Cape Peninsula
University of Technology

THE MARKETABILITY OF SMALL SCALE HYDROPONIC SYSTEMS FOR THE HORTICULTURAL INDUSTRY IN SOUTH AFRICA

By

ALEX NICHOLAS ROSSOUW

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Supervisor: Prof CP Laubscher

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Abstract

Hydroponics, *i.e.* plant cultivation in mineral-rich water is a synergy between plant, human, and machine. For decades the hydroponic garden has been offered on horticultural markets, and was repeatedly innovated to better meet consumer horticultural needs. Currently, platform convergences with electronic control systems can possibly enable more efficient products for direct consumer hydroponic cultivation. This means that, like many appliances in the home; hydroponic plant cultivation can become somewhat automated.

Marketing and product innovation can help calibrate optimal New Product Development NPD of hydroponic gardens for people. The literature review grasps how consumers are subjected to a changing environment together with changing technology such as hydroponics, plant nutrition, and even garden automation. Market research frameworks namely Morphological Analysis (MA) and Conjoint Analysis (CA) are the tools deployed here for profiling and prioritising these products for horticultural consumers.

Firstly, a qualitative analysis identifies conceptual sets for *structures*, *inputs*, and *controls*, which all harmonise into new intersections *cultivation*, *hydroponics*, and *automation* and the *e-garden* concepts. The MA next produces, and organises secondary data into constraints for the CA. Here, general hydroponic cultivation is first decomposed into all its many component parts which collectively describe the whole, where these parts are then classed along various attributes namely: *garden plane* x_A, *automation* x_B, *performance* x_C, *organics* x_D, and *price* x_E So *garden plane* is composed of *level* and *vertical gardens*, *garden automation* is composed of *manual* and *automatic gardens*, *garden performance* is composed of *casual* and *high-performance gardens*, *garden organics* is composed of *non-organic* and *organic gardens*, and *garden price* although quantitative is simply composed of *R2500* and *R5000*. These classes of attributed data can now become treated as categorical factors using indicator or dummy variables.

Secondly, the CA determines how these attributes are most preferred by horticultural consumers at garden centre clusters. This involves measuring respondent preferences

levels, to compute the *part-worth utility* for each attribute found in the MA. Factors such as *garden organics*, *price*, and *automation* hold adjusted alpha significance. Mainly, *garden organics* contributed to response effects, while *price* has negative slope and is second, while *automation* comes third. A combination of *garden automation* and *organics* is found to optimise consumer utility for Hydroponic Garden(s) HG.This research illuminates how horticultural consumers may prefer various HG, by understanding HG and how they can better benefit these people.

To plants and family.

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List of abbreviations:

1 HG: Hydroponic Garden(s)

2 LED: Light Emitting Diode

3 EC: Electrical Conductivity

4 NFT: Nutrient Film Technique

5 ANN: Artificial Neural Network

6 NPD: New Product Development

7 MA: Morphological Analysis

8 CA: Conjoint Analysis

9 PSU: Primary Sampling Unit(s)

10 SSU: Secondary Sampling Unit(s)

11 FFD: Fractional Factorial Design

12 GLM: Generalised linear model

13 OLS: Ordinary Least Squares

14 LCL: Lower confidence limit

15 ULC: Upper confidence limit

16 CI: Confidence Interval

17 PO: Proportional Odds

18 *OR*: Odds Ratio(s)

19 NR: Non-Response(s)

20 NC: Non-Coverage

21 R: South African Rands, currency value, ZAR.

Definition of terms for this research:

- **Horticulture**: The art, science, technology, and business of plant cultivation.
- **Horticultural needs**: These are consumer needs for practical, culinary, or ornamental garden products and services (Warrington, 2014).
- **Horticultural consumers**: These are specified here as the group of consumers who seek live plant products and kits in meeting their gardening needs (Warrington, 2014).
- **Urban horticultural consumers**: This research holds that those horticultural consumers who shop in and around built-up urban centres on the Cape Peninsula; are thus urban horticultural consumers who inherently have particular needs, and so are a theoretical market for the offerings of e-gardens.
- **Garden centre**: Retail plant and lifestyle centre.
- **Hydroponics**: "The science of growing plants in a medium, other than soil, using mixtures of the essential 15 plant nutrient elements dissolved in water" Harris, (1992). Here plant roots are bathed continuously or discontinuously in an aqueous nutrient solution with minimal inert media for support. (Harris, 1992). HG appears to utilise this paradigm for plant cultivation.
- **Hydroponic cultivation**: Plant cultivation in hydroponic systems.
- **Hydroponic Gardens (HG)**: This term used here by this research is for the general application of hydroponic cultivation in gardens by horticultural consumers, which are some decades in existence.
- **E-gardens**: Electronic gardens. This research identifies garden products that are distinct from traditional HG. These are novel hydroponic-based cultivation units or modular kits, which offer particular core features to better meet the needs of urban horticultural consumers. E-gardens are complete garden systems that are ready to use, occupy no larger than a square metre, and are small-scale easy-to-use consumer electronic products. Empirical examples include "*Click and Grow*™" and "*Aerogarden*™" units (see figure. 1.1 and 1.2.).

- **Nutrient solution**: An aqueous solution of essential plant nutrient ions (Bamsey, *et al*., 2012).
- **EC**: Electrical conductivity: a nutrient solution concentration test (Carruthers, 1993).
- Vertical gardening: Vertical landscapes in urban environments such as walls and buildings can be used to accommodate vertical g*ardens* (Abel, 2010).
- **Automation**: Features in HG and especially in e-gardens which serve to automate various crop-maintenance tasks of hydroponic cultivation in greenhouse agriculture, argued by this research however as useful to ideally and better meet urban consumer horticultural needs (Hashimoto *et al*., 2001).
- **Crop performance**: The measures of how hydroponic cultivation delivers outputs from inputs (Sigrimis *et al*., 2001; Duarte-Galvan *et al*., 2012).
- **Organics**: Hydroponic cultivation that seeks to closely mimic nature, which involves decomposition fertiliser, organic molecules such as amino acids, and inert organic media, e.g. coco-peat (Nicholls, 1990; Savvas, 2003; Gruda, 2008).
- **New Product Development** (**NPD**): Innovating products to better meet consumer needs and competitiveness of an enterprise (Alexio & Tenera, 2009).
- **Product innovation**: Improving product benefits for consumers and business, with inventiveness or transfer of technologies between industries. For this research this term is focused towards the product innovation of core technological functions in HG and e-gardens, which can hypothetically be offered to consumers.
- **Converged platform**: The bundling of two or more platform technologies into a common product *i.e.* the camera-phone (Han *et al*., 2009).
- **Product feature**: The part of an offering which potentially meets a particular consumer need, who may see it as beneficial to possess. For this research, each feature is represented by factors x_i in a mathematical model.
- **Morphological Analysis (MA)**: Matrix tables are used to structure observed attributes of a non-quantifiable problem by establishing their variables for rational judgement

(Yoon & Park, 2007). This research employs this technique for profiling the product features of HG into categorical variables.

- **Conjoint Analysis (CA)**: Market research techniques used for estimating consumer utilities for particular product profiles (Orme, 2010). It is an experimental design which attempts to model the implications of each product feature offered to consumers (Orme, 2010). CA is used here to prioritise HG features for consumers.
- **Part-worth utility**: The personal usefulness measure by which consumers place upon a particular product feature x_i, where a model function can describe this parameter for a population of consumers, *i.e.* the model function $\hat{y}_{ji} = \beta_0 + \sum \beta_i$ for product features x_i. (Orme, 2010).
- **Utility**: The personal usefulness measure by which consumers place upon a particular product profile, given by the sum of the part-worths, *i.e.* the model function $\hat{y}_{ji} = \beta_0 + \sum \beta_i$ for product features x_i (Orme, 2010).
- **Main-effect**: The part-worth utility for one factor as opposed to an interaction.
- **Consumer preferences**: The marketing scale used here to measure these part-worth utilities $\hat{y}_{ji}$.

Mathematical notation:

N = cluster population size

n = no of clusters in the sample

n_k = k^{th} cluster in the sample

K = theoretical population size of urban horticultural consumers

M = research population size

m_k = size of cluster k

q = respondents

x_i = i^{th} HG factor *i.e.* $x_i \in \{x_A, x_B, x_C, x_D, x_E\}$

x_A = factor **A** is *garden plane*

x_B = factor **B** is *garden automation*

x_C = factor **C** is *garden* performance

x_D = factor **D** is *garden organics*

x_E = factor **E** is *garden price*

y_{ij} = response outcome j for factor level i *i.e.* $y_{ij} \in \{1, 2, 3, 4, 5\}$

$\hat{y}_i$ = fitted part-worth utility for factor level i

$\hat{y}_i$ = fitted part-worth utility for the i^{th} factor

$\hat{y}_i = 1$ = *least preferable* preference score

$\hat{y}_i = 2$ = *less preferable* preference score

$\hat{y}_i = 3$ = *preferable* preference score

$\hat{y}_i = 4$ = *more preferable* preference score

$\hat{y}_i = 5$ = *most preferable* preference score

$b_{abcde} = b_0$ = intercept for dummy variable multiple regression

$\hat{b}_i$ = i^{th} model slope coefficient estimate statistic

B_i= model slope coefficient population parameter

LCL = lower confidence limit

UCL = upper confidence limit

$\pi(x)$ = Probability as a function of x

Ω = Odds

OR = Odds Ratio

e = Euler's natural growth number, i.e. $e = 2.7182818$

$deff$ = design effect

df = degrees freedom

WOR=Without Replacement.

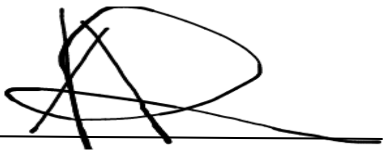
NR = Non-Response(s)

NC = Non-Coverage

μ = Arithmetic mean

DECLARATION

I, Alex Nicholas Rossouw, declare that the contents of this thesis represent my own unaided work, and that the thesis has not been previously been submitted for academic examination towards any qualification. Furthermore, it represents my own opinions and not necessarily those of the Cape Peninsula University of Technology.



14th December 2016

Signed **Date**

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CHAPTER ONE

RESEARCH PROBLEM, AIMS, MAIN HYPOTHESIS, AND OBJECTIVES

CHAPTER ONE

Research problem, aims, main hypothesis, and objectives

1.1. Abstract

Hydroponics is a synergy between plant and machine. For decades the hydroponic garden has been offered on horticultural markets, and was repeatedly innovated to better meet consumer horticultural needs. Currently, platform convergences with electronic control systems can possibly enable more efficient products for direct consumer hydroponic cultivation. This means that, like many appliances in the home, hydroponic plant cultivation in Hydroponic Gardens (HG) can become somewhat automated. Hence these electronic hydroponic gardens are termed "e-gardens" here due to their electronic nature. Product analysis, market research, experimental design, and relationship modelling must be looked at for understanding how urban horticultural consumers would prefer changes in hydroponic e-gardens offered to them.

1.2. Introduction to the research problem

This research focuses on the horticultural and marketing problem of understanding how local urban horticultural consumers prefer novel electronic Hydroponic Gardens (HG) offered to them. These garden products are modules or units, which aim to offer ergonomic features such as automation (see plates 1.1 & 1.2). Hydroponics is perceived here as a few decade's old radical innovation offered to horticultural markets. Since, HG have been further incrementally innovated through platform convergence with other technologies such as electronics in the hope of better meeting urban horticultural consumer needs, so this product type is seen here as an "e-garden" (see plates 1.1 & 1.2).

This study however is limited to the radical innovation of HG to the later incrementally innovated e-gardens; *i.e.* cross-platform bundles such as *Aerogarden*™ and *Click and Grow*™ as illustrated below. HG and e-gardens are small-scale *i.e.* usually less than 1m^2, user-friendly consumer electronic products with automation features to benefit horticultural markets.

Plate 1.1: *Click and Grow LED*^{TM}*.* A non-modular e-garden with a passive fertilisation, and supplemental LED Lighting (Source: https://www.clickandgrow.com)

Plate 1.2: *Aerogarden*^{TM}, an e-garden showing some aspects of its functionality including: lighting, an ergonomic user-machine interface, seeded-plug cartridges, in an arguable water-culture system, and a compact mechanised hydroponic unit with a moderate level of technological convergence (Source: https://www.aerogarden.com)

1.3. Research problem

This research fundamentally asks: "How can HG better fulfil the needs of urban horticultural consumers here on the Cape Peninsula?" To answer this question, a hybrid MA–CA instrument is needed to model HG features and estimate market utilities for them. Firstly, small-scale domestic HG need profiling to describe all possible empirical product features offered to horticultural consumers. Next, to survey a population of these people for their preferences towards the profiled features found. Ordinal regression analysis (using SPSS) is appropriate for estimating part-worth utilities for product features, with other analyses such as homogeneity, residuals checks, and correlation. This research may provide insight on how HG can best interest urban horticultural consumers here on the Cape Peninsula.

1.4. Analytical frameworks

This research uses Morphological Analysis (MA) and Conjoint Analysis (CA) methodologies for answering the research question. Firstly this study will qualitatively profile Hydroponic Gardens (HG) and their features via a MA. CA is used next as a technique for estimating market prioritisation of product features, however a Fractional Factorial Design *(*FFD) is needed here to minimise the number of experimental runs from 32 down to 16. This CA can capture consumer preference levels, thus estimate attribute preferences, and model how they might react towards innovated HG. The parameter of interest is called the part-worth utility $\hat{y}_{ji}$ of a produce feature x_i, *i.e.* how much value a consumer places on any single feature (Orme, 2010). The slope term β determines this value. Urban horticultural consumers can be sampled at clusters, and again systematically for field-work practicalities; thus a cluster sampling design is needed. All this can be interpreted from complex samples ordinal regression in IBM™ SPSS, which is used to estimate the part-worth utility of HG product features for the population in question.

1.5. Delineations of this research:

What this research will involve

HG for growing plants indoors, to produce culinary vegetable plant material, with dirt and hassle-free product features.

This research will not involve:

- Aquaponics. This field involves aqua-culture, where fish are cultured, and these systems are not included in qualitative sampling.
- Aeroponics**.** This field involves intermittently misting plant roots and too won't be sampled.
- Large-scale and commercial markets such as greenhouse agriculture. This research focuses on the preferences of urban horticultural consumers, for small-scale garden

cultivation, *i.e.* indoor domestic plant cultivation. The review and MA however look at this industry for data, not preferences towards e-gardens.

- This research will only investigate garden centre consumers for herbs, vegetables, fruit, and ornamentals, *i.e.* only for culinary, health, or aesthetic purposes in line with ornamental horticulture. This market comprises the specified horticultural consumer population.

- This research is not a brand analysis: the product profile examples given in the MA are only analysed in relation to their product features (attributes and levels) and not brands.

- Demographical information. This research will not investigate demographical segments of populations due to resource constraints. A demographic analysis is too intensive for respondents; instead the questionnaire will only consist of a simple CA.

- This research only draws conclusions regarding the population of urban horticultural consumers on the urban Cape Peninsula (see figure 4.5.2). The main review however more reflects global dynamics.

1.6. Rresearch objectives:

1.6.1. Aims

The core aim of this research is to profile and prioritise HG for urban horticultural consumers at garden centres, by profiling empirical HG features for suggesting how these product features have utility for these people.

1.6.2. Specific objectives to answer the research question:

- Firstly, the e-garden product type needs profiling to describe its possible product features x_i, using qualitative and MA.

- Ultimately, the product features found need market evaluation via a CA:

- This CA first designs an experiment, a Fractional Factorial Design (FFD) using factors i from the MA with combining them into a smaller number of product profiles $\mathbf{x}$ of product features x_i.

- Next, to sample and survey urban horticultural consumers for their preferences towards fraction of product profiles $\mathbf{x}$.

- Lastly, to apply ordinal regression analysis (using *SPSS*) for modelling consumer utilities $p(y \leq j)$ as a function of product features x_i.

1.6.3. Main hypothesis

H_1: Garden automation is favourably preferable by horticultural consumers on the Cape Peninsula.

1.7. Significance and intended outcomes of this research

The burden of conventional plant cultivation on the environment needs to be mitigated (Nicholls, 1990; Hashimoto *et al*., 2004; Chaudhuri, 2009; Bamsey *et al*., 2012; Duarte-Galvan *et al*., 2012; Iliev *et al*., 2012). This may be partly achieved by empowering the consumer to directly be able cultivate their favourite plants easier and better themselves with the aid of technology. The problem here is that requisite knowledge and skill may lack, as a result many urban residents can't always grow quality plants themselves (Nicholls, 1990; Kenyon, 1992; Harris, 1992; Carruthers, 1993). This research proposes a solution be identified that can cultivate plants with autonomy, a higher performance, and in a more environmentally friendly manner than by existing soil/media based practices. This solution is currently offered to markets as innovative garden products *i.e.* e-gardens, where the core attributes and needs for hydroponic-cultivation are established well in theory and practical fields (Hashimoto *et al*., 2004; Sigrimis *et al*., 2001; 2004; Chaudhuri, 2009). This research touches on theories from automation, hydroponics, marketing research, and product innovation. These fields may be enriched by employing these technologies on a smaller but wider scale to directly suit the needs of urban horticultural consumers (Sigrimis *et al*., 2001;

Hashimoto *et al*., 2004; Warrington, 2014). Automation, or control systems, exists in product design and agricultural research (Sigrimis *et al*., 2001; Hashimoto *et al*., 2004); yet marginally in small-scale hydroponic products for domestic applications (e-garden observations, 2012-2016). Applied research here may shed insight into need for plant-machine-user interfacing to better meet urban horticultural consumer needs here on the Cape Peninsula.

CHAPTER TWO

INNOVATING HYDROPONIC CULTIVATION FOR MODERN PEOPLE: A REVIEW

CHAPTER TWO

Innovating hydroponic cultivation for modern people: *A review*

2.1. Abstract

Plant cultivation in mineral-rich water, or *hydroponics* has been researched for centuries, which well-illuminates the relationship between plants and their rooting environment. Hydroponic cultivation of plants has been evolving since its first industrial use in the 20th Century, and its potential for cultivation efficiency is well acknowledged by scientists and industry, but less so with consumers. Modern times have presented environmental situations which call for the efficiency of hydroponics for plant cultivation. The consumer horticultural industry should look into how HG can better fulfil these established market needs for efficiency and sustainability. Marketing and product innovation can help calibrate optimal NDP of hydroponic gardens for people. This literature review grasps how consumers are subjected to a changing environment together with changing technology such as hydroponics, and plant nutrition, for garden automation.

2.2. Overview

Population pressures, congestion, climate-change, soil degradation and erosion, pollution, water and energy-shortages, biodiversity-loss are environmental issues plaguing the modern world (Nicholls, 1990; Savvas 2003; Hashimoto *et al*., 2004; Mason *et al*., 2008; Duarte-Galvan, 2012). Also, modern people may be concerned regarding commercial cultivation practises, produce label-claims, and price premiums around organic produce (Nicholls, 1990; Hoefkens *et al*., 2009; Tice, 2011). Innovation of hydroponic cultivation has helped humans for centuries to cultivate their plants better and more efficiently not only for themselves, but now also to mitigate modern global problems (Nicholls, 1990; Harris, 1992; Carruthers, 1993; Sigrimis *et al*., 2001; Savvas 2003; Gruda, 2008).

Marketing and innovation are two interrelated operations in operations management, used to fine-tune offerings for specific people (Collective authorship [Pearson], 1995; Keller & Warrack, 2000; Story *et al*., 2009; Kuhfeld, 2010). Modern-world urban consumers are likely to be computer literate and technologically fluent, and seek psychologically rewarding products through innovation; thus require combined efforts from marketing and NDP to specifically meet their needs (Halman, 2003; Jun & Jaafar, 2011; Kwong *et al*., 2011). Innovation though, should be calibrated early in the NDP process together with information from market research (Collective authorship [Pearson], 1995). This research will thus apply both concepts for understanding where HG can be most utilised by people.

2.3. Urban horticultural consumers and their needs

Modern people enjoy cultivating plants for their homes; for practical, ornamental, or culinary purposes, thus they have horticultural needs (Warrington, 2014). They may seek gardens and related products available at garden centres to fulfil those needs, who then become horticultural consumers (Warrington, 2014). These horticultural consumers, who live in and around built-up urban areas, are termed urban horticultural consumers by this research, where these people on the Cape Peninsula are its theoretical population.

Urbanised landscapes can be problematic for urban horticultural consumers if they wish to cultivate plants on congested solid surfaces (Nicholls, 1990). Soil-based plant cultivation can be undesirable here as it may be a greater burden on civil engineering than hydroponics, through: excessive bulk and load (Kim *et al*., 2010), and soil-based systems generally are non-recirculating, which is wasteful and makes soil much less efficient for urban areas (Nicholls, 1990; Harris, 1992). Arguably, solid surfaces with plumbing and electrical infrastructures, which construct many urban settings, should create a useful environment for hydroponic-cultivation according to some paperbacks (Nicholls, 1990; Kenyon, 1992; Harris, 1992; Carruthers, 1993). This research requires more empirical information to describe how to actually offer urban horticultural consumers a way to practically cultivate their plants at home.

The mountain and seaboard geography of the urban Cape Peninsula may present a predicament for new homeowners. In the last decade alone; each electoral ward has experienced growth in population size and household number, while many wards have declining house-size (Stats SA & City of Cape Town, 2011). This *census* also reported that the average household size decreased from 3.72–3.50 units in the last decade (Stats SA & City of Cape Town, 2011). Can this affect the potential for HG meeting gardening needs of consumers? Another observation from this municipal report; is that the number of people has increased by 25.6% in the decade 2001–2011, further reinforcing a potential need for space-saving benefits of hydroponics and e-gardens. This report suggests a trend of local urbanisation, which arguably may reduce the garden capacity of the urban horticultural consumer here on the geographically congested Cape Peninsula. In light of this issue, investigating garden innovation is pertinent.

2.4. Product innovation for business and consumers

High-tech business, whose core offer involves technological products, are regularly involved in product innovation operations (Alexio & Tenera, 2009). Product innovation is a marketing instrument that perceives technological and market opportunity, followed by systematically developing and manufacturing product inventiveness to fulfil consumer needs and business goals (Story *et al*., 2009). Thus successful enterprises continually seek to create new and competitive offerings by periodically innovating themselves and their products, using technological and market research for NDP (Alexio & Tenera, 2009).

NDP managers usually obtain information via technological and consumer research on how best to develop and market product innovations, which use analytical methodologies to solve the problem (Pearson *et al*., 1995). Firstly, qualitative morphological research can profile the product features in question (Yoon & Park, 2007). Also, survey interviews are regarded as an economical method for collecting data from consumers, for conjointly estimating the general interest towards those product features (van Iterrsum & Feinberg, 2010). NDP research draws from theories in various fields such as engineering, marketing, economics, and psychology (Nijssen & Frambach, 2000). These are all incorporated into psychological models such as the Theory of Planned Behaviour (Armitage & Conner, 2001; Frischknecht *et al*., 2009). Consumer needs are psychologically motivated by inspiration and interest towards product features that can enhance their lives (Frischknecht *et al*., 2009). Understanding the impact of product features on consumer preference requires these frameworks developed from the behavioural sciences (Armitage & Conner, 2001; Frischknecht *et al*., 2009). Consumer preferences can be estimated conjointly with product features, by using models that describe demand and choice well (Kuhfeld, 2010). This can fulfil consumer needs with an early stage of NDP decision making in order to provide an optimal set of product configurations for people (Kuzmanović *et al*., 2011).

The current market-place requires product innovation in-line with sustainable development (Halman, 2003), and product convenience and novelties (Warrington, 2010); where e-gardens may be a useful offer for these needs (Nicholls, 1990; Kenyon, 1992; Harris, 1992; Carruthers, 1993). According to Mason *et al*., (2008) space-wise container gardens have gained popularity and have enjoyed growth in the lawn-and-garden category. Perhaps, product innovation for NDP is thus an appropriate framework to further develop HG for these markets (Story *et al*., 2009; Reinders *et al*., 2010). Some HG offer automation as product features, which are seen as converged platforms by this research. However, technologies such as hydroponics and automation are most probably too technical for the general population to understand, so might frighten consumers. Interestingly, NDP managers have found convenience benefits in bundling different technological platforms together in a single common platform, e.g. the *camera-phone* (Han *et al*., 2009). Reinders *et al*. (2010) proposed using product bundles as a marketing instrument to aid any limited understanding of radical high-tech products and their features, and to reduce learning costs in communication activities for facilitating consumer adoption of radical and technological innovation (Alexio & Tenera, 2000). This research recognises that hydroponics is a radical innovation in horticulture; yet the problem needs further investigation into exactly how modern HG can be incrementally innovated to better meet urban horticultural consumer needs.

2.5. The innovation of Hydroponic Gardens (HG) to better meet those needs

In the 20th Century, hydroponic cultivation has gained favourability amongst urban horticultural consumers; due to their urban environment, rising food prices, food additive fears, and ecological concerns (Nicholls, 1990; Carruthers, 1993; Tyson, 2001; Savvas, 2003; Gruda, 2008; Mason *et al*., 2008; Bamsey *et al*., 2012). Hydroponic cultivation can be defined as: the collection of methods that involve cultivating plants in inert-media and water supplied with balanced nutrients, to optimise plant-growth (Nicholls, 1990). Formally, all 15 essential elements* (except carbon) which are crucial for healthy plant growth, are supplied to the plant via an aqueous-solution of balanced nutrients (Harris, 1992; Carruthers, 1993; Savvas, 2003). Hydroponic cultivation is versatile and not uncommon in various applications such as: low- and high-tech cultivation platforms, large- and small-scale, in non-arable growing climates and locations, in food and ornamental cultivation, for commercial and private interests, and up in space (Nicholls, 1990; Harris, 1992; Carruthers, 1993; Savvas, 2003; Bamsey *et al*., 2012; Trejo-Téllez & Gomez-Merino, 2012). Hydroponic cultivation was originally used by scientists, commercial farmers, and avid hobbyists; but nowadays a wider range of people are using hydroponics (Nicholls, 1990; Kenyon, 1992; Harris, 1992; Carruthers, 1993).

*[carbon, oxygen, hydrogen, nitrogen, phosphorous, potassium, calcium, sulphur, magnesium, iron, zinc, boron, molybdenum, copper, cobalt, manganese]

2.5.1. Organic cultivation

The horticultural industry damages and destroys soil-systems through mismanagement of fertilisation, giving chemical and artificial inputs a bad name (Nicholls, 1990). Naturally, decomposing organic material and weathering inorganic earth contain essential plant nutrient elements, which must first decay to release available ions to dissolve in an aqueous solution (Nicholls, 1990; Savvas, 2003; Gruda, 2008; Trejo-Téllez & Gomez-Merino, 2012). Organic fertilisers are often derived from secondary sources such as compost, manure and animal by-products; and have use for soil and soilless culture but have limited use in hydroponics because of its detritus nature (Savvas, 2003; Gruda, 2008). Hydroponic nutrient solutions in system reservoirs that mimic this organic nutrient suspension can create imbalances, harbour pathogens, and generate toxic chemicals. Thus conventional hydroponic nutrition dictates practising inorganic ionic-nutrient solutions, by excluding detritus (Nicholls, 1990; Savvas, 2003; Abd-Elmoniem *et al*., 2006; Gruda, 2008). Hydroponics requires only 13 nutrient* ions from mineral salts, dissolved in aerated water, and appropriately supplied to the root-zone using a reliable system (Nicholls, 1990; Kenyon, 1992; Harris, 1992; Carruthers, 1993; Savvas, 2003; Gruda, 2008; Bamsey *et al*., 2012). Replicating nature exactly with an absolute organic paradigm applied in hydroponics is unnecessary, counter-intuitive, and even problematic, yet consumer beliefs might differ (Savvas, 2003; Gruda, 2008; Hoefkens *et al*., 2009).

A dichotomy appears in hydroponics, where organic fertilisers are perceived by some consumers as most natural, while the industry holds that plants generally aren't well suited to purely natural processes (Nicholls, 1990; Savvas, 2003; Gruda, 2008). Inversely, there are negative consumer perceptions towards "chemical" fertilisation, which contrasts modern scientific understanding where plants are less discriminate with their nutrient source (Nicholls, 1990; Harris, 1992; Savvas, 2003; Gruda, 2008; Hoefkens *et al*., 2009). These perceived "chemical" fertilisation practises of hydroponic cultivation may invoke negative consumer perceptions towards produce according to some researchers (Savvas, 2003; Gruda, 2008; Hoefkens *et al*., 2009). Generic fertiliser manufacturers might source ingredients from industrial by-products, albeit somewhat purified (Nicholls, 1990). However Nicholls (1977) argues that “plants do not care whether they get their iron (Fe) from petro-chemicals or a dead rat’; however Savvas (2003), Gruda (2008), Hoefkens *et al*., (2009) may agree, though argue consumers eating those plants do care about the "natural” option. Additionally, negative consumer perceptions towards taste and aroma of hydroponic produce, were again dismissed by these authors and researchers, because hydroponic systems should enable better fertiliser control than soil (Nicholls, 1990; Harris, 1992; Savvas, 2003; Abd-Elmoniem *et al*., 2006; Gruda, 2008). Quality hydroponic grown produce has lower-acidity, higher-sugar and mineral content, all resulting in better taste and aroma than soil, together with improved appearance and colour (Carruthers, 1993; Savvas, 2003; Gruda, 2008).

Conversely, organic HG do offer benefits: inert organic matter such as peat can be useful as a planting medium as it has good water and nutrient absorption (Nicholls, 1990; Savvas, 2003; Gruda, 2008). While chemically organic: chelates, vitamins, amino acids, fulvic and humic acids may assist hydroponic cultivation. Ultimately hydroponics deals with hydroponic nutrient solutions which are mainly ionic solutions, thus should perceive organic per se more in accordance with chemistry than farming—which is as shown above is somewhat biased towards soil and carbon-based cultivation by mimicking nature exactly.

Hydroponic produce may be marketed as organic provided no synthetic chemicals were used, produced in ecological harmony, and sources sustainable and natural materials (du Toit and Crafford, 2003; USDA, 2015).

2.5.2. Crop performance

Soil normally provides the plant with nutrients and support, which can physically be mimicked by a hydroponic-system, and generally with better proficiency (Nicholls, 1990; Harris, 1992; Carruthers, 1993; Savvas, 2003; Gruda, 2008), and with only a fraction of the water and fertiliser needed (Abd-Elmoniem *et al*., 2006). Arguably, hydroponics is independent from soil and problems associated with it, e.g. soil-borne diseases (Nicholls, 1990; Harris, 1992; Carruthers, 1993; Savvas, 2003). From this, commercial advantages generally bode: quicker harvests, higher planting-densities, greater yields, and better quality compared to soil (Kenyon, 1992; Harris, 1992; Carruthers, 1993; Savvas, 2003; Gruda, 2008; Trejo-Téllez & Gomez-Merino, 2012). Now, all this is not guaranteed, but hydroponics should return healthier economic and environmental benefits for commercial growers (Nicholls, 1990; Savvas, 2003; Abd-Elmoniem *et al*., 2006; Gruda, 2008). These advantages are all made possible by understanding the plant’s relationship with the hydroponic rooting environment (Nicholls, 1990).

On the other hand, hydroponics has a lower buffering capacity for problems, which can drastically affect output quality more than the same kinds of problems experienced in soil-based applications (Carruthers, 1993; Sigrimis *et al*., 2001; Gruda, 2008).

2.5.3. Garden automation

Man needs plants, but prefers not to get involved in the repetition of crop maintenance (Nicholls, 1990; Sigrimis *et al*., 2001). So, how can plant cultivation be made easier for people using modern technology? Mason *et al*., (2008) found that people likely prefer educational material supplementing their purchased soil-based container garden.

It is important though to understand how innovating automatic HG can empower urban horticultural consumers, to experience fewer cultivation problems. Urban horticultural consumers though are possibly unable to articulate with hydroponics, as not everyone possess a level of knowledge required to manage hydroponic systems, and thus may fear the concept (Kenyon, 1992; Harris, 1932). According to Carruthers (1993) and Tyson

(2012), the main factor for crop failure in domestic hydroponics is an incorrect nutrient solution and inappropriate cultivation environment, which negatively affects plant growth. Authors and experts generally hold that hydroponic cultivation is more successful with a high level of technological capacity for environmental automation (Nicholls, 1990; Harris, 1992; Carruthers, 1993; Sigrimis *et al*., 2001; Savvas, 2003; Gruda, 2008; Hashimoto *et al*., 2004; Bamsey *et al*., 2012; Duarte-Galvan *et al*., 2012).

Commercially, automation *i.e.* control systems are useful tools to manage a crop's environmental requirements (Nicholls, 1990; Sigrimis *et al*., 2001; Bamsey *et al*., 2012; Duarte-Galvan *et al*., 2012; Iliev *et al*., 2012). The Speaking Plant Concept by Hashimoto *et al*. (1981) resolves plant outputs with environmental inputs in a control model, where these environmental parameters and control operations are treated as computational variables. Since, various control systems which utilise microcontrollers and even machine-learning, have been presented in achieving precise control of operations in large-scale plant-factories, in order to utilise resources optimally in line with sustainability, whilst optimising input–output for profit (Sigrimis *et al*., 2001; Ferentinos and Albright 2002; Hashimoto *et al*., 2004; Chaudhuri, 2009). These control systems should idealistically involve all maintenance procedures such as pH and EC monitoring, reservoir maintenance, and environmental control (Carruthers, 1993; Bamsey *et al*., 2012; Duarte-Galvan *et al*., 2012; Iliev *et al*., 2012). The advancement of processors, controllers, actuators and sensors, information systems, and programming all facilitate a wide availability of automation for commercial hydroponics (Sigrimis *et al*., 2001; Hashimoto *et al*., 2004; Chaudhuri, 2009; Bamsey *et al*., 2012; Duarte-Galvan *et al*., 2012). So it seems that proper hydroponics and automation systems can lead to improved crop performance (Sigrimis *et al*., 2001).

Small-scale HG inherently offer the automation of watering and fertilising; but ideally should be managed by a control system that watches over parameters such as pH and EC, water level and temperature, ambient air conditions, and lighting (Nicholls, 1990; Kenyon, 1992; Harris, 1992; Carruthers, 1993; Bamsey *et al*., 2012). Hydroponics "lends itself to automation” … and “It is possible to install gadgets that monitor and supply all of the plant’s needs”, according to Nicholls (1977). Innovative e-garden units have incidentally entered consumer markets to offer a degree of automation, e.g. products such as Click and Grow™ and Aerogarden™.

2.6. Conclusion and recommendations

Hydroponics materialises our scientific understanding of the relationship between the plant and its environment, into useful technology for people (Savvas, 2003; Gruda, 2008; Nicholls, 1990; Harris, 1992). Urbanisation is creating situations that require hydroponic technology for people’s horticultural needs. The above literature reflects the development of hydroponic gardens as a market offering for meeting urban horticultural consumer needs. There are however shortcomings in conventional hydroponic cultivation that require core improvements; such as the misnomer *organics*, also crop performance issues, and automation to assist users by managing crop maintenance.

Firstly, correct hydroponic nutrition should avoid complex and unnecessary carbonaceous matter, and utilise inorganic mineral salts and simple organic molecules such as amino acids; yet be regarded as organic and environmentally sustainable for consumers. Horticultural enterprises can meet consumer fears by offering organic and sustainable non carbon-based fertilisers. Though a more rigorous definition for marketing organic needs to be found, without involving a paradigm of absolutes; for finding a balance between plant, human, and environmental needs.

Second and thirdly, a stable and balanced nutrient solution is said to be crucial for successful hydroponic cultivation (Nicholls, 1990; Carruthers, 1993; Savvas, 2003; Bamsey *et al*., 2012; Trejo-Téllez & Gomez-Merino, 2012). It is possible that only a minute portion of people can handle a complex aspect of hydroponic cultivation such as nutrient solution management (Kenyon, 1992; Harris, 1992; Carruthers, 1993; Tyson, 2012). Now, the extent of control systems aid many industries; and agriculture, consumers, and the environment have indirectly benefitted in the last few decades from research in automating commercial greenhouse applications (Sigrimis *et al*., 2001; Ferentinos & Albright, 2002; Hashimoto *et al*., 2004; Chaudhuri, 2009; Bamsey *et al*., 2012; Duarte-Galvan *et al*., 2012; Rahane & Dongare, 2012). Also, innovation is described by Kuzmanović *et al*., (2011) as a transfer of technology from one industry to another. So perhaps there is a potential for simplified control systems to further converge with domestic hydroponics, to automate crop management for better meeting the modern needs of people. This may be an innovative strategy for improving plant performance and usability for urban horticultural consumers.

This review outlined how hydroponics in terms of concepts such as automation, organics, and crop performance can possibly benefit the environment and urban horticulture to better meet current and future market needs. However, this information seems part-complete in profiling small-scale hydroponic cultivation, for identifying benefits that innovated products can convey to consumers. Applied research is needed to specifically understand empirical e-garden product features, and also how urban horticultural consumers prefer them. A profile of core product features seen in HG and e-gardens can be described by a MA, and then market prioritisation of each feature can be inferred using CA with a population of urban horticultural consumers. The research problem asks "how can hydroponic gardens better fulfil the needs of urban horticultural consumers on the Cape Peninsula?" This review sets the stage for applied research into this.

CHAPTER THREE

INNOVATING HYDROPONIC GARDENS FOR URBAN HORTICULTURAL CONSUMERS OF THE CAPE PENINUSLA: A MORPHOLOGIAL ANALYSIS (MA)

CHAPTER THREE

Innovating hydroponic gardens for urban horticultural consumers of the Cape Peninsula: A Morphological Analyses (MA)

3.1. Abstract

The qualitative analysis here explores the relationships between HG, automation, e-gardens and identified a useful fit using a Venn diagram. The results identified conceptual sets for *structures*, *inputs*, and *controls*, which all harmonise into new intersections *cultivation*, *hydroponics*, and *automation*. Morphological Analysis (MA) was applied next. Here, general hydroponic cultivation were first decomposed into all its many component parts which collectively describe the whole, where these parts were then classed along various attributes namely: *garden plane* x_A, *automation* x_B, *performance* x_C, *organics* x_D, and *price* x_E. So *garden plane* is composed of *level* and *vertical gardens*, *garden automation* is composed of *manual* and *automatic gardens*, *garden performance* is composed of *casual* and *high-performance gardens*, *garden organics* is composed of *non-organic* and *organic gardens*, and *garden price* although quantitative is simply composed of *R2500* and *R5000*. These classes of attributed data can now become treated as categorical factors using indicator or dummy variables. Lastly, the MA tabled all 2^k factorial experimental runs, which are useful for the Conjoint Analysis (CA) next chapter.

3.2. Qualitative data analyses in review

This initial analysis seeks to simplify and describe data in a more rich and meaningful way than quantitative data that uses mere numbers as thin representations (Saunders *et al*., 1997:378-385; Nijssen & Frambach, 2000). Philosophical spectra include: more structure vs less structure, procedural vs interpretive, and deductive vs inductive (Saunders *et al*., 1997:378-385). Deductive approaches link facts, while inductive approach is the opposite and generalises (Saunders *et al*., 1997:379-385). Strategies include comprehension of language and syntaxical meaning, identifying regularities, and reflecting on the result (Saunders *et al*., 1997:378-385; Yoon & Park, 2007). Saunders *et al*., (1997:378-380) warned that qualitative analyses with inductive non structured interpretivist analyses aren't negatively correlated with analytical rigour and ease.

Saunders *et al*., (1997:380-385) suggests using stages for analysing qualitative data: categorisation, selective unitisation, identifying relationships, and testing hypotheses. Firstly categorising the data applies the research objectives and is the initial step for managing data bulk, which entails naming the data inductively or deductively based on external theory, which requires within and between-category coherence for a firm foundation. Categories can then be ranked hierarchically where needed. Secondly, unitising the data means selecting and fitting data elements into categories, using relevant matrices, charts, or diagrams. Thirdly and consecutively relationships are found or not in fitting data to categories, where illogical relationships leads the process back to reforming the categories and refitting. Fourthly and also consecutively, hypotheses tests of the categories and their apparent relationships, and inductively exploring alternative hypotheses that appear from this process, both add rigour.

3.3. Initial relationships as qualitative sets

3.3.1. Introduction

This initial analysis aims to interpret how the innovation of product features in e-gardens is perhaps tied together. The literature review pointed out the potential usefulness of hydroponic *automation* for plants and people, while *performance* is seen as an inherent result of proper hydroponics and *automation*, and *organics* seems ill-defined. Figure 3.1 below illustrates a qualitative relationship between the subsets *e-gardens*, *hydroponics*, *automation* and *plant cultivation*, which originate from the sets *structures*, *inputs*, and *controls* which all house various qualitative elements. These are deductively obtained from brainstorming components, which again are deductively tested via qualitative analysis where the sets and elements are checked and compared using grammatical definitions and theoretical sources, for ranking set vs set elements for satisfying elements < set or elements ⊂ set (Waner & Constenoble, 2004:317-320).

3.3.2. Background

At the dawn of agriculture, man merged *inputs* such as labour and water etc., with *controls* such as canal and flood management, and basic *structures* such as crop routine and natural, which enabled rudimentary plant cultivation such as agriculture (Sigrimis *et al*., 2001; Cilliers & Retief, 2009:2). A few centuries later, more complex *structures* such as ziggurats supported horticulture e.g. *the Hanging Gardens of Babylon*. These building structures needed horticulture (Cilliers & Retief, 2009:3). Then better *structures* appeared such as *technological* and *systems* that empowered better *control* (Sigrimis *et al*., 2001). So now in modern (and perhaps the future too), new fields seem to appear from cross-convergences such as *hydroponics* from the fields of *structures* and *inputs* (Nicholls, 1990; Kenyon, 1992; Carruthers, 1993), and *automation* from *structures* and *controls* (Hashimoto *et al*., 2004). Here specialised elements have appeared which are common to 2- and 3-way interactions, e.g. *Aerogarden*™ product feature observation (2016).

3.3.3. Methodology:

This process works both backwards and forwards, *i.e.* back from *hydroponics* into its components, similarly *automation* followed suit, while a relationship was discovered between these fields along with *cultivation*. However this report is presented with an outside-in structure to funnel into the specifics.

3.3.3.1. Sets of structures, inputs, and controls

For internal coherence, *structures* need defining (Saunders *et al*., 1997:381). The English definitions according to Oxford Dictionary (2016) are "1. the arrangement of and relations between the parts or elements of something complex" which describes the basic meaning of *structures*, and "1.1 the quality of being organized" describes *structures* more specifically. Also "2. (An) object constructed from several parts" conveys the idea of *physical structures* (Oxford dictionary, 2016). However the set structures and the element *systems* both seem to be widely generalised, and *system* is a synonym for *structure* (Oxford dictionary, 2016), but in terms of this research *system* is defined as "2. A set of principles or procedures according to which something is done; an organized scheme or method." (Oxford dictionary, 2016), hence its need for organisation *structure*. So based on that, it seems *system* is an element within *structure*. Secondly, Oxford Dictionary (2016) provides definition for *input*: "1. what is put in, taken in, or operated on by any process or system" which collectively and generally describes all the elements within inputs, e.g. requisite inputs for *hydroponics* and plant cultivation such as water, nutrients, and energy etc. Lastly, *controls* need definition, where the Oxford Dictionary (2016) states control simply as "1.4 A means of … regulating something" but goes on to create the subsets plant *cultivation* with *inputs* (Sigrimis *et al*., 2001), and *automation* with *structures* (Hashimoto *et al*., 2004). However control is a synonym for the element *management* so competes for set rank; but much crop management may be achieved through control systems (Sigrimis *et al*., 2001; Hashimoto *et al*., 2004), so is seen here as a subset.

Next for external coherence, the semantical meaning of the set *structures*, *inputs*, and *controls* are checked for compliments (Saunders *et al*., 1997:381). From grammatical definitions above, *controls* is a verb while *structures* is a noun with distinct definitions and elements. Similarly *inputs* and *controls* (noun), and *structures* and *inputs* have distinct grammatical definitions and elements. This adds ground for these sets being compliments, except for the intersections governed by and logic.

3.3.3.2. *2*-way subsets of hydroponics, automation, and cultivation

Hydroponics, *automation*, and *cultivation* need definitions and testing for their standing as subsets. Firstly, according to Oxford Dictionaries (2016), hydroponics is "the process of growing plants in sand, gravel, or liquid, with added nutrients but without soil" which needs *inputs* and *structures* for basic operation (Nicholls, 1990; Carruthers, 1993), and is seen as a mutual subset. Arguably *hydroponics* can be replaced with plant tissue culture with appropriate elements, but isn't in-line with research objectives. Next, *automation* is "the use or introduction of automatic equipment in a manufacturing or other process or facility" (Oxford Dictionaries, 2016) where process or facility needs *structures* and *controls* (and even other *inputs* but that goes off topic) (Hashimoto *et al*., 2004), so *automation* is viewed as a mutual subset. Lastly, *cultivate* is defined as "prepare and use (land) for crops or gardening" while *cultivation* is "…the state of being cultivated" (Oxford Dictionaries, 2016) which need *inputs* and *controls* (and even some *structures*, which isn't illustrated) so is also seen as a mutual subset (Sigrimis *et al*., 2001; Rahane & Dongare, 2012).

3.3.3.3. Union vs intersections

Another argument asks if the subsets *hydroponics*, *automation*, and plant *cultivation* are specifically intersections ∩ or a union ∪? *And* plus *or* logic are used by Waner & Constenoble (2004:319-320) to discern between these set operators, where elements common to both sets (*and*) comprise an intersection, and elements that are in either or both sets (inclusive *or*) comprise a union. The strategy to tackle this question must first decide if the subset *hydroponics*, *automation* and *cultivation* have elements common to both sets or not, in line with set operator rules (Waner & Constenoble, 2004:319-320).

If *hydroponics* is a union ∪ as opposed to an intersection between the sets *structures* and *inputs*; then unions allow elements (e.g. *water* or *systems*) in hydroponics to come from either set, which illustrates how basic operation is dependent on a union (Waner & Constenoble, 2004:320). A similar pattern can be found between plant *cultivation* and *automation*. However *hydroponics* requires elements from its sets, along with *cultivation* and *automation*, *i.e.* basic necessities for operation. So this implies the relationships may be unions.

Conversely if the subsets *hydroponics*, *automation* and *cultivation* are intersections ∩ then they'll usefully have delineation, but involve elements common to both sets, also *and* logic excludes important set elements (e.g. *water*, *buildings* etc.) for basic operation. But this is because the three subsets don't show inclusion of the main set elements for simplicity, which is allowed in-line with inclusive *or* logic (Waner & Constenoble, 2004:320). Though they can be argued as intersections if elements inside the intersections have qualitative meaning common to both sets (*and*), that intrinsically involves important elements for basic operation (e.g. *water* and *energy*). For instance in *hydroponics*; brainstorming and theory identifies system *types* such as NFT, flood-and-drain, and aeroponics; also hydroponic *techniques* such as active vs passive systems, recirculating vs non-recirculating, and water- vs aero- vs aggregate-culture (Carruthers, 1993:14-31). These all say how the set *inputs* are involved with the set *structures*. This suggests those elements in the intersection *hydroponics* are common to both (*and*) sets instead of either (*or*) set. This grounds *hydroponics* as an intersection. Though with hydroponic-cultivation, merging specialised *structures* and *controls* are somewhat novel and scarce (literature-review, chapter two). Similarly reasoned, Warrington (2014) outlined modern *horticulture* having several facets such as crop production, molecular sciences, economics, and aesthetics (science, art, and business of plants); which all are geared towards plant *cultivation* that utilises *inputs* and *controls* (and even *structures*), so the sets have a common element *horticulture*. Also, *automation* has theoretical *applications* such as timing, fuzzy-logic and ANN control; along with control *platforms* such as pc's, microprocessors, microcontrollers, sensors such as EC and pH probes, actuators such as dosers and pumps, and embedded systems (Sigrimis *et al*., 2001; Hashimoto *et al*., 2004; Duarte-Galvan *et al*., 2012; Bamsey *et al*., 2012). This suggests the sets *controls* and *structures* share the elements *applications* and *platforms*.

To conclude, both paradigms have placement. It seems that the relationships are better described by unions ∪ when the subsets *hydroponics*, *automation* and *cultivation* where less developed so more reliant on non/less specialised elements from unions. Then as specialised techniques and product features appeared, the subsets developed novel elements with meaning common to both sets, and specific to subset needs, so here *hydroponics*, *automation*, *cultivation* can form set intersections ∩ as opposed to set unions ∪.

3.3.3.4. *3*-way subset: *e-gardens*

Finally, the three intersections illustrate the subset *e-garden* in another intersection of those three, which share the element product *features*. This research observes product *features* in the *Aerogarden™, Click and Grow™*, the *Tower Garden™*, and others (2016). Product *features* here involve cross-platform convergences between *hydroponics*, *cultivation*, and *automation*. Here the element is common to all intersections so the subset *e-gardens* is seen as an intersection. *Product features* are defined by www.businessdictionary.com/ (2016) as "one of the distinguishing characteristics of a product or service that helps boost its appeal to potential buyers, and might be used to formulate a product marketing strategy that highlights the usefulness of the product to targeted potential consumers." The MA next explores the *product features* in *e-gardens* with more analytical structure.

3.3.4. Results

Inputs and *controls* form general plant *cultivation* where *horticulture* is an element here for *e-gardens*. Next, *inputs* and *structures* form the concept of *hydroponics* where various elements come together to create these concepts. Next, *structures* and *controls* come together to form *automation* which is widely used but has importance for the *e-garden*. Lastly, the *e-garden* is really the simultaneous involvement of the intersections *cultivation*, *hydroponics*, and *automation*. Figure 3.1 below illustrates these tested results.

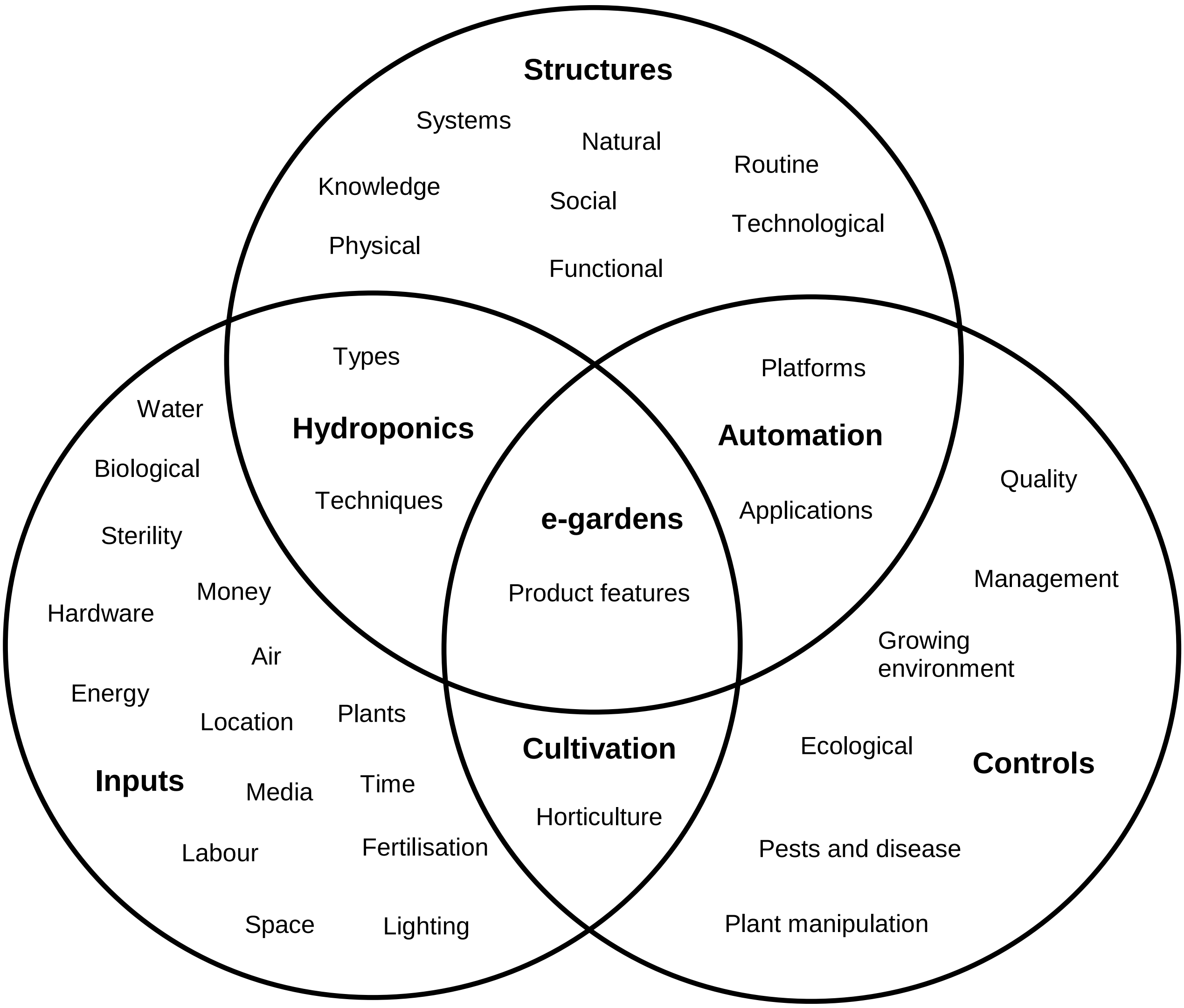

Figure 3.1: A Venn diagram of *e-gardens*

3.3.5. Conclusion and recommendations

This Venn diagram of *e-gardens* above illustrates via deduction how various fields (*i.e.* the sets *structures*, *inputs*, and *controls*) come together to synthesise the concepts seen in the intersections *hydroponics*, *automation*, *cultivation*, and *e-gardens*. This analysis gives definition and conceptualisation to the *e-garden* as a cross-platform convergence, where *automation* and *hydroponics* are inherently involved with the concept for *cultivation*. So far it holds, though this system needs more testing for rigour. The generalised results for this Venn diagram inductively suggest that other complex qualitative systems can be illustrated with the synergy of *structures*, *inputs*, and *controls*. More research is required to model this *e-garden* concept, and to test if *structures*, *inputs*, and *controls* can be used to model other non-quantitative systems.

3.4. Morphological Analysis (MA)

3.4.1. MA in review

Modern businesses often drive inventiveness to better meet consumer needs, where many successful enterprises have all their departments coherently geared towards NDP (Keller & Warrack, 2000; Nijssen & Frambach, 2000; Kuzmanović *et al*., 2011). Incremental changes to product features translate into offering new and different products to consumers, which may improve the enterprise (Desarbo *et al*., 1995; Alexio & Tenera, 2000; Yoon & Park, 2007). Essentially, NDP requires valid methods for making early decisions in product innovation (Yoon & Park, 2007; Frischknecht *et al*., 2009). Thus managers and academics can provide novel solutions though synthesis-analysis techniques such as inductive and deductive brainstorming before structuring the data using a MA (Saunders *et al*., 1997:378-385; Nijssen & Frambach, 2000; Ritchie, 2002; Levin, 2012).

A basic MA is constructed by industry to describe the shape of a complex and non-quantifiable system (Ritchie, 2002). For instance, MA was initially deployed in the design of aerospace systems and to model the physical attributes of natural phenomena (Ritchie, 2002). This technique first works to deductively decompose the system into its components (Ritchie, 2002; Yoon & Park, 2007; Levin, 2012). Here, a basic MA first works backwards from an output; like reverse engineering the system into its parts, and back out again but in a much more defined and structured manner than raw observation (Ritchie, 2002). However there usually is some kind of constraint imposed on the structure found in order to output a particular quality, which consequently affects the MA process (Yoon & Park, 2007; Levin, 2012), *i.e.* here simplified 2^k factorial runs are needed next for the CA. This ultimately is intended to profile HG for factors with levels, which creates suitable antecedents for further judgement (Yoon & Park, 2007; Ritchie, 2002).

The MA used in this research is a matrix structure which examines the qualitative problem of profiling e-garden products and other possible features, which involves many raw qualitative data. This research applies MA to describe empirical and potential product geometries for later conjoint testing with consumer preferences in the CA next chapter.

3.4.2. Methodology for this MA:

Step one: List all observed and potential features of e-gardens

The problem here is e-garden products and their features, which (from figure 3.1) is a broad qualitative system involving several aspects such as hydroponics, control systems, and horticulture. Therefore this system is deductively decomposed into its components; *i.e.* all the observed product features of e-gardens, with other inductive observations from relevant: research and theories, industrial hydroponic cultivation, and control systems. This step sources secondary data from: market needs, product observation, brainstorming, bibliographical sources, scientific sources, existing product features, research applications, and, commercial industry.

Step two: group features along attributes

This step requires a reversal of the previous step, but in a more structured manner. Interestingly, some features share a common attribute, and can accordingly be classed together; e.g. fertilisation control and watering control may be identified as *garden automation*. Some features themselves share simpler common attributes and may be further merged; e.g. *hydroponic cultivation issues* and *seasonal issues* are classed together under their solution namely *garden automation* (see table 3.4.2). Each feature is now used to represent a categorical factor x_i, with the attributions unfortunately represented by many factor levels.

Step three: constrain attribute levels into binary levels

The levels in each factor will most likely be too numerous for practical research, as the factors identified are ultimately needed for factorial research involving busy people. 2^k or binary levels of each factor are necessary for minimising experimental runs in the CA next chapter. This design constraint is needed because of resource constraints in market research. Thus lastly, the MA will constrain the many levels of each factor into binary levels, to basically where each factor either is offered or is not offered, *i.e.* $x_i \in (1,0)$.

3.4.2.1. Data collection

This MA begins with the brainstorming and is presented as a large listing in Table 3.4.1 below. These data are now prepared for MA.

Table 3.4.1: The observed features and attributes of hydroponic cultivation

Observations:	**Source:**
1. Abundant urban vertical surfaces 2. Accessories 3. Advanced/expert gardens 4. Aesthetic produce 5. Apartments, complexes detached houses 6. Aroma strength 7. Artificial Intelligence 8. Artificial lighting feature 9. Automatic effluent water drainage 10. Automatic watering (inherent) 11. Automation as core offer 12. Available level surfaces and areas 13. Balconies and courtyard *hydroponics* 14. Beneficial microorganisms used 15. Built up surfaces 16. Carbon fertiliser 17. Casual *e-gardens* 18. Concise units 19. Conventional *hydroponic cultivation* practices 20. Conventional systems 21. Cultivation ergonomics 22. Cultivation platforms 23. Curtain gardens 24. Decomposition fertiliser 25. Denser crop planting 26. Drought-wise 27. Ease of use 28. EC control 29. Electronic 30. Environmental friendliness 31. Faster growth cycle 32. Fertilising automation 33. Few core features 34. Fewer pest-problems for root crops 35. Flavour strength 36. Free-standing houses 37. *Hydroponics* based on artificial processes 38. *Hydroponics* based on natural processes 39. Heat-stress-wise 40. High yields 41. Hobby kits 42. Indoor locations 43. Input efficiency 44. Intensive gardens 45. Kitchen counter gardens 46. Kits 47. Knowledge and skill replacement 48. Lamp height control 49. Large gardens 50. Less chemical control needed	1. Abel, 2010 2. *Aerogarden^{TM} observation*, 2015; *Click and Grow^{TM}*, 2015 observation 3. Hortishop observation, 2014 4. Savvas, 2003; Gruda, 2008; Trejo-Téllez & Gomez-Merino, 2012 5. Mason *et al*., 2008; City of Cape Town Municipal Report observation, 2011 6. Savvas, 2003; Gruda, 2008 7. Hashimoto *et al*., 1981; Sigrimis *et al*., 2001; Hashimoto *et al*., 2004; Duarte-Galvan *et al*., 2012 8. Hortishop, 2014; *Aerogarden^{TM}*, 2015; *Click and Grow^{TM}*, 2015 9. Nicholls, 1990 10. Nicholls, 1990; Harris, 1992; Carruthers, 1993 11. Nicholls, 1990; Kenyon, 1992; Harris, 1992; Carruthers, 1993; Bamsey *et al*., 2012; Click and Grow^{TM} and Aerogarden^{TM} 12. Harris, 1992; Carruthers, 1993 13. Kenyon, 1992; Carruthers, 1993 14. Observation 15. Nicholls, 1990; Kenyon, 1992; Harris, 1992; Carruthers, 1993; Abel, 2010 16. Nicholls, 1990; Savvas, 2003; Gruda, 2008; Trejo-Téllez & Gomez-Merino, 2012 17. Nicholls, 1990; Kenyon, 1992 18. *Mason et al., 2008; Click and Grow^{TM}* observation, 2015 19. Nicholls, 1990 20. Nicholls, 1990; Kenyon, 1992; Harris, 1992 21. Mason *et al*., 2008 22. Carruthers, 1993 23. *Windowfarms^{TM}* observation, 2015 24. Nicholls, 1990; Gruda, 2008 25. Nicholls, 1990; Kenyon, 1992; Harris, 1992; Carruthers, 1993; Savvas, 2003; Gruda, 2008; Trejo-Téllez & Gomez-Merino, 2012 26. Harris, 1992; Carruthers, 1993 27. Nicholls, 1990; Kenyon, 1992 28. Carruthers, 1993; Bamsey *et al*., 2012 29. Carruthers, 1993; *Aerogarden^{TM} observation*, 2015; *Click and Grow^{TM}*, 2015 observation 30. Nicholls, 1990; Carruthers, 1993 31. Nicholls, 1990; Kenyon, 1992; Harris, 1992; Carruthers, 1993; Savvas, 2003; Gruda, 2008; Trejo-Téllez & Gomez-Merino, 2012; Bamsey *et al*., 2012; Duarte-Galvan *et al*., 2012; Iliev *et al*., 2012 32. Carruthers, 1993; Bamsey *et al*., 2012; Duarte-Galvan *et al*., 2012; Iliev *et al*., 2012 33. *Click and Grow^{TM}* observation 34. Nicholls, 1990; Harris, 1992; Carruthers, 1993; Savvas, 2003 35. Savvas, 2003; Gruda, 2008 36. City of Cape Town Municipal Report observation, 2011

51. Light shading
52. Lighting intensity control
53. Lighting spectral control
54. Many core features
55. Material-wise
56. Mechanisation
57. Modernism
58. Modular systems
59. No carbon in fertiliser
60. No synthetic chemicals
61. Nutrient composition control
62. Optimised water quality (Filtration, R/O etc.)
63. Organic media
64. Payment plans
65. Performance gardening
66. Pest management
67. pH control
68. Plant growth sensing and feedback
69. Planting/ seeding automation via seed-cartridges
70. Premium gardens
71. Quicker maturation
72. Rapid growth
73. Ready-to-use gardens
74. Reduced cultivation intensity of e-garden compared to soil
75. Reduced cultivation tasks compared to soil
76. Relative humidity control
77. Requisite knowledge needed
78. Self-sufficiency
79. Simple gardens
80. Small garden area
81. Small gardens
82. Soil profile Independence
83. Space efficiency
84. Standard gardens
85. Structures needed
86. Sunny windowsills
87. Sweetness
88. System simplicity
89. System hygiene
90. table-top gardens
91. Temperature control
92. Tools needed
93. Tower gardens
94. Up-front payment
95. Visual appeal of produce
96. Wall gardens
97. Warrantee
98. Water-wise
99. Weed management
100. Windowsill gardens
101. Tube systems

37. Savvas, 2003; Gruda, 2008; Hoefkens *et al*., 2009
38. Savvas, 2003; Gruda, 2008; Hoefkens *et al*., 2009
39. Harris, 1992; Carruthers, 1993
40. Nicholls, 1990; Kenyon, 1992; Harris, 1992; Carruthers, 1993; Savvas, 2003; Gruda, 2008; Trejo-Téllez & Gomez-Merino, 2012
41. Nicholls, 1990; Kenyon, 1992; Carruthers, 1993
42. Nicholls, 1990; Kenyon, 1992; Carruthers, 1993; Hortishop, 2014
43. Hashimoto *et al*., 2004; Ferentinos and Albright 2002; Chaudhuri, 2009
44. Carruthers, 1993
45. Kenyon, 1992; *Aerogarden™ observation*, 2015; *Click and Grow™*, 2015 observation
46. Nicholls, 1990; Kenyon, 1992; Harris, 1992; Carruthers, 1993; Tyson, 2012
47. Carruthers, 1993; Bamsey *et al*., 2012; Tyson, 2012
48. *Aerogarden™ observation*, 2015; *Click and Grow™*, 2015 observation
49. Harris, 1992; Carruthers, 1993
50. Nicholls, 1990; Savvas, 2003; Gruda, 2008
51. Carruthers, 1993
52. *Aerogarden™ observation*, 2015
53. *Aerogarden™ observation*, 2015
54. *Aerogarden™ observation*, 2015
55. Nicholls, 1990
56. *Aerogarden™ observation*, 2015, Carruthers, 1993; Bamsey *et al*., 2012; Tyson, 2012
57. *Aerogarden™ observation*, 2015; *Click and Grow™*, 2015 observation
58. Carruthers, 1993; Hortishop observation, 2014
59. Nicholls, 1990; Savvas, 2003; Gruda, 2008; Trejo-Téllez & Gomez-Merino, 2012; Bamsey *et al*., 2012
60. du Toit and Crafford, 2003; USDA statement, 2015
61. Bamsey *et al*., 2012; Trejo-Téllez & Gomez-Merino, 2012
62. Harris, 1992; Trejo-Téllez & Gomez-Merino, 2012
63. Harris, 1992; ; Gruda, 2008
64. *Windowfarms™* price observation, 2015
65. Nicholls, 1990; Harris, 1992; ; Gruda, 2008; Carruthers, 1993
66. Nicholls, 1990; Kenyon, 1992; Carruthers, 1993
67. Carruthers, 1993; Ferentinos & Albright, 2002; Bamsey *et al*., 2012; Duarte-Galvan *et al*., 2012
68. Hashimoto *et al*., 1981
69. *Click and Grow™*, 2015 observation, *Aerogarden™ observation*, 2015
70. *Click and Grow™*, 2015 observation, *Aerogarden™ observation*, 2015
71. Nicholls, 1990; Kenyon, 1992; Harris, 1992; Carruthers, 1993; Savvas, 2003; Gruda, 2008; Trejo-Téllez & Gomez-Merino, 2012; Bamsey *et al*., 2012; Duarte-Galvan *et al*., 2012; Iliev *et al*., 2012
72. Nicholls, 1990; Kenyon, 1992; Harris, 1992; Carruthers, 1993; Savvas, 2003; Gruda, 2008; Trejo-Téllez & Gomez-Merino, 2012; Bamsey *et al*., 2012; Duarte-Galvan *et al*., 2012; Iliev *et al*., 2012
73. Tyson, 2012
74. Nicholls, 1990; Harris, 1992; Carruthers, 1993
75. Nicholls, 1990; Harris, 1992; Carruthers, 1993
76. Kenyon, 1992
77. Nicholls, 1990; Harris, 1992; Carruthers, 1993; Savvas, 2003
78. Hashimoto *et al*., 1981
79. Nicholls, 1990; Kenyon, 1992; *Click and Grow™*, 2015 observation
80. Nicholls, 1990; Kenyon, 1992; Carruthers, 1993; Abel, 2010; Tyson, 2012
81. Nicholls, 1990; Kenyon, 1992; Carruthers, 1993; Abel, 2010; Tyson, 2012

	82. Nicholls, 1990; Harris, 1992; Carruthers, 1993; Savvas, 2003
	83. Mason *et al*., 2008
	84. Nicholls, 1990; Kenyon, 1992; *Click and Grow*™, 2015 observation
	85. Harris, 1992; Iliev, *et al*., 2012
	86. *Click and Grow*™, 2015 observation
	87. Savvas, 2003; Gruda, 2008; Hoefkens *et al*., 2009; Nicholls, 1990; Carruthers, 1993
	88. Nicholls, 1990; Kenyon, 1992; *Click and Grow*™, 2015 observation
	89. Carruthers, 1993
	90. Nicholls, 1990; Kenyon, 1992; Carruthers, 1993
	91. Kenyon, 1992
	92. Nicholls, 1990; Kenyon, 1992; Harris, 1992; Carruthers, 1993; Bamsey *et al*., 2012
	93. *Tower Garden*® observation, 2015; *Foody*™ observation, 2015
	94. *Windowfarms*™ price observation, 2015
	95. Savvas, 2003; Gruda, 2008; Hoefkens *et al*., 2009; Nicholls, 1990; Carruthers, 1993
	96. *Florafelt*™ observation, 2015
	97. *Windowfarms*™ price observation, 2015
	98. Nicholls, 1990; Kenyon, 1992; Harris, 1992; Carruthers, 1993; Savvas, 2003; Abd-Elmoniem *et al*., 2006; Gruda, 2008
	99. Nicholls, 1990; Carruthers, 1993
	100. *Click and Grow*™, 2015 observation
	101. Carruthers, 1993

3.4.2.2. Data analysis

These features are classed along similar attributes and grouped together under a factor (step two). Moreover, these factors require further classification into binary variations of themselves, *i.e.* the levels $x_i \in \{0,1\}$ because this decomposition yielded many attributes and far too many levels for any practical factorial experiment (step three). This classification and grouping of product features as factor levels is important for constraining each feature into only a handful of two-level categorical variables (see tables 3.4.2–3.4.6).

Table 3.4.2: MA of *garden plane* attributed levels

Similar attributes: *Garden plane*		
Observations:	**Categorical variables of observations**	
	Level gardens	*Vertical gardens*
Vertical hydroponic cultivation ▪ Abundant urban vertical surfaces ▪ Cultivation ergonomics ▪ Light shading **Growing location**: ▪ Apartments complexes, and detached houses ▪ Available level surfaces and areas ▪ Balcony and courtyards *hydroponics* ▪ Built up surfaces ▪ Curtain gardens ▪ Free-standing houses ▪ Hospitals and Care-homes ▪ Indoor locations ▪ Kitchen counter gardens ▪ Small garden area ▪ Space efficiency ▪ table-top hydroponic gardens ▪ Tower gardens ▪ Wall gardens ▪ Windowsill e-garden	▪ Available level surfaces and areas ▪ Balcony and courtyard *hydroponics* ▪ Free-standing houses ▪ Kitchen counter gardens ▪ table-top hydroponic gardens	▪ Abundant urban vertical surfaces ▪ Apartments, complexes, and detached houses ▪ Available vertical urban landscapes ▪ Built up surfaces ▪ Cultivation ergonomics ▪ Curtain gardens ▪ Hospitals and Care-homes ▪ Indoor locations ▪ Light shading ▪ Small garden area ▪ Space efficiency ▪ Tower gardens ▪ Wall gardens ▪ Windowsill gardens
Conjoint variable:	*Level garden*	*Vertical garden*
Binary variable:	*0*	*1*

Table 3.4.3: MA of *garden automation* attributed levels

Similar attributes: *Garden automation*		
Observations:	**Categorical variable of observations**	
	Manual gardens	*Automatic gardens*
Hydroponic cultivation issues ▪ Artificial Intelligence ▪ Artificial lighting feature ▪ Automatic effluent water drainage ▪ Automatic watering (inherent) ▪ Automation as core offer ▪ Conventional systems ▪ Ease of use ▪ EC control ▪ Fertilising automation ▪ Knowledge and skill replacement ▪ Lamp height control ▪ Lighting intensity control ▪ Lighting spectral control ▪ Modernism ▪ Mechanisation ▪ Nutrient composition control ▪ Nutrient sterilisation ▪ Pest management ▪ pH control ▪ Plant growth sensing and feedback ▪ Planting/ seeding automation via seed-cartridges ▪ Reduced cultivation intensity of hydro-culture compared to soil ▪ Ready-to-use gardens ▪ Reduced cultivation tasks compared to soil ▪ Relative humidity control ▪ Requisite knowledge needed ▪ Soil profile Independence ▪ Structures needed ▪ System hygiene ▪ Temperature control ▪ Weed management **Seasonal issues:** ▪ Spring and Autumn conditions ▪ Summer conditions ▪ Winter conditions	▪ Conventional systems ▪ Pest management ▪ Requisite knowledge needed ▪ Spring and Autumn conditions ▪ System hygiene	▪ Artificial Intelligence ▪ Artificial lighting feature ▪ Automatic effluent water drainage ▪ Automatic watering (inherent) ▪ Automation as core offer ▪ Ease of use ▪ EC control ▪ Fertilising automation ▪ Knowledge and skill replacement ▪ Lamp height control ▪ Lighting intensity control ▪ Lighting spectral control ▪ Mechanisation ▪ Modernism ▪ Nutrient composition control ▪ Nutrient sterilisation ▪ pH control ▪ Plant growth sensing and feedback ▪ Planting/ seeding automation via seed-cartridges ▪ Ready-to-use gardens ▪ Reduced cultivation intensity of hydro-culture compared to soil ▪ Reduced cultivation tasks compared to soil ▪ Relative humidity control ▪ Soil profile Independence ▪ Structures needed ▪ Summer conditions ▪ Sunny windowsills ▪ Temperature control ▪ Weed management (inherent) ▪ Winter conditions
Conjoint variable:	*Manual* control	*Automatic* control
Binary variable:	*0*	*1*

Table 3.4.4: MA of *garden performance* attributed levels

Similar attributes: Crop *performance*		
Observations:	**Categorical variable of observations**	
	Standard-performance gardens	*High-performance gardens*
Performance of hydroponic cultivation: ▪ Aesthetic produce ▪ Beneficial nutrient microorganisms ▪ Denser crop planting ▪ Drought-wise ▪ Faster growth cycle ▪ Quicker maturation ▪ Fewer pest-problems for root crops ▪ Heat-stress-wise ▪ High yields ▪ Input efficiency ▪ Less chemical control needed ▪ Material-wise ▪ Optimised water quality (Filtration, R/O etc.) ▪ Rapid growth ▪ System simplicity ▪ Water-wise **Subjective traits of produce:** ▪ Aroma strength ▪ Flavour strength ▪ Sweetness ▪ Visual appeal of produce **Product types and features:** ▪ Casual gardens ▪ Cultivation platforms ▪ Electronic ▪ Hobby kits ▪ Intensive gardens ▪ Modular systems ▪ Performance gardening	▪ Casual gardens ▪ System simplicity ▪ Less crop performance	▪ Aesthetic produce ▪ Aroma strength ▪ Beneficial nutrient microorganisms ▪ Cultivation platforms ▪ Denser crop planting ▪ Drought-wise ▪ Electronic ▪ Faster growth cycle ▪ Quicker maturation ▪ Fewer pest-problems for root crops ▪ Flavour strength ▪ Heat-stress-wise ▪ High yields ▪ Hobby kits ▪ Input efficiency ▪ Intensive gardens ▪ Less chemical control needed ▪ Material-wise ▪ Modular systems ▪ Optimised water quality (Filtration, R/O etc.) ▪ Performance gardening ▪ Rapid growth ▪ Sweetness ▪ Visual appeal of produce ▪ Water-wise
Conjoint variable:	*Casual*	*High-performance*
Binary variable:	*0*	*1*

Table 3.4.5: MA of *garden organics* attributed levels

<table>
<tr><td colspan="3">Similar attributes: Organic cultivation</td></tr>
<tr><td>Observations:</td><td colspan="2">Categorical variable of observations</td></tr>
<tr><td rowspan="2">Organic hydroponic cultivation:
▪ Beneficial microorganisms used
▪ Carbon fertiliser
▪ Conventional hydroponic cultivation practices
▪ Decomposition fertiliser
▪ Environmental friendliness
▪ Hydroponics based on artificial processes
▪ Hydroponics based on natural processes
▪ Mechanisation
▪ No carbon in fertiliser
▪ No synthetic chemicals
▪ Organic media
▪ Self-sufficiency</td><td>Non-organic gardens</td><td>Organic gardens</td></tr>
<tr><td>▪ Conventional hydroponic cultivation practices
▪ Hydroponics based on artificial processes
▪ Inorganic media
▪ Mechanisation
▪ No carbon in fertiliser
▪ Synthetic fertiliser</td><td>▪ Beneficial microorganisms used
▪ Carbon fertiliser
▪ Decomposition fertiliser
▪ Environmental friendliness
▪ Hydroponics based on natural processes
▪ No synthetic chemicals
▪ Organic media
▪ Self-sufficiency</td></tr>
<tr><td>Conjoint variable:</td><td>Non-organic</td><td>Organic</td></tr>
<tr><td>Binary variable:</td><td>0</td><td>1</td></tr>
</table>

Table 3.4.6: MA of *garden price* attributed levels

<table>
<tr><td colspan="3">Similar attributes: Garden costs</td></tr>
<tr><td>Observations:</td><td colspan="2">Categorical variable of observations</td></tr>
<tr><td rowspan="2">Hydroponic cultivation costs
▪ Accessories
▪ Advanced/expert gardens
▪ Concise units
▪ Few core features
▪ Kits
▪ Large gardens
▪ Many core features
▪ Payment plans
▪ Premium gardens
▪ Simple gardens
▪ Small gardens
▪ Standard gardens
▪ Tools needed
▪ Up-front payment
▪ Warrantee</td><td>Gardens around R2500</td><td>Gardens around R5000</td></tr>
<tr><td>▪ Concise units
▪ Few core features
▪ Simple gardens
▪ Small gardens
▪ Standard gardens
▪ Tools needed
▪ Up-front payment</td><td>▪ Accessories
▪ Advanced/expert gardens
▪ Kits
▪ Large gardens
▪ Many core features
▪ Payment plans
▪ Premium gardens
▪ Warrantee</td></tr>
<tr><td>Conjoint variable:</td><td>R2500</td><td>R5000</td></tr>
<tr><td>Binary variable:</td><td>0</td><td>1</td></tr>
</table>

3.4.3. Results and discussion:

3.4.3.1. Results

This MA profiled the e-garden concept into of categorical factors and their binary variables. These factors are now concise yet useful categorical packages which organise and describe the product features of hydroponic gardens. From this, a full factorial design can now be demonstrated post hoc using dummy coded factors with their variables presented as binary values (see table 3.4.7 below). The CA next will then receive at most $i=2^5=32$ runs, and where each variable phrased is articulate for respondents (table 3.4.7).

Table 3.4.7: The results of the MA which describe HG factors in terms of familiar marketing clichés

Factor x_i	Product features	Binary variables x_i	
A	Garden *plane*	*Level garden*	*Vertical garden*
B	Garden *automation*	*Manual control*	*Automatic control*
C	Garden *performance*	*Casual*	*High-performance*
D	Garden *organics*	*Non-organic*	*Organic*
E	Garden *price*	*R2500*	*R5000*

Table 3.4.8: The full results of the MA in terms of a 2^5 factorial design coded with dummy variables which can be used for modelling (bold=FFD selected profiles)

Run:	Factor A *Garden plane*	Factor B *Garden automation*	Factor C *Garden performance*	Factor D *Garden organics*	Factor E *Garden price*
1.	0: Level	0: Manual	0: Casual	0: Non-organic	0: R2 500
2.	**0: Level**	**0: Manual**	**0: Casual**	**0: Non-organic**	**1: R5 000**
3.	**0: Level**	**0: Manual**	**0: Casual**	**1: Organic**	**0: R2 500**
4.	0: Level	0: Manual	0: Casual	1: Organic	1: R5 000
5.	0: Level	0: Manual	1: High-performance	0: Non-organic	0: R2 500
6.	0: Level	0: Manual	1: High-performance	0: Non-organic	1: R5 000
7.	0: Level	0: Manual	1: High-performance	1: Organic	0: R2 500
8.	**0: Level**	**0: Manual**	**1: High-performance**	**1: Organic**	**1: R5 000**
9.	**0: Level**	**1: Automatic**	**0: Casual**	**0: Non-organic**	**0: R2 500**
10.	0: Level	1: Automatic	0: Casual	0: Non-organic	1: R5 000
11.	0: Level	1: Automatic	0: Casual	1: Organic	0: R2 500
12.	**0: Level**	**1: Automatic**	**0: Casual**	**1: Organic**	**1: R5 000**
13.	0: Level	1: Automatic	1: High-performance	0: Non-organic	0: R2 500
14.	**0: Level**	**1: Automatic**	**1: High-performance**	**0: Non-organic**	**1: R5 000**
15.	**0: Level**	**1: Automatic**	**1: High-performance**	**1: Organic**	**0: R2 500**
16.	0: Level	1: Automatic	1: High-performance	1: Organic	1: R5 000
17.	1: Vertical	0: Manual	0: Casual	0: Non-organic	0: R2 500
18.	1: Vertical	0: Manual	0: Casual	0: Non-organic	1: R5 000
19.	**1: Vertical**	**0: Manual**	**0: Casual**	**1: Organic**	**0: R2 500**
20.	**1: Vertical**	**0: Manual**	**0: Casual**	**1: Organic**	**1: R5 000**
21.	1: Vertical	0: Manual	1: High-performance	0: Non-organic	0: R2 500
22.	**1: Vertical**	**0: Manual**	**1: High-performance**	**0: Non-organic**	**1: R5 000**
23.	**1: Vertical**	**0: Manual**	**1: High-performance**	**1: Organic**	**0: R2 500**
24.	1: Vertical	0: Manual	1: High-performance	1: Organic	1: R5 000
25.	1: Vertical	1: Automatic	0: Casual	0: Non-organic	0: R2 500
26.	**1: Vertical**	**1: Automatic**	**0: Casual**	**0: Non-organic**	**1: R5 000**
27.	**1: Vertical**	**1: Automatic**	**0: Casual**	**1: Organic**	**0: R2 500**
28.	1: Vertical	1: Automatic	0: Casual	1: Organic	1: R5 000
29.	**1: Vertical**	**1: Automatic**	**1: High-performance**	**0: Non-organic**	**0: R2 500**
30.	1: Vertical	1: Automatic	1: High-performance	0: Non-organic	1: R5 000
31.	1: Vertical	1: Automatic	1: High-performance	1: Organic	0: R2 500
32.	**1: Vertical**	**1: Automatic**	**1: High-performance**	**1: Organic**	**1: R5 000**

3.4.3.2. Discussion

Technology forecasting using MA is applied for creating alternatives, but has come under scrutiny for being non-quantifiable and vague (Nijssen & Frambach, 2000; Ritchie, 2002; Yoon & Park, 2007; Levin, 2012). Conversely, quantitative models can illogically "… fit unruly data into mathematical straight-jackets …" (Yoon & Park, 2007). These authors Yoon & Park (2007) resolve this issue by using a hybrid MA–CA to enable a simultaneous and thorough product-market evaluation; who argue this framework is most suitable for understanding product innovation, through both observation and experimentation.

The initial step of this MA was to list the observed features of hydroponic cultivation, which secondly allowed for the classing of those features along their attributes. This used secondary data from bibliographic techniques, however most technology forecasting techniques such as MA rely on "intuitive opinions from domain experts" (Nijssen & Frambach, 2000; Ritchie, 2002; Yoon & Park, 2007; Levin, 2012). Data is ideally sourced from expert opinion via focus-groups; however this research practically obtains expert opinion via more convenient bibliographic-based sources. Ultimately this profile of innovated HG or e-gardens can be judged by its potential consumers in a CA next chapter.

The third step imposed constraints, where binary outcomes are the preferred variables for each factor. This simplifies CA to a minimal number of factorial runs, however many more factors exist in the MA and in reality. Furthermore, the CA may be seen as a screening experiment where two-point levels are sufficient for estimating models. This CA thus requires 2^k factor levels to minimise exponential increase of the experimental runs, because the n of CA e-garden products will become very large —for instance a $3^5 = 243$ runs. A $2^5 = 32$ factorial might allow for a CA which can explore several factors without the number of runs exceeding respondent comfort, though a FFD should be considered. Respondents can then be able to better grasp this topic in a shorter questionnaire.

CA analysis mandates that the stimulus terminology be expressed as people-friendly as possible (Orme, 2010), like where *automation* became *automatic*. The matrix in table 3.4.8 intended to plug technical information directly into a people-friendly CA survey. This presented a *post hoc* issue for this analysis, because the intended respondent population of consumers likely are not very familiar with any technical jargon of HG. Thus, the MA simultaneously aimed to escape this problem and re-term technical aspects into familiar marketing clichés for the respondents taking the survey (see table 3.4.7). Adequate respondent–topic understanding is crucial for a realistic and successful CA next chapter.

CHAPTER FOUR

INNOVATING HYDROPONIC GARDENS FOR URBAN HORTICULTURAL CONSUMERS ON THE CAPE PENINSULA: A CONJOINT ANALYSIS (CA)

CHAPTER FOUR

Innovating hydroponic gardens for urban horticultural consumers on the Cape Peninsula: A Conjoint Analysis (CA)

4.1. Abstract

This chapter asks “what are the part-worth utilities for HG and e-garden product features?” CA is a consumer psychological trade-off methodology which involves measuring respondent preferences levels to indicate the part-worth utility for each product feature. Thus CA is used in this chapter to prioritise product-features for consumers in the Cape Town horticultural market. This resulted in factors such as *garden organics*, *price*, and *automation* having significant slope. Mainly, *garden organics* contributed to response effects, with *price* having negative slope and coming second. *Automation* has positive slope and is the second most useful factor but third most significant. This research illuminates how horticultural consumers may prefer various HG by understanding and how HG can better benefit these people.

4.2. Introduction

This research applied information provided by the MA from chapter three to prioritise the factors in a model for horticultural consumers on the Cape Peninsula via this CA. First this analysis identified a sampling strategy for accessing these people. Next, it was important to design an experiment suited for these people. Lastly, this analysis applied statistical methodologies to process the information generated by many respondents sampled on the Cape Peninsula.

4.3. Conjoint Analysis (CA) in review

Analytical product design is crucial for designing successful products for markets (Nijssen & Frambach, 2000; Frischknecht *et al*., 2009; Kuhfeld, 2010). For this purpose, CA is a powerful yet elegant analysis which models an optimal combination of product attributes for consumers (Desarbo *et al*., 1995; Alexio & Tenera, 2000; Nijssen & Frambach, 2000; Orme, 2010; Kuzmanović *et al*., 2011). CA is argued to be well-suited to test consumer preferences for incremental changes in new products (Desarbo *et al*., 1995; Alexio & Tenera, 2000; Nijssen & Frambach, 2000; Kuzmanović *et al*., 2011). It applies a fixed-effects experiment, where all the questionnaire stimuli or factors are outlined from another framework such as a MA (Orme, 2010). Respondents are requested in a questionnaire setting to rate product profiles of factor-level combinations by making trade-offs for their desired *vs* undesired product features (Kuhfeld, 2010; Kuzmanović *et al*., 2011).

CA originated out of fields such as mathematical psychology and theories such as the Theory of Planned Behaviour, yet is criticised to reflect poorly on consumer intentions if they cannot comprehend the product in question, so this may be an issue with a technical survey (Kuhfeld, 2010; Kuzmanović *et al*., 2011). Response error may result from the difference between assumed-intention and actual intentions (Armitage & Conner, 2001). Nevertheless, CA is regarded as useful, even for pre-prototype concept testing where respondents have little knowledge and experiences regarding high-tech product topics, where consumers with high technical expertise are avoided (Alexio & Tenera, 2000; Kuhfeld, 2010; Orme, 2010). CA is best taken place in a real shopping setting because of parallel consumer behaviour here (Kuzmanović *et al*., 2011).

CA has been used before in modelling consumer utilities for similar horticultural research such as container gardens, floriculture, vegetables, and ornamentals by Mason (Mason *et al*., 2008). Regression is ubiquitously applied for modelling uncertainty of data, especially with the noise introduced in the CA from the response errors and other nuisance factors (Kuhfeld, 2010; Orme, 2010; Kuzmanović *et al*., 2011).

4.4. Sampling analysis in review:

4.4.1. Initial sampling considerations

Business research activities are required to be most cost-wise, for profit and survival of the business enterprise, whilst maintaining a useful degree of certainty and precision in order to make informed decisions (Keller & Warrack, 2000; Kuzmanović *et al*., 2011). Sampling methodologies are most useful for keeping data collection costs down, however in applying these tools, business managers must trade-off with uncertainty and imprecision (Keller & Warrack, 2000; Kuhfeld, 2010). Various sampling techniques are utilised for general research, where particular tools each have their merits and liabilities (Jennings, 2009).

Foremost, a Simple Random Sample (SRS) is considered, which out of all sampling methodologies, is powerful and seems to offer relatively simplistic analyses for inference and arriving at conclusions (Jennings, 2009). However it is difficult for this research to access the individual sampling elements that are scattered over some area over the urbanised Cape Peninsula. But mainly, a complete sampling frame of horticultural consumers is not available.

Cluster sampling methodology offers this research a practical window from which to gather information about these people. Garden centre retailers can conveniently serve as primary sampling units to access main sampling units (horticultural consumer population of the Cape Peninsula) for data collection.

4.4.2. Cluster sampling issues

Cluster sampling methodology has considerations. Cluster sampling techniques applied in practice usually have greater variation of analysed data which should be expected compared to other probabilistic sampling methodologies (Jennings, 2009). This unfortunately means wider estimation intervals, and having larger and fewer clusters can increase the error (Jennings, 2009). Clusters should thus be heterogeneous within and homogenous between (Jennings, 2009; SPSS *complex samples 23*, 2016). The clusters sampled require testing for homogeneity of cluster parameters to detect weakness in the relative efficiency of this sampling plan.

4.4.3. Design effect *deff* of cluster sampling

Cluster sampling begs the question “how does the selection of cluster sampling differ from say the selection of SRS for estimation?” Clusters are likely to have similar units in practice, and sampling more than needed number of units contributes less information as the size of the cluster increases (Jennings, 2009). The impact of this choice can be measured from the design effect *deff* which involves the ratio of within *vs* between cluster variances along with cluster size. It is interpreted as the multiple of variation compared to an SRS. This value must be involved for producing accurate results for this research(ee *SPSS complex samples* printouts later in the results.

4.4.4. Sampling errors and controls

4.4.4.1. Sampling error:

If researchers are willing to accept less than 100% certainty, because of finite resources, then sampling becomes feasible (Keller & Warrack 2000). Error here is managed through analysis of sample errors that suggest the difference between parameters and statistics. If appropriate logistical measures are taken, this error can be suggested to be due to chance or exposure (Keller & Warrack 2000). Cluster sampling is used in this research which has implications for this error. Probability sampling is applied to the clusters; thus this sampling error is more likely due to random chance.

Sampling bias

The elements m are only selected once that day. However there's no guarantee though, because some elements might be more frequent users than others, and this invokes systematic sampling bias where there is some degree of replacement.

Sampling weights

Sampling weights are the inverse of the probability of an element being sampled *i.e.* each cluster n_k can be represented as $w_k = N_k / n_k$ (Jennings, 2009; *SPSS Complex Samples 23*, 2016). A simple random sample of clusters was taken, so this then suggests the cluster sample is self-weighting (Jennings, 2009). SPSS printed the sampling weights for each cluster (see table 4.5.4) *i.e.* $w_k=3$ for each cluster in the sample. This is interpreted as each sample cluster analytically represents 3 other clusters. Complex samples procedures requires calculating the sampling weights to properly analyse the sample in *SPSS Complex Samples 23*, 2016.

4.4.4.2. Systematic errors:

In the real world measurement is seldom perfect (Keller & Warrack 2000). In addition to sampling error, surveys are subject to many other types of error, or non-sampling errors—which plague both *census* and sampling research (Statistics Canada, 2013). Systematic coverage errors can result from imperfect sampling frames and fieldwork. These accumulate as the sample is taken, and are created by systematic issues such as survey design and compromises, and does not lend itself well to measurement nor fixing (Statistics Canada, 2013).

Coverage error

Overcoverage and undercoverage both are problems for accurate measurement. This error needs to be eliminated, but inevitable real-world omissions do happen. Sampling units may be omitted in research, especially research involving people or places (Statistics Canada, 2013). If coverage error is part of the measurement, then adjustments to the data need to be made, (Statistics Canada, 2013). This survey must record non-coverage errors as much as possible.

Estimation error

A poor instrument reads poor measurements. Careful design and processing of this CA questionnaire is needed to reduce instances of measurement error and inaccurate results.

Response errors

Respondent errors result from errors respondent comprehension, recollection, exaggeration, and social issues (Statistics Canada, 2013). Interviewer bias occurs if the researcher is not neutral somehow.

Processing and analysis errors

Error may result from inappropriate and insufficient analytical methods being used on the data, an issue examined in this research's analytical reviews. Problems can result from inaccurate data capture, coding errors, even computer glitches (Statistics Canada, 2013). Thus care and checking is required, with a second analytical opinion from other tests (Keller & Warrack, 2000). Also double checking of data input from data registers is important.

HG run pictures

Systematic bias can be introduced in the aesthetics of the product-types. A graphical illustration of each product is arguably important for respondent comprehension. This leaves the research with bias and a catch: products need to be shown with a balance between consumer comprehension though should be sterile from extraneous factors. This research is specifically investigating the factors generated from the MA, and measurement should be as orderly, precise, and focused as is possible.

4.4.5. Sampling parameters and statistics:

Theoretical population K

Inferences here are intended to be made about these consumers K, who are difficult to directly locate, count, and sample (Jennings, 2009). These are the elements of interest, the total number of urban horticultural consumers who live on a congested peninsula, thus may have particular horticultural needs relating to HG. These people may seek plants and gardens for their homes; they exist as consumers who have horticultural needs and seek to fulfil them at garden centres (Kenyon, 1992; Nicholls, 1990; Harris, 1992; Carruthers, 1993; Warrington, 2014). Only the area of the Cape Peninsula is delineated as research scope, as the entire City of Cape Town is currently too vast for this research (see figure 4.5.2).

Sampling elements m

These units are individual consumers within garden centre clusters, who form the urban horticultural consumer population on the Cape Peninsula, who are the survey respondent sample from the population K. Specifically; m_k is the number of SSU in the sample for the k^{th} cluster (Jennings, 2009). For a single-stage sampling design with clusters of equal sizes, $m = M$ for all M_k (Jennings, 2009).

Saunders *et al*. (1997) tabled a sample size m of at least 384 cases for a margin of error of *5%* and *95%* confidence interval, for an estimated population size K of between 1 000 000 to 100 000 people. Also, with many variables x_i, a larger sample size of up to 1000 may then be needed (Orme, 2010). Cluster sizes m_k of K may initially be pre-determined from: a needed margin of error, or plugged-in from a pilot study, together with cluster size issues, also resource constraints like time and money, all affect the end sample size taken (Keller & Warrack, 2000; Orme, 2010).

Cluster population size N

The number of clusters in the population is the number of garden centres on the urbanised Cape Peninsula, which is also the total units in the sampling frame, and randomised in table 4.5.2, where $N=9$.

Cluster sample size n

n is kept for the number of clusters in the sample (Jennings, 2009). It is better to sample many clusters, (Jennings, 2009).

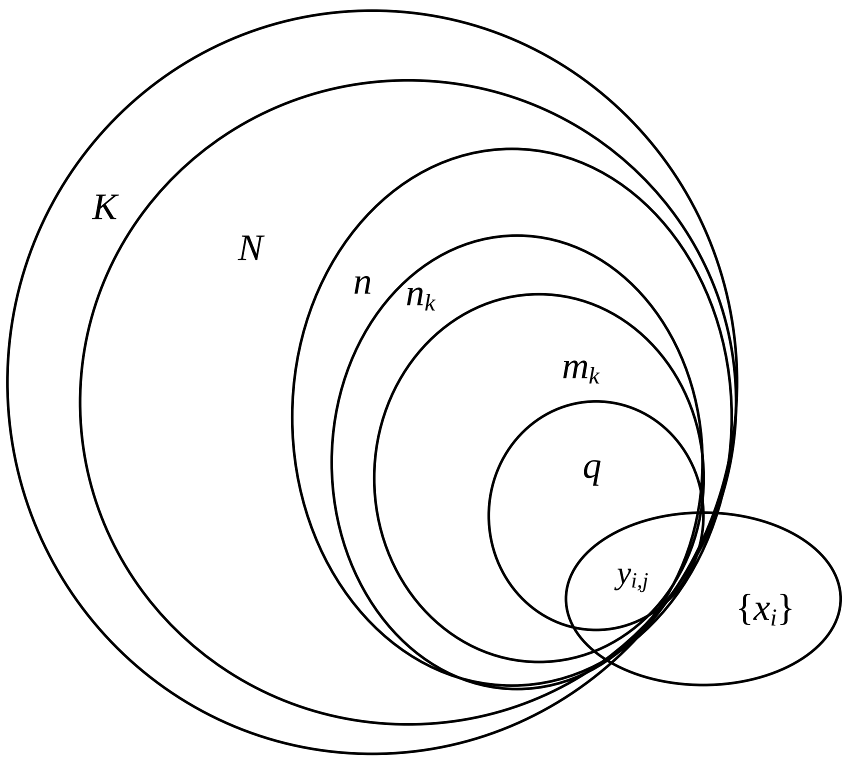

Figure 4.5.1: Venn diagram for the basic set geometry of this sampling plan

4.4.6. Sampling sets

Figure 4.5.1 roughly illustrates the sampling sets using a Venn diagram. There are $\{n\}$ randomly selected clusters n_k of a population of N, for accessing the respondents q of the research population K. The set of HG product features in the CA instrument are represented by $\{x_i\}$, which has an intersection forming the subset for survey responses y_{ij}. Because a single stage design is used in this research, where a *census* is taken within sampled clusters; all the m elements within the n clusters should be sampled, whilst reducing inevitable non-responses and coverage error. This illustrates how the sampling strategy gives the factor set x_i direct access to the research population K. Mathematically, $q_j \subseteq m_k \subseteq \gamma_n \subseteq n \subseteq N \subseteq K$ and $q \cap x_i = y_{i,j}$ where $y_i \in \{1, 2, 3, 4, 5\}$ and $x_i \in \{x_A, x_B, x_C, x_D, x_E\}$ (Waner and Constenoble, 2004; Jennings, *2009*).

4.5. Sampling and fieldwork plan

A sample of $n=3$ clusters is randomly selected, followed by interviewing all urban horticultural consumers entering the premises.

Table 4.5.1: SPSS sampling plan file used for this research

			Stage 1
Design Variables	Cluster	1	Garden centre population
Sample Information	Selection Method		Simple random sampling without replacement
	Number of Units Sampled		2
	Variables Created or Modified	Stagewise Inclusion (Selection) Probability	InclusionProbability_1_
		Stagewise Cumulative Sample Weight	SampleWeightCumulative_1_
		Stagewise Population Size	PopulationSize_1_
		Stagewise Sample Size	SampleSize_1_
		Stagewise Sampling Rate	SamplingRate_1_
		Stagewise Sample Weight	SampleWeight_1_
Analysis Information	Estimator Assumption		Equal probability sampling without replacement
	Inclusion Probability		Obtained from variable InclusionProbability_1_

Weight Variable: SampleWeight_Final_

4.5.1. Sampling frame

A complete sampling frame is not available, though there are clusters of garden centres and retail nurseries on the urban Cape Peninsula, with access to the theoretical population (see table 4.5.2). Thus coverage errors may be an issue. The cluster population was obtained as a sampling frame from the sources: the *SANA* website (2015), *Yellow-pages* (2015), and *Google Maps* (2015). Figure 4.5.2 shows the electoral wards of the City of Cape Town (white) with the smaller Urban Cape Peninsula and the theoretical population for sampling and inference (dark grey); here the sample frame identifies 9 garden centre clusters.

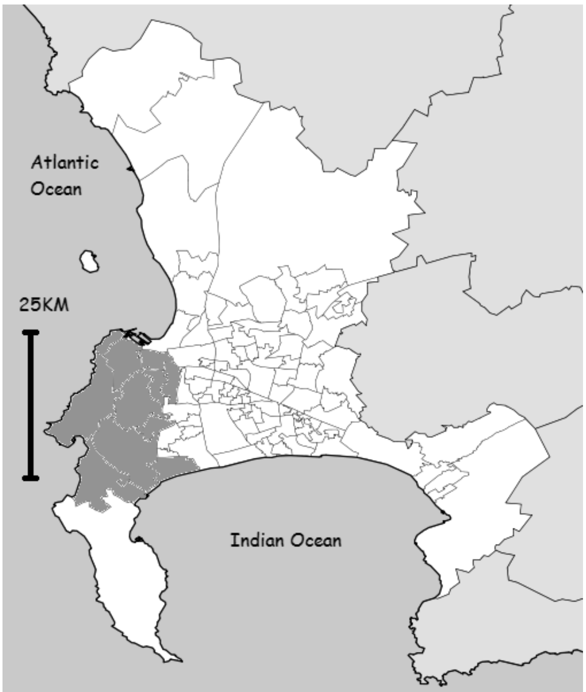

Figure 4.5.2: Electoral wards of the Cape Peninsula (dark grey)

Table 4.5.2: Population of N clusters on the Cape Peninsula, from the sampling frame

```
VALUE LABELS
N
1. Noordhoek Garden Emporium
Noordhoek
2. Ferndale Constantia
3. Harry Goeman’s Kommetjie
4. Kirstenbosch nursery
5. Starke Ayres Mowbray
6. Stodels Constantia
7. Stodels Kenilworth
8. Super Plants Tokai
9. Earthworx Houtbay.
```

4.5.2. Sampling garden centre clusters

This research will randomly select $n=3$ clusters to sample from the garden centre population N. Below are SPSS printouts of the garden centre cluster samples drawn for this research, with their sampling weights.

Table 4.5.3: SPSS sample drawn WOR for garden centre clusters n_k

```
VALUE LABELS
n_k
1   Harry Goeman’s Kommetjie
2   Starke Ayres Mowbray
3   Stodels Constantia (Non-response)
4   Super Plants


VALUE LABELS
N
1 Noordhoek Garden Emporium Noordhoek
2 Ferndale Constantia
3 Harry Goeman’s Kommetjie
4 Kirstenbosch nursery
5 Starke Ayres Mowbray
6 Stodels Constantia
7 Stodels Kenilworth
8 Super Plants Tokai
9 Earthworx Hout Bay.
```

Table 4.5.4: Sampling weight for the sample of clusters *n*

Cluster population ***N***	Sampled clusters ***n***	Inclusion probability *p*	Sampling rate	Final sample weight
9	*3*	*0.333*	*0.333*	*3*

4.5.3. Fieldwork methodology and materials.

The patrons of garden centres were invited take part in a nursery shopping survey. Respondents were invited to sit down and presented with two magazines; first the cognitive aid magazine, and then together with the CA survey experiment magazine (see the Appendix for magazine 1 & 2), to ensure their complete understanding of each aspect of the product-types and their various features. They were charmed with a fun survey and charisma without a patronising demeanour, for a professional and realistic nursery shopping setting. Only a table, chair, and the printed survey magazines were essential materials.

4.6. Experimental design: A Fractional Factorial Design (FFD)

4.6.1. FFD in review:

4.6.1.1. Background

Market research gathers information using the least amount of resources, whilst ensuring respondent fatigue is minimised (Kuhfeld, 2010). For these reasons, a fractional factorial experimental design is used by industry to minimise the number of runs in conjoint experiments (Kuhfeld, 2010).

FFD and more specifically 2^k experimental designs are used by industry for preliminary studies and screening experiments, which suggest preliminary effect sizes and comparisons for subsequent research for more precision (Borkowski, 2009; Kuhfeld, 2010). These experimental designs are used extensively in CA, because factorial designs with a few number of product factors and levels can create exponentially large number of experimental runs (Desarbo *et* al., 1995; Borkowski, 2009; Kuhfeld, 2010; Orme, 2010).

FFD applies principles such as the *sparsity-of-effects* and the *hierarchal effects*; which assert that systems are simply dominated by testable main-effects and low order interactions, where three-factor interactions and higher are initially assumed rare or less important (Borkowski, 2009; Kuhfeld, 2010). FFD can be classed according to their power via their design resolution number (Borkowski, 2009; Kuhfeld, 2010).

4.6.1.2. Blocking and confounding issues

FFD has a price—confounding—any confounded and interacting factors cannot be separately measured as main-effects and individual parameters B (Keller & Warrack, 2000; Borkowski, 2009). In FFD, alternate blocks are identified among the factors where the design generator is positive or negative (Borkowski, 2009). Here, the goal is to yield 2^{k-p} blocks *i.e.* half factorial replicates for screening and economic purposes. Idealistically in a full factorial design, the columns each require factor sign differences in order to separate the effects of the alias from one another.

If the design generator is **ABCDE**, *i.e.* the "negative block" which contains two- and four-factor interactions, and are seen as less important—nevertheless may be run in later research for more precision (Keller & Warrack, 2000; Borkowski, 2009; Kuhfeld, 2010).

Three-factor interaction effects cannot be estimated where they are confounded with significant two-factor interaction effects (see table 4.6.1), though the interaction is unknown at this stage of the research, though may become an issue. Moreover, the interaction **ABCDE** is confounded with the block itself. Similarly **E**=**ABCD**, the design generator, shows that *garden price* is confounded with a possible interaction. This means in a matrix that the sign products of **A*B*C*D** for each row is equal to the sign in column **E** in each row, thus the effects from this alias cannot be distinguished between the same runs. This means that, say for the HG part-worth utility for *price*, the FFD statistic is equal to the difference between a full factorial design's statistics, i.e.:

$b_E = b_E - b_{ABCD}$, where $b_{ABCD} \approx 0$ (assumingly 0).

4.6.1.3. Balance and orthogonality

Balanced experimental designs have the levels occur as frequently for each factor. Here the intercept is perpendicular to the main-effect; while orthogonal experimental designs have all pairs of levels occurring as frequently over all the factors, *i.e.* perfect zero correlation (Kuhfeld, 2010, *Minitab™, 2016*). A balanced and orthogonal experimental design is ideal but not necessarily perfect (Kuhfeld, 2010). *Orthogonal arrays* however are actually *resolution III* FFD, and there seems to be contention in the literature on the quality and even definition of orthogonal arrays (Kuhfeld, 2010). This research nevertheless should take the lesser of two evils and remove only one high-order block from the full factorial design.

4.6.2. FFD strategy for this research: alias table and design matrix

Here, the idea was to estimate single and two-factor interactions, by ensuring they are not aliased with each other *i.e.* no confounded low-order interactions with each other, while assuming higher-order interactions are negligible. This means that the slopes terms β_i may be purely estimated where they are not confounded with two- or three-factor interactions, and two-factor interactions can be purely estimated where they are not confounded with other three-factor interactions. In this FDD, the slopes β_i are only confounded with four-factor interactions, as this can provide relatively good information (see table 4.6.1).

This is achieved by keeping the design generators at a single five-factor interaction to obtain a resolution V design, as resolution III is too weak to handle two- and three-factor interactions. This resolution V design can obtain good information (*Minitab™*, 2016).

The full factorial design here sits at $2^i = 2^5 = 32$ possible exposure-control combinations aka product profiles, with the fractional design sitting at a more articulate φ of *16* profiles. The strategy for determining this fraction is set out below:

1. Determine the possible design generators for the principle fraction: $\varphi = 2^{i-p}$ with i factors and p blocks (Borkowski, 2009)
2. The identity statement is: $\mathbf{I} + \mathbf{ABCDE}$.
3. Defining relation: $\mathbf{E}$ is confounded with the higher-order interaction $\mathbf{ABCD}$.
4. Design generator: $\mathbf{E} = \mathbf{ABCD}$.
5. Design resolution: Resolution V, as $\mathbf{I} + \mathbf{ABCDE}$ involves "*5* characters".
6. The full factorial design is: $2^i = 2^5 = 32$ possible runs.
7. The principle fraction φ is given by: $\varphi = I_V{}^{i-p} = 2_V{}^{5-1} = 16$ (Borkowski, 2009)
   i.e. 16 experimental runs product profile runs.
8. The alias structure is displayed in table 4.6.1.
9. This design now has $i - 1 = 15$ *degrees of freedom*.
10. From *Minitab™*, this identity statement and alias structure, the main-effects and other important low-order interactions available for clear evaluation are thus (see table 4.6.1):

This all illustrates the impact of a FFD on interpreting specific model effects.

Table 4.6.1: The alias structure *via Minitab*™

Fractional Factorial Design

```
Factors:   5   Base Design:         5, 16   Resolution:    V
Runs:     16   Replicates:              1   Fraction:    1/2
Blocks:    1   Centre pts (total):      0

Design Generators: E = ABCD

Alias Structure:
I + ABCDE

A + BCDE
B + ACDE
C + ABDE
D + ABCE
E + ABCD
AB + CDE
AC + BDE
AD + BCE
AE + BCD
BC + ADE
BD + ACE
BE + ACD
CD + ABE
CE + ABD
DE + ABC
```

Table 4.6.2: Randomised design matrix *via Minitab™*

Run	A	B	C	D	E
1	+	+	+	−	−
2	+	+	+	+	+
3	+	−	+	−	+
4	+	+	−	−	+
5	−	−	+	−	−
6	−	+	−	+	+
7	−	+	+	−	+
8	+	−	−	−	−
9	+	−	−	+	+
10	−	−	−	+	−
11	−	+	+	+	−
12	−	−	−	−	+
13	+	+	−	+	−
14	+	−	+	+	−
15	−	+	−	−	−
16	−	−	+	+	+

4.6.3. Balance and orthogonality of this FFD:

Balance of experimental factors

If all factors have equally occurring levels in the DOE, *i.e.* this experimental design is balanced when:

H_0: A = a = B = b = C = c= D = d = E = e

H_1: This equality does not hold.

Table 4.6.3: Test for the balance of factor levels

A	Count	B	Count	C	Count	D	Count	E	Count
1	8	1	8	1	8	1	8	1	8
N=	16	N=	16	N=	16	N=	16	N=	16

The frequencies for each factor level were counted by *Minitab™* and simply observed to be equal (a significance test isn't necessary or applicable here), thus the null hypothesis of balance is supported.

Orthogonality of factors

Orthogonality suggests factor independence, for interpreting separate interaction effects from main-effects in an experiment (Berenson *et* al., 1983; *Minitab^{TM}, 2016*). These factorial runs φ here should be orthogonal (because they were outputted by reputable software; nonetheless manually checking orthogonality is done below, so any deviation from this reasoning is not supported by a null hypothesis of orthogonality. For multifactorial designs Pearson's correlation r should be used, as many possible factor interactions require testing for orthogonality between each other by co-equalling zero (*Minitab^{TM}*, 2016). Therefore the null hypothesis of zero correlation is supported by:

H_0: $r = A*B = A*C = A*D = A*E = B*C = B*D = B*E = C*D = D*E = 0$

H_1: $r \neq 0$

(*Minitab^{TM}*, 2016).

Table 4.6.4: Test for the orthogonality of factors used in this design

	A	B	C	D
B	0.000 1.000			
C	0.000 1.000	0.000 1.000		
D	0.000 1.000	0.000 1.000	0.000 1.000	
E	0.000 1.000	0.000 1.000	0.000 1.000	0.000 1.000

Cell Contents: Pearson correlation
P-Value

These results above in table 4.6.4 show that $r=0$ for all factors, which all have full p-values. This suggests strong evidence for not rejecting the null hypothesis of orthogonality between factor pairs in this experimental design.

4.7. Data analysis:

4.7.1. Analytical methodology in review

4.7.1.1. Introduction: response scale

This research investigates consumer product utilities and asks "…*which attributes are most preferable for horticultural consumers*?", and there are 5 factors each with 2 levels (Keller & Warrack, 2000; Agresti, 2002). Consumer preferences *per se* are categorical thus shouldn't be measured by numbers with equal intervals—though marketing industry finds efficiency assuming continuous scales according to Orme (2010). Categorical data can either have nominal or an ordinal nature (Agresti, 2002). Ordinal categorical data can be named and ranked, but not simply measured like real numbers as the interval between ordered categories is unknown (Keller & Warrack, 2000; Agresti, 2002; Jennings, 2009; Orme, 2010).

The response categories y_j for this scale use insightful and expert consideration, because poor or unbalanced scoring will confuse respondents, distort results, so harm interpretation (Agresti, 2002; Orme, 2010). This study uses a univariate discreet preference scale $y_j = 1,\ldots,5$ with ranked response ratings from *least preferable* to *most preferable* respectively. Therefore this scale requires categorical, ordinal, and ultimately modelling analyses (Keller & Warrack, 2000; Agresti, 2002).

4.7.1.2. Tests for categorical homogeneity

Here, basic categorical estimation needs looking at for an overview. If the response scale's ordinality is ignored (for interest sake), then data may be treated as multinomial, *i.e.* $y_j = y_1 +,\ldots,+\ y_5$ (Agresti, 2002). Results may be organised into I x J contingency table, more specifically a 2x5x5 table for each level in row i of each binary predictor x_i, and responses y_j in J columns for each $j,\ldots,\ J$ outcome (Keller & Warrack, 2000; Agresti, 2002). Usefully, homogeneity between two categorical variables can be measured using contingency tables of their frequencies (Keller & Warrack, 2000; Agresti, 2002). Responses are tested using

Pearson X^2 and likelihood ratio G^2 tests of the distribution of the null hypothesis of the frequencies of outcomes y_j varying by chance (Keller and Warrack, 2000; Agresti, 2002). Standardised z residuals *i.e.* the difference between observed and expected frequencies per deviation, may highlight which cells have null failures using the standard normal distribution z (Agresti, 2002). Regarding the Central Limit Theorem; residuals with z values bigger than α fail H_0 (Keller & Warrack, 2000). Agresti (2002) implicates X^2 and G^2 tests for having small sample size problems that can bias results.

4.7.1.3. Ordinal measures of association

Tests for independence merely question "are two variables somehow related in any way?" (Keller & Warrack, 2000; Agresti, 2002). More appropriately, slightly more powerful tests exist such as correlation that relay more information by asking "how close does one variable linearly move with another?" *i.e.* an ordinal goodness of fit measurement (Keller & Warrack, 2000; Waner & Constenoble, 2004:69; Agresti, 2002). This yields smaller p-values which improve test power, but ordinal tests are more sensitive to type I error, unless a linear trend is apparent (Agresti, 2002). A useful directional x on y test here is Somers' D (Newton, 2002).

4.7.1.4. Modelling continuous responses: OLS regression

OLS is an algorithm which minimises the SSE for finding the ML of a best-fit line in a function plot (Keller and Warrack, 2002, Agresti, 2002; Waner & Constenoble, 2004:65). In CA, the appropriate objective is to infer the consumer utilities for product features via a GLM (Orme, 2010), so the research question in chapter one is best answered by choice-modelling horticultural consumers (Keller and Warrack, 2002, Agresti, 2002; Waner & Constenoble, 2004:3; Mason *et* al., 2008; Kuhfeld, 2010; Orme, 2010; Kuzmanović *et al*., 2011). Models can powerfully describe which MA variables are most likely to influence consumer preference, and how consumers trade-off between particular factors and levels, illustrated by tables and plots (Keller and Warrack, 2000, Agresti, 2002; Waner &

Constenoble, 2004:3; Mason *et* al., 2008; Kuhfeld, 2010; Orme, 2010; Kuzmanović *et al*., 2011). The slope β_i helpfully describes the how each factor x_i in the model effects response y_{ji} *i.e.* part-worth utilities (Mason *et* al., 2008; Kuhfeld, 2010; Orme, 2010; Kuzmanović *et al*., 2011).

Modelling continuous and ratio data use the identity link function where the fitted response of consumer preference scores $\hat{y}_j$ for factors x_i of linear slope β_i is interpolated using OLS—ideally with statistical software packages (Keller & Warrack 2000; Waner & Constenoble, 2004:5,66; Agresti, 2002). A sampling distribution is used to test the probability of model statistics occurring, with the probabilities of type I and type II errors, α and β_{II} (not beta coefficients β_i) (Keller & Warrack 2000).

Checking model fit

Before model parameters are actually interpreted, the model needs checking by examining: SE, SSE, an anova *F*-test of MSE's for parameters co-equalling zero, checking residual assumptions, and checking linear approximation by applying correlation techniques such as Pearson's r, ρ_{p} and the coefficient of determination R^2 (Keller and Warrack, 2000; Waner & Constenoble, 2004:69). The error variable ε needs assessment by inspecting standardised residual plots for normality, homoscedasticity, non-independence, also dodging outliers and influential observations in main plots (Keller & Warrack, 2000). The test for r though is more applicable for bivariate association rather than experimental XY relationships, which require R^2 (Keller & Warrack, 2000).

Interpreting multiple regression parameters B_i and factor interaction

After checking that the model fits, it is wise to test interactions between factor pairs before interpreting main-effects and interpreting HG utilities (Keller and Warrack, 2000). The fact that the other model factors are held constant empowers interpretation for each specific coefficient in the model (Keller and Warrack, 2000). This is because uniquely interpreting each coefficient β_i needs controlling or holding the other coefficients β_i and their factors in the model constant (Keller and Warrack, 2000). However interpretation of a particular factor effect becomes problematic if it interacts with another factor, as the other factor's effect cannot hold steady at non-constant values while the first factor increases its levels to measure its own effect (Keller and Warrack, 2000). Here the effect of one factor's level depends on another (Keller and Warrack, 2000). Interaction can be tested by adding interaction terms into the model and testing their slopes for significance from zero (Agresti, 2002). Two- and three-factor interactions are common, and require inspection before model parameters are interpreted, while some factor interactions in FFD are often confounded with other factors and interactions, thus their effects cannot be separated (see FFD, section 4.6) (Keller and Warrack, 2000; Borkowski, 2009; Kuhfeld, 2010).

The next step can compare the levels of any significant slope terms $\hat{\hat{b}}_i$ to determine which factors contribute or remove the greatest part-worth utility for consumers (Keller and Warrack, 2000).

These model slope values $\hat{\hat{b}}_i$ can be illustrated by graphing the statistics from the software analysis printout (Keller and Warrack, 2000; Agresti, 2002; *SPSS Regression*, 2016). But because of a sampled line's uncertainty, the slope statistic $\hat{\hat{\hat{b}}}_i$ needs testing for the probability under the null that its size is due to chance, *i.e.* H_0: $\hat{\hat{b}}_i = 0$, using t-tests, or preferably a single anova F-test of all model slopes $\hat{\hat{b}}_i$ co-equalling zero (Keller and Warrack, 2000). For estimation, software tests also yield a CI for each parameter displayed in tabled printouts, where there's a 95% probability that the population parameter B is inside that interval (Keller & Warrack 2000). Though hypothesis testing is weaker and more controversial than estimation (Keller & Warrack, 2000; Agresti, 2002).

Interpreting main-effects using dummy variable models

Each predictor x_i in the model uses a dummy variable, *i.e.* a Boolean or binary predictor where a level set to $x_i=1$ characterises exposure and $x_i=0$ for control (Keller & Warrack, 2000; Agresti 2002). Mathematically, the effect size $\hat{y}_i$ is equal to the sum of the coefficient $\hat{b}_i$ at exposure level $x_i=1$ with the model's intercept $\hat{b}_0$. While at the control or non-exposure level $x_i=0$ the factor's coefficient is switched off in the model, thus it plays no role in the effect size, only leaving the intercept in the model (and other switched-on factors); *i.e.* $\hat{y}_i=\hat{b}_0+\hat{b}_i(1,0)$ (Berenson *et al*., 1983; Keller & Warrack, 2000; Agresti, 2002). So the intercept term $\hat{b}_0$ becomes a baseline to compare each factor from, only because data actually is collected at $x_i=0$ with dummy variables (Keller & Warrack, 2000). Thus each dummy variable x_i has $c - 1$ levels, where the setting of all removed categories c are collectively represented by the model intercept's setting i.e.:

$\hat{y}_i = \hat{b}_{abcde} + \hat{b}_a(x_a)_a + \hat{b}_b(x_b)_b + \hat{b}_c(x_c)_c + \hat{b}_d(x_d)_d + \hat{b}_e(x_e)_e$ where $x_i \in \{1,0\}$ here (Agresti, 2002).

These omitted levels in each factor x_i is called the reference or control group, and all comparisons are made from this baseline b_{abcde} where $x_i=0$ to factor levels at a higher setting $x_i=1$—which level to remove though is arbitrary (Keller & Warrack, 2000; Agresti 2002). HG product profiles that are set to *level*, *manual*, *casual*, *non-organic*, and *R2500* are the benchmark (not just the concerning factor) from which other factor effects (*vertical*, *automatic*, *high-performance*, *organic*, or *R5000*) are compared.

Towards GLM

This research uses a discreet consumer preference scale where a categorical model can represent the probability of consumer preference responses $\hat{y}_j$ for each dummy variable setting; *i.e.* $\hat{p}(y_j) = \hat{b}_0 + \hat{b}_i(1,0)$ (Keller and Warrack, 2000; Agresti, 2002; Orme 2010). Quantitative techniques that apply means, variances, coefficients, and ratios etc. assume equal intervals—a property that categorical variables lack (Agresti, 2002). Consequently, a model using OLS is not optimally suited for modelling categorical data; as in practice there is non-linearity, uneven variance, non-normality of errors, estimation errors, explanatory weakness, and multifactorial problems (Agresti, 2002; Agresti, 2010). Categorical data analysis hence requires other techniques (Keller & Warrack, 2000; Agresti, 2002; Orme, 2010). Clearly another modelling methodology needs looking, with parsimony and the usefulness of OLS.

4.7.1.5. Probability, odds, and odds ratios

With uncertainty, it is only meaningful to talk about the probability of an event occurring (Keller & Warrack, 2000). Probability, p is the chance of an outcome occurring, given by the ratio of the outcome of interest over all possible outcomes, *i.e.* $P_j = j/J$ (Agresti, 2002). The odds Ω are defined as the ratio of the probability p of an success over the probability of a failure $1–p$; for instance $p = 0.75$ in terms of odds is represented by $\Omega = p / (1–p) = 3$, or triple odds, which means that a success is 3 times as likely as a failure, *i.e.* in the long run a researcher should expect a failure event for every three success events (Agresti, 2002; Norušis, 2011). This is an important interpretation for modelling odds.

Furthermore, a ratio can be taken for comparing two odds; *i.e.* the convenient Odds Ratio (OR) (Agresti, 2002). The OR rationalises the difference between odds of success given exposure vs the odds of success given non exposure, *i.e.* OR affects how the Ω change as X changes (Agresti, 2002; Norušis, 2011). The domain is $0<OR<\infty$ where $1<OR<\infty$ suggests a higher likeliness for success in row x_1 (exposure) than row x_0 (control) whereas $0<OR<1$ suggests a negative trend (Agresti, 2002).

4.7.1.6. Ordinal regression and the Proportional Odds (PO) model

Given the ordinality of the responses y_j for this survey, with *5* being the highest rank and *1* the lowest rank, ordinal regression needs looking at. Ordinal data are used in biostatics, social sciences, and quality control (Agresti, 2002). Ordinal assumptions empower models with few parameters and parsimony (Agresti, 2002).

Here cumulative logits describe the probability of an outcome together with the probabilities of preceding outcome, *i.e.* $P(Y \leq j)$ for accounting ordinality of responses Y_j (Agresti, 2002; Norušis, 2011). Interestingly, PO models concurrently incorporate all $J – 1$ logits in one parsimonious model, assumingly with equal parameters b_i for each response outcome, but with different intercepts b_{0j} for each probability (Agresti, 2002).

Checking the PO model:

The PO assumption

The PO model inherits its name from the assumption of same slopes B_i from different logits of $P(Y \leq j)$; which should be tested for non-parallelism that can violate rankings (Agresti, 2002; Norušis, 2011). Here the model's parallel slopes are tested against an alternative improved model with parameters that are allowed to vary, thus high p-values favoured here (Norušis 2011).

Model fit

The model needs checking for fit, *i.e.* the null hypothesis is consistent non-significant parameters B_i:

$$H_0: B_a = B_b = B_c = B_d = B_e = 0$$

where low p value suggests a significant modelled relationship (Norušis, 2011).

Goodness of fit X^2 and deviance G^2 tests of observed and calculated expected frequencies under the null of can suggest adequate model fit (Agresti, 2002). Furthermore, examining Pearson and deviance residuals can suggest where the model poorly fits (Agresti, 2002). This is the reason for employing multinomial and contingency table tests.

Interpreting the PO model

A PO model has j intercepts β_0 and is given by:

$$\text{logit}[P(Y \leq j)] = \hat{b}_{0j} + \hat{b}_1 x_1 + \ldots + \hat{b}_i x_i, \text{ where } j, \ldots, J-1 \qquad \text{(Agresti, 2002, 2010)}$$

The cumulative response odds at the exposure level $x_i=0$ is e^b times the odds at the control level $x_i=1$ (Agresti, 2002). This interpretation of parameters seems "backwards" to other modelling techniques, but makes sense as y_j is cumulative up to a point j for this equation above, which is the logits probability being modelled, and where row 1 in contingency tables is conventionally the exposure level. Simply transforming the parameter to $\exp(b_0 - b_1x_1)$ for an increasing scale such that $y_j=5$ maintains its highest rank, can usefully orient interpretation (Norušis, 2011). Inverted OR in SPSS printouts can be divided into 1 to achieve this (Norušis, 2011). Consequently a *PO* model is most useful for this research, nevertheless other techniques are useful.

4.7.1.7. Managing type I error

Type I error results when the null is incorrectly rejected, furthermore in multifactorial experiments this familywise error rate becomes more probable as the number of tests increase, so research must account for this problem (Holm, 1979; Keller & Warrack, 2000).

Bonferroni correction

Firstly, the Bonferroni correction α_B is applied here to these contingency tests for each possible model term, the formula $\alpha_B = \alpha / C$ where according to sharp (2015), C = number of two tail tests *i.e.* total cells = 150 cells for 25 tests of 2 levels of 5 response categories here.

95%: $\alpha_B = \alpha / 150 = 0.000333$

For modelling, the number of tests C is much lower at $C=36$ which includes all interactions and square terms, thus for identifying significant slope terms:

95%: $\alpha_B = \alpha / 36 = 0.001388$

Ŝidák correction

α = type I error probability under the curve

α_s = Ŝidák corrected type I error probability under the curve

C = number of tests/cells for main-effects and low-order interactions = 150

95%: $\boldsymbol{\alpha_s} = 1-(1-a)^{1/C} = 1\text{-}(1\text{-}0.05)^{1/150} = 1 - \sqrt[150]{(0.95)} = 0.000456$

and for model slopes where $C=36$:

95%: $\boldsymbol{\alpha_s} = 1-(1-a)^{1/C} = 1\text{-}(1\text{-}0.05)^{1/36} = 1 - {}^{36}\sqrt{(0.95)} = 0.0014237$

4.7.1.8. Type II error considerations and power of tests

Type II error β_{II} needs testing to suggest the probability of not rejecting a false null hypothesis as missing favourable consumer preferences for a HG factor weakens this research. Much hypothesis testing is done without consideration for when reality actually has an alternative effect H_1, also the Bonferroni adjustments α_B are strict leaving the experimental interpretations more prone to type II error β_{II} (Guenther, 1977; Cohen, 1992; Keller & Warrack, 2000; Hélie, S. 2007). Type II error β_{II} measures long term probability of not rejecting a false null *i.e.* $p(H_0 = false \mid H_1 = true)$; and gives the test's power by $1 - \beta_{\mathrm{II}}$ *i.e.* sensitivity for detecting real effects (Cohen, 1992; Keller & Warrack, 2000; Hélie, S. 2007). A non-centrality parameter is needed to test assumptions about a non-true null (Guenther, 1977; Agresti, 2002; Hélie, 2007). Here, type II error tests ask: "what is the long run probability for erroneously not rejecting a null when HG factors have alternative consumer preference probabilities?" While the test power here asks: "how significantly can this CA detect actual consumer preferences for each HG?" (Cohen, 1992; Keller & Warrack, 2000). So a value as closest to one as possible is preferable.

4.8. Results and discussion

4.8.1. Sampling and systematic issues

4.8.1.1. Coverage and response omissions

Systematic coverage error of taking only garden centres results here as the target population isn't completely accessed. Sample frames are expected to be perfect, but in practice this can be an issue. Possible cluster sites that are not full garden centres were omitted from this sample. Also, the sampling frame does not capture urban all horticultural consumers fulfilling their needs at *quasi* horticultural clusters such as grocery where plants and garden merchandise are sometimes retailed. This is non-ideal as bias may be introduced. Non-coverage resulted within the clusters as some garden centre patrons slipped around the sampling net so to speak, and whilst the researcher was occupied in an interview. This error seems to dependant on getting a respondent, and traffic factors etc. can bias response to skewing respondent type (slow walkers/drivers). However this error can simply be reduced by having more than one interviewer present in future research. Also non-response errors such as complete and partial response errors both occurred during fieldwork, with former being most which are accounted for in table 4.8.1.

4.8.1.2. Possible response bias

It was noted that from early on in the fieldwork that there were reasons for successful responses. Weekdays had non-responses from busy people, though the weekends seemed to gain more and quality responses—perhaps because people were more relaxed and had more patience to do a survey. Also, people of a different language avoided response; perhaps as this survey has English jargon and marketing clichés. Furthermore younger people are more keen to complete the survey, also as some were curious students. This may be because cognitive effort is needed to complete this survey. These are all problematic issues.

4.8.1.3. Cognitive inertia

The ordering of the products in the survey, although are randomised, did introduce a sequence pattern of successive HG products for consumer rating. Some respondents were somewhat confused at the beginning of the conjoint-survey, as they needed time to adjust features and their particular variations. Consequently the first few runs involved more confusion and less pace than the last runs. Hence the comprehension of the survey content is inertial, in a manner of speaking.

All these issues taken into account speak the need for stratification, sampling weights in subsequent research.

4.8.2. Survey case, non-response, and non-coverage counts

Below, table 4.8.1 summarises sampling information, while table 4.8.2 portrays the respondent counts obtain from garden centre clusters. Non-Responses (NR) on average where around 16.6 while Non-Coverage (NC) rates are at 10.83 people who slipped past the sampling net, while the mean daily respondents is around 8.32 consumers per sampling day. NC rates can be improves in future by having more fieldworkers to interview the influx of consumers into the clusters. The clusters are $n=52$, 50, and 38 respondents, which aren't too equivalent.

Table 4.8.1: Survey counts for the 3 sampled clusters n_k

		n_1			n_2			n_3	
Days	***NR***	***NC***	m_k	***NR***	***NC***	m_k	***NR***	***NC***	m_k
1	9	2	9	16	6	11	12	14	11
2	6	12	8	20	10	11	5	6	6
3	8	18	16	52	33	11	12	10	7
4	17	8	11	21	6	8	5	2	5
5	10	8	8	25	3	9	15	15	4
6							21	21	5
$\sum$	50	48	52	134	58	50	70	68	38
%	51%	58%		27%	46%		35%	36%	
μ per day	10	9.6	8.67	26.8	11.6	10	11.7	11.3	6.3

Grand values

$\sum\sum NR$	254
$\sum\sum NC$	174
m	140
Grand potential population	568
Grand μ *NR* per day	16.16
Grand μ *NC* per day	10.83
Grand response μ per day	8.32

Response or coverage % = $m_k / m_k + NR \text{ or } NC$
Grand mean μ is given by $\mu_1 + \mu_2 + \mu_3 / 3$
Grand potential population = $m + NR + NC$

Table 4.8.2: Basic descriptives for responses y_j

N Valid		2187
N Missing		53
Mean		3.26
SE mean		0.024
Median		3
Mode		3
Std. deviation		1.141
Skewness		-0.159
SE skewness		0.052
Kurtosis		-0.787
SE of kurtosis		0.105
Minimum		1
Maximum		5
Percentiles	25	2
	50	3
	75	4

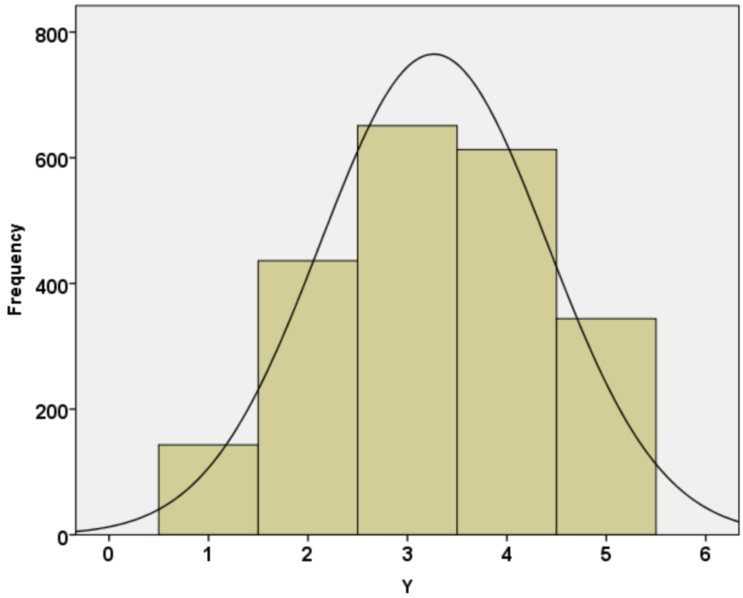

Figure 4.8.1: Frequency distribution of consumer responses y_j

Next, basic descriptive information is presented. In table 4.8.2 and figure 4.8.1 above, the median and mode share the same value 3, though the mean is less conservative at 3.26, with a low SE of 0.024. The standard deviation is $s=1.14$. The interquartile range is balanced around the median and spans from 2 to 4. Other printed tests and the graph above suggest that the overall data is X^2 normally distributed with a fatter right tail, though test suggests negatively skewed. The distribution's skewness = –0.159, which should be of little concern, but its significance is tested by $z= -0.159 / 0.052 = -3.058$ which has $p< 0.05$, thus the null hypothesis of non-skewness has evidence for rejection. Nevertheless this distribution's symmetry is mostly symmetric. Similarly, the distribution's Kurtosis seems platykurtic at -0.787, and testing its significance is given by $z = -0.787 / 0.105= -7.5$ which suggests platykurtosis.

4.8.3. Building an OLS model

A model can describe consumer utilities for the HG product features found in the MA to answer the initial research question in chapter one. This modelling analysis can treat consumer response scale as interval data, $\hat{y}$ using OLS multiple linear regression for efficiency. Before looking at model slope terms, residual and correlation statistics need investigating to check if the model has linear fit and meets particular assumptions to begin with (Keller & Warrack, 2000).

Before main-effects, interaction effects between each factor are investigated as interacting factors affect interpretation of them. The FFD in section 4.4 warned of confounding between particular two- and three-way interactions. Four- and five-factor interactions should not be significant, though they are checked nonetheless because single-factor and block interactions are confounded with them.

This analyses best begins here with generating significant model terms using SPSS a stepwise algorithm including main-effects and all possible interaction terms, with rechecking how those terms affect their models via residual and correlation information, by assuming an SRS.

4.8.3.1. Modelling and hypotheses

All interactions and quadratic factors need checking for significant slope and power.

Hypotheses for factor interaction are given by:

H_0: there is no significant factor interaction

H_1: there is significant factor interaction

Hypotheses for polynomial factors are given by:

H_0: there are no polynomial terms

$$B_A x^2_A = B_B x^2_B = B_C x^2_C = B_D x^2_D = B_E x^2_E = 0$$

H_1: there is at least one polynomial term.

Hypotheses for main-effects or part-worth utilities are given by:

H_0: there are no significant factors

$B_A x_A = B_B x_B = B_C x_C = B_D x_D = B_E x_E = 0 H_1$: there is at least one significant factor

4.8.3.2. Checking error term assumptions

The first residual check is for the assumed normal distribution, which figure 4.8.3 below presents. It seems that the normalities of the significant-terms-only and all-term models have better normality than the main-effects model. A similar result appears from the normal P-P plots in figure 4.8.4 below. Next, plotting observed standardised (z) residuals as function of predicted z residuals may highlight heteroscedasticity, with caution (Keller & Warrack, 2000). In figure 4.8.5 all scatterplots reveal some degree of heteroscedasticity with a slight negative slope *i.e.* when the predicted z residuals increase, the observed z residuals decrease, which suggests the assumed stochastic variance of the error variable is non-constant (Keller & Warrack, 2000). Though binning the residual cases suggests that the majority of residuals aren’t too problematic.

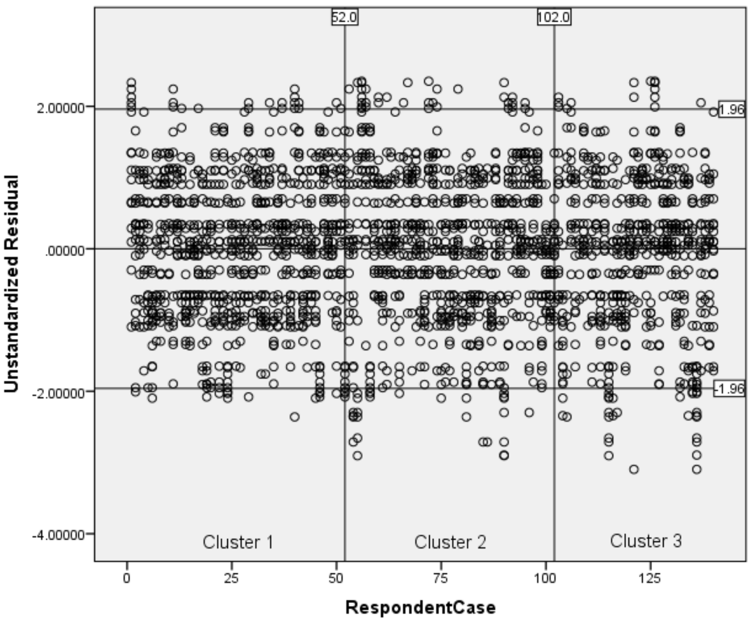

Figure 4.8.2: Unstandardized residuals plotted against the 3 sampled clusters to visualise discrepancies

Figure 4.8.2 above plots the residuals as a function of respondent *id*, where the first third belong in garden centre cluster 1 (*n=52*) the second in cluster 2 (*n=50*) and the third is for cluster 3 (*n=38*). There appears to be a visible difference between the two. Here slight patterns emerge between the clusters suggesting a sizable *deff*.

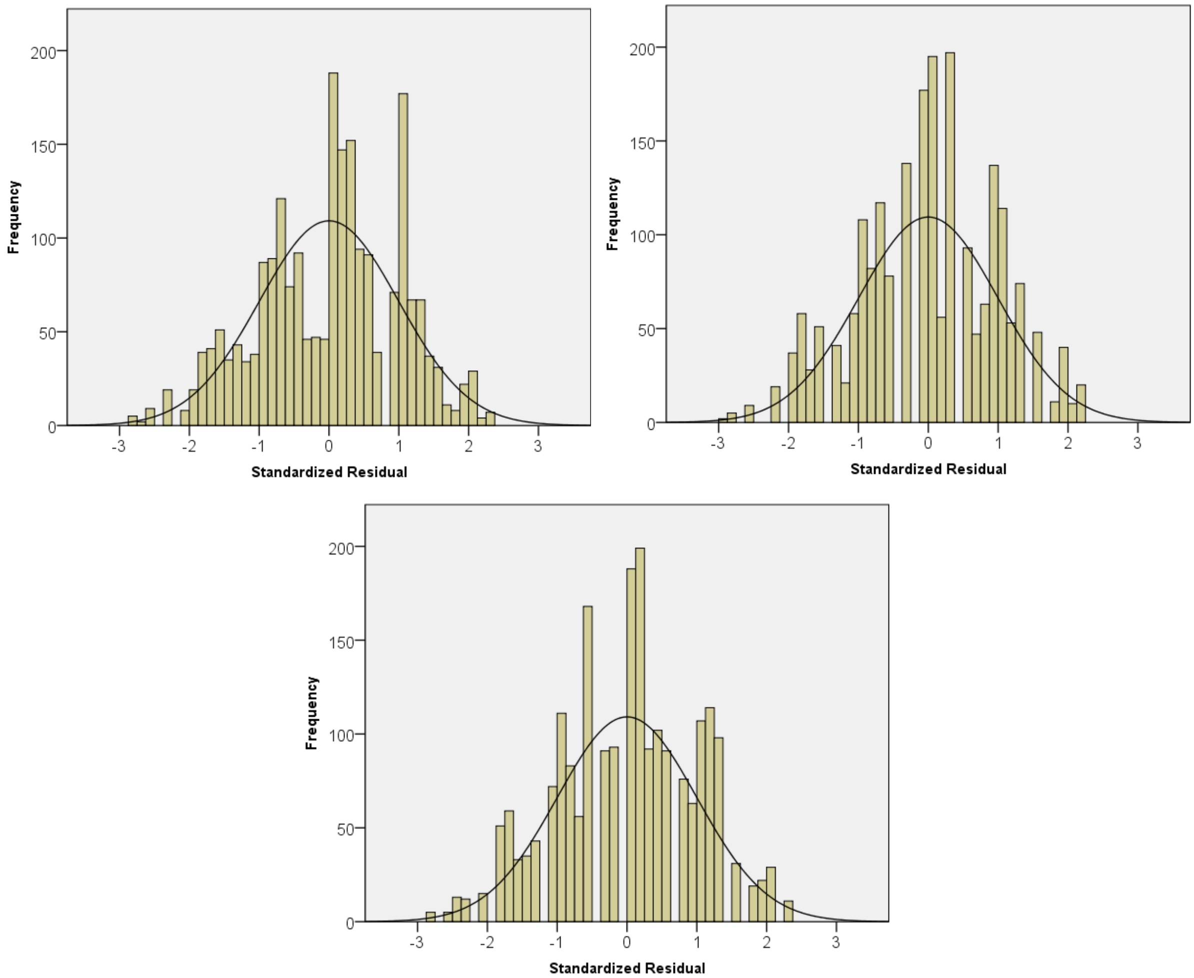

Figure 4.8.3: Frequency distribution of residuals for the main-effects model (top left), all-terms model (top right), and the significant-terms-only model (bottom)

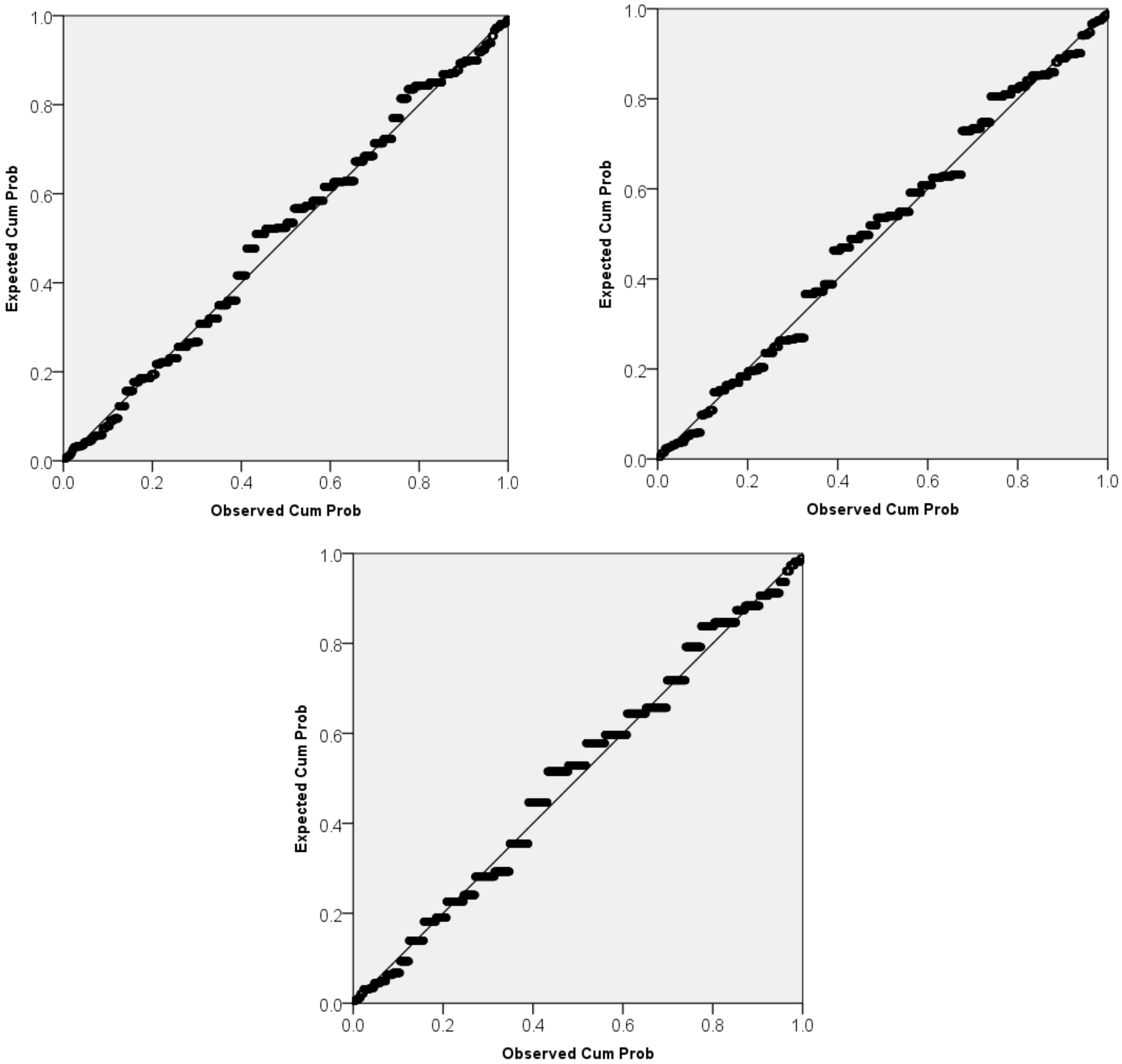

Figure 4.8.4: Normal P-P Plot of *z* residual of responses for the main-effects model (top left), all-terms model (top right), and the significant-terms-only model (bottom)

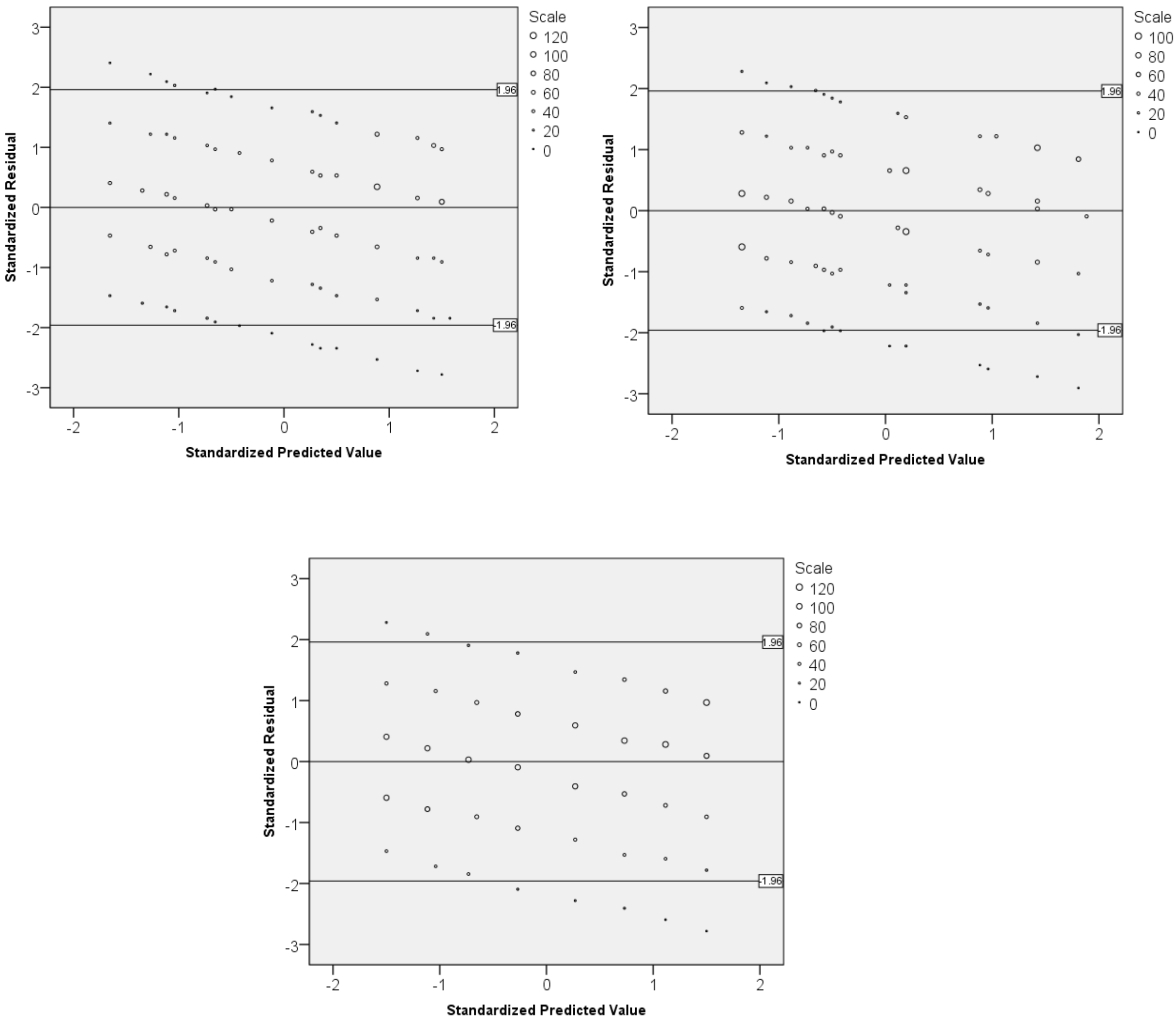

Figure 4.8.5: Scatterplots for checking heteroscedasticity for the main-effects model (top left), all-terms model (top right), and the significant-terms-only model (bottom)

4.8.3.3. Comparing model fits

Many models were checked, but two models performed best, while the all terms model is really here for comparison. These are main-effects and significant terms models.

Apart from the explained variation between x and $\hat{y}$ given by R^2, residuals (unexplained but observable difference between the line fit $\hat{y}$ and responses y_i) are the statistics for the error variable ε (unexplained but unobservable difference between the parameter $\hat{Y}$ and responses y_i) (Keller & Warrack, 2000). If residuals show correlation, the model factors used need reconsideration, perhaps adding higher order interaction and quadratic terms, than simple main factors (Keller & Warrack, 2000; Frost & *Minitab*™, 2016).

First, overall model fit is checked via correlation such as R^2 and adjusted R^2, where the main-effects and significant models below in table 4.8.3 have similar R^2 at just below 15%, with the lowest being 14.6 for the significant-terms-only model, and the highest at 15.1% for the all-terms model. The adjusted R^2 is similar for most models, except the all-terms model where it dives by 0.6 *i.e.* 2–6 times the other R^2 vs adjusted R^2 values.

Table 4.8.3: Comparing the fits between the 3 potential models using Pearson correlation

Model	Pearson ρ	R^2	Adj. R^2	SE	Durbin-Watson
Main	0.387	0.150	0.148	1.053	1.971
Significant-terms-only	0.384	0.147	0.146	10.54	1.964
All terms	0.396	0.157	0.151	1.051	1.988

Next, ANOVA outputs are printed below in table 4.8.4. Here the main effect model has the smallest F-ratio of around 77 with $df=4$, while the significant-terms-only model suggests even better evidence (F≈126) for rejecting the null hypothesis for main-effects. This further merits the significance model. The Durbin-Watson tests all provide little evidence for autocorrelation with values just below 2.

Table 4.8.4: ANOVA output for comparing hypothesis tests between a main effect model and a model with only significant terms

Model		*SS*	*df*	*MS*	*F*	*p*
Main effects	Regression	426.172	5	85.234	76.895	0.000
	Residual	2417.540	2181	1.108		
	Total	2843.712	2186			
Significant-terms-only	Regression	418.786	3	139.595	125.668	0.000
	Residual	2424.926	2183	1.111		
	Total	2843.712	2186			

4.8.3.4. Interaction slopes

The interaction terms in these models somewhat meet the experimental-wise error rate, so may be false positives. Ŝidák $\alpha_s=0.0014237$ and Bonferroni corrections $\alpha_B=0.001388$ means the the **BCD** interaction term has a probability under the null that is greater than the experimental wise error rates. Also, the **DE** interaction appears which hasn't got sufficient experimental significance. Next, an **AB** interaction appeared but isn't less than the corrected α, so is dropped from the model. These interactions are noted but discarded from the model. Ultimately these interaction effects may cloud the main-effects or be clouded, as *garden organics* may be powering this interaction and the factors **B** and **C** may be artificially and randomly significant. The adjusted alphas fortunately safeguard this model from interaction effects that could much possibly be here by chance. Though more tests are needed to see if these factors have tendency to be significant. Four and five factor interactions were ran with the stepwise procedure with no significances. For satisfying FFD requirements from section 4.4, confounded terms here is **E**=**ABCD**, where its alias is not significant, which allows the effect size to be attributed to *garden price* **E**. There are no significant polynomial terms, so its null hypothesis is not rejected.

4.8.3.5. Main factor slopes

Garden organics has the greatest effect moving from the intercept b_{abcde} to *organic gardens*, with a slope of $\hat{b}=0.782$ where $p\approx 0$, and its interval ranges between $CI=0.694–0.871$. *Garden price* negatively affects responses moving from b_{abcde} to *R5000 gardens*, with a slope term of $\hat{b}= –0.349$, which is expected seeing the high up-front costs of these product types. *Garden automation* has a slope of $\hat{b}=0.182$ jumping from the intercept to *automatic gardens* where $p\approx 0.000055$ *i.e.* less than the experimental-wise α levels, and has a relatively wide interval $0.094<\boldsymbol{B_A}<0.271$. *Garden plane* (removed) had slight significance at $p=0.033$ but greater than adjusted α levels, with a similar wide interval to *automation* which just misses crossing zero. *Garden performance* (removed) is least significant and its interval spans zero, and is the least significant factor. Overall, the significance model seems sounder for interpretation, as it is parsimonious, and offers the least heteroscedasticity, while relatively maintaining good fit, thus *garden plane* and *performance* are dropped from the model.

Table 4.8.5: Significant slope terms for the model

Model	$\hat{b}$	SE	t	p	LCL	UCL
$\hat{b}_{abcde}$	2.960	0.045	65.861	0.000	2.872	3.048
Garden automation $\boldsymbol{x_B}$	0.182	0.045	4.040	0.000055	0.094	0.271
Garden organics $\boldsymbol{x_D}$	0.782	0.045	17.351	0.000	0.694	0.871
Garden price $\boldsymbol{x_E}$	–0.0349	0.045	–7.752	0.000	–0.438	–0.261

p^a = significant at adjusted alpha
p^b = significant at unadjusted alpha.

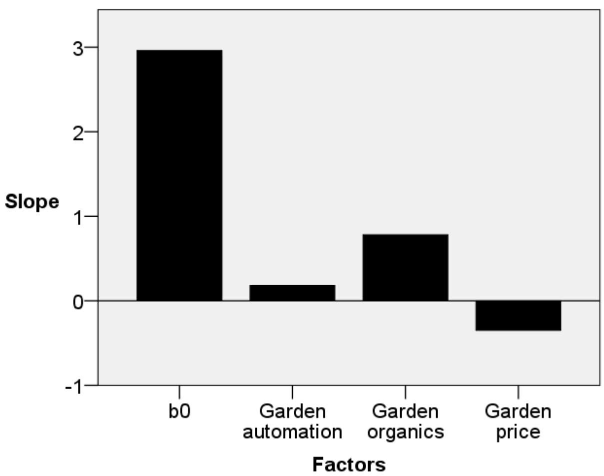

Figure 4.8.6: A bar chart of OLS slope sizes

4.8.3.6 Applying the model for utilities

To use the model, the SPSS printout in table 4.8.6 above usefully provides the model terms, and figure 4.8.6 above that illustrates the magnitude and sign of the model factors. The intercept $\hat{b}_0=2.96$ says when $x_i=0$, then $\hat{y}_{ij}=\hat{b}_0=\hat{b}_{abcde}$, so consumer preferences for a HG product profile at the low factor settings $x_i=0$ for all i gives an expected preference rating of $\hat{y}_{ij}=2.96$, while factors in the model set high will add or subtract from this benchmark according to the slope term. All terms are individually interpreted by holding other model terms constant. This model can be expressed as:

$$\hat{y}_{ij} = \hat{\hat{\hat{b}}}_{abcde} + \hat{b}_B x_B + \hat{b}_D x_D + \hat{b}_E x_E + \hat{\varepsilon_i}$$

$$\hat{y}_{ij} = 2.96 + 0.182(x_B) + 0.783(x_D) - 0.350(x_E) + \hat{\varepsilon_i}$$

and from this horticultural consumer part-worth utilities are computed with intervals below in table 4.8.6.

Table 4.8.6: Part-worth utilities $\hat{y}_{ij}$ for HG

x_i	$\hat{y}_{LCL}$	$\hat{y}_i$	$\hat{y}_{UCL}$
x_0	2.872	2.960	3.048
Garden automation x_B	2.966	3.142	3.319
Garden organics x_D	3.566	3.742	3.919
Garden price x_E	2.434	2.925	2.787

The model's benchmark utility interval doesn't depart from $\hat{y}_i$=*3=preferable*. It seems that *garden price*, holds a tendency to be below $\hat{y}_i$=*3=preferable*, is negatively affecting utilities here. Only *organics* consistently raises its value above $\hat{y}_i$=*3=preferable*, but below $\hat{y}_i$=*4=more preferable*. *Garden automation* has a part-worth utility around $\hat{y}_i$=*3=preferable* which isn't too favourable.

Utilities for significant model terms are given by:

BD: $\hat{y}_i$ = 2.96 + 0.182(x_A) + 0.782(x_D) = 3.924

DE: $\hat{y}_i$=2.96 + 0.782(x_D) – 0.349(x_E) = *3.393*

BE: $\hat{y}_i$=2.96 + 0.182(x_A) – 0.349(x_E) = 2.793

BDE: $\hat{y}_i$=2.96 + 0.182(x_A) + 0.782(x_D) – 0.349(x_E) = 3.575

Garden organics alone has a part-worth utility given by $\hat{y}_i=3.662$ which gives these utilities most of their value. Having an *automatic* and *organic* with the *R5000 price* HG keeps the utility somewhat above $\hat{y}_i=3$=*preferable*, while dropping *automation* slightly drops the utility to $\hat{y}_i=3.12$, and dropping *organics* but keeping *price* and *automation* has a utility of below $\hat{y}_i$=2.793 *i.e.* below *preferable*. A *R2500 automatic* and *organic* HG has a slightly higher utility at $\hat{y}_i=3.924$.

Additionally, responses were tested as a function of clusters and respondent case number, where the model has $R^2=0.001$ and $F=1.38$ with a significance of $p=0.25$, together suggesting that a null hypothesis of these factors un-affecting utilities is sound.

Lastly, power of test $1–\beta_{\mathrm{II}}$ is checked here for all terms, using a general linear model ANOVA in SPSS, where the non-centrality parameter is 404.5 with a power of 1.000 which suggests that the possibility of type II error is miniscule here, while detecting actual effects is excellent.

Though this analysis didn't apply the cluster sampling design and the categorical nature of the responses categories y_j, which is addressed next using contingency tables and complex sample PO modelling.

4.8.4. Multinomial fit, homogeneity, and residuals

4.8.4.1. Testing multinomial counts

For random multinomial outcomes, X^2 tests use the $X^2_{df=J-1}$ distribution (Guenther, 1977; Keller & Warrack, 2000; Agresti, 2002). Hypotheses assume:

H_0: Expected and observed frequencies of responses y_j are equivalent

H_1: Expected and observed frequencies of responses y_j are not equal.

Null multinomial counts meeting expectation alternatively has rejection supported by:

$P(X^2 \geq X^2_{\alpha,df=J-1})$.

Table 4.8.7: Multinomial test of frequencies assuming an SRS

y_j		Observed n	Expected n	Residual	%
Least preferable		143		–294.4	6.3%
Less preferable		436		–1.4	19.1%
Preferable		651	437.4	213.6	28.6%
More preferable		613		175.6	26.9%
Most preferable		344		–93.4	15.1%
Total		2187	2187		96.0%
Missing		53			4.0%
X^2	392.906				
$df = 4$	p= 0.000				

Table 4.8.8: Multinomial test of frequencies assuming this cluster sampling design

y_j	Unweighted n_j	Expected n_j	*SE*	*CV*	95% CI *LCL*	95% CI *UCL*	*deff*
Least preferable	143	429	8.834	0.114	390.991	467.009	0.097
Less preferable	436	1308	148.550	0.077	668.842	1947.158	10.531
Preferable	651	1953	150.816	0.071	1304.093	2601.907	8.287
More preferable	613	1839	130.960	0.141	1275.524	2402.476	6.476
Most preferable	344	1032	145.178	0.086	407.351	1656.649	12.112
Total	2187	6561	564.604	0.021	4131.706	8990.294	.

Table 4.8.8 above has the frequencies behind figure 4.8.2. The analysis again was repeated using SPSS *complex samples* where the *deff* suggests that the clusters have much variation between responses categories y_j. A test for homogeneity via complex samples, again suggests that there is deviation between responses, $X^2_{a,df=4} = 275.849$ and $p(X^2_{a,df=4}) = 0.000$.

4.8.4.2. Testing homogeneity in contingency tables

Contingency tables were used here to test homogeneity in 5x5x2-tables, each association is printed below in table 4.8.9, providing basic clues for this research.

Testing the conditional probabilities for homogeneity assumes either:

H_0: All conditional probabilities $p_{j|i}$ for column j are equivalent to their column marginal probabilities p_{+j}, which are statistically supported by:

$p_{j|i} = p_{+j}$, for all i, or more formally as $\{p_{j|1} = \ldots = p_{j|I}\}$ for columns $j, \ldots, J$ (Agresti, 2002),

or alternatively:

H_1: There is evidence to reject the null hypothesis, supported by:

$X^2_{df=(r-1)(c-1)} > X^2_{df=(r-1)(c-1);1-\alpha}$ (Guenther, 1977; Agresti, 2002).

These tests are printed below using X^2 tests via SPSS in table 4.8.9.

Table 4.8.9: Contingency table for responses y_j at x_i assuming an SRS via SPSS crosstabs

Test:	$X^2_{a,df}$	p
Garden plane		
X^2	8.678	0.070
Garden automation		
X^2	20.260	0.00044
Garden performance		
X^2	5.586	0.232
Garden organics		
X^2	266.999	0.0000[a]
Garden price		
X^2	52.930	0.000[a]

0 cells (0.0%) have expected count less than 5
p^a = significant at Bonferroni adjusted alpha

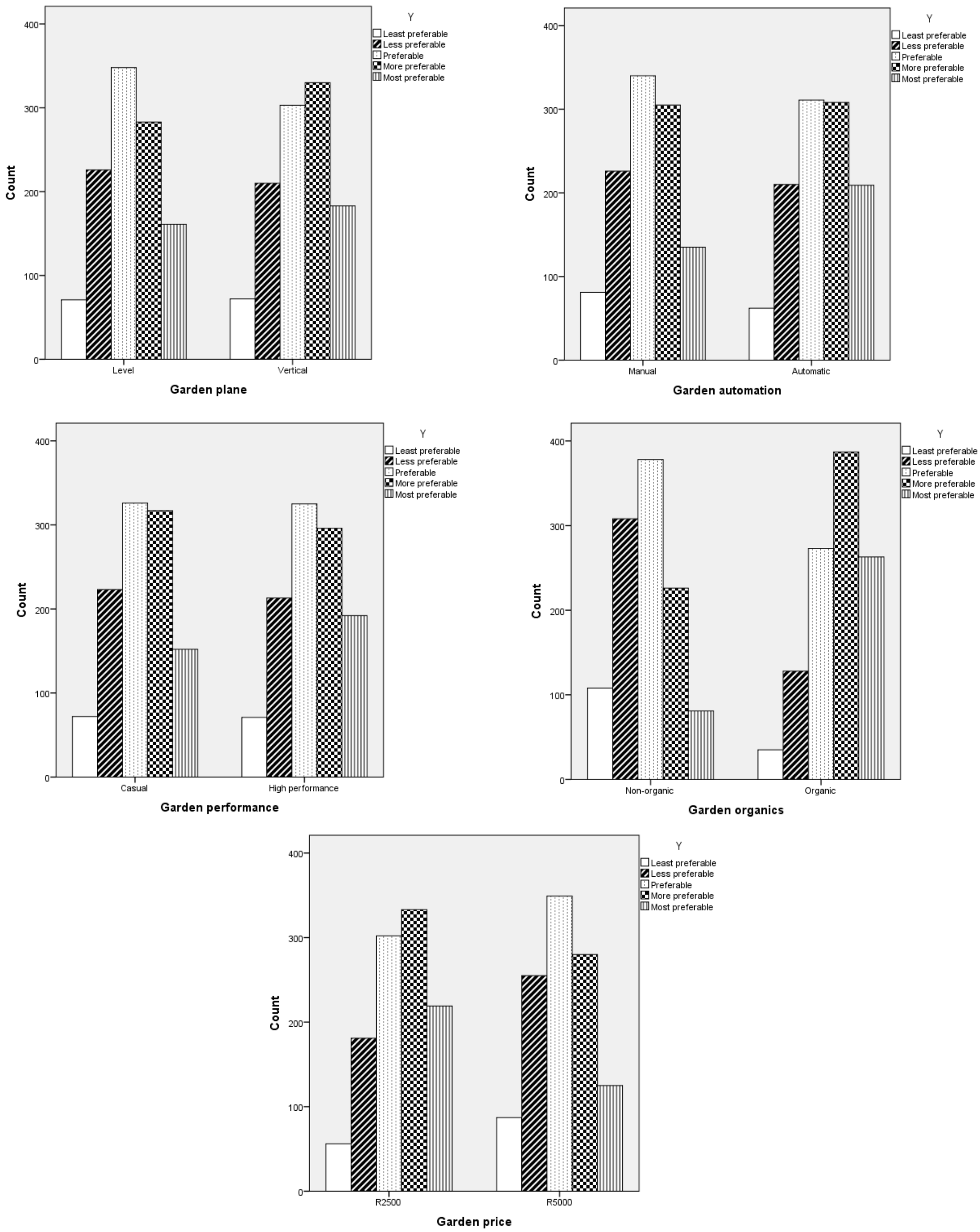

Figure 4.8.7: Frequency distribution for y_j at x_i

Table 4.8.10: Significant and near significant interactions

BD * Y	X^2	156.373	0.000
CD * Y	X^2	150.567	0.000
BCD * Y	X^2	124.616	0.000
AD * Y	X^2	117.352	0.000
ACD * Y	X^2	80.161	0.000
DE * Y	X^2	29.895	0.000005
BDE * Y	X^2	22.660	0.00015
BC * Y	X^2	21.902	0.00021
CDE * Y	X^2	19.146	0.00074
ADE * Y	X^2	19.048	0.00077
AB * Y	X^2	18.752	0.000879
CE * Y	X^2	14.396	0.00613
ABE * Y	X^2	11.513	0.0214

Next in table 4.8.10 above, all 2 and 3 way interactions are tested for homogeneity, where there are several significant terms generated, under the Bonferroni adjustment (*95%*: $\alpha_B = \alpha / 150$ cells$= 0.000333$). This raises the question why are there more significant interactions here than the OLS model that only has **BCD** and **DE** with hardly significant slopes? These factors have *garden organics* as a common factor, which itself strongly outsizes other factors, so these interactions may be jumping on the *organics* bandwagon. In-fact, the only interaction with organics that isn't at all significant is **ABD**.

4.8.4.3. Testing ordinality in contingency tables

The response scale's ordinal nature needs a quick look in a contingency table, with the cluster sampling design in mind. Table 4.8.11 below has directional x_i on y_j correlation statistics of hypotheses tests and intervals. These results are much similar to the OLS and chi square results, where *garden automation*, *organics*, and *price* have significant ordinal association.

Table 4.8.11: Correlation for garden factors using the sampling design and bootstrapping

Factors x_i	Somers' *D*	Asymptotic *SE*	*t*	*p*	Bootstrap Bias	*LCL*	*UCL*
Plane	0.050	0.024	2.109	0.035[b]	–0.001	0.006	0.102
Automation	0.089	0.024	3.728	0.000193[a]	0.000	0.041	0.138
Performance	0.030	0.030	0.024	1.262	0.001	–0.016	0.078
Organics	0.389	0.022	18.003	0.00000[a]	0.000	0.344	0.433
Price	–0.171	0.023	–7.293	0.00000[a]	0.001	–0.220	–0.125

n=1000 bootstrapped samples with strata variables from the cluster design (BCa)

p^a = significant at adjusted alpha

p^b = significant at unadjusted alpha.

4.8.4.4 Residual analysis

Here the X^2 distribution can describe the data, with transformed standardised residuals given by $z^2 = X^2_{df=1}$ and their probabilities (Keller & Warrack, 2000, Agresti, 2002).

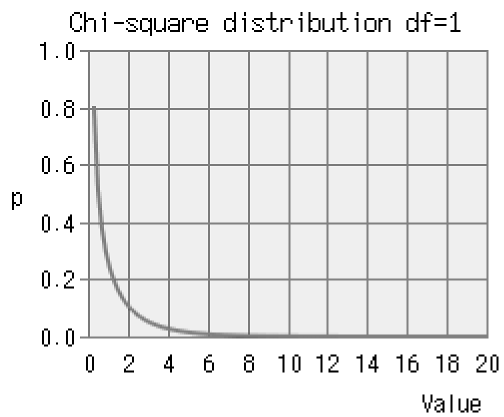

Figure 4.8.8: $X^2_{df=1}$ distribution used for residuals (Source: http://keisan.casio.com/exec/system/1180573182)

Previous results require *post hoc* X^2 tests on residuals to highlight where on the consumer response scale expectations are least likely. Thus residuals are looked at below. Pearson standardised residuals from the SPSS printout in table 4.8.12 are needed to test the hypothesis of observed cells counts falling within expectancy, with probabilities $p \leq 0.00033$ not falling under X^2 null expectation. This deviance among cells can be interpreted as unexpected consumer preferences, which add up to support alternative hypotheses of non-expectation in X^2 testing. Hypotheses are:

H_0: The standardised residual has $z_r = z_r^2 = X^2_{df=1} = \; p \geq 0.00033$ or a for cell ij

H_1: The standardised residual has $p<0.00033$ for cell ij

Table 4.8.12: Probabilities of X^2 z residuals of responses y_j at x_i

Factor x_i	$p(z^2=X^2_{df=1})$	y_1 *Least preferable*	y_2 *Less preferable*	y_3 *Preferable*	y_4 *More preferable*	y_5 *Most preferable*
A	p	1.00000	0.54851	0.19360	0.19360	0.42371
B	p	0.23014	0.54851	0.36812	1.00000	0.00511[b]
C	p	0.92034	0.68916	0.92034	0.48393	0.13361
D	p	0.00003[a]	0.00000[a]	0.00511	0.00000[a]	0.00000[a]
E	p	0.07186	0.01242[b]	0.19360	0.10960	0.00032[a]

p^a = below adjusted alpha
p^b = above adjusted alpha but below alpha.

Here only *garden organics* and *price* show large residuals, while *automation* doesn't make the Bonferroni cut, though shows deviance at *most preferable*. *Garden plane* and *performance* have a similar trend but much weaker. *Garden organics* suggests the strongest deviance, which is expected. *Garden price* suggests that its variation happens mainly with the response cell *most preferable* for *R2500 gardens*. These results agree with the previous results.

Below in table 4.8.13, many interactions are found to have no significant X^2 residuals, which don't quite meet the Bonferroni cut. **AE**, **BE**, **CE**, **ABC**, **ACE**, **BCE** have too little evidence for even an unadjusted alpha, so are dropped, while **AB**, **DE**, **ABE**, **BDE**, **CDE** don't make the Bonferroni cut. This is strange seeing that **DE** almost made it into the OLS model. The **BD**, **CD**, and **ABD** interactions have a similar story with strong negative residuals at *less preferable* and even stronger positive residual for *most preferable* at $x_i=1$, suggesting a positive response. **AD**, **ACD** are similar with the deviation in *more preferable* column also adding to residual significances at $x_i=1$. **BC** at $x_i=1$ has sufficient evidence for suggesting wide residuals only with the response cell *most preferable*. These results outlined where these cells in the contingency table suggest their deviation.

Table 4.8.13: Probabilities of X^2 z residuals of responses y_j at x_i for interactions

	$p(z^2=X^2_{df=1})$	y_1 Least preferable	y_2 Less preferable	y_3 Preferable	y_4 More preferable	y_5 Most preferable
AB	$x_i=0$	0.841481	0.548506	0.230139	0.483927	0.109599
	$x_i=1$	0.689157	0.317311	0.035729[b]	0.230139	0.006934[b]
AD	$x_i=0$	0.089131	0.006934[b]	0.089131	0.012419[b]	0.001935[b]
	$x_i=1$	0.0032[b]	0.000003[a]	0.003732[b]	0.000017[a]	0.000000[a]
BC	$x_i=0$	.0423711	0.689157	0.689157	0.617075	0.035729[b]
	$x_i=1$	0.193601	0.548506	0.483927	0.423711	0.000318[a]
BD	$x_i=0$	0.089131	0.002700[b]	0.089131	0.109599	0.000003[a]
	$x_i=1$	0.002700[b]	0.000000[a]	0.003732 [b]	0.005110[b]	0.000000[a]
CD	$x_i=0$	0.045500[b]	0.006934[b]	0.071861	0.089131	0.000007[a]
	$x_i=1$	0.000674[b]	0.000004[a]	0.001935[b]	0.003732[b]	0.000000[a]
DE	$x_i=0$	0.317311	0.089131	0.920344	0.057433	0.920344
	$x_i=1$	0.071861	0.002700[b]	0.841481	0.001374[b]	0.920344
ABD	$x_i=0$	0.423711	0.133614	0.271332	0.230139	0.027807
	$x_i=1$	0.035729	0.000096[a]	0.002700[b]	0.001935[b]	0.000000[a]
ABE	$x_i=0$	0.689157	1.000000	0.423711	0.920344	0.423711
	$x_i=1$	0.271332	0.920344	0.027807 [b]	0.841481	0.045500[b]
ACD	$x_i=0$	0.368120	0.161513	0.230139	0.193601	0.045500[b]
	$x_i=1$	0.021448	0.000318[a]	0.000967 [b]	0.000318 [a]	0.000000[a]
ADE	$x_i=0$	0.689157	0.368120	0.689157	0.317311	0.617075
	$x_i=1$	0.271332	0.016395[b]	0.317311	0.006934 [b]	0.230139
BCD	$x_i=0$	0.368120	0.133614[a]	0.193601	0.617075	0.000967[a]
	$x_i=1$	0.021448	0.000096[a]	0.000674 [b]	0.161513	0.000000[a]
BDE	$x_i=0$	0.617075	0.317311	0.689157	0.317311	0.548506
	$x_i=1$	0.230139	0.006934[b]	0.317311	0.006934 [b]	0.109599
CDE	$x_i=0$	0.548506	0.423711	0.764177	0.368120	0.548506
	$x_i=1$	0.109599	0.027807[b]	0.368120	0.021448 [b]	0.089131

p^a = below adjusted alpha

p^b= above adjusted alpha but below alpha

4.8.5. Modelling ordinal responses using Proportional Odds (PO)

This analysis was prepared using *IBM™ SPSS 23 complex samples ordinal regression* procedure to account for the categorical response scale and cluster sampling design used here. The model tested is for main-effects only. All interpretations are made at the $J–1$ cumulative logit, so the cut-off is $j \leq 4$.

Firstly, a test of the parallel lines assumption is checked via a Wald X^2 test. This test fortunately has too little evidence (Wald $X^2_{df=2} = 2.389$, $p=0.303$) to suggest an alternative hypothesis of different slopes between the different cut-offs in the cumulative logits

Next, pseudo R^2 correlation tests attempt to mimic linear approximation. These pseudo R^2 squares need to be interpreted with caution, nonetheless suggest a similar but lower value for the *Cox and Snell* ($R^2=0.153$) while the *Nagelkerke* value reaches $R^2=0.161$, though the *Mc Fadden* is much lower than both ($R^2=0.055$).

Below in table 4.8.14, the PO for the $J–1$ cumulative logit is displayed. The Bonferroni adjustment here is $\alpha_B=\alpha/C=0.05/9$ tests$=0.00555$, which allows only *garden automation* and *price* experimental-wise significance. Firstly *garden plane* x_A has a positive slope power term with adequate $deff$, and its CI misses 0, with small SE. Its OR suggests 17.2% more favourable events jumping from the intercept b_{abcde} to a *vertical* HG. Next, *garden automation* x_B has a positive slope with less SE, and as a HG profile jumps from its intercept to *automatic*, the log slope increases by 37%, *i.e.* an *automatic garden* expects 37% more number of favourable preference events compared to favourable events expected from a *manual garden*. Next, *garden performance* x_C surprisingly has small error and a positive slope, where the CI misses 0 so may have useful significance here under the smallest $deff=0.034$ suggesting more between-cluster agreement and within-cluster heterogeneity. However, *garden performance* misses experimental-wise significance. Next, *garden organics* x_D first indicates a strong slope and $OR=3.9$, but is crippled by large SE and intervals, with a $deff=14.6$ times the expected variation of a SRS, which is problematic. This measure proposes more between-cluster disagreement than within. Nevertheless, a strongly positive relationship is apparent as *organics* has an implying that *organic gardens* have 3.9 times the favourable preference events moving from the intercept to *organic gardens*. Lastly *garden price* has the only negative trend where *R2500 gardens* expect 1.86 times favourable preferences compared to *R5000 gardens*, the greatest significance here where $p=0.002$.

Table 4.8.14: Cumulative parameter estimates for the PO model

			SE	LCL	UCL	P	$deff$	exp(–b_i)	LCL	UCL
b_{0j}	$y=1$	–3.584	0.268	–4.736	–2.433	0.006[b]	6.095	0.028	0.009	0.088
	$y=2$	–1.849	0.143	–2.466	–1.232	0.006[b]	2.647	0.157	0.085	0.292
	$y=3$	–0.410	0.126	–0.952	0.132	0.083	2.411	0.664	0.386	1.142
	$y=4$	1.190	0.113	0.702	1.677	0.009[a]	1.785	3.286	2.019	5.348
$-(b_ix_i)$	$x_A=1$	0.159	0.043	0.345	0.026	0.066	0.467	1.172	0.97	1.41
	$x_B=1$	0.315	0.022	0.409	0.222	0.005[a]	0.120	1.372	1.25	1.51
	$x_C=1$	0.141	0.012	0.192	0.091	0.007[b]	0.034	1.152	1.10	1.21
	$x_D=1$	1.362	0.259	2.475	0.250	0.034[b]	14.660	3.906	1.28	11.90
	$x_E=1$	–0.625	0.029	–0.501	–0.749	0.002[a]	0.202	0.535	0.47	0.61

$\{x_i=0\}$ are set to redundant and removed by transforming $b_i=-(b_i)$ and $OR=1/OR$ for oriented interpretation

p^a= below adjusted alpha

p^b= above adjusted alpha but below alpha

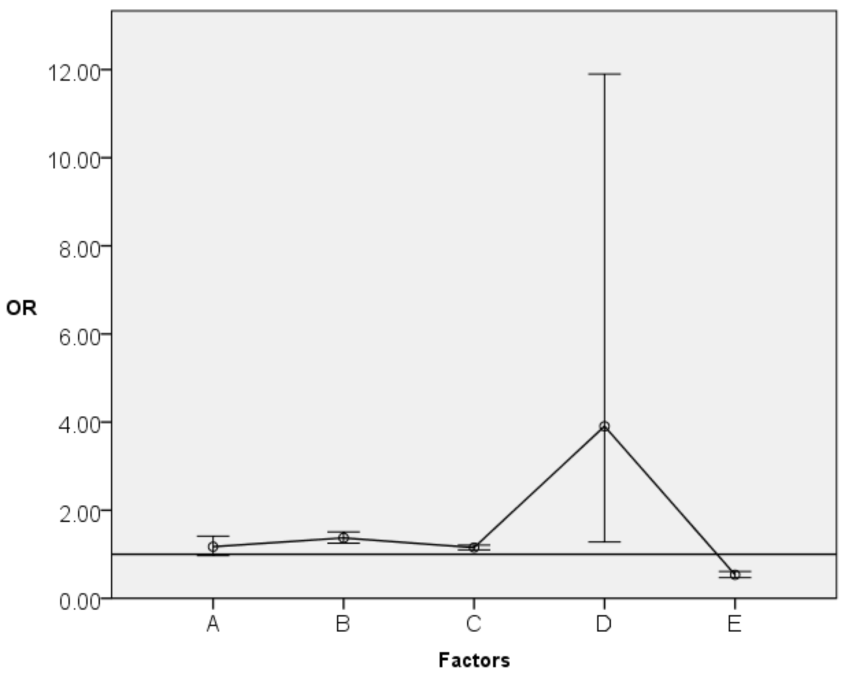

Figure 4.8.9: Cumulative OR for factors

In figure 4.8.9 above, *garden organics* x_D is above the lot, though has a vast interval. *Automatic gardens* x_B is the second greatest OR as a HG product profile jumps from the intercept b_{abcde} to *automatic. Garden plane* and *performance* x_C sit close to $OR=1$ with weaker part-worth utilities. *Garden price* expectedly contributes negatively to utilities where the $OR=0.53$.

4.7.6 Statistical conclusions for this chapter

The counts for NR and NC are much higher than the actual number of daily responses. The OLS model produces main-effects with slope interpretations for consumer part-worth utilities β_i. A*utomation* has around *preferable* part-worth utilities for horticultural consumers, while *organics* holds *more preferable* part-worth utilities for them. Price is much steeper and negative, while organics is positive and the steepest slope. From this and the part-worth utilities, a HG product profile with the intercept, *organics*, and *automation* contributes to the most change in horticultural consumer utility. The contingency tables somewhat agreed with the findings in the OLS analysis, while the ordinal association test Somers' D supported this. In the PO model, some factors have disappointing effects, namely *garden plane* and *performance*. These two factors have weak positive yet mixed consumer preference, so a solution can involve segmenting the respondents along biographical factors to investigate who preferred what and investigate why. Horticultural consumers likely prefer to be offered *organic* over *non-organic* in HG and e-gardens*.* The *garden price* slope is steeper than any separate factor but still weaker than *organics*, which suggests that *organics* is more preferable to horticultural consumers than less expensive HG. Similarly, this slope is about twice as steep as *garden automation* than *garden price* which implies that the people here are not willing to trade-off *R5000* for an *automatic garden*. Interestingly, increasing a basic HG to *automatic* expects that an extra 37% of horticultural consumers will have more utility for this product feature. From figure 4.8.9, a combination of *garden automation* and *organics* should optimise consumer utility for a HG profile.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

CHAPTER FIVE

Conclusions and recommendations

5.1. Conclusions and recommendations

The literature review suggested that HG has *automation*, *performance*, and *organics* being obvious issues for industry and people. *Organics* as a marketing tool seems to use emotion and fallaciously appeals to nature. The literature review identified several issues plaguing the world such as consumer fears, population and environmental issues, with partial solutions such as domestic hydroponics for horticulture. This creates additional issues for some users who cannot or care not to articulate HG. HG are technical concepts that most people find difficult. So perhaps simple control systems merged with hydroponic cultivation may offer them the ability to operate a HG to better meet their horticultural needs, and reduce wastages. Much like the automation features offered in many other consumer appliances.

E-gardens have the capacity to offer the above points.. These products were deductively decomposed into component parts which have relationships found and illustrated in the Venn diagram of *e-gardens* (see figure 3.1) where *e-gardens* was found to be a core intersection of the intersections *hydroponics*, *cultivation*, and *automation*, which again are intersections of the fields of *structures*, *inputs*, and *controls*. This describes the synergy between somewhat separate fields which can define what these HG and e-garden products types are, and how they interrelate with one another.

In chapter three, the MA identified attributes of hydroponic cultivation which were then simplified in terms of factors. This qualitative analysis generated factors namely; *garden plane* x_A , *automation* x_B, *performance* x_C, *organics* x_D, and *price* x_E which are antecedents for horticultural consumer preferences. These factors were simply constrained into categorical variables where the factor is offered or not. So *garden plane* is composed of *level* and *vertical gardens*, *garden automation* is composed of *manual* and *automatic gardens*, *garden performance* is composed of *casual* and *high-performance gardens*, *garden organics* is composed of *non-organic* and *organic gardens*, and *garden price* although quantitative is simply composed of *R2500* and *R5000*. Dummy variables were used to code these categorical variables for modelling.

Next in chapter four, these factorial runs of HG product profiles were constrained again into a half-run 2^{5-1} FFD that reduced the number of runs down from 32 to 16. These steps were taken to minimise respondent fatigue.

Meanwhile, a sampling strategy was devised to capture information conjointly between the factors and horticultural consumers on the Cape Peninsula, who exist at garden centres and nurseries in this location. This experimental survey achieved 140 respondents, though can use a larger sample sourced from other clusters to bring the errors and *deff* down, and equalise sampled cluster sizes, and to expand the sampling universe beyond the Cape Peninsula. The *deff* for *garden organics* is very large, which implies much within cluster similarities and between cluster heterogeneity.

With the advent of automation technologies empowering a degree of hands-free plant cultivation, the findings from cumulative *OR* suggest that an extra 37% of horticultural consumers on the Cape Peninsula will have more preference and utility for *automatic* products features compared to a basic HG. *Garden plane* and *performance* are seen as least important though exploring these factors further with market segmentation research may delineate particular kinds of people that have distinct preferences. It also is useful to explore other conjoint models by testing other sub-attributes and new attributes from the MA as potential factors, to improve model explanatory power. The factor interaction effects may be a problem if their significances become evidential. *Garden price* is really quantitative so future research should test this factor with more resolution, which means applying a more complicated Fractional Factorial Design FFD.

CHAPTER SIX

GRAND REFERENCES

CHAPTER SIX

Grand references

6.1. Grand references

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APPENDIX

Magazine 1: The cognitive aid magazine for respondents

Cape Peninsula
University of Technology

Nursery shopping survey

2016

We are looking for some lucky individuals to take part in a quick shopping survey, to rate some future garden products…

It should take 5 minutes, and it's not an advert or a promotion. This is a survey designed and administered by a student at the Cape Peninsula University of Technology (CPUT).

Your honest participation would be much appreciated.

Alex Rossouw, Horticultural Sciences department. Cape Peninsula University of Technology

Student number: 207016135

Should you have any queries, feel free to contact myself at egardencontact@gmail.com or the Horticultural Sciences department at CPUT at: laubscherc@cput.ac.za

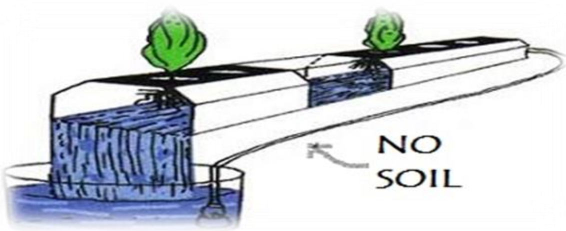
Let’s **quickly** skim through a few things…

So, **what is in this survey?**

- ✓ Indoor and outdoor gardens
- ✓ Ready-to-grow systems
- ✓ Dirt-free ***hydroponic gardens***

What are ***hydroponic gardens***?

Hydroponic gardens **don't need soil…**

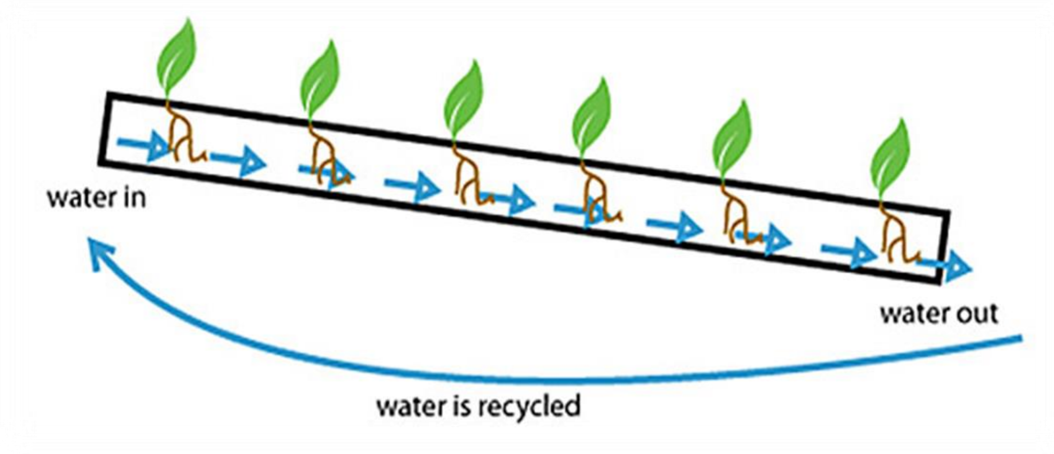


Familiar?

Hydroponic gardens **grow plants in mineral-rich water…**

Faster growth than soil!

Hydroponic gardens **recycle**
water and nutrients using a **system…**



Uses **10% water** and fertiliser compared to soil

Hydroponic gardens are better **suited for small areas and modern built-up surfaces**…

Do they have **any useful product features for me**?

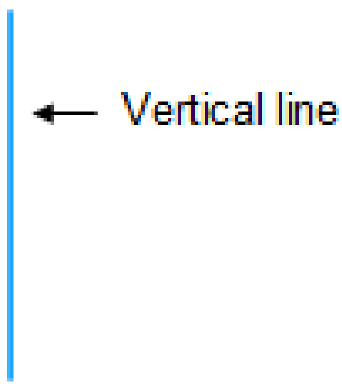
Level gardens:

✓ These are **regular flat** gardens…

Horizontal line

Vertical gardens:

✓ These gardens **stand upright…**



Manual control:

- ✓ These gardens **need your care…**

Automatic control:

- ✓ These gardens **grow by themselves…**

Casual:

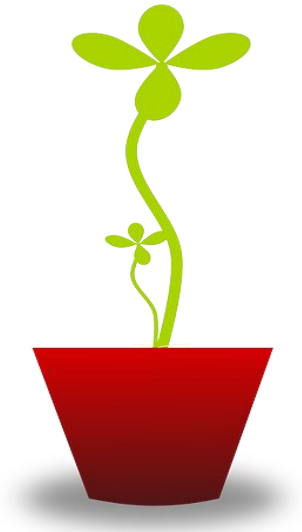
- ✓ **Quick** growth…

High-performance:

✓ **Quickest** growth…

Non-organic:

- ✓ Less Carbon…



Organic:

✓ More Carbon…

R2500:

- ✓ **Standard** value…

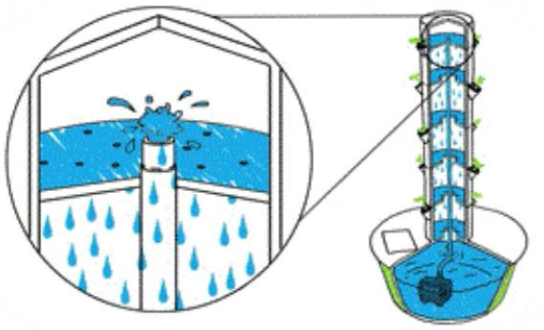
R5000:

- ✓ Premium value…

Summary of **product features** in hydroponic gardens:

- ✓ Level **or** Vertical garden
- ✓ Manual **or** Automatic control
- ✓ Casual **or** High-performance
- ✓ Non-organic **or** Organic
- ✓ R2500 **or** R5000

Some **examples of hydroponic garden products:**




Lights
Add Water
SELECT
Add Nutrient

Magazine 2: The CA survey experiment

Cape Peninsula University of Technology

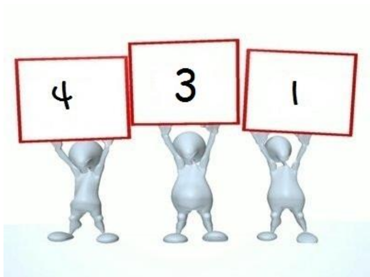
Nursery shopping survey:

Page through this magazine and look at each hydroponic garden and their different features. You don't have to think too hard…

How much do you prefer each product shown?

Just **rate each product separately** on a **1—5 scale**:

1	**2**	**3**	**4**	**5**
Least preferable	***Less preferable***	***Preferable***	***More preferable***	***Most preferable***



<u>Product A</u>

- ✓ Vertical
- ✓ Automatic
- ✓ High-performance
- ✓ Non-organic
- ✓ R2500

Product B

- ✓ Vertical
- ✓ Automatic
- ✓ High-performance
- ✓ Organic
- ✓ R5000

Product C

- ✓ Vertical
- ✓ Manual
- ✓ High-performance
- ✓ Non-organic
- ✓ R5000

Product D

- ✓ Vertical
- ✓ Automatic
- ✓ Casual
- ✓ Non-organic
- ✓ R5000

Product E

- ✓ Level
- ✓ Manual
- ✓ High-performance
- ✓ Non-organic
- ✓ R2500

Product F

- ✓ Level
- ✓ Automatic
- ✓ Casual
- ✓ Organic
- ✓ R5000

Product G

- ✓ Level
- ✓ Automatic
- ✓ High-performance
- ✓ Non-organic
- ✓ R5000

Product H

- ✓ Vertical
- ✓ Manual
- ✓ Casual
- ✓ Non-organic
- ✓ R2500

Product I

- ✓ Vertical
- ✓ Manual
- ✓ Casual
- ✓ Organic
- ✓ R5000

Product J

- ✓ Level
- ✓ Manual
- ✓ Casual
- ✓ Organic
- ✓ R2500

<u>Product K</u>

- ✓ Level
- ✓ Automatic
- ✓ High-performance
- ✓ Organic
- ✓ R2500

Product L

- ✓ Level
- ✓ Manual
- ✓ Casual
- ✓ Non-organic
- ✓ R5000

Product M

- ✓ Vertical
- ✓ Automatic
- ✓ Casual
- ✓ Organic
- ✓ R2500

Product N

- ✓ Vertical
- ✓ Manual
- ✓ High-performance
- ✓ Organic
- ✓ R2500

Product O

- ✓ Level
- ✓ Automatic
- ✓ Casual
- ✓ Non-organic
- ✓ R2500

Product P

- ✓ Level
- ✓ Manual
- ✓ High-performance
- ✓ Organic
- ✓ R5000