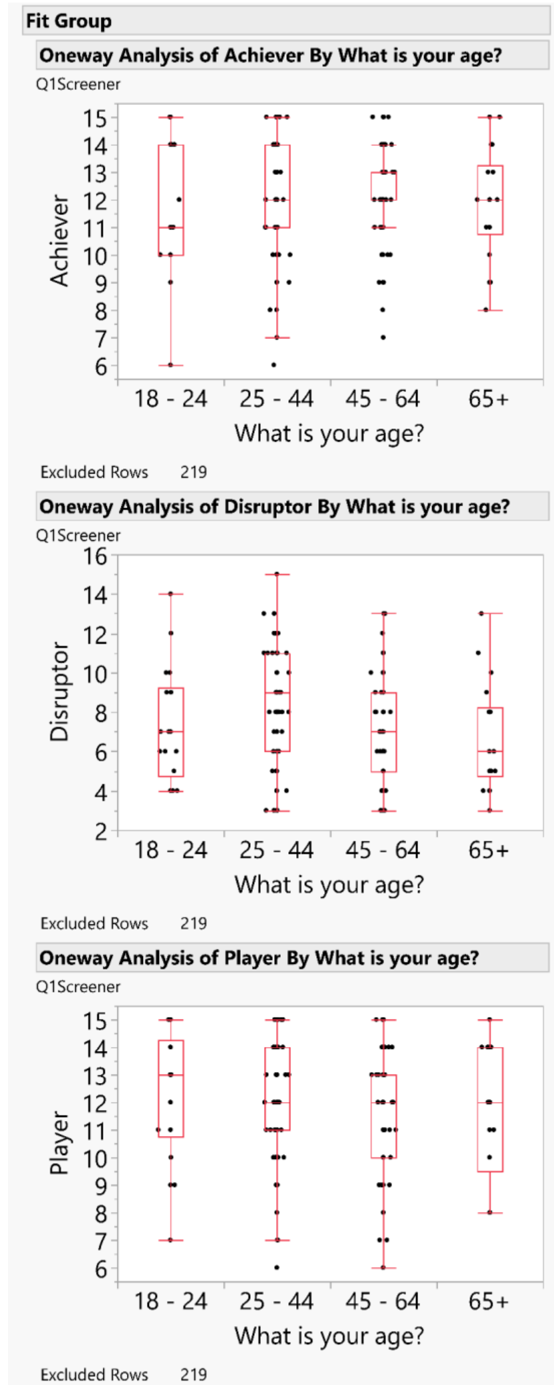


A7: Scores for all HEXAD player types as a function of gender for clusters 4, 5 and 6.

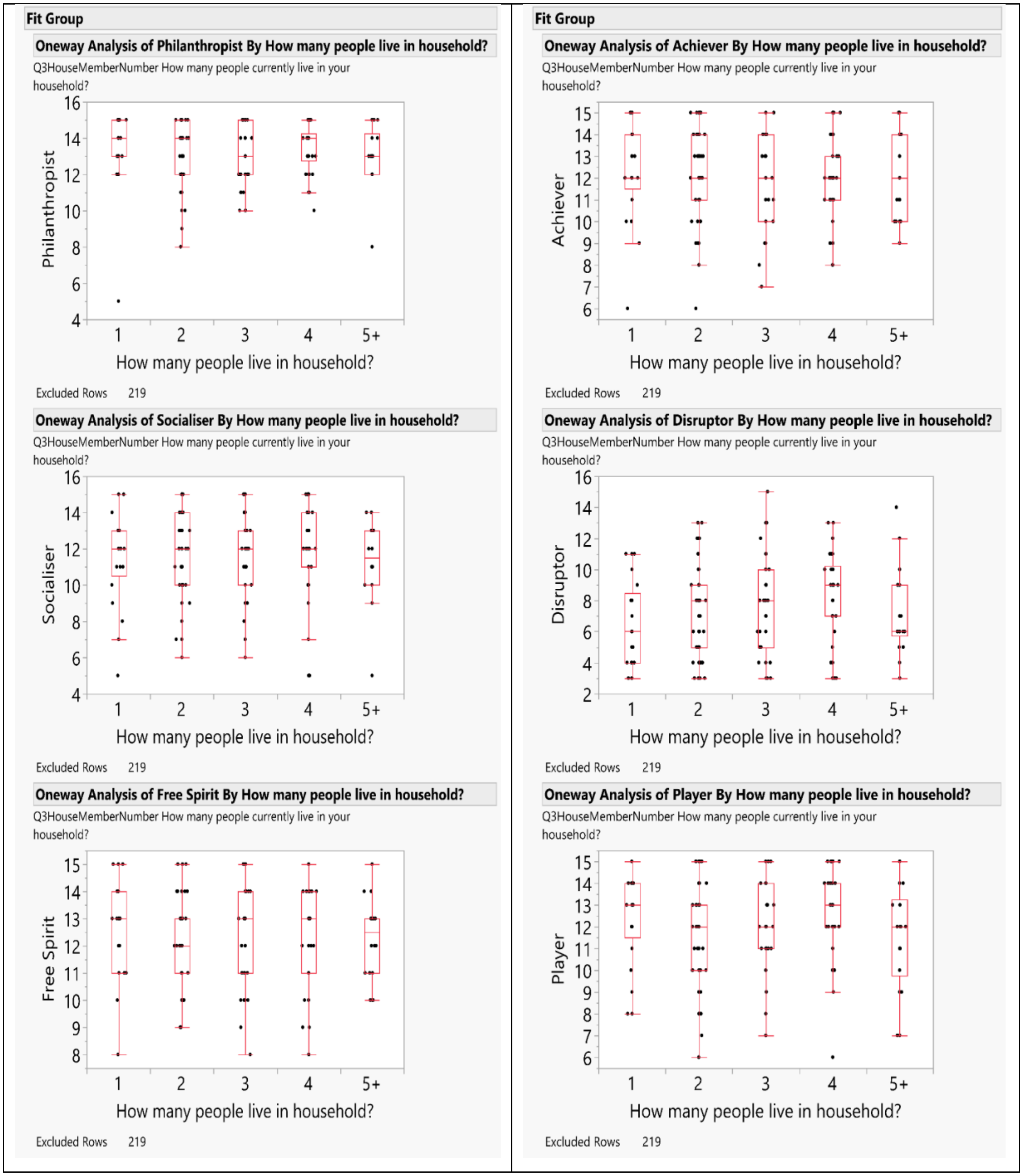


A8: Scores for all HEXAD player types as a function of age bracket for clusters 4, 5 and 6.

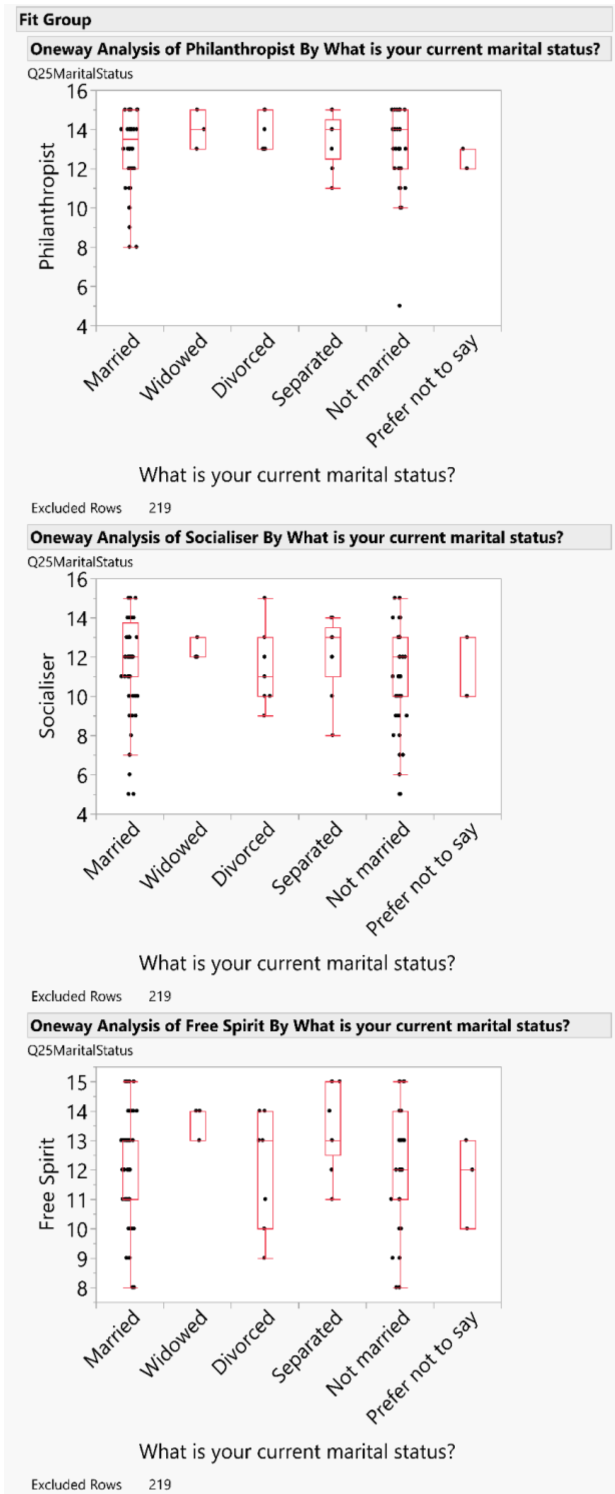


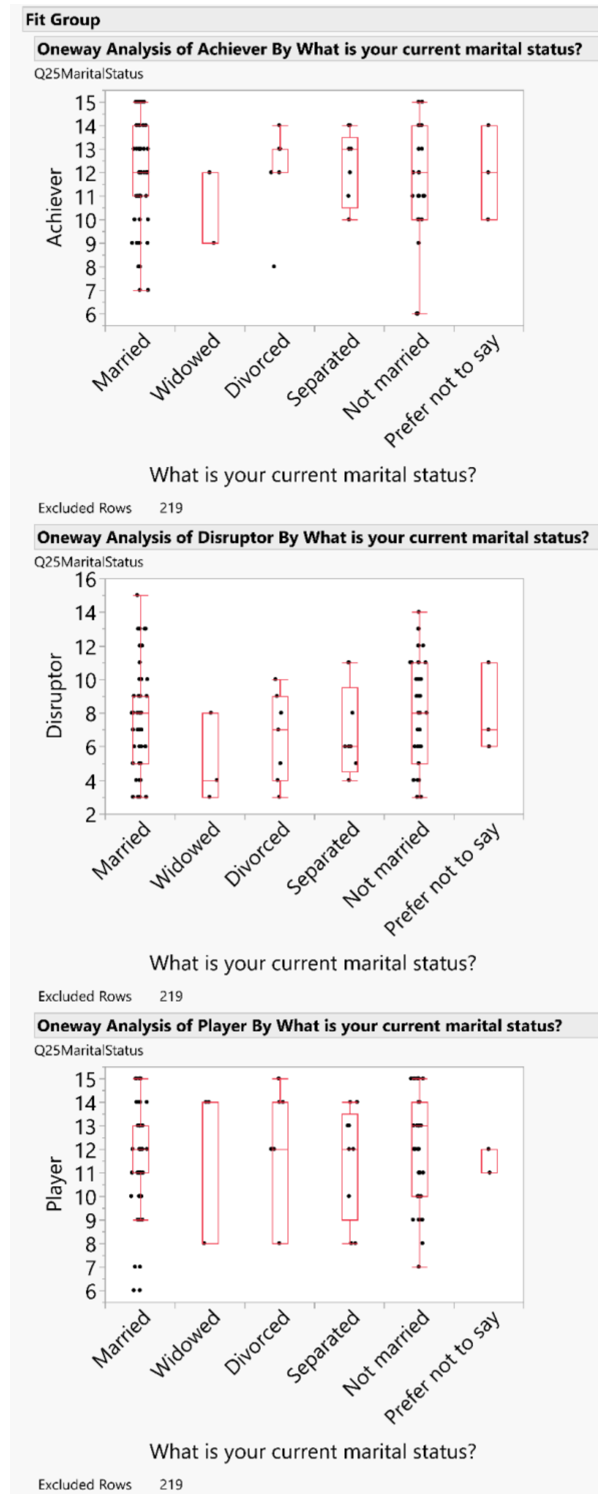


A9: Scores for all HEXAD player types as a function of how many people living in household for clusters 4, 5 and 6.



A10: Scores for all HEXAD player types as a function of marital status for clusters 4, 5 and 6.



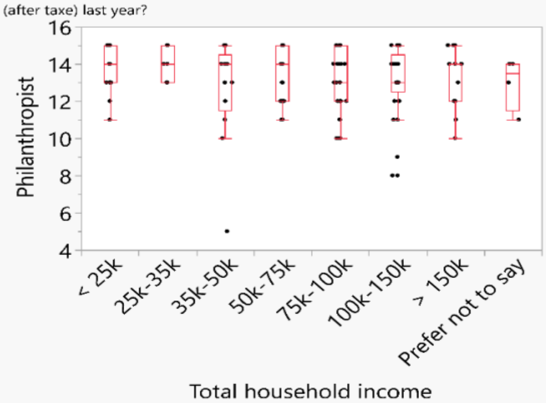


A11: Scores for all HEXAD player types as a function of household income for clusters 4, 5 and 6.

Fit Group

Oneway Analysis of Philanthropist By Total household income

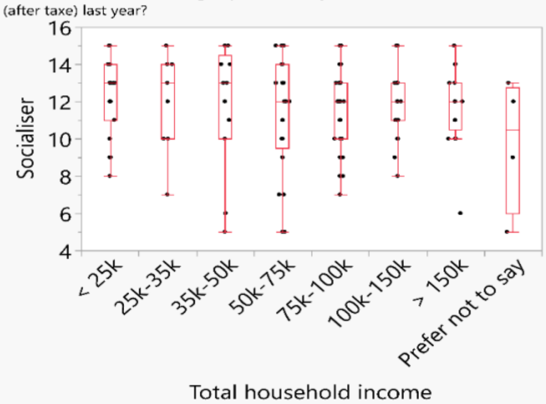
Q23Income Which of these groups describes your total household income (after taxe) last year?



Excluded Rows 219

Oneway Analysis of Socialiser By Total household income

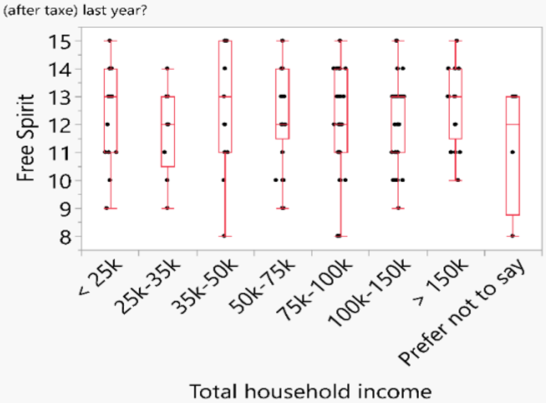
Q23Income Which of these groups describes your total household income (after taxe) last year?



Excluded Rows 219

Oneway Analysis of Free Spirit By Total household income

Q23Income Which of these groups describes your total household income (after taxe) last year?

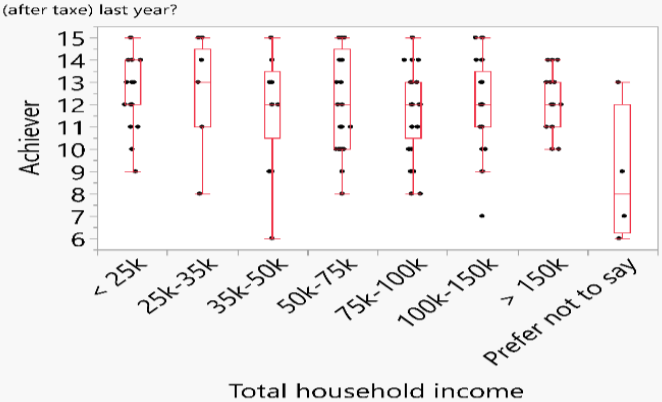


Excluded Rows 219

Fit Group

Oneway Analysis of Achiever By Total household income

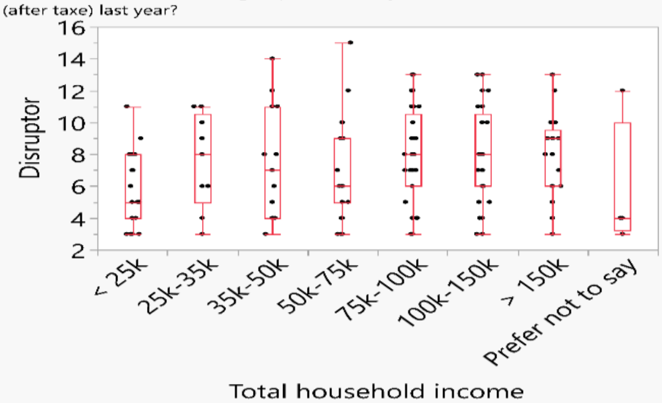
Q23Income Which of these groups describes your total household income (after taxe) last year?



Excluded Rows 219

Oneway Analysis of Disruptor By Total household income

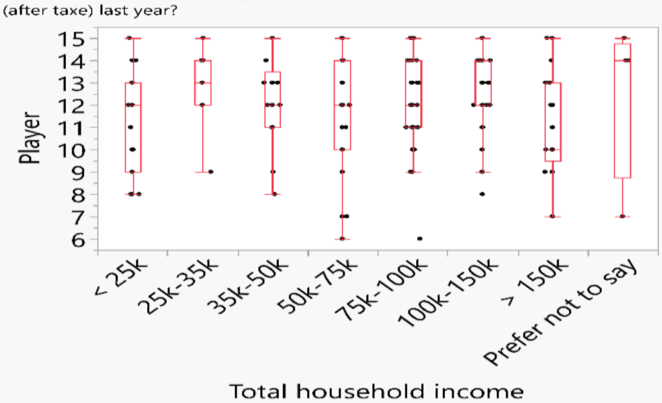
Q23Income Which of these groups describes your total household income (after taxe) last year?



Excluded Rows 219

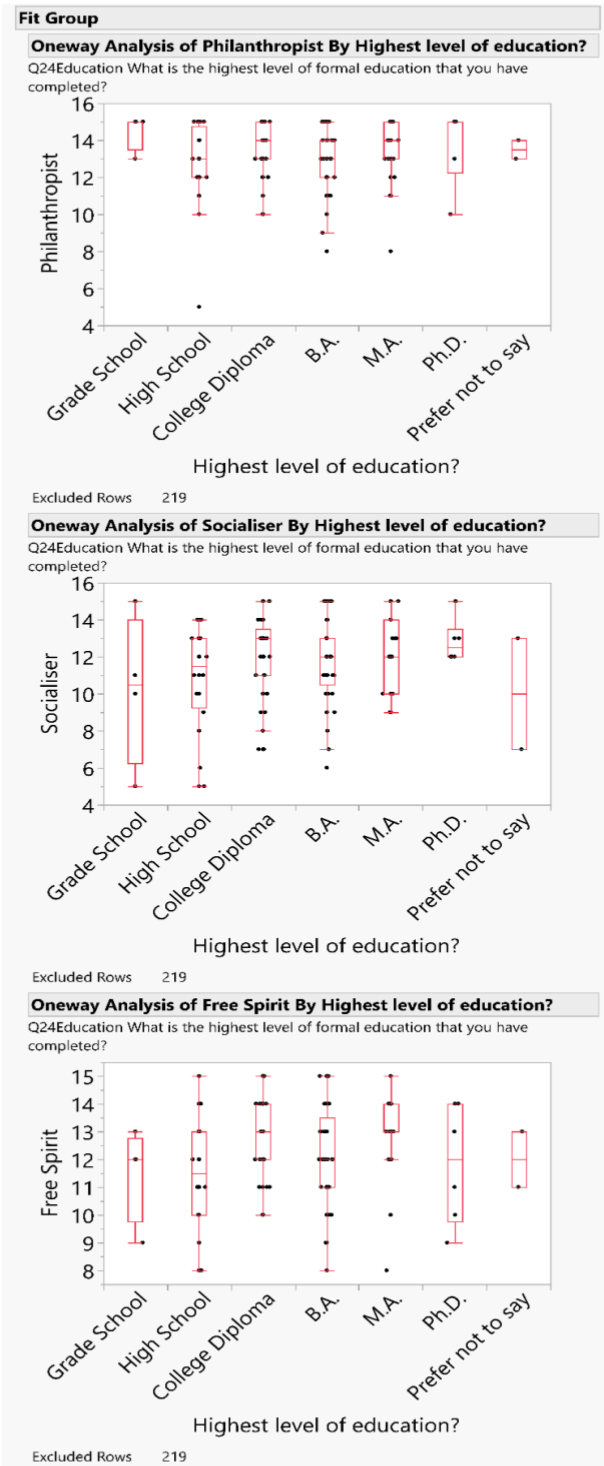
Oneway Analysis of Player By Total household income

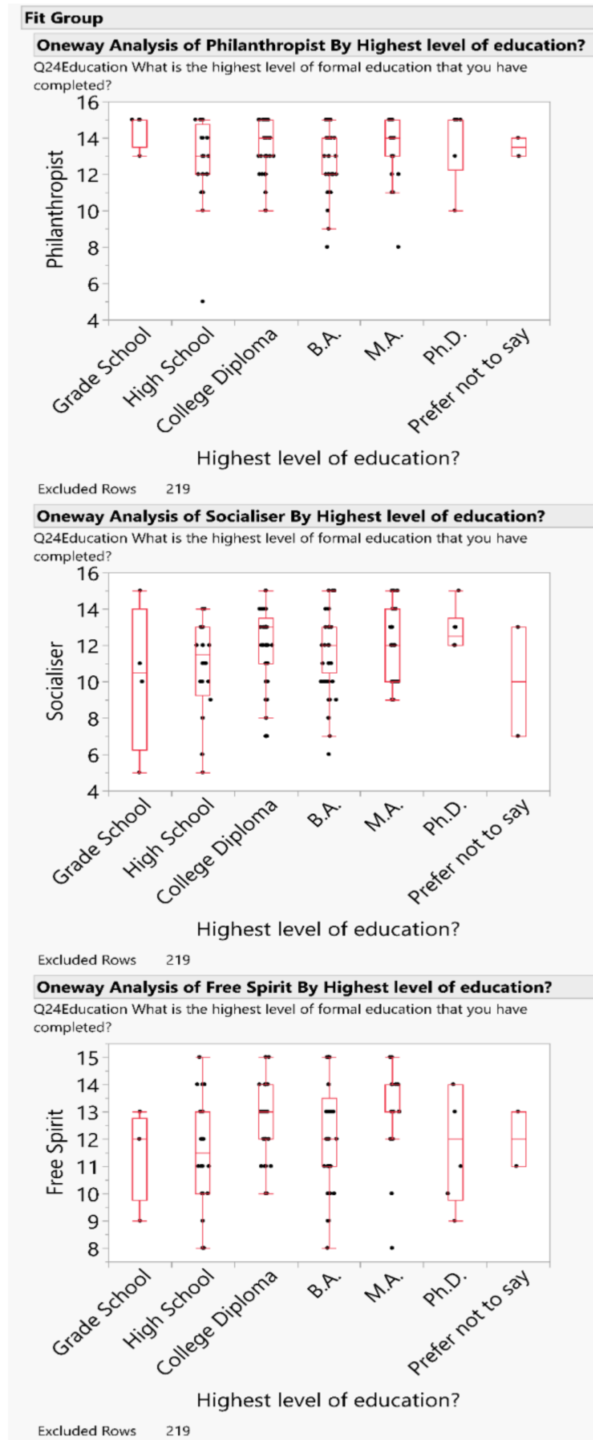
Q23Income Which of these groups describes your total household income (after taxe) last year?



Excluded Rows 219

A12: Scores for all HEXAD player types as a function of education level for clusters 4, 5 and 6.

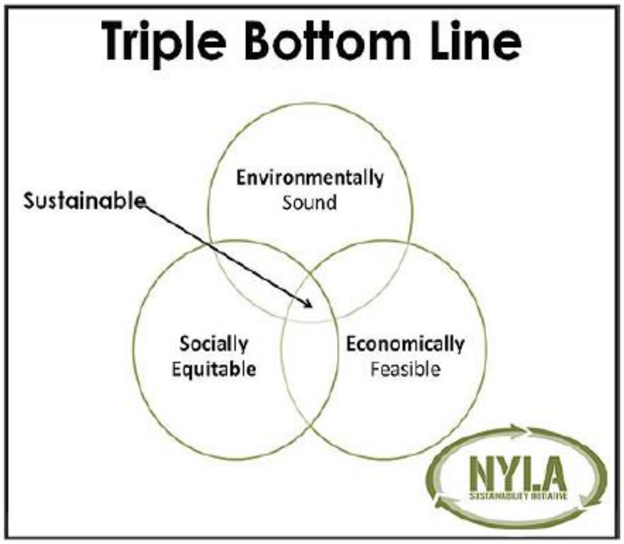
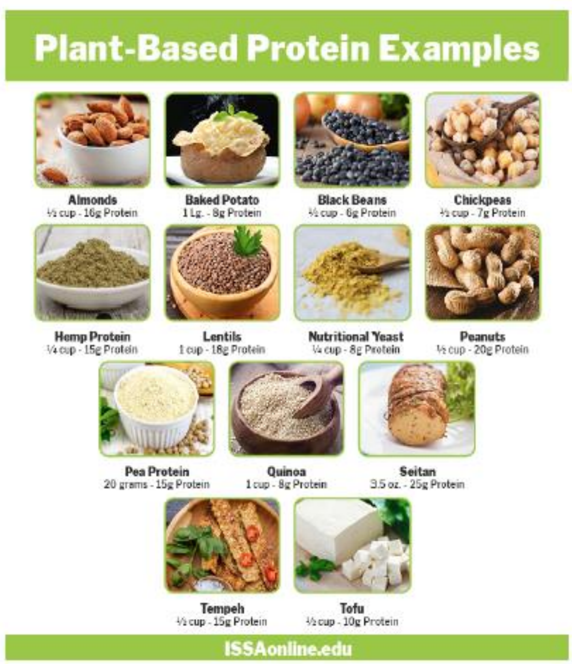


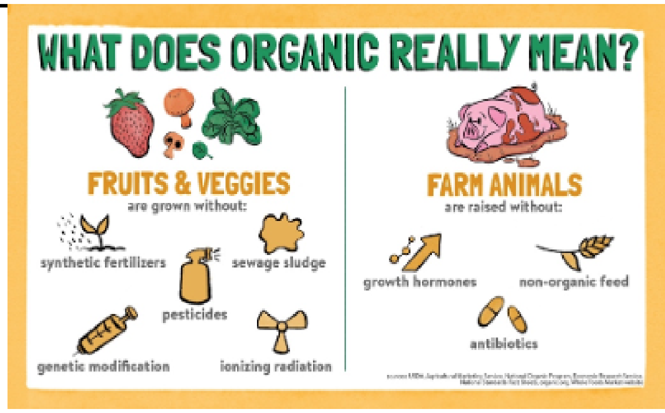


Appendix B : Tables

B1: Survey distributed to potential respondents.

Variables (This column will not be included in the online survey.)	**Questions:** Notes to supervisors will be highlighted	**Potential Responses**
Consent	**Consent to Participate:** With full knowledge of all foregoing, I agree, of my own free will, to participate in this study: (If the answer (B) "I do not wish to participate" is selected, the participant will immediately be directed to the end of the survey and the data collected will be deleted.)	A) I agree to participate B) I do not wish to participate
Age	1. What is your age? If Under 18 is selected the following message will be displayed in the survey: "Thank you for considering participating in this study, however you are not eligible to participate because you are not over 18 years old." The participant that selects the answer (A) "Under 18 will" will immediately be directed at the end of the survey and the data collected will be deleted.	A) Under 18 B) 18 to 24 years old C) 25 to 44 years old D) 45 to 64 years old E) 65 and older
Ontario Residence	2. Are you currently living in the Canadian province of Ontario?	A) Yes B) No
Gender	3. What is your gender?	A) Male B) Female C) Other (Specify)
Number of People living in the Household	4. How many people live in your household?	A) 1 B) 2 C) 3 D) 4 E) 5 or more
	Please take the time to read over the following definitions in order to answer the questions below.	
	Definition of Sustainable Foods: Sustainable Foods must offer nutrition for all in a way that the **economic**, **social,** and **environmental** parts of the food supply are protected so that future generations can have access to food as well.	

<table>
<tr><td></td><td>
</td><td></td></tr>
<tr><td></td><td>Definition of Plant-Based Protein: Any source of protein which is found in plants. Examples of plant-based protein include beans, peas, lentils, tempeh, tofu, nuts, seeds, and certain grains like quinoa and buckwheat.

</td><td></td></tr>
<tr><td></td><td>Definition of Local Food: Food produced in the same province in which it is sold, or food sold across borders within 150 kilometers of the production site.</td><td></td></tr>
<tr><td></td><td>Definition of Organic Food: Organic food always means foods with no genetically modified organisms, no artificial flavors, no artificial colors, and no artificial preservatives.</td><td></td></tr>
</table>

		
Description of sustainable food	In your opinion, how would you rank the following in terms of sustainability? Rank the three options below in order with #1 being more sustainable and #3 being less sustainable (compared to the other two options). 5. Plant-based proteins. 6. Organic foods. 7. Local foods.	Three options ranked in order with #1 being more sustainable and #3 being less sustainable (compared to the other two options).
	URL Hyperlinks will be attached to the underlined terms previously defined throughout the survey to provide information in case the definitions of the terms: <u>Plant-based protein</u>, <u>Local food</u>, and <u>Organic food</u> are forgotten. Please open the URL hyperlink in a new page so that your progress on the survey hosted on Qualtrics can be saved.	
Food buying practice Behavior (Redman & Redman, 2014)	When buying food, indicate how often you buy the following: 8. Food at a local farmer' market. 9. Non-organic food. 10. Grocery-store foods locally grown. 11. Plant-based protein. 12. Animal product. 13. Certified organic foods.	A) Always B) Most of the time C) About half the time D) Sometimes E) Never
	The scores of items 9. And 12. were reversed because those question items measure the opposites of the behaviors addressed in this study.	
Intent to consume (#1) (Dependent Variable) (Wang et al, 2019)	Indicate to what extent you agree or disagree with the following statements: (Ranging from 1= Strongly Disagree, 3=Neutral to 5= Strongly Agree) 14. I am willing to buy **<u>local foods</u>** on a regular basis if they are available. 15. I am willing to buy **<u>organic foods</u>** on a regular basis if they are available. 16. I am willing to buy **<u>plant-based proteins</u>** on a regular basis if they are available.	A) Strongly disagree B) Somewhat disagree C) Neither agree nor disagree D) Somewhat agree E) Strongly agree
Intent to consume Question (#2) (Dependent Variable) (Stancu et al. 2017)	Please indicate your level of agreement with the following statements: 17. I intend to buy more **<u>local foods</u>** soon. 18. I intend to buy more **<u>organic foods</u>** soon. 19. I intend to buy more **<u>plant-based proteins</u>** soon.	A) Strongly disagree B) Somewhat disagree C) Neither agree nor disagree D) Somewhat agree E) Strongly agree

Food Abilities (Bagher et al, 2018) Redman & Redman, 2014)	Indicate your skill level in the following activities: (with 5 stars being extremely skilled and 1 star being not at all skilled). 20. Reading and understanding food labels (Nutrition facts table, ingredient lists, certifications, etc.) 21. Planning meals ahead (using recipes, grocery lists, budgets, etc.) 22. Cooking food using different methods (roast, fry, boil, stew, steam, etc.)	5 stars being extremely skilled and 1 star being not at all skilled. 5 stars) Extremely skilled 4 stars) Very skilled 3 stars) Moderately skilled 2 stars) Slightly skilled 1 star) Not at all skilled
Subjective Norm (Al Swidi, 2014)	Indicate your level of agreement with the following statements: 23. I have noticed that many people around me are buying **local food.** 24. I have noticed that many people around me are buying **organic food.** 25. I have noticed that many people around me are buying **plant-based protein.**	A) Strongly disagree B) Somewhat disagree C) Neither agree nor disagree D) Somewhat agree E) Strongly agree
Personal Moral Norm (Seol-A Kwon et al, 2019) (TARA MCBRIDE MINTZ, 2005)	Indicate your level of agreement with the following statements: 26. I feel that I must do everything I can to reduce the climate change problem. 27. I feel a sense of responsibility to do something about climate change issues for future generations. 28. I feel a moral obligation to read and compare package labels for environmentally safe ingredients when I shop.	A) Strongly disagree B) Somewhat disagree C) Neither agree nor disagree D) Somewhat agree E) Strongly agree
(Perceived) Behavioral Control (Al Swidi, 2014)	Indicate your level of agreement with the following statements: I can handle any challenges (money, time, information related, etc.) associated with buying: 29. **Organic foods.** 30. **Local foods.** 31. **Plant-based proteins.**	A) Strongly disagree B) Somewhat disagree C) Neither agree nor disagree D) Somewhat agree E) Strongly agree
Perceived Barriers of buying plant-based foods: (M. von Meyer-Höfer and A. Spiller,2015); (Aertsens et al, 2009)	Indicate your level of agreement with the following statements: It is difficult to buy **plant-based proteins** because: 32. I do not have time to cook them. 33. I do not know much about their nutrition/quality. 34. They are not available where I shop. 35. I do not believe they provide me with the nutrition I need. 36. They are too expensive. 37. I do not like their taste. 38. I am concerned with food safety.	A) Strongly disagree B) Somewhat disagree C) Neither agree nor disagree D) Somewhat agree E) Strongly agree
	39. **Optional:** Can you think of another reason why it is difficult for you to buy **plant-based proteins**? (If yes, please specify what it is)	Text Entry

Perceived Barriers of buying organic foods: (M. von Meyer-Höfer and A. Spiller,2015); (Aertsens et al, 2009)	Indicate your level of agreement with the following statements: It is difficult to buy **<u>organic foods</u>** because: 40. I do not have time to cook them. 41. I do not know much about their nutrition/quality. 42. They are not available where I shop. 43. I do not believe they provide me with the nutrition I need. 44. They are too expensive. 45. I do not like their taste. 46. I am concerned with food safety.	A) Strongly disagree B) Somewhat disagree C) Neither agree nor disagree D) Somewhat agree E) Strongly agree
	47. **Optional:** Can you think of another reason why it is difficult for you to buy **<u>organic foods</u>**? (If yes, please specify what it is)	Text Entry
Perceived Barriers of buying local food: (M. von Meyer-Höfer and A. Spiller,2015); (Aertsens et al, 2009)	Indicate your level of agreement with the following statements: It is difficult to buy **<u>local foods</u>** because: 48. I do not have time to cook them. 49. I do not know much about their nutrition/quality. 50. They are not available where I shop. 51. I do not believe they provide me with the nutrition I need. 52. They are too expensive. 53. I do not like their taste. 54. I am concerned with food safety.	A) Strongly disagree B) Somewhat disagree C) Neither agree nor disagree D) Somewhat agree E) Strongly agree
	55. **Optional:** Can you think of another reason why it is difficult for you to buy **<u>local foods</u>**? (If yes, please specify what it is)	Text Entry
Emotions/ Concerns (Verhoef, 2005) Fear Guilt (X. Wang et al, 2019) Empathy (Batson, 1987)	Indicate your level of agreement with the following statements: I choose food that: 56. Is heathy for me. 57. Is produced in a way that does not harm the environment. 58. Is produced in a way that does not cause animals to experience emotional or physical pain. 59. Is produced in a way that does not cause farmers and food workers emotional or physical pain.	A) Strongly disagree B) Somewhat disagree C) Neither agree nor disagree D) Somewhat agree E) Strongly agree
Attitude (Von Meyer Hofer et al, 2015)	Indicate how important is it for you to buy the following foods: 60. **<u>Plant-based protein.</u>** 61. **<u>Organic food.</u>** 62. **<u>Local food.</u>**	A) Extremely important B) Very important C) Moderately important D) Slightly important E) Not at all important
Intention to consume (#3) **<u>(Dependent variable)</u>** (Tarkiainen et al, 2005)	Indicate how likely you are to buy the following foods in the next year: 63. **<u>Plant-based proteins</u>** 64 **<u>Organic foods</u>** 65. **<u>Local foods</u>**	A) Extremely unlikely B) Somewhat unlikely C) Neither likely nor unlikely D) Somewhat Likely E) Extremely likely

HEXAD Framework of Player Types These questions (#65- 82), will be displayed in a randomized order.	Please indicate to what extent you agree or disagree with the following statements: (Ranging from **1= Strongly disagree, 3= Neutral** to **5= Strongly agree**)	Slider format (5-point Likert slider scale)
Philanthropist	66. It makes me happy if I can help others. 67. I like sharing my knowledge with others. 68. The wellbeing of others is important to me.	A) Strongly disagree B) Somewhat disagree C) Neither agree nor disagree D) Somewhat agree E) Strongly agree
Socialiser	69. Interacting with others is important to me. 70. It is important to me to feel like I am part of a community. 71. I enjoy group activities.	A) Strongly disagree B) Somewhat disagree C) Neither agree nor disagree D) Somewhat agree E) Strongly agree
Free Spirit	72. I often let my curiosity guide me. 73. I like to try new things. 74. Being independent is important to me.	A) Strongly disagree B) Somewhat disagree C) Neither agree nor disagree D) Somewhat agree E) Strongly agree
Achiever	75. I like defeating obstacles. 76. It is difficult for me to let go of a problem before I have found a solution. 77. I like mastering difficult tasks.	A) Strongly disagree B) Somewhat disagree C) Neither agree nor disagree D) Somewhat agree E) Strongly agree
Disruptor	78. I like to provoke people. 79. I see myself as a rebel. 80. I dislike following rules.	A) Strongly disagree B) Somewhat disagree C) Neither agree nor disagree D) Somewhat agree E) Strongly agree
Player	81. I like competitions where a prize can be won. 82. Rewards are a great way to motivate me. 83. If the reward is enough, I will put in the effort to get the reward.	A) Strongly disagree B) Somewhat disagree C) Neither agree nor disagree D) Somewhat agree E) Strongly agree
Gaming Behavior Type Frequency	Indicate how often you play the following in your free time: 84. Board games (e.g. Monopoly, Scrabble, Risk, Clue, Chess). 85. Casino games (e.g. poker, blackjack, roulette). 86. Games without equipment (e.g. charades, truth or dare, never have I ever, tag). 87. Video games (e.g. on phones, consoles, computers). 88. Card games (e.g. UNO, solitaire, go fish, hearts).	A) Always B) Most of the time C) About half the time D) Sometimes E) Never

Previously Gamified Application(s) Preferences These questions (#88-99), will be displayed in a randomized order.	Which of the following categories of mobile applications are you most likely to use? Rank up to 12 categories in the order of which ones you are most likely to use (most likely to use item as #1, and least likely to use item as #12). 89. Personal Fitness 90. Language Acquisition 91. Coding Instruction 92. Productivity/ Time management 93. Dating services 94. Social media 95. Personal finance 96. Cash-back and coupons 97. Video game 98. Cooking/ Recipe instructions 99. Food Delivery service 100. Networking	Categories in the ranked order from most likely to use to least likely to use (likely to use item as #1, and least likely to use item as #12).
Income	101. Which of these groups describes your total **household** income last year?	A) Less than 25 000 CAD B) 25 000 – 35 000 CAD C) 35 001 – 60 000 CAD D) 60 001 – 80 000 CAD E) 85 001 – 100 000 CAD F) 100 001 – 125 000 CAD G) 125 001 – 150 000 CAD H) 150 001 – 200 000 CAD I) Over 200 000 CAD J) I prefer not to say
Education	102. What is the highest level of formal education that you have completed?	A) Grade School B) High school diploma C) College diploma or trade apprenticeship D) Bachelor's degree E) Master's degree F) Ph.D. G) I prefer not to say
Marital Status	103. What is your current marital status?	A) Married B) Living with a partner C) Widowed D) Divorced or separated E) Never Married F) I prefer not to say

B2: HEXAD Scale questionnaire used to measure player types (Tondello et al. 2016).

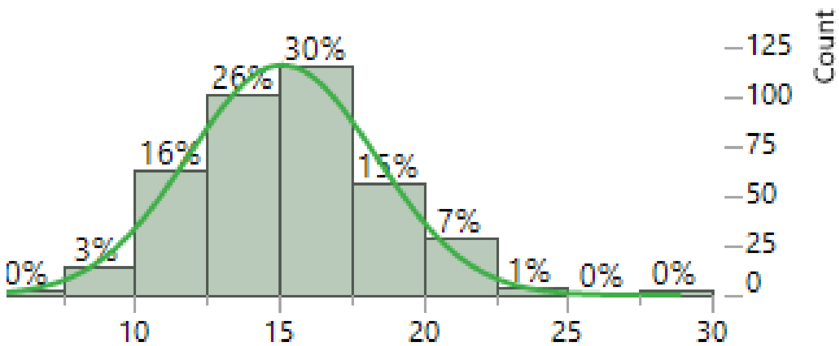
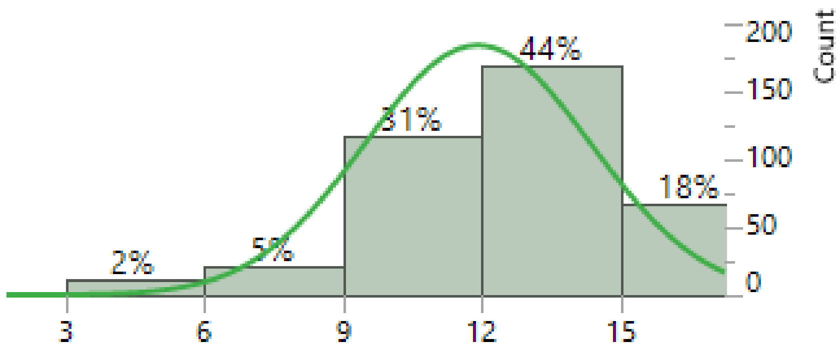
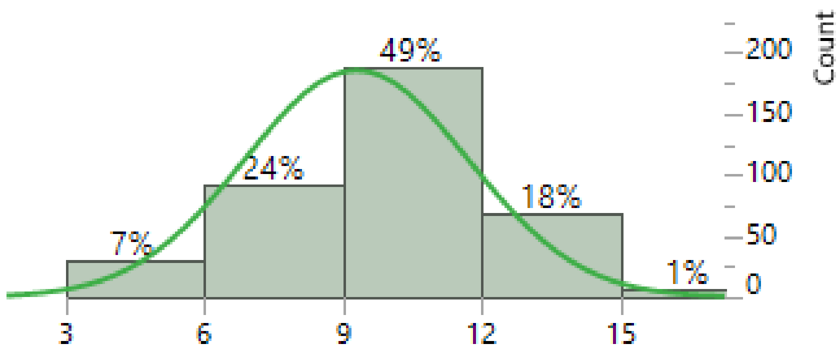
User Types		Items	5-items subscale correlation (r)	4-items subscale correlation (r)
Philanthropist	P1	It makes me happy if I am able to help others.	0.786	0.780
	P2	I like helping others to orient themselves in new situations.	0.779	0.775
	P3	I like sharing my knowledge.	0.733	0.783
	P4	The wellbeing of others is important to me.	0.771	0.763
	~~P5~~	~~I feel good taking on the role of a mentor.~~	0.667	removed
Socialiser	S1	Interacting with others is important to me.	0.730	0.734
	S2	I like being part of a team.	0.624	0.617
	S3	It is important to me to feel like I am part of a community.	0.670	0.676
	S4	I enjoy group activities.	0.688	0.662
	~~S5~~	~~It is more fun to be with others than by myself.~~	0.569	removed
Free Spirit	F1	It is important to me to follow my own path.	0.529	0.480
	F2	I often let my curiosity guide me.	0.491	0.546
	F3	I like to try new things.	0.507	0.525
	F4	Being independent is important to me.	0.538	0.496
	~~F5~~	~~I prefer setting my own goals.~~	0.373	removed
Achiever	A1	I like defeating obstacles.	0.603	0.574
	A2	It is important to me to always carry out my tasks completely.	0.483	0.485
	A3	It is difficult for me to let go of a problem before I have found a solution.	0.553	0.569
	A4	I like mastering difficult tasks.	0.612	0.604
	~~A5~~	~~I am very ambitious.~~	0.454	removed
Disruptor	D1	I like to provoke.	0.579	0.588
	D2	I like to question the status quo.	0.451	0.398
	D3	I see myself as a rebel.	0.569	0.569
	D4	I dislike following rules.	0.523	0.577
	~~D5~~	~~I like to take changing things into my own hands.~~	0.323	removed
Player	R1	I like competitions where a prize can be won.	0.445	0.459
	R2	Rewards are a great way to motivate me.	0.561	0.622
	R3	Return of investment is important to me.	0.359	0.313
	R4	If the reward is sufficient I will put in the effort.	0.580	0.568
	~~R5~~	~~I look out for my own interests.~~	0.305	removed

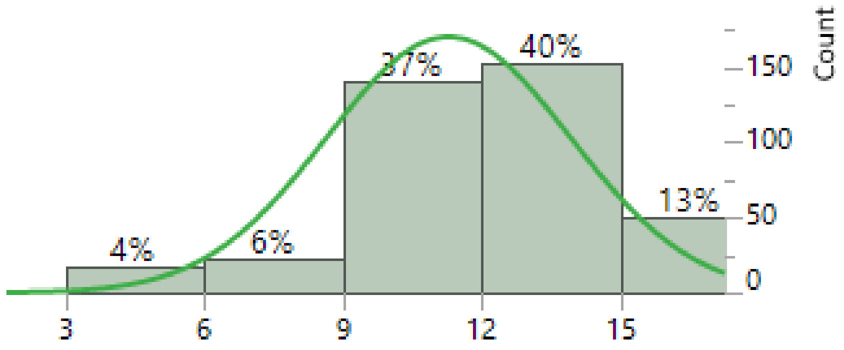
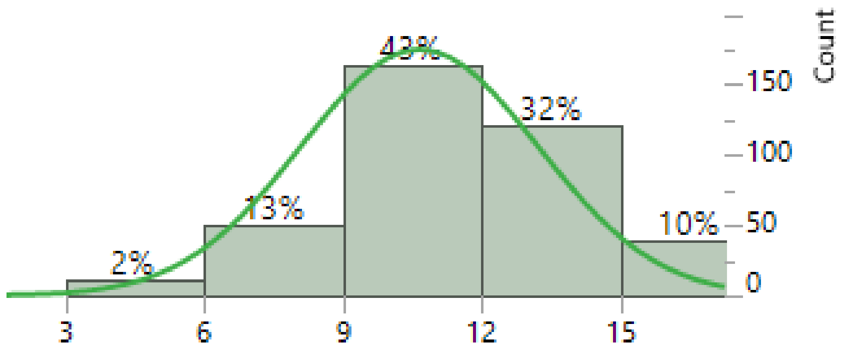
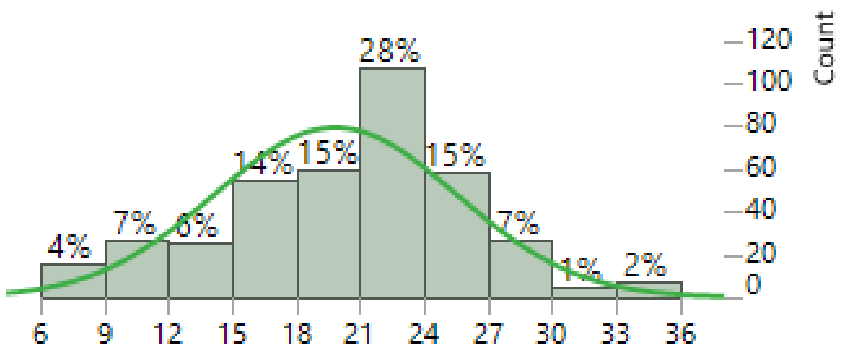
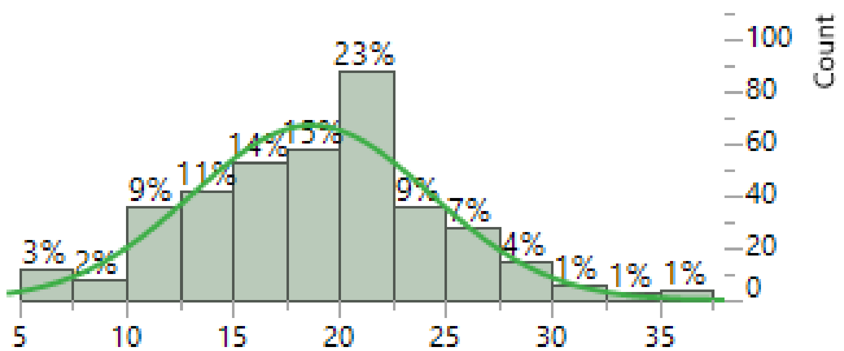
B3: Correlations of HEXAD player types with game design elements (Tondello et al. 2016).

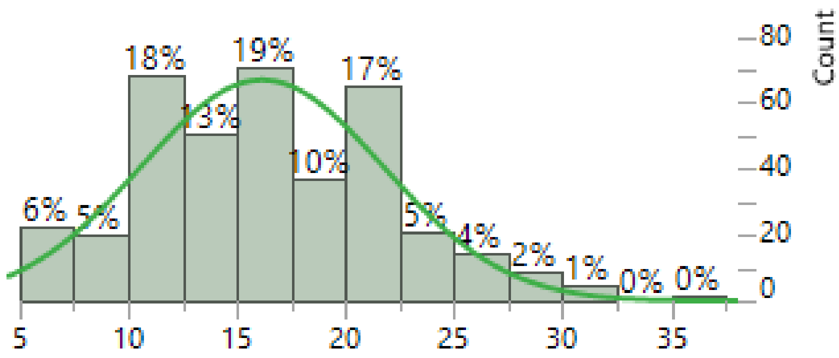
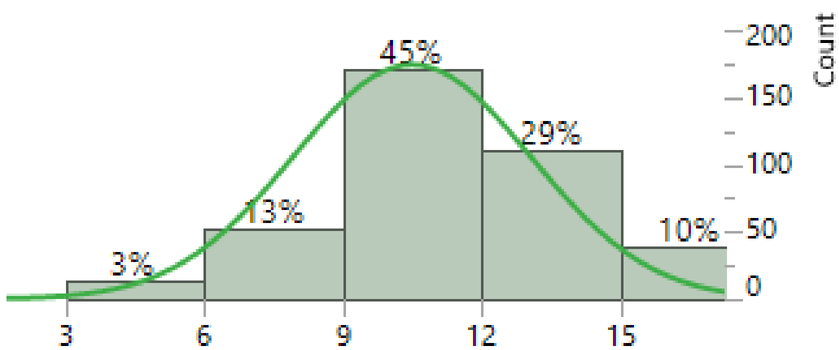
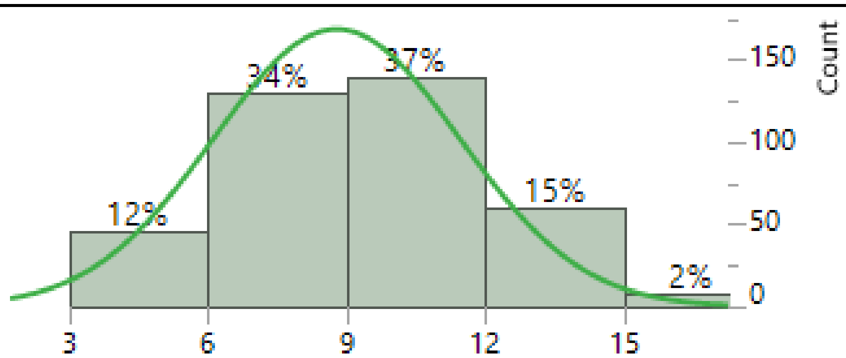
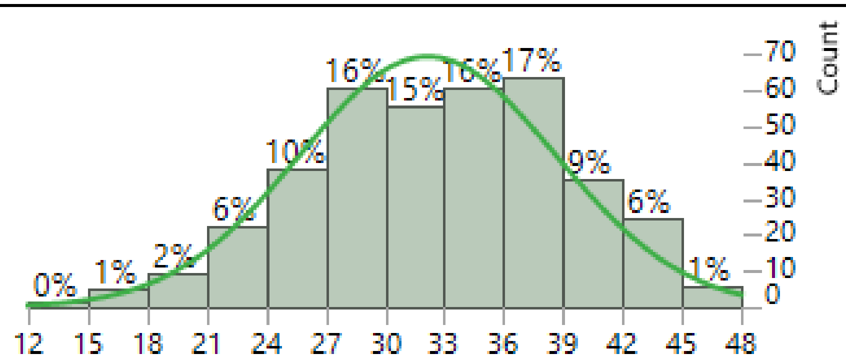
Suggested by Marczewski	Game Element	Improved Associations					
		Socialiser	Free Spirit	Achiever	Disruptor	Player	Philanthropist
Philanthropist	Collection and Trading	.153*	.148*	.172*		**.259****	
	Gifting	.163*				.207**	
	Knowledge sharing	.184**	.138*		.167*	.231**	
	Administrative roles				.199**		
Socialiser	Guilds or Teams	**.179****			.169*	.192*	
	Social networks	**.150****			.197**	.143*	
	Social comparison or pressure	**.152****				**.239****	
	Social competition	**.216****	.249**	.161*	**.320****	**.239****	
	Social discovery	**.205****			.179**	**.217****	
Free Spirit	Exploratory tasks		**.352****			.152**	.139*
	Nonlinear gameplay		**.221****				.179*
	Easter eggs	.137*	**.246****		.153**	.162*	
	Unlockable or rare content		**.225****			.149*	.140*
	Creativity tools		**.230****		**.252****		
	Customization		**.198****		.136**	.162**	
Achiever	Challenges		**.412****	**.463****	**.207****	**.317****	.212**
	Certificates	.142*	.200**	**.229****		**.228****	
	Learning		**.391****	**.215****			
	Quests		.236**	**.266****		**.245****	
	Levels or Progression	.170*	.204**	**.239****		**.302****	
	Boss battles						
Player	Points	.168*	.201**	.172**		**.259****	
	Rewards or Prizes		.139*	.167**		**.301****	
	Leaderboards	.199*			.170**	**.276****	
	Badges or Achievements	.164*		**.208****		**.271****	
	Virtual economy					**.273****	
	Lotteries or Games of chance	.148*				.190**	
Disruptor	Innovation platforms				**.302****	.166*	
	Voting mechanisms				**.236****	.138*	
	Development tools				**.294****	.144*	
	Anonymity		**.318****	**.289****		.211*	
	Anarchic gameplay		**.285****		**.268****		

Notes.
All correlations measured by Kendall's τ. Only significant correlations are shown.
The bold cells in each column mark the new suggestions of game design elements to support each Hexad user type.
* $p < 0.05$. ** $p < 0.01$.

B4: Data distributions from responses from the TPB variables part of the survey. Green curve is a fitted normal curve.

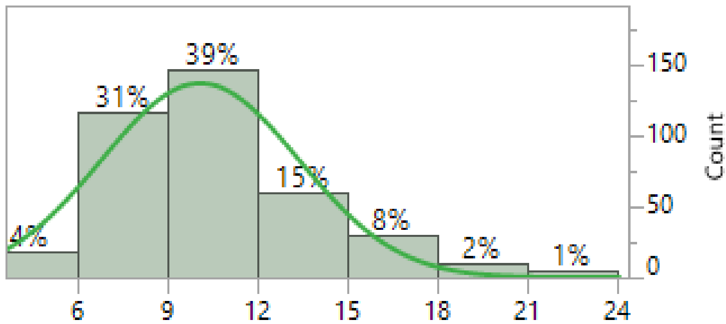
<table>
<tr><th>Category</th><th>Distribution</th><th>Statistics</th></tr>
<tr><td>Food Buying Practice</td><td>
</td><td>Mean 15.10
Std Dev 3.24
Std Err Mean 0.17
Upper 95% Mean 15.43
Lower 95% Mean 14.78
N 376.00
Skewness 0.26
Kurtosis 0.19
Median 15.00</td></tr>
<tr><td>Food abilities</td><td>
</td><td>Mean 11.92
Std Dev 2.44
Std Err Mean 0.13
Upper 95% Mean 12.17
Lower 95% Mean 11.67
N 376.00
Skewness -0.84
Kurtosis 0.73
Median 12.00</td></tr>
<tr><td>Subjective Norm</td><td>
</td><td>Mean 9.30
Std Dev 2.42
Std Err Mean 0.12
Upper 95% Mean 9.54
Lower 95% Mean 9.05
N 376.00
Skewness -0.31
Kurtosis 0.12
Median 9.00</td></tr>
</table>

<table>
<tr>
<td>Personal Moral Norm</td>
<td>
</td>
<td>Mean 11.29
Std Dev 2.64
Std Err Mean 0.14
Upper 95% Mean 11.56
Lower 95% Mean 11.02
N 376.00
Skewness -0.81
Kurtosis 0.88
Median 12.00</td>
</tr>
<tr>
<td>Perceived Behavioural Control</td>
<td>
</td>
<td>Mean 10.66
Std Dev 2.57
Std Err Mean 0.13
Upper 95% Mean 10.92
Lower 95% Mean 10.40
N 376.00
Skewness -0.34
Kurtosis 0.20
Median 11.00</td>
</tr>
<tr>
<td>Perceived Barriers - Plant based food</td>
<td>
</td>
<td>Mean 19.84
Std Dev 5.67
Std Err Mean 0.29
Upper 95% Mean 20.41
Lower 95% Mean 19.26
N 376.00
Skewness -0.29
Kurtosis 0.06
Median 21.00</td>
</tr>
<tr>
<td>Perceived Barriers - Organic foods</td>
<td>
</td>
<td>Mean 18.70
Std Dev 5.59
Std Err Mean 0.29
Upper 95% Mean 19.27
Lower 95% Mean 18.14
N 376.00
Skewness 0.11
Kurtosis -0.10
Median 19.00</td>
</tr>
</table>

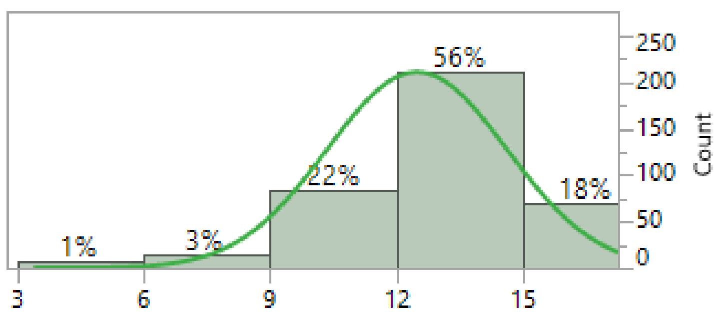
Perceived Barriers - Local foods		Mean 16.17 Std Dev 5.59 Std Err Mean 0.29 Upper 95% Mean 16.73 Lower 95% Mean 15.60 N 376.00 Skewness 0.40 Kurtosis -0.31 Median 15.00
Emotions /Concerns		Mean 10.50 Std Dev 2.58 Std Err Mean 0.13 Upper 95% Mean 10.76 Lower 95% Mean 10.24 N 376.00 Skewness -0.18 Kurtosis 0.02 Median 10.00
Attitude		Mean 8.79 Std Dev 2.66 Std Err Mean 0.14 Upper 95% Mean 9.06 Lower 95% Mean 8.52 N 376.00 Skewness 0.16 Kurtosis -0.51 Median 9.00
Intent to Consume		Mean 32.16 Std Dev 6.47 Std Err Mean 0.33 Upper 95% Mean 32.82 Lower 95% Mean 31.51 N 376.00 Skewness -0.18 Kurtosis -0.38 Median 32.00

B5: Data distributions from responses from the Gamification variables part of the survey. Green curve is a fitted normal curve.

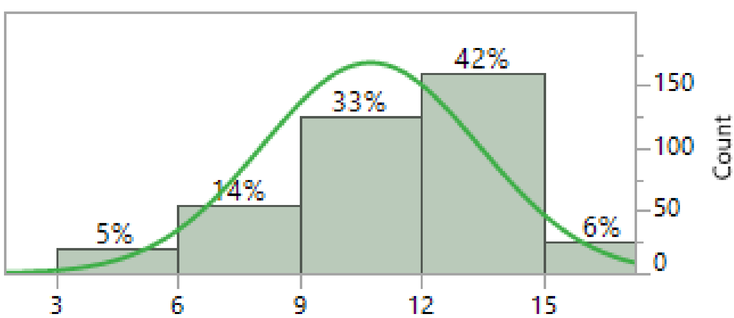
<table>
<tr><th>Category</th><th>Distribution</th><th>Statistics</th></tr>
<tr><td>Gaming behaviour frequency</td><td>



</td><td>Mean 10.11
Std Dev 3.28
Std Err Mean 0.17
Upper 95% Mean 10.45
Lower 95% Mean 9.78
N 376.00
Skewness 1.06
Kurtosis 1.46
Median 10.00</td></tr>
<tr><td>Philanthropist type</td><td>

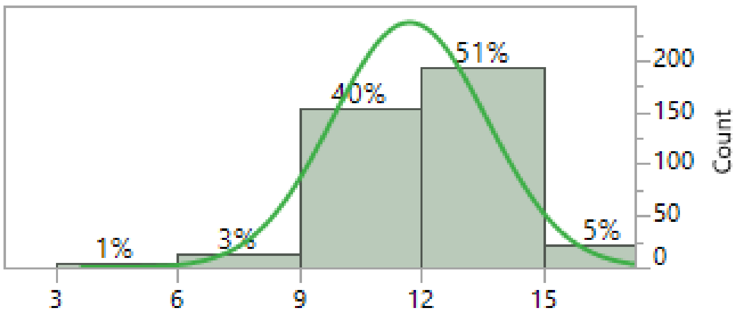


</td><td>Mean 12.48
Std Dev 2.13
Std Err Mean 0.11
Upper 95% Mean 12.69
Lower 95% Mean 12.26
N 376.00
Skewness -1.07
Kurtosis 1.39
Median 13.00</td></tr>
<tr><td>Socializer type</td><td>



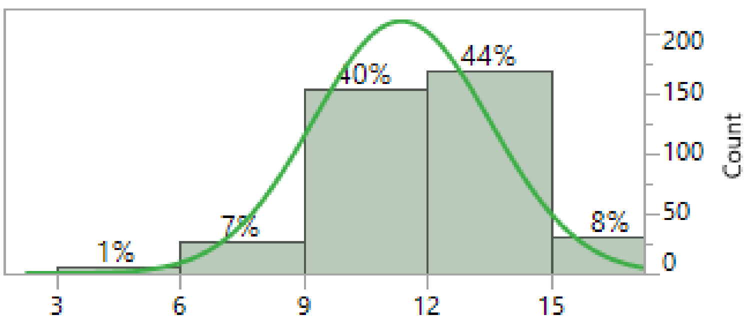
</td><td>Mean 10.76
Std Dev 2.67
Std Err Mean 0.14
Upper 95% Mean 11.03
Lower 95% Mean 10.49
N 376.00
Skewness -0.62
Kurtosis -0.05
Median 11.00</td></tr>
</table>

Free spirit type



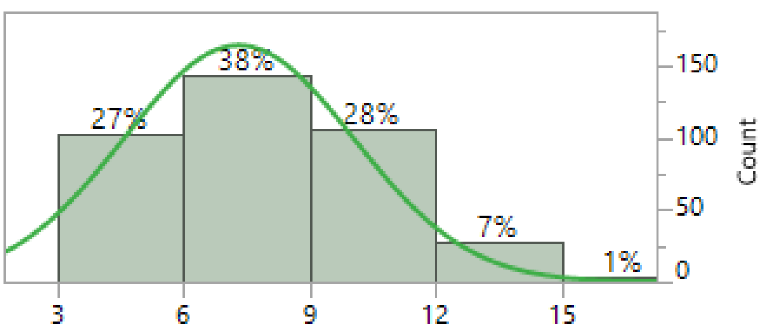
Mean	11.72
Std Dev	1.90
Std Err Mean	0.10
Upper 95% Mean	11.92
Lower 95% Mean	11.53
N	376.00
Skewness	-0.55
Kurtosis	0.83
Median	12.00

Achiever type



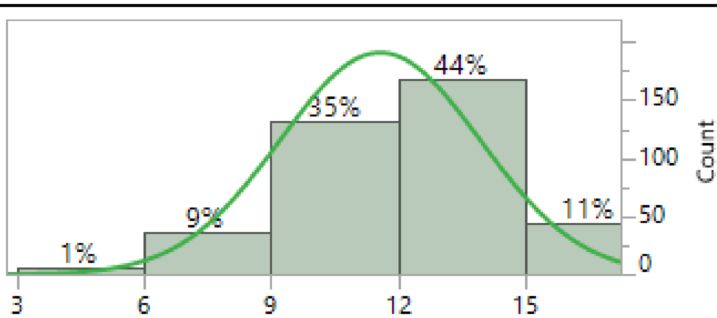
Mean	11.39
Std Dev	2.14
Std Err Mean	0.11
Upper 95% Mean	11.60
Lower 95% Mean	11.17
N	376.00
Skewness	-0.50
Kurtosis	0.59
Median	12.00

Disruptor type



Mean	7.32
Std Dev	2.73
Std Err Mean	0.14
Upper 95% Mean	7.60
Lower 95% Mean	7.05
N	376.00
Skewness	0.24
Kurtosis	-0.55
Median	7.00

Player type



Mean	11.57
Std Dev	2.36
Std Err Mean	0.12
Upper 95% Mean	11.81
Lower 95% Mean	11.34
N	376.00
Skewness	-0.52
Kurtosis	-0.20
Median	12.00

B6: Contingency table for preferences of mobile apps as a function of cluster membership.

Mobile applications	Hierarchical cluster	Responses (Frequence & Share)			Total Responses
		1-2	3-6	7-12	
Personal Fitness/ Wellness	1	15 15.6%	49 51.00%	32 33.3%	96
	2	5 14.3%	12 34.3%	18 51.4%	35
	3	4 11.8%	13 38.2%	17 50.00%	34
	4	10 18.5%	27 50.00%	17 31.5%	54
	5	17 44.7%	14 36.8%	7 18.4%	38
	6	7 21.9%	18 56.3%	7 21.9%	32
Language Acquisition	1	10 11.6%	24 27.9%	52 60.5%	86
	2	2 6.1%	12 36.4%	19 57.6%	33
	3	1 3.2%	9 29.00%	21 67.7%	31
	4	2 4.3%	15 32.6%	29 63.00%	46
	5	1 2.9%	11 32.4%	22 64.7%	34
	6	5 19.2%	10 38.5%	11 42.3%	26
Coding Instruction	1	4 4.8%	11 13.3%	68 81.9%	83
	2	0 0	3 9.4%	29 90.6%	32
	3	1 3.2%	5 16.1%	25 80.6%	31

	4	1 2.2%	7 15.6%	37 82.2%	45
	5	0 0	4 11.8%	30 88.2%	34
	6	4 14.8%	4 14.8%	19 70.4%	27
Productivity Management	1	5 6.00%	25 29.8%	54 64.3%	84
	2	0 0	15 42.9%	20 57.1%	35
	3	2 6.7%	13 43.3%	15 50.00%	30
	4	2 4.2%	18 37.5%	28 58.3%	48
	5	3 8.6%	13 37.1%	19 54.3%	35
	6	3 10.7%	10 35.7%	15 53.6%	28
Dating service	1	3 3.6%	5 6.00%	75 90.4%	83
	2	4 11.4%	8 22.9%	23 65.7%	35
	3	1 3.1%	11 34.4%	20 62.5%	32
	4	1 2.2%	2 4.3%	43 93.5%	46
	5	3 8.3%	2 5.6%	31 86.1%	36
	6	1 3.6%	5 17.9%	22 78.6%	28
Social media	1	59 55.1%	30 28.00%	18 16.8%	107
	2	23 56.1%	8 19.5%	10 24.4%	41

	3	15 40.5%	12 32.4%	10 27.00%	37
	4	40 64.5%	12 19.4%	10 16.1%	62
	5	27 64.3%	11 26.2%	4 9.5%	42
	6	13 43.3%	3 10.00%	14 46.7%	30
Personal finance	1	39 36.4%	51 47.7%	17 15.9%	107
	2	17 39.5%	17 39.5%	9 20.9%	43
	3	15 41.7%	13 36.1%	8 22.2%	36
	4	18 29.00%	37 59.7%	7 11.3%	62
	5	18 41.9%	18 41.9%	7 16.3%	43
	6	8 26.7%	17 56.7%	5 16.7%	30
Cash-back and coupons	1	37 33.9%	48 44.00%	24 22.00%	109
	2	13 32.5%	15 37.5%	12 30.00%	40
	3	15 44.1%	11 32.4%	8 23.5%	34
	4	17 29.3%	24 41.4%	17 29.3%	58
	5	8 20.5%	19 48.7%	12 30.8%	39
	6	7 22.6%	11 35.5%	13 41.9%	31
Video Games	1	19 20.00%	28 29.5%	48 50.5%	95

	2	17 43.6%	11 28.2%	11 28.2%	39
	3	11 30.6%	8 22.2%	17 47.2%	36
	4	15 27.3%	15 27.3%	25 45.5%	55
	5	10 25.6%	10 25.6%	19 48.7%	39
	6	5 17.9%	10 35.7%	13 46.4%	28
Cooking/ Recipe instructions	1	41 41.00%	41 41.00%	18 18.00%	100
	2	6 17.1%	16 45.7%	13 37.1%	35
	3	9 25.00%	18 50.00%	9 25.00%	36
	4	14 25.00%	26 46.4%	16 28.6%	56
	5	9 22.00%	21 51.2%	11 26.8%	41
	6	11 32.4%	13 38.2%	10 29.4%	34
Food Delivery service	1	7 8.1%	27 31.4%	52 60.5%	86
	2	6 16.7%	14 38.9%	16 44.4%	36
	3	8 23.5%	13 38.2%	13 38.2%	34
	4	7 13.2%	19 35.8%	27 50.9%	53
	5	5 13.2%	12 31.6%	21 55.3%	38
	6	8 25.8%	11 35.5%	12 38.7%	31

Networking	1	13 14.1%	52 56.5%	27 29.3%	92
	2	3 9.1%	15 45.5%	15 45.5%	33
	3	5 16.1%	9 29.00%	17 54.8%	31
	4	8 14.5%	29 52.7%	18 32.7%	55
	5	5 13.9%	16 44.4%	15 41.7%	36
	6	5 19.2%	7 26.9%	14 53.8%	26

B7: Contingency table for gaming behaviour as a function of cluster membership.

Questions	Hierarchical cluster	Responses (Frequence & Share)					
		Never	Sometimes	Half of the time	Most of the time	Always	Total Responses
Indicate how often you play the following in your free time: - Board games (e.g. Monopoly, Scrabble, Risk, Clue, Chess).	1	38 30.6%	73 58.9%	7 5.6%	6 4.8%	0 0.0%	124
	2	12 24.0%	25 50.0%	7 14.0%	4 8.0%	2 4.0%	50
	3	12 27.9%	23 53.5%	6 14.0%	1 2.3%	1 2.3%	43
	4	12 17.1%	51 72.9%	6 8.6%	1 1.4%	0 0.0%	70
	5	8 16.7%	30 62.5%	2 4.2%	6 12.5%	2 4.2%	48
	6	3 7.7%	20 51.3%	6 15.4%	7 17.9%	3 7.7%	39
Indicate how often you play the following in your free time: - Casino games (e.g. poker, blackjack, roulette).	1	81 65.3%	38 30.6%	3 2.4%	2 1.6%	0 0.0%	124
	2	32 64.0%	11 22.0%	4 8.0%	2 4.0%	1 2.0%	50
	3	21 48.8%	15 34.9%	3 7.0%	4 9.3%	0 0.0%	43
	4	46 65.7%	21 30.0%	2 2.9%	1 1.4%	0 0.0%	70
	5	33 68.8%	13 27.1%	1 2.1%	1 2.1%	0 0.0%	48
	6	16 41.0%	10 25.6%	6 15.4%	5 12.8%	2 5.1%	39
Indicate how often you play the following in your free time: - Games without equipment (e.g. charades, truth or dare, never have I ever, tag).	1	71 57.3%	43 34.7%	7 5.6%	2 1.6%	1 0.8%	124
	2	22 44.0%	20 40.0%	6 12.0%	2 4.0%	0 0.0%	50
	3	21 48.8%	18 41.9%	4 9.3%	0 0.0%	0 0.0%	43

	4	36 51.4%	29 41.4%	3 4.3%	2 2.9%	0 0.0%	70
	5	16 33.3%	25 52.1%	4 8.3%	1 2.1%	2 4.2%	48
	6	10 25.6%	17 43.6%	6 15.4%	5 12.8%	1 2.6%	39
Indicate how often you play the following in your free time: - Video games (e.g. on phones, consoles, computers).	1	38 30.6%	40 32.3%	19 15.3%	18 14.5%	9 7.3%	124
	2	9 18.0%	12 24.0%	10 20.0%	10 20.0%	9 18.0%	50
	3	9 20.9%	16 37.2%	11 25.6%	2 4.7%	5 11.6%	43
	4	14 20.0%	27 38.6%	10 14.3%	14 20.0%	5 7.1%	70
	5	15 31.3%	11 22.9%	10 20.8%	7 14.6%	5 10.4%	48
	6	7 17.9%	12 30.8%	10 25.6%	6 15.4%	4 10.3%	39
Indicate how often you play the following in your free time: - Card games (e.g. UNO, solitaire, go fish, hearts).	1	29 23.4%	71 57.3%	12 9.7%	9 7.3%	3 2.4%	124
	2	8 16.0%	26 52.0%	10 20.0%	5 10.0%	1 2.0%	50
	3	8 18.6%	26 60.5%	5 11.6%	3 7.0%	1 2.3%	43
	4	15 21.4%	38 54.3%	11 15.7%	5 7.1%	1 1.4%	70
	5	6 12.5%	24 50.0%	8 16.7%	7 14.6%	3 6.3%	48
	6	2	15	10	9	3	39

Contingency Analysis - Clusters and Socio-demographics

In the following tables, each cluster has been assigned a letter for convenience and readability. The letters are given to the immediate right of the cluster number. Cluster 1 is denoted "A", cluster 2 "B" etc. The “Compare” column shows us which clusters are significantly different (at the 95% confidence level) by the appearance of a letter. We see “B,C,D,E,F” in the row for cluster 1 (A). This means that clusters 2-6 (identified by B,C,D,E,F) are all significantly different from cluster 1 in terms of age bracket distributions. Of more interest are the letters observed in the cells. These are pairwise comparisons within the columns, determined using Fishers Exact Test so the number of counts in each cell is not a concern as it would be if we were using a Pearson chi-squared test. Looking at cluster 1 in the 65+ age bracket, one finds “B,C,D”. This means cluster 1 contains significantly more 65+ people than clusters 2,3, and 4 (B, C and D). The reason the letters are assigned is that one can well imagine how large and busy this table would be if Cluster 1, Cluster 2 etc. were input everywhere a letter is observed.

B8-1: Contingency Analysis – Clusters and Age

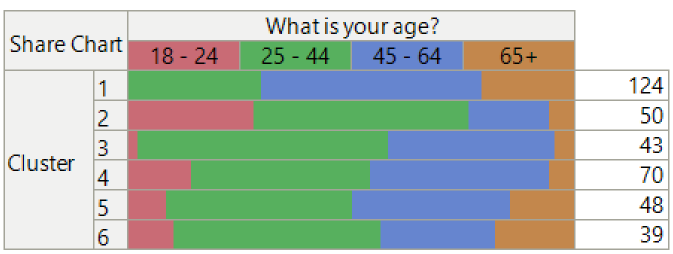
What is your age? By Cluster

Freq / Share / Comparisons			What is your age? 18 - 24	25 - 44	45 - 64	65+	Total Responses	Compare
Cluster	1	A	0 0.0%	37 29.8%	61 49.2% B,F	26 21.0% B,C,D	124	B,C,D,E,F
	2	B	14 28.0% A,C,E	24 48.0% A	9 18.0%	3 6.0%	50	C,E
	3	C	1 2.3%	24 55.8% A	16 37.2%	2 4.7%	43	
	4	D	10 14.3% A,C	28 40.0%	28 40.0% B	4 5.7%	70	
	5	E	4 8.3% A	20 41.7%	17 35.4%	7 14.6%	48	
	6	F	4 10.3% A	18 46.2%	10 25.6%	7 17.9%	39	

Default Comparison Groups: A/B/C/D/E/F

Shows letter of the category it is significantly different from at the higher share level

* Base count warning	30	Uppercase Alpha Level	0.05
** Base count minimum	10	Lowercase Alpha Level	0



For the age variable, we observe Cluster 5 and 6 have significantly more 18-24 year olds than cluster 1. There are no significant differences between clusters 4,5 and 6. Cluster 2 (least likely to consume) does have significantly more young people (18-24) than cluster 5 (mostly likely to consume), but not clusters 4 or 6 which are also likely to consume a sustainable diet.

B8-2: Contingency Analysis – Clusters and Gender

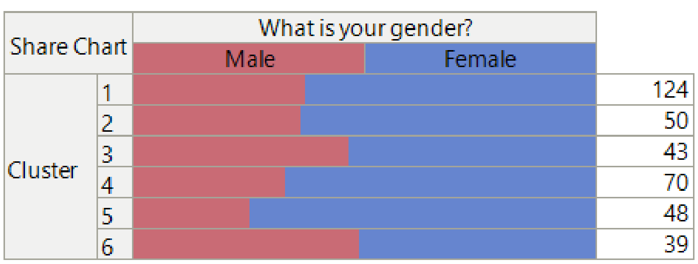
What is your gender? By Cluster

Freq Share Comparisons			What is your gender? Male	Female	Total Responses	Compare
Cluster	1	A	46 37.1%	78 62.9%	124	
	2	B	18 36.0%	32 64.0%	50	
	3	C	20 46.5% E	23 53.5%	43	
	4	D	23 32.9%	47 67.1%	70	
	5	E	12 25.0%	36 75.0% C,F	48	C,F
	6	F	19 48.7% E	20 51.3%	39	

Default Comparison Groups: A/B/C/D/E/F

Shows letter of the category it is significantly different from at the higher share level

* Base count warning	30	Uppercase Alpha Level	0.05
** Base count minimum	10	Lowercase Alpha Level	0



In terms of gender, cluster 5 is significantly different than cluster 3 and cluster 6. It is far more female dominated. This is also borne out in the column analyses, where cluster 6 has significantly more males than cluster 5. However, there does not appear to be any significant differences in clusters 4,5 or 6 (most likely to consume) with cluster 2 (least likely to consume).

B8-3: Contingency Analysis – Clusters and Household members

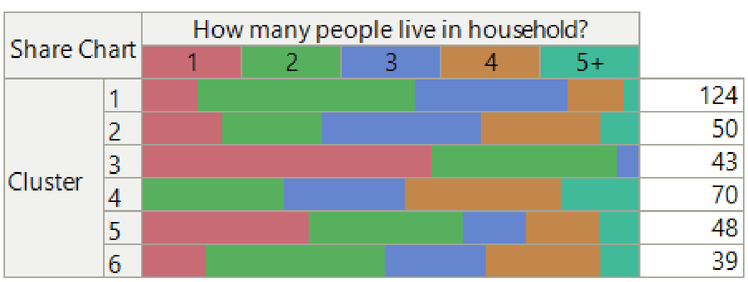
How many people live in household? By Cluster

Freq Share Comparisons			How many people live in household?						
			1	2	3	4	5+	Total Responses	Compare
Cluster	1	A	14 11.3% D	54 43.5% B,D	38 30.6% C,E	14 11.3% C	4 3.2%	124	B,C,D,E
	2	B	8 16.0% D	10 20.0%	16 32.0% C,E	12 24.0% C	4 8.0%	50	C,E
	3	C	25 58.1% A,B,D,E,F	16 37.2%	2 4.7%	0 0.0%	0 0.0%	43	F
	4	D	0 0.0%	20 28.6%	17 24.3% C	22 31.4% A,C,E	11 15.7% A,C	70	B,C,E,F
	5	E	16 33.3% A,D,F	15 31.3%	6 12.5%	7 14.6% C	4 8.3%	48	C
	6	F	5 12.8% D	14 35.9%	8 20.5% C	9 23.1% C	3 7.7%	39	

Default Comparison Groups: A/B/C/D/E/F

Shows letter of the category it is significantly different from at the higher share level

* Base count warning	30	Uppercase Alpha Level	0.05
** Base count minimum	10	Lowercase Alpha Level	0



In terms of how many people live in the household, cluster 4 is significantly different from the other two high intent to consume clusters 5 and 6. It is also significantly different from cluster 2, the least likely to consume. There are significantly more members from cluster 4 coming from household’s containing 4 people compared to cluster 5, but not cluster 6 or the cluster 2 (the least likely to consume).

B8-4: Contingency Analysis- Clusters and Martial Status

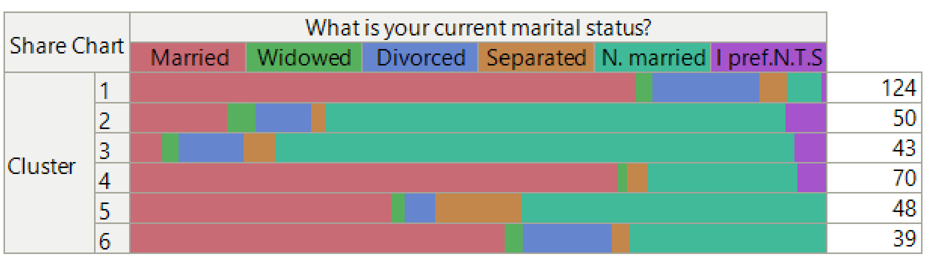
What is your current marital status? By Cluster

Freq Share Comparisons		Married	Widowed	Divorced	Separated	N. married	I pref.N.T.S	Total Responses	Compare
Cluster	1 A	90 72.6% B,C,E,F	3 2.4%	19 15.3% D	5 4.0%	6 4.8%	1 0.8%	124	B,C,D,E,F
	2 B	7 14.0%	2 4.0%	4 8.0% D	1 2.0%	33 66.0% A,D,E,F	3 6.0%	50	E,F
	3 C	2 4.7%	1 2.3%	4 9.3% D	2 4.7%	32 74.4% A,D,E,F	2 4.7%	43	F
	4 D	49 70.0% B,C,E	1 1.4%	0 0.0%	2 2.9%	15 21.4% A	3 4.3%	70	B,C,E,F
	5 E	18 37.5% B,C	1 2.1%	2 4.2%	6 12.5%	21 43.8% A,D	0 0.0%	48	C
	6 F	21 53.8% B,C	1 2.6%	5 12.8% D	1 2.6%	11 28.2% A	0 0.0%	39	

Default Comparison Groups: A/B/C/D/E/F

Shows letter of the category it is significantly different from at the higher share level

* Base count warning	30	Uppercase Alpha Level	0.05
** Base count minimum	10	Lowercase Alpha Level	0



Clusters 5 and 6 are not significantly different in terms of marital status, nor are there any significant differences in the various marital status categories between clusters 5 and 6. However, there is a significant difference between cluster 4, and clusters 5 and 6. Those in cluster 4 are predominantly married. There is also a significant difference between cluster 2 and clusters 4-6. There are significantly more unmarried people in cluster 2.

B8-5: Contingency Analysis-Clusters and Income

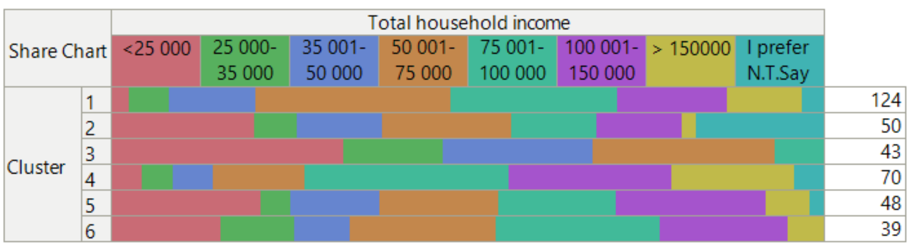
Total household income By Cluster

Freq Share Comparisons			Total household income									
			<25 000	25 000-35 000	35 001-50 000	50 001-75 000	75 001-100 000	100 001-150 000	> 150000	I prefer N.T.Say	Total Responses	Compare
Cluster	1	A	3 2.4%	7 5.6%	15 12.1%	34 27.4% D	29 23.4% C	19 15.3% C	13 10.5% C	4 3.2%	124	B,C,E
	2	B	10 20.0% A,D	3 6.0%	6 12.0%	9 18.0%	6 12.0%	6 12.0% C	1 2.0%	9 18.0% A,C,D,E,F	50	C
	3	C	14 32.6% A,D	6 14.0%	9 20.9% D	11 25.6%	3 7.0%	0 0.0%	0 0.0%	0 0.0%	43	F
	4	D	3 4.3%	3 4.3%	4 5.7%	9 12.9%	20 28.6% B,C	16 22.9% C	12 17.1% B,C	3 4.3%	70	B,C
	5	E	10 20.8% A,D	2 4.2%	6 12.5%	8 16.7%	8 16.7%	10 20.8% C	3 6.3%	1 2.1%	48	C
	6	F	6 15.4% A	4 10.3%	3 7.7%	8 20.5%	9 23.1%	7 17.9% C	2 5.1%	0 0.0%	39	

Default Comparison Groups: A/B/C/D/E/F

Shows letter of the category it is significantly different from at the higher share level

* Base count warning	30	Uppercase Alpha Level	0.05
** Base count minimum	10	Lowercase Alpha Level	0



Clusters 5 and 6 are not significantly different in terms of household income, nor are there any significant differences in the various levels of income between clusters 5 and 6. However, cluster 4 is significantly different from cluster 2. Cluster 2 has more people in the lowest income bracket compared to cluster 4, and cluster 2 also has more people that prefer not to say what their income is compared to all those who have high intent to consume in clusters 4,5 and 6.

B8-6: Contingency Analysis – Clusters and Education

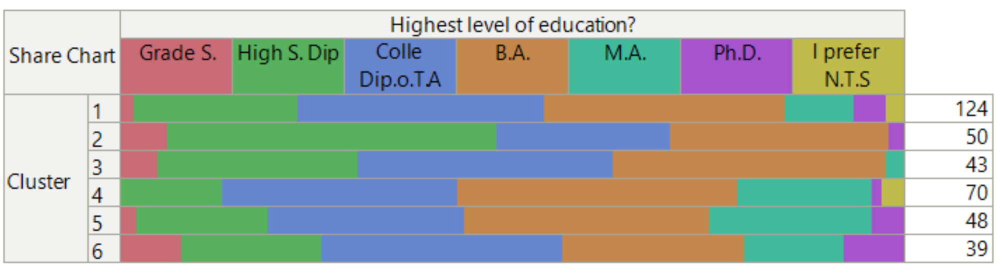
Highest level of education? By Cluster

Freq Share Comparisons			Highest level of education?								
			Grade S.	High S. Dip	Colle Dip.o.T.A	B.A.	M.A.	Ph.D.	I prefer N.T.S	Total Responses	Compare
Cluster	1	A	2 1.6%	26 21.0%	39 31.5%	38 30.6%	11 8.9% B	5 4.0%	3 2.4%	124	B
	2	B	3 6.0%	21 42.0% A,D,E,F	11 22.0%	14 28.0%	0 0.0%	1 2.0%	0 0.0%	50	E,F
	3	C	2 4.7%	11 25.6%	14 32.6%	15 34.9%	1 2.3%	0 0.0%	0 0.0%	43	
	4	D	0 0.0%	9 12.9%	21 30.0%	25 35.7%	12 17.1% B,C	1 1.4%	2 2.9%	70	B,C
	5	E	1 2.1%	8 16.7%	12 25.0%	15 31.3%	10 20.8% A,B,C	2 4.2%	0 0.0%	48	
	6	F	3 7.7% D	7 17.9%	12 30.8%	9 23.1%	5 12.8% B	3 7.7%	0 0.0%	39	

Default Comparison Groups: A/B/C/D/E/F

Shows letter of the category it is significantly different from at the higher share level

* Base count warning	30	Uppercase Alpha Level	0.05
** Base count minimum	10	Lowercase Alpha Level	0

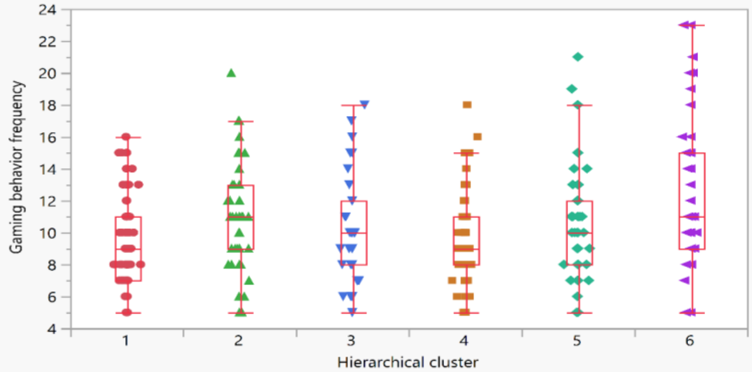


There is a significant difference in the distribution of education levels between clusters 5 and 6 and cluster 2. Cluster 2 has a significantly higher number of members with a high school diploma, while clusters 4,5 and 6 have a higher number with MA degrees.

Oneway Analysis of Gamification variables by Hierarchical cluster

B9-1

Oneway Analysis of Gaming behavior frequency By Hierarchical cluster



Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean
1	124	9.23	2.47	0.22
2	50	10.78	3.45	0.49
3	43	9.98	3.16	0.48
4	70	9.61	2.71	0.32
5	48	10.56	3.38	0.49
6	39	12.64	4.72	0.76

Means Comparisons

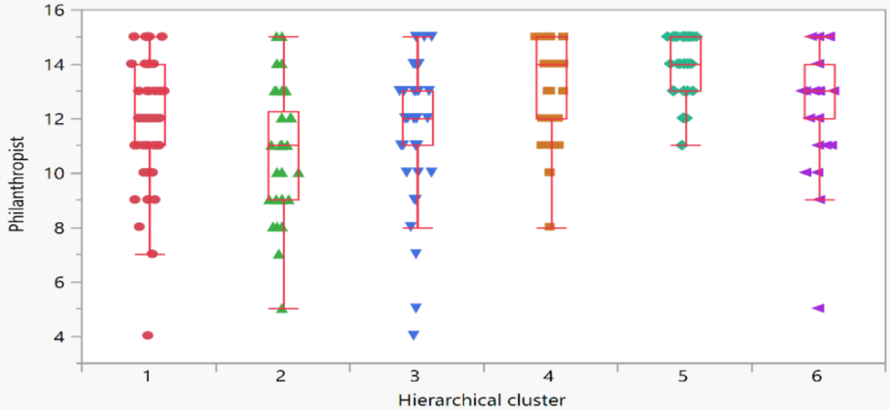
Comparisons for all pairs using Tukey-Kramer HSD

Ordered Differences Report

Level	- Level	Difference	p-Value
6	1	3.42	<.0001*
6	4	3.03	<.0001*
6	3	2.66	0.0021*
6	5	2.08	0.0280*
6	2	1.86	0.0647
2	1	1.55	0.0394*
5	1	1.34	0.1267
2	4	1.17	0.3434
5	4	0.95	0.5933
2	3	0.80	0.8230
3	1	0.75	0.7573
5	3	0.59	0.9495
4	1	0.39	0.9626
3	4	0.36	0.9914
2	5	0.22	0.9994

Missing Rows 2

Oneway Analysis of Philanthropist By Hierarchical cluster



Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean
1	124	12.43	1.95	0.17
2	50	10.68	2.22	0.31
3	43	11.79	2.49	0.38
4	70	13.16	1.74	0.21
5	48	14.00	1.11	0.16
6	39	12.56	1.92	0.31

Means Comparisons

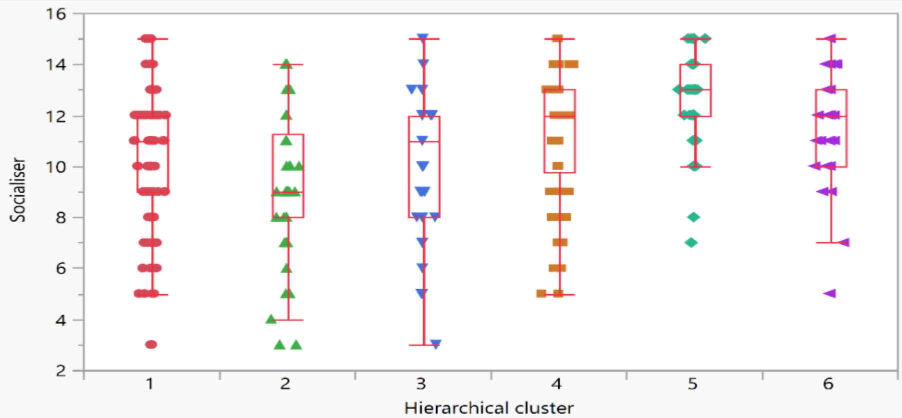
Comparisons for all pairs using Tukey-Kramer HSD

Ordered Differences Report

Level	- Level	Difference	p-Value
5	2	3.32	<.0001*
4	2	2.48	<.0001*
5	3	2.21	<.0001*
6	2	1.88	0.0001*
1	2	1.75	<.0001*
5	1	1.57	<.0001*
5	6	1.44	0.0083*
4	3	1.37	0.0041*
3	2	1.11	0.0659
5	4	0.84	0.1860
6	3	0.77	0.4610
4	1	0.73	0.1195
1	3	0.64	0.4280
4	6	0.59	0.6416
6	1	0.14	0.9989

Missing Rows 2

Oneway Analysis of Socialiser By Hierarchical cluster



Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean
1	124	10.33	2.64	0.24
2	50	9.30	2.70	0.38
3	43	10.14	2.62	0.40
4	70	11.16	2.45	0.29
5	48	12.75	1.84	0.27
6	39	11.56	2.38	0.38

Means Comparisons

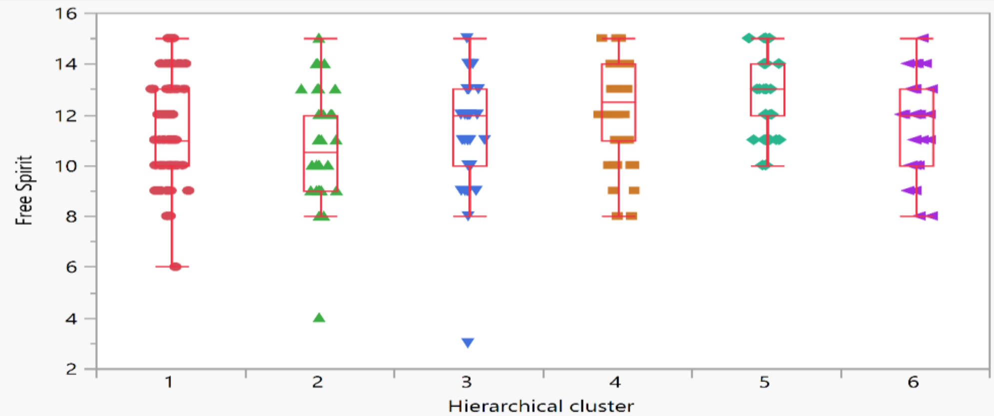
Comparisons for all pairs using Tukey-Kramer HSD

Ordered Differences Report

Level	- Level	Difference	p-Value
5	2	3.45	<.0001*
5	3	2.61	<.0001*
5	1	2.42	<.0001*
6	2	2.26	0.0004*
4	2	1.86	0.0010*
5	4	1.59	0.0095*
6	3	1.42	0.1043
6	1	1.23	0.0791
5	6	1.19	0.2380
1	2	1.03	0.1371
4	3	1.02	0.2870
3	2	0.84	0.5873
4	1	0.83	0.2330
6	4	0.41	0.9645
1	3	0.19	0.9981

Missing Rows 2

Oneway Analysis of Free Spirit By Hierarchical cluster



Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean
1	124	11.53	1.74	0.16
2	50	10.72	2.08	0.29
3	43	11.28	2.16	0.33
4	70	12.21	1.70	0.20
5	48	13.00	1.44	0.21
6	39	11.69	1.75	0.28

Means Comparisons

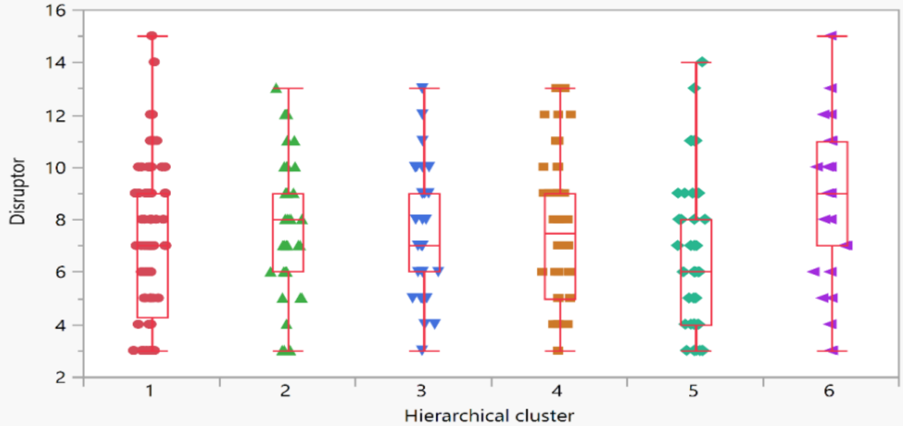
Comparisons for all pairs using Tukey-Kramer HSD

Ordered Differences Report

Level	- Level	Difference	p-Value
5	2	2.28	<.0001*
5	3	1.72	0.0001*
4	2	1.49	0.0001*
5	1	1.47	<.0001*
5	6	1.31	0.0109*
6	2	0.97	0.1196
4	3	0.94	0.0822
1	2	0.81	0.0797
5	4	0.79	0.1863
4	1	0.68	0.1179
3	2	0.56	0.6701
4	6	0.52	0.6967
6	3	0.41	0.9053
1	3	0.25	0.9685
6	1	0.16	0.9967

Missing Rows 2

Oneway Analysis of Disruptor By Hierarchical cluster



Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean
1	124	6.81	2.65	0.24
2	50	7.88	2.37	0.34
3	43	7.56	2.40	0.37
4	70	7.46	2.66	0.32
5	48	6.42	2.91	0.42
6	39	8.92	2.97	0.48

Means Comparisons

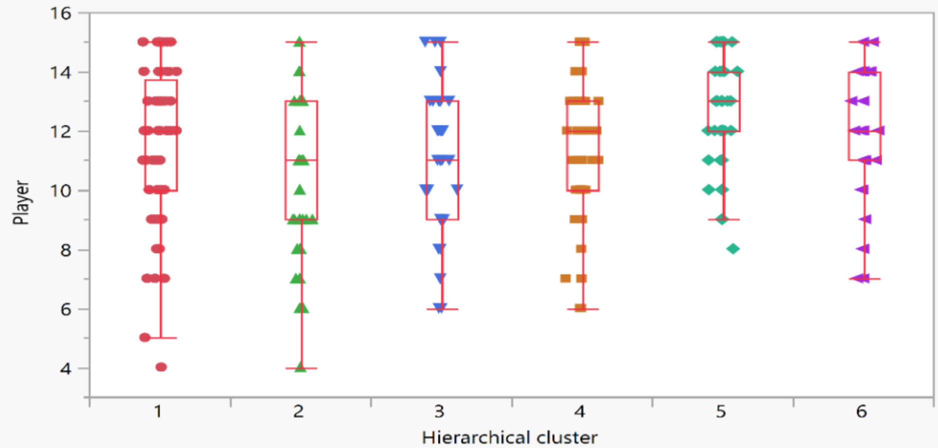
Comparisons for all pairs using Tukey-Kramer HSD

Ordered Differences Report

Level	- Level	Difference	p-Value
6	5	2.51	0.0002*
6	1	2.11	0.0003*
6	4	1.47	0.0664
2	5	1.46	0.0729
6	3	1.36	0.1878
3	5	1.14	0.3190
2	1	1.07	0.1615
6	2	1.04	0.4434
4	5	1.04	0.2955
3	1	0.74	0.6119
4	1	0.64	0.5878
2	4	0.42	0.9558
1	5	0.40	0.9510
2	3	0.32	0.9922
3	4	0.10	1.0000

Missing Rows 2

Oneway Analysis of Player By Hierarchical cluster



Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean
1	124	11.60	2.32	0.21
2	50	10.50	2.54	0.36
3	43	11.21	2.43	0.37
4	70	11.67	2.22	0.27
5	48	12.60	1.95	0.28
6	39	11.82	2.30	0.37

Means Comparisons

Comparisons for all pairs using Tukey-Kramer HSD

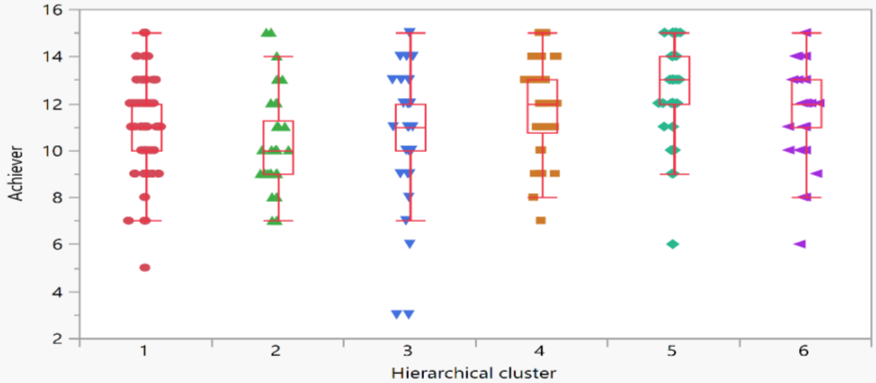
Ordered Differences Report

Level	- Level	Difference	p-Value
5	2	2.10	0.0001*
5	3	1.39	0.0470*
6	2	1.32	0.0804
4	2	1.17	0.0682
1	2	1.10	0.0527
5	1	1.01	0.1059
5	4	0.93	0.2577
5	6	0.78	0.6124
3	2	0.71	0.6759
6	3	0.61	0.8361
4	3	0.46	0.9053
1	3	0.39	0.9326
6	1	0.22	0.9950
6	4	0.15	0.9995
4	1	0.07	0.9999

Missing Rows 2

B9-7

Oneway Analysis of Achiever By Hierarchical cluster



Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean
1	124	11.27	1.89	0.17
2	50	10.10	1.96	0.28
3	43	10.84	2.60	0.40
4	70	11.74	1.96	0.23
5	48	12.65	1.99	0.29
6	39	11.79	2.08	0.33

Means Comparisons

Comparisons for all pairs using Tukey-Kramer HSD

Ordered Differences Report

Level	- Level	Difference	p-Value
5	2	2.55	<.0001*
5	3	1.81	0.0004*
6	2	1.69	0.0016*
4	2	1.64	0.0002*
5	1	1.38	0.0011*
1	2	1.17	0.0091*
6	3	0.96	0.2762
4	3	0.91	0.1989
5	4	0.90	0.1714
5	6	0.85	0.3809
3	2	0.74	0.5062
6	1	0.53	0.7187
4	1	0.48	0.6220
1	3	0.43	0.8417
6	4	0.05	1.0000

Missing Rows 2

Appendix C: Text Analysis

Three questions were posed in the survey that gave the respondents the opportunity to write in open text responses in case they could think of another barrier to purchasing the different types of sustainable foods that were not already listed in the questionnaire (e.g., “Can you think of another reason why it is difficult for you to buy plant-based proteins? (If yes, please specify what it is)”). These were all designed to help understand the perceived barriers to buying local, organic foods, and plant-based proteins. All responses not containing a reason explaining the difficulty of purchase of sustainable foods were considered void and thus removed from the text analysis. For instance, numerous participants answered the open text question to say that they could not think of another reason why it is difficult to buy the specified sustainable food type. Next, some participants wrote responses that were out of context with the questions (e.g. “ok yes hi thanks dudes”, or even “lol”). Moreover, some respondents answered the question with suggestions (e.g. “Offer sample and let people judge for themselves”). All those responses were considered not valid since they did not explicitly mention a difficulty to purchase the three sustainable foods types as defined in this study. Finally, the distribution of responses cannot be expressed in ratios because some participants mentioned two or even three response categories within the same response.

The data were then analysed by using text analysis, examining the most common words and phrases that were used. Word stemming was employed (e.g., available and availability would both count towards the stemmed response “avail-”). The results were expressed in terms of a stemmed word count from all the respondents that chose to answer these questions and a word cloud, where the words or stemmed words observed the most often were shown in larger font. A table summarising the text analysis results can be found in Table Appendix C1 below. Additionally, the Figures C2, C3, and C4 detail the results to understand the perceived barriers to buying local, organic foods, and plant-based proteins, respectively. The salient points are also discussed in the next three sections on perceived barriers to buying local and organic foods, and plant-based proteins.

C1: Summary Table of results for all open-ended questions

Open-ended questions	Response Category	Number of times mentioned
Optional: Can you think of another reason why it is difficult for you to buy local foods? (If yes, please specify what it is)	Availability	44
	Financial Cost	15
	Health concern	6
	Uncertainty	4
Can you think of another reason why it is difficult for you to buy plant-based proteins? (If yes, please specify what it is)	Preference for animal products	41
	Availability	25
	Health concern	19
	Financial Cost	18
	Uncertainty	17
	Environmental Concern	5
	Habits	4
Can you think of another reason why it is difficult for you to buy organic foods? (If	Financial Cost	34
	Distrust	17

yes, please specify what it is)	Availability	8
	Shelf-life	5
	Health concern	3
	Taste	3

1. **Text Analysis - Why is it difficult to buy local foods?**

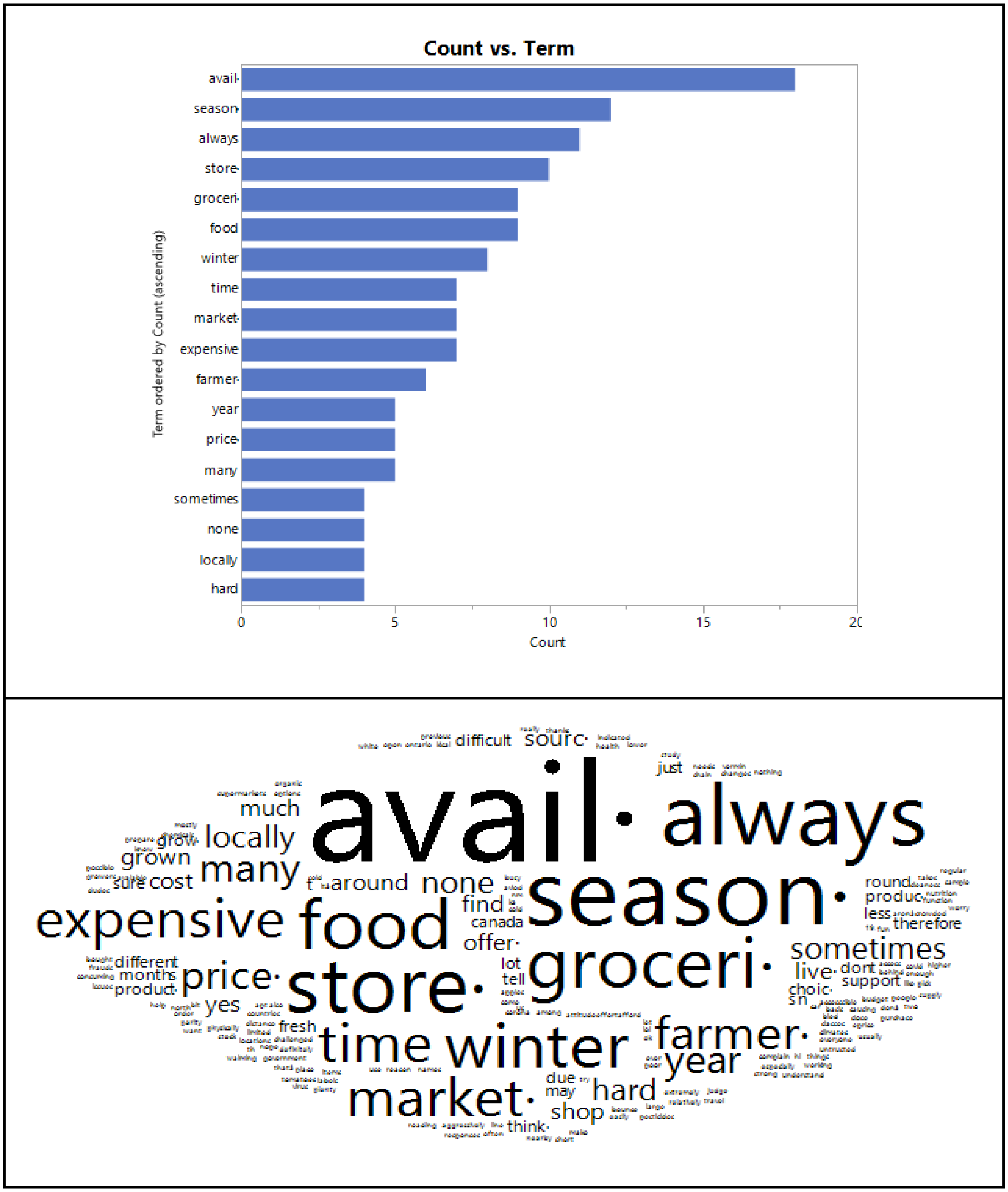
The top three barriers that were identified were: availability, cost, and health concerns. The number one reason why most respondents who answered this open text question believed it was difficult to buy local foods was the lack of availability. A total of 44 of the responses that offered reasons why it was difficult to buy local foods mentioned availability as being a barrier preventing them from purchasing more local food. Within those 44 responses, 21 of them explained that availability is an issue when purchasing local foods due to seasonality. For example, one participant wrote that “Canada has many season changes causing many items not to be locally available through the winter”. Seven responses specified that the lack of availability was because local products could not be found in the store they usually shop at. For example, one respondent wrote that “Grocery stores do not make an effort to stock. Not always in chain grocery”, someone else wrote “the store I shop at doesn't supply them”. Three people mentioned that the lack of availability was due to the local food being sold too far away from them.

The second main barrier to buying local food most often mentioned by participants was its financial cost, which was mentioned by a total of 15 people as being a barrier to their local food consumption. For example, one person wrote that “they are too expensive, the price needs to come down a bit”.

The third barrier to buying local food mentioned by participants was health concerns, which was mentioned by a total of six people. Two people mentioned the potential usage of chemical products present during the production of local foods. For example, one person wrote that “Local food grown locally may or may not use strong pesticides, and that is not indicated on the product”. One participant wrote “I worry about the cleanliness and health issues”. Another person mentioned concerns regarding health and cleanliness surrounding local food products. Finally, one individual explained that concerns about the transmission of Covid-19 was a barrier to accessing local foods at the farmers’ market due to the elevated proximity between people present there.

The fourth barrier to purchasing local food products is uncertainty. Four participants wrote about their uncertainty regarding the agricultural practices employed as well as lacking product information that would usually be found on labels. For instance, one participant wrote “Local food grown locally and found at farmer’s market may or may not use strong pesticides, and that is not indicated on the product”.

C2: Term count and word cloud from write-in text responses on perceived barriers to buying local foods.



2. Text Analysis - Why is it difficult to buy plant-based proteins?

The top three barriers that were identified were: preference for animal products, availability, and health concerns. The subject most often mentioned by respondents explaining why it is difficult to buy plant-based proteins was related to the preferences of consumers towards animal products. A total of 41 participants that offered reasons as to why it was difficult to buy plant-based proteins mentioned that they enjoyed consuming animal-based proteins more than plant-based protein. More specifically, 11 people wrote that they simply prefer animal products to plant based products as their main protein source. For example, one person wrote "I prefer animal proteins", and another said that "For me, the best source of proteins is meat, not plant based food.". Moreover, ten people mentioned that members of their household do not enjoy plant-based proteins as much as animal products. For example, one person wrote "Other members of my household prefer certain animal-based products" and another said "There is no one in my house that will eat it."; and one even wrote "My partner hates them". The taste of plant-based proteins being a barrier to their consumption was mentioned by nine participants. For example, one person wrote " No(t) the biggest fan of the taste". Furthermore, five people mentioned the texture of plant-based proteins as being an issue. For example, respondents wrote "Have never been impressed with the texture" and one even wrote "I do not like their texture".

Next, the availability of plant-based proteins was mentioned 25 times and was therefore the second barrier of consuming plant-based proteins most often mentioned by participants. Some participants were more specific regarding the reasons underlying the lack of availability, for instance, eight persons mentioned that there is a lack of variety, four said that those products were not present in the store they usually shop at, and three people simply said that it was hard to find. For example, one person wrote that "Plant based proteins are more readily available in only certain stores, so you have to travel farther to buy them as well".

The third barrier most often mentioned by participants for this open text question was health concerns regarding the nutritional value of those foods, which was mentioned by 19 respondents. More specifically, four people mentioned that this type of food can be too processed, another four mentioned that they contain artificial ingredients, three people said that they contain too many carbohydrates, and two people wrote that they believed this type of food to be unhealthy. For instance, one person wrote "this stuff is not healthy for you".

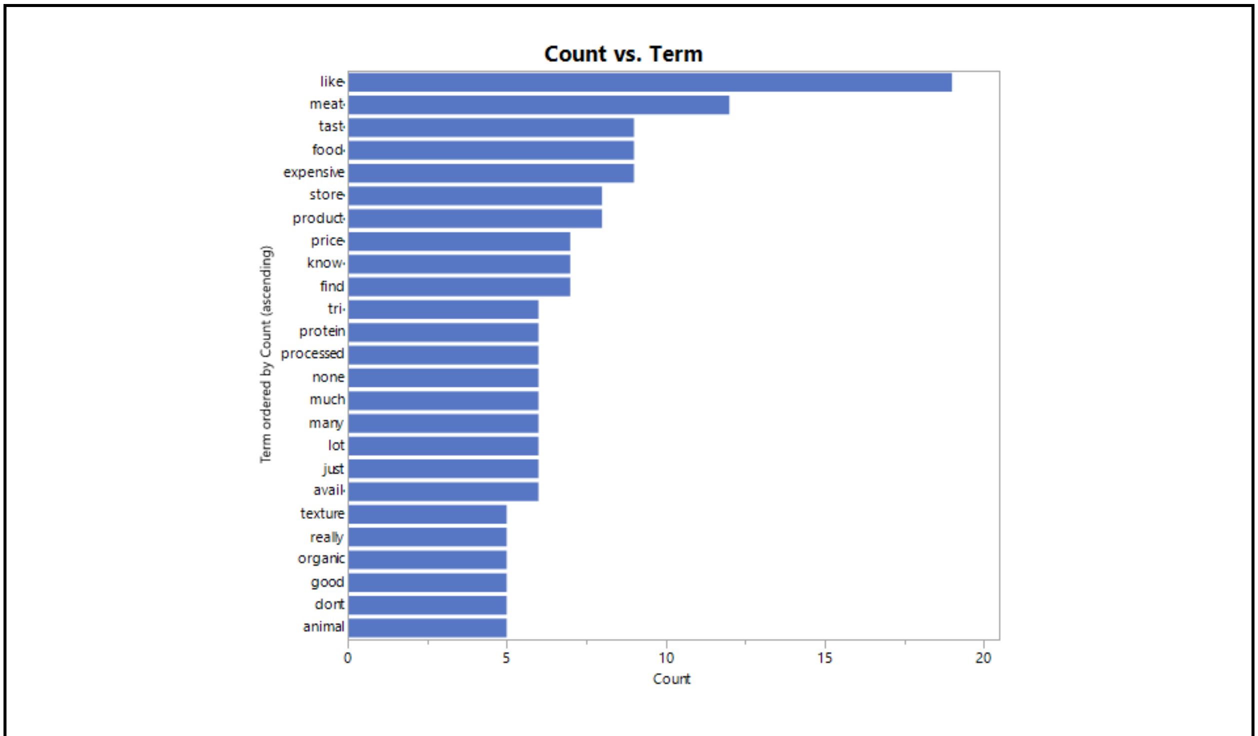
The fourth barrier most often mentioned by participants for this open text question was their higher financial costs, which was mentioned by 18 respondents. Three persons wrote "too expensive". Two individuals simply wrote "expensive".

The next barrier most often mentioned by participants who answered this open text question was uncertainty, which was mentioned 17 times. More specifically seven people mentioned that they had a general lack of information regarding such food products. For example, one person wrote that "Don't know much about it and never really considered it". Two people were not sure how to identify plant-based foods. For instance, one person wrote "not always sure what they are off the top of my head", the other wrote "I am unsure even were to find them in a grocery store. I don't know what to look for.". Two other people mentioned that they were not sure how to add those products into their regular diet, for example one person wrote "Unsure of how to incorporate them into recipes or find good recipes with them".

The next barrier most often mentioned by participants who answered this open text question was environmental concern. The five individuals explained that they did not trust that plant-based protein was more environmentally friendly than animal protein. For example, one person wrote "I don't believe they are better for climate change", another explained that plant-based protein takes more energy in production than animal products.

The final barrier most often mentioned by participants who answered this open text question was their habits. It was mentioned by 4 people. Three individuals explained that they were not used to it and had already established eating habits while growing up, one person simply stated that it is "hard to establish a habit of buying these products."

C3: Term count and word cloud from write-in text responses on perceived barriers to buying plant-based proteins.



3. Text Analysis - Why is it difficult to buy organic foods?

The top three barriers that were identified were: financial cost, mistrust, and availability. The first reason why respondents indicated it was difficult to buy organic foods was their increased financial cost relative to their non-organic counterparts, which was mentioned by 34 participants that supplied reasons as to why it was difficult to buy organic foods.

The second barrier most often mentioned by participants who answered this open text question was a distrust in organic claims, which was mentioned by a total of 17 people. Within those responses 11 said that they did not trust the labels. Those individuals do not trust companies when they claim that products are grown organically, and therefore that organic food labels cannot be trusted. Because the only visible difference between organic and non-organic foods is the presence of a label, many people believed that foods certified as organic are not grown organically. For example, one person wrote that “Anyone can claim something is organic. I just don't believe half the food out there truly is organic.”, another said “I’m not really sure if the labels are 100% honest”, one individual stated that “a lot of what is called organic-isn't”, and someone else simply wrote that “It is a scam”. Moreover, five individuals did not trust claims that organic foods are better than conventionally grown foods. For example, one individual wrote “I don’t believe they are any better than regular food”. One person did not trust that organic foods are better for the environment than conventionally grown food.

As with plant-based proteins and local foods, there was some concern expressed about their availability, but this was relatively minor compared to the expense factor since only ten people mentioned it for this question. Out of eight people who mentioned availability issues, six of them specified that it is because not many stores sell them. For example, one person wrote “Not many stores sell these products”.

Five participants talked about the reduced shelf life of organic foods as one barrier to their consumption. For example, one respondent wrote “They are only good for a few days before rotting”, and another one wrote “A lot of times the food has brown marks on them”.

Three individuals mentioned that the taste of organic products is the same as non-organic foods even though it is more expensive. One wrote “more expensive and doesn't taste any different”. Three other people mentioned health related reasons preventing the purchase of organic food. One of those three person talk wrote “non-organic food is nutritionally equivalent and cheaper”. Another person mentioning health simply wrote “Dirty”.

Consequently, within all the open text responses given by participants, four categories of barriers to purchase were identified for local foods and six categories for organic foods. A total of seven categories of barriers to purchase were identified for plant-based proteins. Availability, financial cost, and health concern are the three categories of barriers to purchase that are common to all sustainable food types.C3: Term count and word cloud from write-in text responses on perceived barriers to buying organic foods.