End-of-life strategies for used mobile phones: what influences a student's recycling intention and does levying a recycling fee increase collection rates?

Master Thesis

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EXECUTIVE SUMMARY

Mobile phones are replaced on a high frequency leading to large volumes becoming obsolete within several years, of which the majority is hibernating in households. In terms of volume, mobile phones are the largest contributor to the e-waste stream and due to their high reusability and intrinsic material values it is important to collect used phones for reuse and recycling purposes. Countries use different e-waste management systems and legislation to force producers and consumers to recycle e-waste. It appears that regions that levy explicit recycling fees on behalf of consumers have higher collection rates compared to regions that don't. Examples of such regions are Switzerland and Japan. This thesis examines if such an explicit recycling fee on the sale or disposal of mobile phones is likely to increase mobile phone collection rates in the Netherlands. The hibernation stock of used mobile phones in the Netherlands is measured with a material flow analysis for the year 2013. Results show that around 5.6 Mln mobile phones became obsolete of which around 3.4 Mln (60%) entered the hibernation stock. With average obsolete flows of 5.1 Mln units annually, it is not expected that this hibernation stock is shrinking anytime soon. A survey among Dutch students has been conducted to assess their mobile phone use and disposal behaviour. Findings suggest that the majority of the Dutch students replace their mobile phones within 2.5 years, mainly because their phones are broken or technically obsolete. Over 60% of the students have stockpiled unused mobile phones equalling 1.64 units per student on average. Understanding recycling behaviour is key to create a sustainable waste management strategy. The Theory of Planned Behaviour provides a framework to understand and explain behaviour, and is used in this study to generate insights into factors that underpin recycling behaviour of mobile phones among Dutch students. Findings suggest that moral norms, attitudes, perceived behavioural control, monetary incentives, and being female positively and significantly influence a student's intention to recycle their mobile phones in the future. The findings also provide support for the proposition that a recycling fee on the sale or disposal of mobile phones provides a tool for creating awareness and incentivise students to recycle their mobile phones. A deposit-refund system has found to be the most promising in this respect and is therefore found to be the most effective strategy for increasing collection rates of mobile phones in the Netherlands. The majority of the respondents (64%) are willing to accept a depository fee of €11-15, and 53% is willing to return their mobile phones for this tariff. The highest collection rate (76%) is expected by levying a deposit fee of €25+, however, acceptance would be low (19%). In order to make such a deposit fee a success it is important to complement it with a high visible return infrastructure, a better information platform for consumers about mobile recycling options and its importance. Also providing additional services like data transfer and data removal services are likely to attract consumers to hand in their used handsets.

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ABBREVIATIONS

Abbreviation	Definition
ARF	Advanced Recycling FEE
ASP	Average Selling Prince
BAN	Basel Action Network
CLSC	Closed-Loop Supply Chains
DRS	Deposit-Refund System
EEE	Electrical and Electronic Equipment
EOL	End-of-life
EPA	Environmental Protection Agency
EPR	Extended Producer Responsibility
EPS	Electronics Product Stewardship
ERP	European Recycling Platform
ESM	Environmental Sound Management
EU	European Union
HWFD	Hazardous Waste Framework Directive
K	Kilo (1000)
LCA	Life Cycle Analysis/ Life Cycle Assessment
LWEEE	Large Waste Electrical and Electronic Equipment
MFA	Material Flow Analysis
Mln	Million
NEPSI	National Electronics Products Stewardship Initiative
NPO	Non-Profit Organization
OECD	Organization for Economic Co-operation and Development
ORDEE	The Ordinance on The Return, the Taking and the Disposal of Electrical and Electronic Equipment
PDF	Pre-Disposal Fee
PPP	Polluter Pays Principle
PRO	Producer Responsibility Organizations
RERA	Responsible Electronic Recycling Act
ROHS	Restriction of Hazardous Substances
RQ	Research Question
RRR/3R	Reduce, Reuse Recycling
SQ1	Sub Question 1
SQ2	Sub Question 2
SQ3	Sub Question 3
StEP	Solving the E-waste Problem
SWEEE	Small Waste Electrical and Electronic Equipment
t	Tonne
TPB	Theory of Planned Behavior
UN	United Nations
US	United States
WA	Weighted Average
WEEE	Waste Electrical and Electronic Equipment
WFD	Waste Framework Directive

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1.INTRODUCTION

1.1 BACKGROUND ON E-WASTE

Globally, waste electrical and electronic equipment (WEEE) is the fastest growing waste stream with an estimated 41.9 million (Mln) tonnes being generated annually (UNU, 2014). WEEE is defined as Electrical and electronic equipment (EEE) that has reached its end-of-life (EoL) phase either by ceasing to be of any value to its owners or stops functioning (Widmer et al, 2005). Dealing with e-waste is important from many perspectives making it a priority waste stream (Ogondo & Williams, 2011c), which the European Union has officially declared it in 1991 (Kiddee et al, 2013). Technological progress and decreasing life spans result in large volumes of EEE to be discarded (Goosey, 2004). Decreasing this volume that ends up at landfills and increasing valuable material recovery from WEEE is considerably important. WEEE must be properly treated because it contains over a hundred different materials, many of which are highly toxic for the environment (Widmer et al, 2005). Illegal exports of WEEE to developing countries must stop to avoid environmental disasters resulting from informal and uncontrolled recovery practices (Ogondo & Williams, 2011c). Key in this process is developing environmentally sound management (ESM) processes and enforcement strategies. Over 20 years governments have become increasingly involved in addressing e-waste. Initiatives, like the Basel Convention and WEEE legislation, aim to reduce e-waste volumes and illegal trade-flows while promoting efficient and ESM of e-waste (Silveira & Chang, 2010; Tanskanen, 2013).

Although comprehensive legislation exists collection rates for most products are still low (Oliveira et al, 2012), especially in case of small e-waste (SWEEE) (Mishima & Nishimura, 2016a). Recent studies identified problems raised by the implementation of the WEEE legislation related to SWEEE. A 'one size fits all' approach is an unacceptable way of recovering WEEE (Darby & Obara, 2005; Ogondo & Williams, 2011c); some studies underscore the need for SWEEE specific collection targets (Polak & Drapalova, 2012) or a revision of WEEE legislation (Huisman et al, 2007; Ogondo & Williams, 2011c). Large e-waste (LWEEE) is more likely to be recycled since it is easily separated from waste streams (King & Burgess, 2005). Alternatively, SWEEE is more likely to be discarded (Darby & Obara, 2005). The true value embedded in WEEE is therefore not displayed in terms of weight. For example, retired (EoL) mobile phones (typically less than 150 grams) have considerable value embedded in its materials (e.g. gold, silver, rare earth metals) and components (EMF, 2012).

EoL mobile phones are a special WEEE category, and its size is growing faster than any other category (Geyer & Blass, 2010). It represents a unique niche in the WEEE mix because they are high in value, high in number, and transient (Ogondo & Williams, 2011b). Mobile phones have high penetration rates, rapidly decreasing life spans, and a complex composition with high concentrations of precious metals (Duygan & Meylan, 2015). Unlike other SWEEE, mobile phones may be profitable reused or recycled (Neira et al, 2006). However, large amounts – varying from 38% to 64% (Ogondo & Williams, 2011b; GSMA, 2012; Li et al, 2012; Cruz, 2014; Yin et al, 2014; Telecompaper, 2016) – are stored, or hibernating, in households (Duygan & Meylan, 2015; Mishima et al, 2016b). Industries face increasing shortages of key metals, especially the ones found in mobile phones (Ogondo & Williams, 2011a). Mobile phone hibernation is therefore an important issue. Mobile phones are one of the few EEE that have a thriving secondary market. In fact, more handsets are reused than recycled. The resale value of mobile phones, however, depends on the handset's brand, model, grade, age, condition and timing of sale. The latter is important since handsets may lose 20-30% of their resale value within 8 months of hibernation (Geyer & Blass, 2010). Therefore the main challenge for take-back companies is lowering the hibernation period of retired handsets by collecting them sooner.

1.2 THE EXTENDED PRODUCER RESPONSIBILTY PRINCIPLE

European legislation places the responsibility of handling WEEE on producers and importers via the 'Extended Producer Responsibility' (EPR) principle. EPR extends the responsibility of producers to all phases of a product's life, including the post-consumption phase. (Silveira & Chang, 2010). Most EPR approaches are build on voluntary take-back schemes where consumers can return their products for free at collection points provided by the public and private sector. However, EPR approaches that use economic instruments to more actively incorporate consumers in the EoL phase of EEE are not widely used. Examples of such approaches are advanced recycling fees (ARF); pre-disposal fees (PDFs) and deposit refund schemes (DRS) (Widmer et al, 2005). ARFs are fees that are levied on the purchase of electronic products, PDFs are fees that are levied when products are disposed/handed in for recycling, and DRS is comparable with the deposit refund system on plastic bottles. Multiple studies back up the need for such mechanisms. Research has shown that voluntary take-back schemes yield unsatisfactory collection rates for mobile phones. Explanations are that consumers lack the incentives (Ogondo & Williams, 2011b; Mishima & Nishimura, 2016a), have safety concerns (Li et al, 2012; Yin et al, 2014;), perceive the return infrastructure as inconvenient (Darby & Obara, 2005; Li et al, 2012), think their phone isn't worth anything (Ogondo & Williams, 2011b; Ogondo & Williams, 2011c; Cruz, 2014) or are unaware of disposal options (Cooper & Mayers, 2000; Darby & Obara, 2005; Ogondo & Williams, 2011b**;** Li et al, 2012; Yin et al, 2014). Hence: incentives and consumer awareness are both too low.

1.3 BACKGROUND ON RECYCLING FEES AND COLLECTION RATES

Most countries use free and voluntary take-back schemes as main EPR approach. Some countries use ARF or PDF approaches, which explicitly apply the polluter pays principle (PPP) to make consumers explicitly financially liable for discarding their EEE (StEP, 2010). ARF approaches are used in Switzerland (Schluep, 2014), Norway (Streicher-Porte, 2005), California (Oliveira et al, 2012), Canada (THE SOURCE, 2017) and Sweden (Widmer et al 2007); Japan uses the PDF approach (Sthiannopkoa & Wong, 2013). In terms of system finance, it doesn't really matter who bears the financial responsibility since it is always incorporated in the market price (Namias, 2013). The difference lies more subtly in terms of who feels responsible for it (Neira et al, 2006). Interestingly, however, is that countries that implemented take-back programs using ARFs or other direct "compliance costs" have developed their WEEE recovery infrastructure at a higher pace realizing larger economies of scale (Huisman et al, 2006) and are among the regions with the highest collection rates (Eurostat, 2017). In Japan, end-users pay a recycling fee for certain products ranging between $20-50 depending on the item, by using public and private collection services. This way, 74% of e-waste reaches a recycler, compared to the US average of 12.5%, which makes Japan to have perhaps other best-functioning system in terms of scope and compliance (Sthiannopkoa & Wong, 2013). In California an ARF system was introduced in 2003 on televisions and monitors charging between $6-10 depending on the screen size. This resulted in the recycling of 65 million pounds (± 29,500 tons) of televisions and monitor in the first year compared to a US nationwide WEEE recycling of 290,000 tons (Nixon &

Saphores, 2007). The mandatory recycling system in California resulted in a mobile phone recycling rate of 25% compared to the US average of 10% (Silveira & Chang, 2010). In Switzerland consumers pay a recycling fee upon purchase of each electronic product levied by two compliance schemes: SWICO or S.EN.S (Streicher-Porte, 2005) and is together with Denmark, Norway and Sweden the only country in the European continent that consistently collects over 12 kilogram (kg) of WEEE per capita each year after 2006 ranking highest in 2014 with a collection rate of almost 15.5kg/capita (Eurostat, 2017; SSS, 2013; SSS, 2017). In Norway, Elretur is the compliance scheme that collects ARFs for all new electronics sold (Streicher-Porte, 2005). In the Netherlands only recently between 2011 and 2013 the explicit "removal fee" on white and brown EEE has been replaced by an implicit recycling fee (Tweakers, 2010), which varied between €1-17 depending on the product (NVMP, 2009). However, Dutch collection rates remained below 8kg/capita until 2014 (Eurostat, 2017). Still, above information suggests that countries that use ARFs or PDFs do exceptionally well compared to other countries that have free take-back schemes. This leads to the belief that ARFs are not just only good for financing recycling systems, but also that it has a positive influence on the collection rate itself and by making people more aware about WEEE recycling and by providing financial incentives.

1.4 THESIS AIM

The Dutch government is currently researching options of a deposit refund scheme on mobile phones (AfvalOnline, 2017), which is an example of a DRS approach. DRS is an alternative to current voluntary take-back schemes where consumers can return their products for free, and may positively influence consumer awareness and collection rates. This thesis explores the options of implementing an ARF, PDF, or DRS approach on the purchase or disposal of mobile phones as a strategy to increase collection rates of retired mobile phones in the Netherlands. So far, DRS are used effectively in the collection of plastic bottles, but in WEEE management it is not implemented yet. ARF and PDF are approaches used on other types of WEEE in countries discussed in the **Chapter 1.3**. The aim of this thesis is to look what influences a consumer's intentions to recycle, if consumers are open to an ARF, PDF or DRS system on the purchase or disposal of mobile phones, which scheme is expected to yield the best results, and what is the maximum amount of fee that people are willing to pay. This scope is captured in the following research question (RQ):

RQ: "Which EPR approach is most effective in reducing mobile phone hibernation in the Netherlands?

The term "effective" refers to which method is the best to motivate consumers to recycle or hand in their hibernating mobile phones rather than keeping these stored at home. Based on previous research, it is expected that a positive relationship exists between a country's EPR approach (ARF, PDF, DRS, free) and its WEEE collection rates, where fee based systems yield higher collection rates. Since mobile phones are the fastest growing waste streams in terms of numbers (Geyer & Blass, 2010; Andarani & Goto, 2014) it is important to analyze whether a fee or deposit system increases consumer awareness and whether it incentivizes consumers to recycle their EoL phones. To generate a good answer on the research questions, one first must identify: What is the current performance of mobile phone collection programs in the Netherlands? What influences a consumer's intention to recycle their mobile phones in the first place? How much are consumers willing to pay for the recycling/collection of their mobile phones? These are questions defined and elaborated at a more detailed level in **Chapter 1.5**.

1.5 THESIS SCOPE

To analyze the research question, this thesis is divided in two sections each having a different scope.

The first section analyses the current mobile phone recovery process in terms of dominant disposal strategies and volumes by stream. To do this, it is important to map how mobile phones flow into, within, and out of the Netherlands. This way one can determine how many phones are imported, sold, obsolete, landfilled, recycled, reused and exported. This can be done by means of a Life cycle analysis (LCA). Various methodologies of LCA are available for WEEE management, of which material flow analysis (MFA) is most suitable to analyze such flow structures. MFA is used to study the route of materials or units flowing into recycling sites, disposal areas and stocks in space and time; it links sources, pathways, and final destinations of materials (Kiddee et al 2013). Important in this thesis' context is that the focal unit of the material flow analysis is "units of mobile phones" rather than the materials mobile phones are composed of. Therefore the focus is purely on flows of (EoL) mobile phones. The first sub-question (SQ1) to be addressed is:

SQ1: What are the current hibernation, landfilling, reuse, and recycling status of mobile phones in the Netherlands?

To this date, MFA studies have been conducted on mobile phones: in Switzerland (Duygan & Meylan, 2015), Japan (Mishima et al, 2016b), Finland, Germany, Sweden, Switzerland, and the UK (Naoko & Manomaivibool, 2011). These case studies are used to compare the outcomes from SQ1 with. An abstract representation of the scope of SQ1 in terms of product life cycle is presented in **Figure 1**.

The second section analyses what drives consumers in their recycling behavior. This is investigated by issuing a questionnaire among Dutch students. Student mobile phone recycling behavior is analyzed based on two sub-questions: SQ2 and SQ3. This serves as a basis of how one can improve the current mobile phone collection system in the Netherlands.

SQ2: To what extend are a student's behavioral intentions to recycle their mobile phones influenced by their attitude to recycle, subjective norm, moral norm, perceived behavioral control, perceived inconvenience, monetary incentives, other recycling behavior, and past recycling behavior?

SQ2 analyses the psychological factors influencing the behavioral intention to recycle mobile phones of Dutch students. A variety of psychological models exist aimed to explain and predict recycling behavior. The Theory of Planned Behavior (TPB) of Ajzen (1991) is a revision of the Theory of Reasoned Action and states that a person's actions dependent on their intentions of performing that action. These intentions are in turn influenced by their attitudes, subjective norm and perceived behavioral control, which is the basic way of reasoning of the TPB. The TPB model can be extended with additional variables, which in this thesis is done by including an individual's moral norm (Tonglet et al, 2004a; Saphores et al, 2012), perceived inconvenience of recycling (Tonglet et al, 2004a), other recycling behavior (Ogondo & Williams, 2011b), past recycling experience (Bentler & Speckhart, 1979; Philippsen, 2015), and monetary incentives (Nixon & Saphores, 2007; Bian et al, 2015). These variables are included because studies have indicated that these factors have a significant influence on recycling in general, or on WEEE recycling in particular.

The third sub-question aims to identify mobile phone consumption and disposal behavior of Dutch students to generate a picture of the drivers affecting the decision to recycle, reuse, dispose, or keep their old mobile phones. A main goal is identifying their willingness to pay for recycling their used mobile phones and whether they differ in preferences considering the way of payment in the form of an ARF, a PDF, or a DRS payment system. Sub-question three (SQ3) is defined below. The scope of sub-questions two and three are shown in **Figure 2**.

SQ3: Are students being motivated to recycle their old handsets by imposing a fee-based EPR approach on the sale or disposal of mobile phones and which maximum fee would be accepted?

What SQ3 aims to answer is whether students are open to a recycling fee on their mobile phone purchases or disposals and whether there is a general preference amongst the three approaches (e.g ARF > PDF > DRS). This will be measured by surveying directly if each type fee would make students more aware about recycling and whether it motivates them to recycle/hand-in their old handsets. Students are also asked directly what is their willingness to pay for recycling their mobile phones and, in case of a DRS system, which amount of deposit is the threshold for people to hand in their mobile phones to claim back their deposits.

Figure 1: Scope SQ1: Mobile Phone Material Analysis in The Netherlands

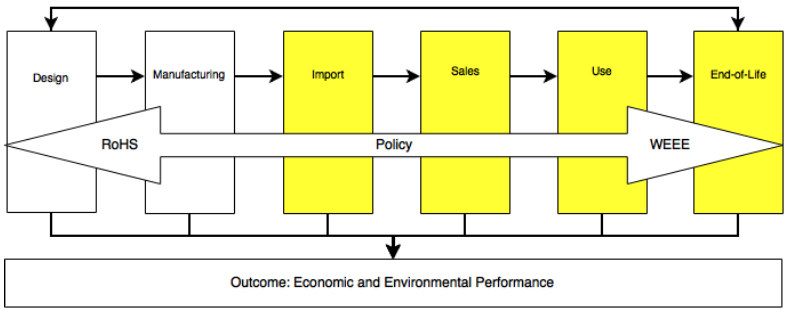
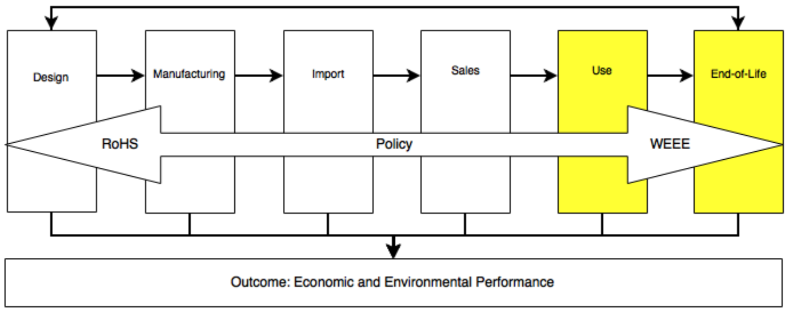


Figure 2: Scope SQ2 and SQ3 - Dutch Consumer and Disposal Behavior of Mobile Phones



1.6 RELEVANCE

Consumer recycling behavior is an area that has been extensively studied and different theories have been developed to predict, explain and promote recycling behavior. However, academic research addressing mobile phone recycling for European consumers is relatively scarce. There are European based studies that focus on mobile phone flows (Naoko & Manomaivibool, 2011; Duygan & Meylan, 2015), on take-back schemes (Ogondo & Williams, 2011a), and on mobile phone consumption and disposal behavior (Ogondo & Williams, 2011b). However, no such study has ben conducted in the Netherlands, which is a gap that this thesis aims to fill by conducting a material flow analysis and a consumer recycling behavioral analysis on mobile phones. This is in line with Duygan & Meylan (2015) who emphasized the need for more research to get a better understanding of consumer recycling behavior in order to further improve collection programs and by giving a more accurate estimation on the stock of mobile phones that are being stored at households.

Much research addressing recycling is focused on providing consumers with information and monetary incentives. However, less frequently it is investigated if recycling can be increased if consumers must pay for it. Switzerland and Japan both are praised for their WEEE management system (Sthiannopkoa & Wong, 2013) based on an ARF and a PDF system where consumers pay explicitly for recycling system and have high WEEE collection rates. This thesis aims to get an understanding whether Dutch consumers are open to such a fee, and whether it functions as an incentive to recycle their mobile phones. This is done by doing in a case study among Dutch students.

1.7 STRUCTURE OF THE THESIS

In order to answer the research question and the sub-questions, this thesis is divided in eight Chapters. **Chapter 2** summarizes trends on WEEE generation, legislation and developments towards a more closed-loop supply chain system. This is done to create an overview of current developments in WEEE generation, how countries are combatting it and how this thesis fits in the area supply chain management. **Chapter 3** is a literature review that addresses previous research done in the area of this research's sub-questions and therefore address mobile phone life cycle analysis, consumer recycling theories and mobile phone recycling behavior of consumers. **Chapter 4** addresses the methodology used to conduct the material flow analysis, it explains how the data for the material flow analysis is obtained, and it explains the material flow analysis assumptions. **Chapter 5** addresses the methodology used in the consumer behavior analysis. It explains how the Theory of Planned Behavior is used and how the model variables are defined and operationalized and measured. **Chapter 6** addresses the results of the material flow analysis and **Chapter 7** does the same for the consumer behavioral analysis. **Chapter 8** discusses the implications of the results on the sub-questions and formulates a conclusion on the research question. Research limitations and recommendations are given at the end of this chapter.

2. TRENDS OF WASTE ELECTRICAL AND ELECTRONIC EQUIPMENT

Consumer electronics have become more popular in past decades revolutionizing the way people behave. Changes in consumption patterns influence product turnover rates and the amount of products sold, which are both determinants of waste generation. **Chapter 2** outlines trends that lead to an increase in waste generation and the increase in legislation combatting this development.

2.1 INCREASING ILLEGAL HAZARDOUS WASTE TRADES

During the 1960s-1970s one started questioning the limits of our planet, the consequences of the industrial city and the evolution towards a consumer society (Barles, 2005). This process resulted in the first waste policies being created with the Resource Conservation and Recovery Act (RCRA) of 1976 in the United States (US) (EPA, 2016) and the Waste Framework Directive (WFD) of 1975, and Hazardous Waste Framework Directive (HWFD) of 1978 in Europe Union (EU). These are the first legislative bodies addressing the environmentally sound management (ESM) of hazardous and non-hazardous wastes (EC, 1978; EC, 1991). Because tightening regulations on the treatment of hazardous wastes, companies started to export increasing volumes of hazardous wastes to developing countries leading to several infamous environmental disasters (Knight, 1998; Babade, 2014). A first attempt in battling these hazardous waste trades was the establishment of the Basel Convention (1989), which is ratified by 186[1] countries. The first aim was to reduce hazardous waste flows between nations, especially from developed to developing countries. A second aim was reducing hazardous waste generation and promoting sound management (EPA, 2017; BC, 2011a). In 2001, the OECD Council passed Decision C(2001)107, which is legally binding to OECD members and prohibits the exports of hazardous waste to non-OECD countries (EC, 2013). In 2006, the EU transposed the Basel Convention and the OECD Decision in EU regulation via the Waste Shipment Regulation (StEP, 2013). The United States did something similar in 2017 by amending its hazardous waste trade law (40 C.F.R. Part 262 Subpart E and F) to include trades to both OECD and non-OECD countries (Goldberg, Hagen, & Carra, 2016) and with the establishment of the Responsible Electronic Recycling Act (RERA) in 2010. Both are meant to control hazardous (e-waste) flows to developing countries (Sthiannopkoa & Wong, 2013). Despite al efforts, it is estimated that between 60-90% of the world's e-waste is still illegally traded or dumped annually and thousands of tonnes of e-waste are falsely declared as second-hand goods before being exported form Europe, the US, Japan and Australia to West African and Asian countries. This implies that only 10%-40% is properly recycled (The Guardian, 2015; UNEP, 2015).

2.2 INCREASED WEEE LEGISLATION: PRINCIPLES AND INITIATIVES

2.2.1 Electronic waste legislation and principles

In Europe, WEEE became a priority waste stream in 1991 (Kiddee et al, 2013). In the mid-1990s over 90% of WEEE was landfilled, incinerated or found in municipal waste streams (EC, 2000). In the late 1990s, countries like Switzerland, Norway, the Netherlands, and Sweden began to prepare national WEEE legislations (Ylä-Mella et al, 2014). Switzerland was pioneering in WEEE management by using Producer Responsibility Organizations (PROs) to separate and recover WEEE since 1992 (Duygan & Meylan, 2015). The Ordinance on The Return, the Taking and the Disposal of Electrical and Electronic

[1] Haiti and the United States were participating at the convention but did not sign or ratify it. Source: (BC, 2011)

Equipment (ORDEE) of 1998 sets the legal basis for WEEE recycling in Switzerland (Oliveira et al, 2012). Norway introduced WEEE legislation in 1998 and set up a recovery system in 1999 (Ylä-Mella et al, 2014). The first European legislative frameworks are EU Directives 2002/95/EC and 2002/96/EC, also known as the Restriction of Hazardous Substances (RoHS) and the WEEE Directives respectively.

Both Directives are based on the polluter pays principle (PPP), which makes those responsible for environmental pollution accountable for it, and the Extended Producer Responsibility (EPR) (EC, 2012; EC, 2015). EPR builds on PPP as it shifts away financial responsibility from the public sector to the private sector by internalizing environmental costs in sales prices (Widmer et al, 2005). EPR pushes producers to dematerialize their supply chain by using fewer resources and to adjust product design to reduce waste. EPR aims to prevent waste generation and closing material loops by stimulating companies to adhere to the waste hierarchy principle (OECD, 2001). The waste hierarchy is a five-tier system of preferred recovery practices: prevention, reuse, recycling, recovery and landfilling, and is part of each comprehensive framework regarding WEEE (Van Ewijk & Stegemann, 2016). Both the RoHS and WEEE Directive mandate environmentally sound reuse, recycling and recovery of WEEE by restricting the use of hazardous substances and setting collection and recovery targets. The initial collection target is 4kg/capita/year, which is achieved by most countries. The Directives must be signed into law by all member states (EC, 2012; EC, 2015). Norway and Switzerland have followed up EU legislation (Ylä-Mella et al , 2015).

The EU Directives have been influential in shaping legislation in other developed countries like the US, Canada, Australia, Japan, and South Korea (Kiddee et al, 2013). The US has no federal WEEE legislation, however, state level legislation is in place in twenty-five states. California was the first state signing WEEE regulation into law in 2003 (Oliveira et al, 2012). In Canada, only certain provinces have adopted WEEE legislation (EC, 2013). In both Latin America and Africa comprehensive WEEE management systems are not in place. Many Asian countries have legislation, but countries cope with issues related to large WEEE trade flows causing high volumes to end up in the informal sector. Still, Japan and South Korea are examples of Asian countries that have a working formal system in place (Oliveira et al, 2012). In Oceania only Australia has a WEEE management system in place for the disposal of computers and televisions as laid out in "The Product Stewardship ACT 2011". These regulations require all producers and importers to join an approved co-regulatory arrangement and industry recycling targets are progressively increased annually (UNU, 2014).

1.2.1 Initiatives combating WEEE related issues

Besides legislative frameworks and the Basel Convention, several initiatives have been set up tackling WEEE issues from various perspectives (Widmer et al, 2005). First, "Solving the E-waste Problem (StEP), a United Nations (UN) initiative founded in 2007, created a global platform of non-profits, governments and multinationals to initiate and facilitate environmentally, economically and socially sound ways to reduce WEEE flows. Second, the Basel Action Network (BAN), founded in 1997 is a non-profit organization (NPO) advocating the Basel Ban and ESM policies, managing e-Stewards (certification standard for recycling), and acting as investigative watchdog. The US Environmental Protection Agency (EPA) formally recognizes the e-Steward Certificate (Oliveira et al, 2012; BAN, 2015) Third, the WEEE-Forum was founded in 2002 by a number of European PROs. Their mission is to seek a harmonized European approach in the battle against WEEE and develop high-quality pan-European standards for the collection, treatment, and disposal of WEEE (WEEE Forum, 2017). The European

Recycling Platform (ERP) is another pan-European organization offering compliance and recycling services for WEEE, batteries, and packaging in 32 countries. In Europe, 30 compliance schemes (PROs) are offered in 15 countries (ERP, 2017). WEEE-Europe is a third pan-European NPO based in Munich founded in 2013 with 18 members. The organization provides consulting services on contract coordination, product classification and producer obligation (WEEE Europe, 2017). The National Electronics Products Stewardship Initiative (NEPSI) in the US, and the Electronics Product Stewardship Canada (EPS Canada) are similar initiatives in North America (Widmer et al, 2005).

2.3 AN INCREASE IN GLOBAL WEEE QUANTITIES

2.3.1 WEEE growth drivers: urbanization, economic, and technological Advancements

Around 54% of the global population lives in urban areas, which is expected to be 66% by 2050. Urbanization is a driver of economic growth and a larger share of the global population is becoming part of the middle class, from 1.8 billion in 2009, to 4.9 billion in 2030 (OECD, 2012; UN, 2014). A larger middle class implies increased purchasing power, which increases consumption and waste generation (Kumar et al, 2017). EPA estimates that global WEEE generation increases 5-10% a year (StEP, 2017). According to the Global E-waste Monitor, total WEEE generated is expected to be 50 Mln tonnes annually by 2018, of which 3 Mln tonnes is attributed to small IT equipment like mobile phones (UNU, 2014). Economic prosperity goes hand in hand with technical innovation, which is done at an accelerated pace. In fact, technologies develop so fast that products are replaced and discarded within a few years (Kumar et al, 2017) again increasing WEEE volumes (Goosey, 2004).

In case of mobile phones, life cycles have decreased significantly from ±36 months in the 1990s (Geyer & Blass, 2010) to an average of 20.5 months in 2015 (Kantar, 2016). A main driver is planned obsolesce, which means that producers force consumers to replace their devices on a regular basis, causing mobile phones to have the shortest life spans of all EEE (Wilhelm, Yankov, & Magee, 2011). With global mobile phones sales reaching over 1.9 billion in 2015 (Statista, 2017a), of which 1.4 billion are smartphones (Statista, 2017b), this is a worrying development that has a significant raw material demand. In fact, 475 tonnes (t) of Silver, 45.6t of Gold, 17.1t of Palladium and 17.1Mt of copper are used in the production of 1.9 billion mobile phone, assuming mobile phone composition data from UNEP (2009). To lower the resource impact of mobile phone production it is important that more handsets are collected. Legislation aims to achieve this by forcing producers to set up collection networks and to create sustainably designed products with less hazardous substances.

2.3.2 Trends in mobile phone size and composition

Whereas the trend for cell phones composition went the right way with average unit weights decreasing by 66% and average gold content decreasing by 60% over the period 1992-2006 (Geyer & Blass, 2010), smartphones are getting bigger with average weight increases of 17% (**Appendix 1**) between 2010-2017. This implies that smartphones are consuming more materials, which is not beneficial for the environment if these are not recovered. The reason why phones get bigger is mainly due to increases in screen sizes for improved functioning and aesthetics (Bloomberg, 2014) because people use their smartphones nowadays for more things than just calling. Besides increases in size, smartphones are often not designed to be taken apart easily, making recycling more difficult (FastCompany, 2009).

2.4 CLOSING THE LOOP: THE ROAD TO CIRCULAR SUPPLY CHAINS

The increase in legislation on producers on the one hand and the increased believe that companies can use sustainability as a marketing instrument to create value and reduce risk on the other hand influence supply chain characteristics. Supply chains are making the transition from open-loop (cradle-to-grave) to closed-loop (cradle-to-cradle) systems (Chopra & Meindl, 2016). Closed-loop supply chains (CLSC) focus on taking back used products from consumers and recovering value by reusing whole products or their components. CLSC is defined as: *"the design, control, and operation of a system to maximize value creation over the entire life cycle of a product with dynamic recovery of value from different types and volumes of returns over time"* (Guide & van Wassenhove, 2009).

In order to close the loop, reverse logistics systems must be set up. Many definitions of reverse logistics exist; in this thesis it can best be defined as *"the process of planning, implementing and controlling flows of raw materials, in-process inventory, and finished goods, from a manufacturing, distribution, or use point to a point of recovery or proper disposal" (Brito & Dekker, 2002).*

Reverse logistics differs from waste management as the latter mainly refers to the collection and processing of waste (products with no new use). The former focuses on those streams where value can be recovered and the outcomes can serve as secondary inputs for supply chains (Brito & Dekker, 2002). However, in this thesis the two definitions are used interchangeably as both aim to reduce the amount of waste being generated and increase the amount of resources to be recovered. In this thesis only products returned by customers, are taken into account, which enter the reverse logistics loop for various reasons: commercial returns (e.g. warranty), end-of-use returns (upgrade purchase) and end-of-life returns (obsolete/broken) (Guide & van Wassenhove, 2009). The term CLSC implies that loops are closed, which is often not the case in reality (Brito & Dekker, 2002). In this thesis' context it refers to company efforts to take responsibility over the EoL phase of products in line with the goals set by the EPR principle. **Appendix 2** shows an abstract of a detailed CLSC system (black lines), open-loop systems (red lines) and the place of each process in the waste hierarchy.

2.5 DISCUSSION

Increased legislation on hazardous waste caused waste producers to export their wastes in large volumes to developing countries in order to lower recycling costs. This has led to severe consequences for the environment in countries of destination. Although the global community attempts to stop these illegal flows, large volumes of toxic waste are still being traded. Since the 1990s more regulation has been set in place to reduce WEEE generation and to increase WEEE collection and recovery. Regions with upcoming economies are still struggling in setting up a formal legislative framework, but a large amount of developed countries have WEEE management systems in place using the waste hierarchy, the Polluter Pays and Extended Producer Responsibility as guiding principles. Several international initiatives have been developed dedicated to address issues related to WEEE leading to more countries having WEEE management systems in place and tightening standards. Technological innovation, an increase in global purchasing power, and increased urbanization accelerate product turnover rates and product obsolescence. Mobile phones are a leading example of decreasing product life spans and annual production levels have an enormous resource impact on our planet resulting from the almost two billion units sold each year globally.

Mobile phones are currently not always designed as sustainably as possible, which doesn't help product recovery. Currently green supply chains and closed-loop supply chains are given more attention by companies and an increased amount of return infrastructure is set in place to take back end-of-life or end-of-use electronic products, especially in the European area. These developments affecting WEEE are summarized in **Table 1**.

Table 1: Summary of trends in WEEE generation and efforts to battle this

	Trends/Developments	Area of interest	Scope	Since
1	Increased hazardous waste exports to developing countries creating large WEEE dumping sites in Africa and Asia	Political	Global	1960s
2	Increased hazardous waste legislation and international conventions aimed to avoid leakage of hazardous substances and battle illegal waste trades	Political	Global	1960s
3	Increased number of environmental initiatives tackling hazardous waste related issues	Environmental	Global	1970s
4	WEEE specific legislation is increased in developed countries	Political	Regional	1990s
5	Urbanization of global population, especially in developed countries	Social	Global	1990s
6	Increase in global middle class increases global consumption and waste generation	Economical	Global	2000s
7	Decreasing product life cycles as a consequence of planned obsolescence and increased technological development	Technological	Global	2000s
8	Smartphones get bigger (but thinner) by the year increasing the material demand for some precious metals and products designs are not always beneficial for recycling purposes.	Technological	Global	2010s
9	Shift from open-loop to closed-loop supply chains in developed countries	Economical	Regional	2000s

3. LITERATURE REVIEW

The concept of WEEE is elaborated in **Chapter 2** along with its impacts and the increasing number of public and private initiatives established to deal with WEEE related issues. Economical and technical progress have an ambiguous effect on global welfare, where it increases economic prosperity on the one hand and increases pollution and resource depletion on the other. **Chapter 3** reviews literature that has contributed to research areas addressed in this thesis: product life cycle analysis and consumer recycling behaviour analysis. Both address WEEE and mobile phones but are skewed towards the latter as the main category of interest. **Chapter 3** creates the foundation for the research methodologies outlined in **Chapters 4** and **5** and therefore creates a theoretical foundation of the available models and theories to research the research question and the three sub-questions.

3.1 PRODUCT LIFE CYCLE ANALYSIS

3.1.1 Product life cycle methodologies for WEEE management system analysis

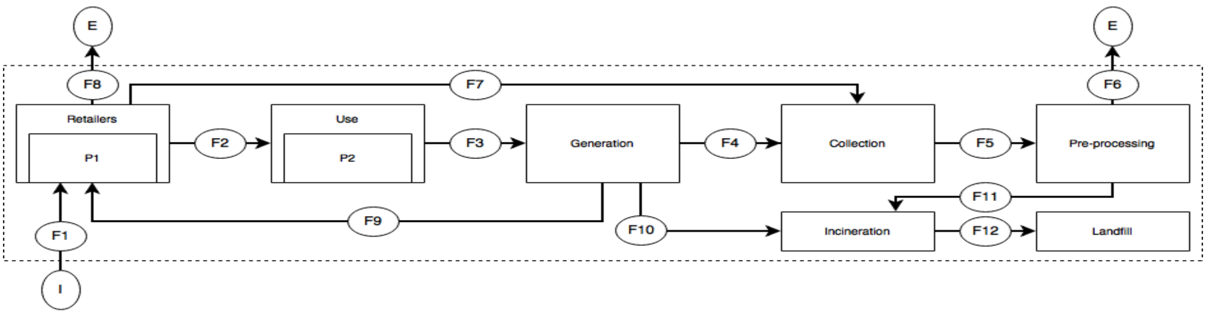
EPR is based on a product life cycle approach (Premalatha et al, 2014); several tools have been developed around this life cycle concept and are applied to WEEE management: life cycle assessment (LCA), Material Flow Analysis (MFA), and Multi-Criteria Analysis (MCA). Optimal WEEE management requires a combination of LCA, MFA and MCA together with EPR (Kiddee et al, 2013). LCA is widely used to evaluate the environmental impact or cost of WEEE from cradle to grave (Premalatha et al, 2014) and can therefore be valuable for product design, product development (Kiddee et al, 2013), and evaluations of EoL treatment processes (Scharnhorst et al, 2005). LCAs on mobile phones are done focusing on the product level (McLaren et al, 1999; RANDA-GROUP, 2000; Singhal, 2005; Yu et al, 2010; Zink et al, 2014), network level (Weidman & Lundberg, 2001; Faist-Emmenegger et al, 2004; Scharnhorst, 2006), and component level (Soo & Doolan, 2014). Generally it is looked at which recovery options are more economically and environmentally efficient. MFA is the most appropriate tool to study the flow of WEEE units/materials into recycling sites, disposal areas and stocks within time and space (Kiddee et al, 2013). MFA has been applied on mobile phones in terms of units (Yu et al, 2010; Naoko & Manomaivibool, 2011; Andarani & Goto, 2014; Mishima et al, 2016b), in terms of weight (Duygan & Meylan, 2015) and in terms of recycling processes (Navazo, Mendez, & Peiro, 2014). MCA is used to develop strategies based on quantitative and qualitative aspects but is not widely applied to WEEE (Kiddee et al, 2013). MCA on mobile phones is done by Duygan & Meylan (2015), who showed that WEEE recycling in Switzerland is mostly controlled by international rather than domestic factors. MCA is also used to evaluate alternative WEEE management systems in Cyprus (Rousis et al, 2008) and recycling facility location optimization in Spain (Queiruga et al, 2008).

3.1.2 Material flow analysis: the basic model and its applications on mobile phones

Although all approaches can be combined in one analysis, the scope of this thesis is focused on the generation of WEEE related to the consumption and disposal of mobile phones. Therefore a MFA analysis is the most appropriate method of conduct**.** **Figure 3** shows a generic MFA. MFA aims to identify flows that enter a system (imports F1), flows within the system (sales F2 - obsolescence F3 - collection, F4 F7 F9 – pre-processing F5), and out of the system (exports and re-exports F8 - end-processing F6 – disposal/leakage/hibernation F10 F11 F12). Together these flows indicate how much units are purchased, become ready for collection and are collected. P1 and P2 are stock indicators and measure the number of mobile phones in stock of retailers and consumers (Naoko & Manomaivibool, 2011; Duygan & Meylan, 2015). MFA is capable of providing a rich description of observed patterns in material flows, but it doesn't explain why these patterns are occurring. Still, MFA forms a crucial basis for material flow management (Duygan & Meylan, 2015). Several mobile phones MFA analyses considering mobile phones have been done and are discussed below.

Table 2 summarizes mobile phones MFAs done in Switzerland, Japan, Finland, Germany, Sweden, and the UK. For Switzerland, a large fraction of mobile phones is not engaging in recycling schemes leading to unsatisfactory collection rates of 37%, of which 58% is exported, and 42% is recycled (Duygan & Meylan, 2015). For Japan, it is estimated that 37%, 28%, and 32% of all phones collected in 2010 are recycled, reused and landfilled respectively and that 16.7 Mln phones were hibernated out of 37.4 Mln (44.7%) that became obsolete (Mishima et al, 2016b). MFAs done by Naoko & Manomaivibool (2011) showed that EU hibernation percentages are very high (>70%) and landfilling percentages are very low (<5%). The former is partially explained by the fact that the authors omit re-exports and hence assume that imports equal sales. If one assumes this for the Netherlands, where re-exports are high due to its gateway function, outcomes would be overestimated.

Figure 3: A generic material flow analysis



Source: (Duygan & Meylan, 2015)

Table 2: An overview of mobile phone material analyses

Source	[A]		[B]		[C]		[C]		[C]		[C]		[C]		[C]	
Country	Switzerland		Japan		Finland		Germany		Sweden		Switzerland		UK		UK	
Year	2011		2010		2008		2007		2010		2007		2005		2008	
Measure	Weight		Phones		Phones		Phones		Phones		Phones		Phones		Phones	
Unit*	Tons	±	Units	±	Units	±	Units	±	Units	±	Units	±	Units	±	Units	±
Import	590	89	N/A	N/A	1,992	0,1	24,0	1,20	3,2	0,16	2,800	0,700	25,3	1,27	34,230	1,720
Re-export	22	3	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Export***	88	13	5,58	N/A	0,039	0,01	0,326	0,12	0,06	0,02	0,326	0,115	4,59	0,96	5,940	1,240
Δ Retailer stock	93	116	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Sales**	475	71	0,14	N/A	1,992	0,1	24,00	1,20	3,2	0,16	2,800	0,700	25,35	1,27	34,290	1,720
Use stock	N/A	N/A	N/A	N/A	4,298	0,185	65,63	3,28	7,35	0,37	5,878	0,294	45,33	2,27	48,880	7,920
Δ Use stock	61	95	N/A	N/A	0,119	0,103	0,144	3,77	0,179	0,48	0,249	0,798	1,73	3,76	0,600	5,340
Obsolete	414	62	37,4	N/A	1,873	0,028	23,87	3,58	3,021	0,45	2,551	0,383	23,63	3,54	33,690	5,050
Hibernation	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	16,827	4,21	4,000	1,000	90	22,5	150,25	23,67
Δ Hibernation	N/A	N/A	16,7	N/A	1,609	0,04	21,45	3,60	2,135	0,47	1,995	0,390	16,56	3,67	24,880	5,170
Collected	152	20	20,7	N/A	0,264	N/A	2,414	N/A	0,886	N/A	0,556	N/A	7,07	N/A	8,810	N/A
Landfill	262	65	6,54	N/A	0,094	0,023	1,195	0,30	0,00	0,01	0,128	0,032	0,95	0,24	1,350	0,340
Reuse	88	0	5,72	N/A	0,039	0,01	0,326	0,12	0,06	0,02	0,128	0,045	4,59	0,96	5,940	1,240
Recycling	64	0	8,44	N/A	0,131	0,015	0,884	0,14	0,826	0,13	0,301	0,046	1,48	0,71	1,470	0,890
Import	590	89	N/A	N/A	1,992	0,1	24,00	1,20	3,2	0,16	2,800	0,700	25,3	1,27	34,23	1,72
Δ Stock	154	111	N/A	N/A	1,822	0,101	22,79	1,21	2,314	0,21	2,372	0,703	19,23	1,57	26,83	0,02
Export	436	66	N/A	N/A	0,17	0,018	1,210	0,18	0,886	0,14	0,428	0,065	6,07	0,91	7,40	1,04
Landfilled	63%****		17%		5%		5%		0%		5%		4%		4%	
Reused	21%		15%		2%		1%		2%		5%		19%		18%	
Recycled	15.5%		23%		7%		4%		27%		12%		6%		4%	
Hibernated	0%		45%		86%		90%		71%		78%		70%		74%	
Total Obsolete	100%		100%		100%		100%		100%		100%		100%		100%	

** Units are in millions ; ** Japan = Domestic Reuse; *** Equals Foreign Reuse; **** leakage for system (can either by hibernated or landfilled);*
Source: Author's own elaboration on [A] = Duygan & Meylan (2015); [B] = Mishima et al (2016); [C] = Naoko & Manomaivibool (2011)

What **Table 2** makes clear is that the recovery rates of mobile phones (reused +recycling) are low compared to the alternative (hibernation + landfilling) emphasizing that WEEE performance measurement in terms of weight is misleading. The country that appears to have made considerable progression is Switzerland, which recovered 37% in 2011 compared to just 17% in 2007. However, one must be cautious due to differences in research methodology. Another MFA in Indonesia showed that mobile phone flows differ considerable between lower and higher income groups in terms of volumes. Indonesian reuse rates tend to be high for all income groups with an average reuse rate of 57% mainly due to economic reasons (Andarani & Goto, 2014).

3.2 CONSUMER RECYCLING BEHAVIOR

3.2.1 Two models of consumer recycling behavior

Everyone can start behaving pro-environmentally to decrease his or her impacts on the environment, but the fraction that does this is small. There is no one treatment – or silver bullet – that is effective to stimulate all types of pro-environmental behaviors (e.g. recycling or energy saving) across all people. Certain treatments are more effective for certain behaviors (Osbaldiston & Schott, 2012). Several frameworks have been created to analyze these differences in recycling behavior.

A model of consumer recycling behavior by Hornik et al (1995)

Hornik et al (1995) conducted a meta-analysis of 67 empirical studies and concluded that there are four antecedent factors influencing recycling behavior, which are summarized in the "empirically derived" rather than "conceptually based" model of **Table 3**. Because of the research scope, it presents a good overview of factors influencing recycling behavior. A social dilemma like recycling comes down to two fundamentals: an individual does "good" because it feels good (altruistic) or the individual does good because it is "enforced to" (utilitarian). The facilitators in **Table 3** can be arrayed along this altruistic-utilitarian scale. Effects of altruistic variables last longer than utilitarian ones since the former can be sustained by someone themselves while the latter is set externally. A matrix of this is shown in **Appendix 3.** Also demographic variables are commonly investigated as predictors for recycling, where education (+), age (+), being a woman (+), and owning a house (+) are often strongly correlated with recycling behavior, however, it explains only a small part of recycling behavior. (Hornik et al, 1995). Although, single demographic measures may be weak predictors, composite measures like social class might have greater predictive power (Iyer & Kashyap, 2007).

Iyer and Kashyap (2007) used the altruistic-utilitarian framework to look at two mechanisms – incentives and information – that could increase recycling rates. It turned out that both programs are effective, but informational programs appear to have more long-term effects compared to incentives, which are very strong in increasing short-term waste collection rates. Especially information that increases the knowledge of consumers has a lasting effect on recycling output since it influences a person's values and beliefs. This is in line with developments in the literature as indicated by Hornik et al (1995) who concluded that consumer recycling motivation research has switched emphasis from solely external incentives (1970-1982) towards a wider scope including internal incentives (1982-later), where information can be seen as more internal and monetary rewards as more external of nature. This change was fuelled because later research suggested that desired behavior would vanish once purely economic incentives were withdrawn (Hornik et al, 1995). Recycling attitudes and behavior are weakly correlated to environmental attitude implying that both aren't always mutually inclusive and women tend to recycle significantly more than men (Iyer & Kashyap, 2007). There is some evidence that people who recycle plastics, glass, paper and tins are more willing to return their EoL mobile phones (Ogondo & Williams, 2011b). At last, social class is an important factor influencing recycling behaviour (Iyer & Kashyap, 2007).

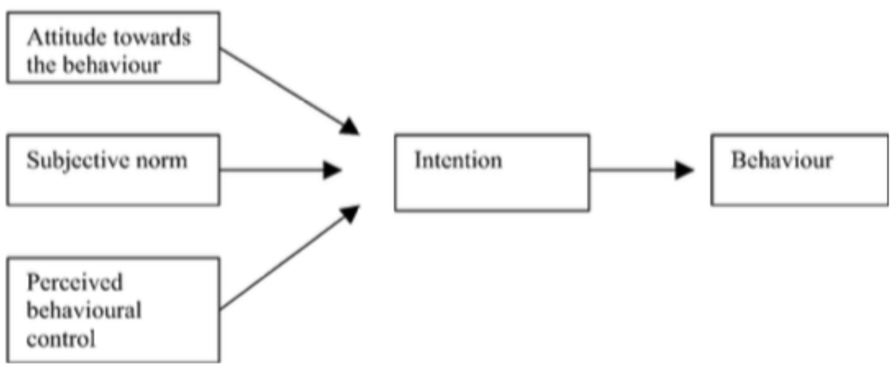
Table 3: A model of consumer recycling behavior by Hornik et al (1995)

Facilitator	Extrinsic incentives	Intrinsic incentives	Internal facilitators	External facilitators
Dependent on	**Utilitarianism**	**Altruism**	**Altruism**	**Utilitarianism**
Factors	Economic Incentives Social Influence Laws and regulation	Locus of control Personal satisfaction Self-sufficiency General satisfaction Resource conservation Psychological attachment	Knowledge of regulations Knowledge of recycling programs Environmental Awareness Internal barriers	Time/money/effort needed Convenience of service
Demographics	Education	Age	Income	Gender

A model of consumer recycling behavior by Ajzen (1991)

Ajzen (1991) proposed another model to predict behaviour which was an extension of the Theory of Reasoned Action, where an individual's intention to perform certain behavior is crucial. This model is known as the Theory of Planned Behaviour (TPB) and with 50.495 citations (Google Scholar, 11-8-2017) the TPB paper of Ajzen (1991) is a well-established theory in cognitive behavioral psychology, which is summarized in **Figure 4**. In general, the stronger the behavioral intention, the higher the chance behavior occurs. TPB provides a framework for systematically investigating factors that influence behavioral choices. Intentions are influenced by three factors: attitudes (evaluation of performing a behavior), the subjective norm (Social pressure to perform a behavior), and perceived control (individual's perception of their ability to perform the behavior) (Tonglet et al, 2004a). TPB recognizes that factors external to the model may influence behavior, and allows adding extra variables as long as these contribute significantly to explaining behavior (Ajzen, 1991). Tonglet et al (2004a) suggested that recycling attitude is a major determinant of recycling behavior. Attitudes can be influenced by having appropriate opportunities, and knowledge to recycle and by not being deterred by time, money and effort required to recycle. Ajzen (1991) has summarized empirical findings of sixteen studies conducted between 1985-1991 that all indicated that the three components of the TPB account for a considerable amount of variance in explaining behavioral intentions (**Appendix 4**). TPB is most commonly used in the form of a questionnaire research design with Likert scale type questions. Commonly used methods to implement TPB are a factor analysis – where attitude, subjective norm, and perceived control are latent variables that are measured by a dedicated set of questions – and regression analysis (Tonglet et al, 2004a; Philippsen, 2015).

Figure 4: The theory of planned behavior by Ajzen (1991)



Extending the Theory of Planned Behavior with respect to recycling behavior

(1) Past and other recycling behavior: According to (Bentler & Speckhart, 1979) past behavior directly affects a person's intention rather than indirect as claimed by Ajzen (1991). Although past behavior doesn't cause future behavior, high behavioral frequency increases the likelihood of similar future behavior (Conner & Armitage, 1998), which is confirmed by Bentler & Speckhart (1979), and Tonglet et al (2004a). As noted by Ogondo & Williams (2011b), there is evidence that people who recycle plastics, glass, paper and tins are more willing to return their mobile phones via take-back services. Tonglet et al (2004b) indicated that perceived control and situational factors are strongly correlated with recycling attitudes. Therefore *(2) knowledge* and *(3) inconvenience* are added to the model, which is in line with facilitators as presented in **Table 3** and with research done by Philippsen (2015) and Kruijs (2016). Knowledge about how to recycle waste has found to be a significant factor by multiple studies as described by Philippsen (2015). When recycling is made easier and more convenient for people who do not even care about the environment, recycling rates will increase (Derksen & Gartrell, 1993). Inconvenient recycling structures are a major deterrent of student recycling behavior (McCarty & Shrum, 1994) and households that regard recycling facilities as more convenient are likely to recycle more frequently (Domina & Koch, 2002). As indicated by Ogondo & Williams (2011b) and Mishima & Nishimura (2016a) people are less likely to hand in their phones if the return infrastructure is perceived as inconvenient. *(4) Moral Norms* complement subjective norms since people can act in a certain way because they truly think it is the right thing to do. Such persons are intrinsically motivated as explained by Hornik et al (1995). Beck & Ajzen (1991), Conner & Armitage (1998), Chu & Chiua (2003), Tonglet et al (2004a), Philippsen (2015) and Saphores et al (2012) extended their models with moral norm factors and found that moral norms significantly influence recycling intentions. (*5) Monetary incentives* can also be included in the TPB model. Amini et al (2014) used the TPB model including monetary incentives and found that rewards and penalties significantly influence a consumer's recycling intention (at the 1% significance level) and that rewards have a higher (β =0.414) influence on the recycling intention than penalties (β =0.214). Tanham et al (2014) have used the TPB methodology in an experimental setting and have also shown that financial incentives serve as motivational techniques in assisting people to perform certain behavior. Bian et al (2015) used TPB to investigate mobile phone disposal willingness for Chinese consumers aged 16-28 and concluded that gender, education, past recycling experience, emotional factors, costs and convenience significantly influence the willingness intention to recycle.

3.2.2 Consumer recycling behavior of mobile phones

Studies addressing mobile phone recycling behavior of consumers are predominantly structured in a similar way in terms of surveying methodology and type of questions. **Chapter 3.2.2** gives a brief, theme based, review of each study that is reviewed and its findings. This gives an overview of which type of questions can be included in this study's questionnaire and provides a basis for comparison.

Replacement frequency. Several studies have shown that people replace their phone on average every year (13-34%), every two years (28-29%), every three years (11-48%) or longer (26%) (Rathore et al, 2011; Ogondo & Williams 2011b; Li et al, 2012; Yin et al, 2016). Other surveys assume that mobile phone life spans are little over a year (Mishima & Nishimura, 2016a), 18 months (GSMA, 2012), 3±1.25 years (Duygan & Meylan, 2015), and in North America a shift is occurring from two-year contracts to one-year lease/upgrade programs indicating shortening life cycles (Deloitte, 2016a). Mobile phones are retiring on average within 22 months in the US (NYT, 2013) within 18-30 months in China (Li et al, 2012; Yin et al, 2014; Kantar, 2016), within 18-25 months in Europe (Polak & Drapalova, 20112; Kantar, 2016). Average storage times are ±4.35 years (Polak & Drapalova, 2012).

Replacement reasons. People replace their phone mainly because it is broken (27-66%), or its technology/style is obsolete/out-fashioned (37-79%) (Rathore et al, 2011; Ogondo & Williams 2011b; Li et al, 2012; Yin et al, 2016). Other reasons mentioned (mainly in Asia) are that phones get lost or stolen (19-37%) (Rathore et al, 2011; Li et al, 2012), or due to upgrades by network operators (13-19%) (Li et al, 2012; Yin et al, 2016), which is significant in the UK with 42% (Ogondo & Williams, 2011b). After replacement, old handsets are hibernating in most cases (30-76%), or are reused (donation/ sold/stolen) by someone else (3-45%). A fraction of the retired devices is recycled (4-21%) or disposed (3-7%) (Rathore et al, 2011; Ogondo & Williams, 2011b; Li et al, 2012; GSMA, 2012; Yin et al, 2014). People keep their old handsets mainly to use it as a spare (28-77%), because they do not know what to do with it (30-60%), due to safety concerns (17-21%) or because they rather give it to a friend than recycle it (11-28%) (Ogondo & Williams, 2011b; Li et al, 2012; Yin et al, 2014).

Hibernation reasons. In the UK, a country with widespread take-back services, over 80% of the people never used such a take-back service and 30-75% are not even aware of them. People that did use them generally say that the take-back schemes are convenient, have nice incentives and have good services (33-54%) (Ogondo & Williams, 2011b). Generally, people are unaware of the recovery opportunities available (Darby & Obara, 2005; Li et al; 2012; Yin et al 2014) or lack the willingness to participate because programs are perceived inconvenient or do not offer the right incentives (Ogondo & Williams, 2011b; Mishima & Nishimura, 2016a). Solutions to increase collection include old-for-new options, and more collection points in communities and business halls (Yin et al, 2016). Important is enhancing convenience and ease of take-back services (Ogondo & Williams, 2011a). Alternately, companies must clarify how recycling contributes to the environment (Li et al, 2012), provide higher monetary incentives/discounts, and better opportunities to safely remove personal data from EoL phones (Ogondo & Williams, 2011a; Li et al, 2012; Mishima & Nishimura, 2016a; Yin et al, 2016). Each strategy aimed to increase collection rates can only be successful when combined with programs that aim to increased consumer awareness (Silveira & Chang, 2010).

Take-back schemes collectors. Collection schemes are mainly set up by charities, retailers, network operators, manufacturers, and specialized “3R” operators (Ogondo & Williams, 2011a). Common methods are postal services (pre-paid envelopes and free shipping labels) (Silveira & Chang, 2010; Ogondo & Williams, 2011a), courier pick-up services (Ogondo & Williams, 2011a), courier take-back-upon-delivery services (Naoko & Manomaivibool, 2011; Weeelectronic, 2017), collection points at service providers, retailers, or kiosks (Silveira & Chang, 2010; Ogondo & Williams, 2011a; Outerwall Inc, 2014), old-for-new discount programs (Silveira & Chang, 2010; Naoko & Manomaivibool, 2011), special take-back events (Silveira & Chang, 2010; TNP, 2013; Telenorgroup, 2017), or municipal collection sites (Wecycle, 2017). In the US and the UK, free shipping labels and envelopes are most popular (Silveira & Chang, 2010), while drop-off locations are popular in Korea (Jang & Kim, 2010).

Willingness to pay. According to Nnorom et al (2009) 50% of the Nigerians surveyed are willing to pay a premium of 20% for sound management of EoL phones. In China 48% agrees to pay the costs of recycling via deposit systems (20%), sales prices (16%), or directly to recyclers (12%) (Yin et al, 2014). Most people think recycling costs should be shared across all stakeholders (37%), born by the private sector (45%) or born by the public sector (18%) (Li et al, 2012). In Macau over 64% agrees to pay between $1.25-12.5 for WEEE disposal (excl. phones) either via an ARF (74%), PDF (64%) or monthly fee (64%) with age, income and education significantly influencing WTP (Song et al, 2012). Wang et al (2011) found that people that prefer ARF dispose their e-wastes in a way that is most confortable for them, people that prefer PDF hold more responsibility to deliver e-wastes to recovery sites, and people that prefer deposit systems are more willing to ask specialized collectors to reclaim on site with certain payment. However, consumers that have a higher WTP to recycle their handsets do not necessarily significantly differ in their disposal habits even though they believe such programs are good (Hanks et al, 2008). In California, the majority of households support an ARF of 1% on consumer electronics. Younger people are more willing to support a 5% ARF (Nixon & Saphores, 2007). One must bear in mind that “stated WTP” often exceeds actual WTP (Brown et al, 1995).

3.3 DISCUSSION

Of all life cycle analysis methodologies, material flow analysis (MFA) is the most suitable to identify mobile phone flow directions and volumes, whereas life cycle assessment (LCA) is more suitable to identify determine the environmental impact and cost of WEEE. Multi-criteria analysis (MCA) is not a widely used tool on WEEE flows and is therefore not used. Hence, MFA will be the method of conduct. MFA studies specifically on mobile phones have been done in multiple countries and each of them differs in the degree of recycling, reuse, disposal, and hibernation. In any case, there is a high potential to increase collection rates. These findings will be compared to outcomes from this thesis in **Chapter 6.** The MFA methodology used in this thesis is addressed in **Chapter 4**.

In terms of behavioral modeling, the TPB of Ajzen (1991) is preferred over the facilitator model of Hornik et al (1995) since TPB serves more as a predictive model rather than a theoretical framework. The TPB emphasizes the effect that attitudes, subjective norm, and perceived behavioral control have on a person’s intention to perform certain behavior. Other studies have extended the TPB by including past and related recycling experiences, moral norms, situational factors (knowledge and inconvenience), and monetary incentives. These are included in this thesis. TPB can be implemented by means of a questionnaire design with a factor and regression analysis where the factors mentioned above are latent (endogenous) and measured by means of questions or observations.

In terms of mobile phone recovery, it can be concluded that mobile phones are replaced mostly within 2.5 years depending on the region, suggesting that people use their mobile phones longer than the typical contract terms (1 or 2 years) offered by telecom service providers. A large share of people keeps their old phones to use it as a spare, or due to a perceived lack of alternatives. People replace a phone mainly because it is broken, technologically obsolete or old fashioned. People are not very eager to participate in recovery programs because they are unaware of them, due to a lack of informational and economic incentives, or inconvenient take-back infrastructures. Best is to educate people about the take-back options, increase the amount of (monetary) incentives and enhance the return infrastructure. In terms of take-back schemes, free postal services and in-store collection points are most commonly used. Some studies have indicated that consumers are willing to pay for the recovery of their EoL devices, however, this doesn’t always express itself in their disposal behavior implying the need for both external and internal facilitators. The methodology for the consumer analysis will be addressed in **Chapter 5**, and its results are discussed **in Chapter 7**.

4. MATERIAL FLOW ANALYSIS RESEARCH METHODOLOGY

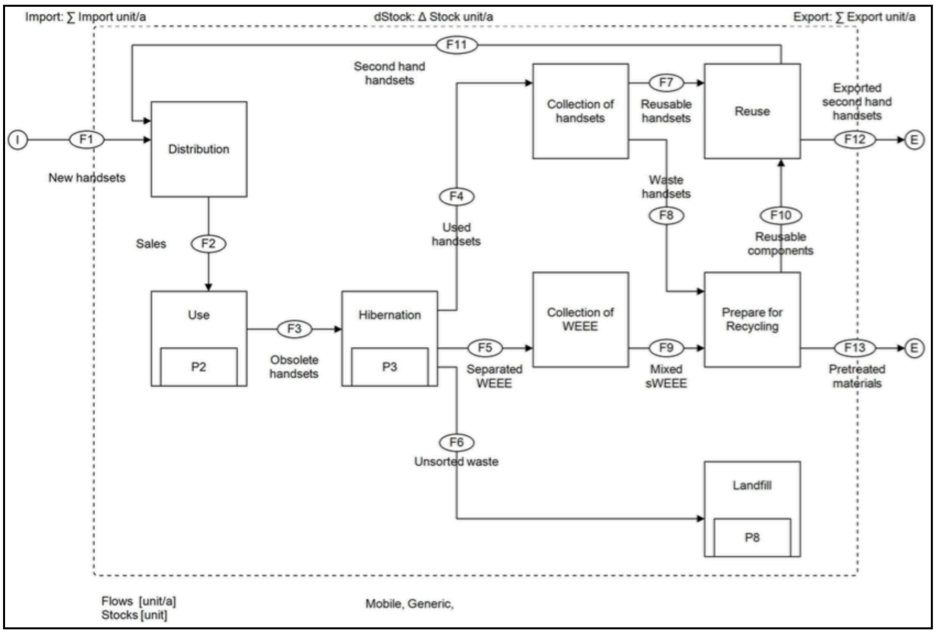
In order to answer SQ1, this study investigates the material flow of (used) mobile phones in the Netherlands for the year 2013. This year chosen because there is no uniform data available for more recent years. So far no comprehensive study on this subject applied to the Netherlands has been published yet. Several methods can be used to estimate the amount of mobile phones that retire and reach the end-of-life phase (Jang & Kim, 2010). **Chapter 4** addresses the way each flow can be measured (based on previous research) by "cluster of flows" from the moment new mobile phones are imported up to the point where EoL mobile phones are exported. **Chapter 4** addresses where data is retrieved from to measure each flow or stock unit and what assumptions are made. This chapter functions as a basis for the MFA of which the results are presented in **Chapter 6**. The research design of this analysis is of a descriptive nature focused on describing mobile phone flows in the Netherlands without any causal relations in mind.

4.1 MEASURING EACH STAGE OF THE MATERIAL FLOW ANALYSIS

This section discusses which options are available to estimate the size of different flows within the MFA system and which option is selected. The MFA framework used in this paper is shown **Figure 5**. Because the system has a certain number of entrances and exists, it follows the mass balance principle [1], which means that a change in a system's stock equals the difference between inflows and outflows (Naoko & Manomaivibool, 2011).

$\Delta M_{stock} = \sum M_{input} - \sum M_{output}$, *with M as the flow mobile phones* [1]

Figure 5: A generic material flow analysis



Source: (Naoko & Manomaivibool, 2011)

Mobile phone imports and sales. All mobile phones that enter the system are assumed to be in the form of imports (F1). Import, and re-export (F8) data are obtained from The Dutch Central Bureau of Statistics (CBS). Furthermore, national sales (F2) estimations are obtained from market research bureaus such as GfK. To simplify the model, the stock of phones in the distribution chain (P1) is ignored, in line with (Naoko & Manomaivibool, 2011; Duygan & Meylan, 2015). A change in the P1 stock is calculated as the difference between imports and sales.

Mobile phones in use. The stock of mobile phones that is in use is assumed to equal the number of mobile phone data subscriptions. Data for this is used from TNO (2012), CBS (2016), ACM (2013), WorldBank (2017), and Oneworld (2017). Naoko & Manomaivibool (2011) used a formula in their MFA to correct for the amount of subscriptions per user (some people use multiple SIM cards per mobile phone, which would otherwise overestimate the number of phones in use). However the formula used from Garner (2007) is based on data that is over ten years old (no smartphones) and its mechanics are not well explained. Therefore and adjusted methodology of Duygan and Meylan (2015) is preferred. In the Netherlands it was estimated that 19.2 million phones were in use in 2016 (VSO, 2016), with 23.3 million mobile phone subscriptions in 2015 (CBS, 2016) this comes down to and average of 1.2 SIMs per mobile phone. The number of mobile phones in the use stock will be corrected with this factor. For the stock in use (P2) this implies that ΔM_{stock} in formula [1] equals the amount of corrected subscriptions at the end of 2013 minus the amount at the beginning of 2013. A positive value for ΔM_{stock} indicates the amount of additional first-time users in 2013. A negative value means that more phones became obsolete than that there were purchased. The differences between total sales and ΔM_{stock} equals replacement sales (Naoko & Manomaivibool, 2011).

Mobile phones obsolescence. It is assumed that the amount of replacement sales equals the amount of mobile phones becoming obsolete that enter the hibernation stock (P3). The Obsolescence flow (F3) can be calculated with different methods. The first method is a theoretical calculation based on the number of mobile phone subscribers and life-span assumptions of mobile phones. Life spans can be averaged (fixed) as done by Jang & Kim (2010), who use multiple cases assuming different life spans. Second, a time-step method can be applied, which basically is the application of formula [1] using mass balances. This method is applied by (Naoko & Manomaivibool, 2011). Third, life spans can be assumed to follow a distribution like a normal (Gaussian) or Weibull Distribution (Chancerel, 2010; Duygan and Meylan, 2015). A Weibull Distribution requires knowing a time-varying shape and a scale parameter (Chancerel, 2010), which are estimated to be 0.7 and 7.6 respectively for the Netherlands in 2005 (Huisman et al, 2013). Duygan and Meylan (2015) used a normal distribution to estimate the number of obsolete mobile phones in Switzerland with an assumed average lifetime of 3 years and a standard deviation of 1.25 years. Although the Weibull distribution is often cited as the best approach to use (Chancerel, 2010), accurate shape and scale parameters are required (Davis et al, 2007). Data from 2005 is too old to be used in this respect. This thesis uses the time step-method and a normal distribution, where the volume of mobile phones becoming obsolete is calculated by multiplying sales in year (t) with the probability of becoming obsolete in year (t,…,T).

Mobile Phones Separate Collection. After mobile phones become obsolete they enter the recycling system mainly through in-store take-back schemes, public collection points, and free postal services as explained in **Chapter 3.2.2** that collect mobile phones separately (F4) for reuse (F7) or recycling (F8) purposes. Whether a phone is reused or recycled depends on its conditions upon collection. It is assumed that 75% of the EoL mobile phones collected by producers can be reused (F7) and 25% is "beyond economic Repair" and is hence send for recycling (F8) (Geyer & Blass, 2010). Also consumer-to-consumer secondary markets are included in the model, for which data is retrieved from

Telecompaper (2016b). To simplify the model, It is assumed that the reusable mobile phones that are collected separately by businesses are exported, which is in line with assumptions made by Chancerel (2010), Naoko & Manomaivibool (2011), and Duygan and Meylan (2015). This has no consequences for the outcomes of the analysis and its implications.

Mobile phones mixed collection*.* Mobile phones can also be collected mixed with other obsolete electronics at designated collection points for reuse and recycling (F5). In Europe, countries rapport their WEEE collection data to the European Union measured in weight per product category (mobile phones are part of category 3 "IT and telecom equipment"). Since mobile phones are not separately collected it is assumed that the probability of reuse is zero, although some components can be reused (F10), which is less than 5% (Chancerel, 2010). To determine the number of mobile phones collected in mixed WEEE, category 3 WEEE data provided by Eurostat (2017), Wecyle (2017), Nederland ICT (2017), and TKSG (2017) is used to make an estimation of the amount of mobile phones in mixed WEEE streams. Since this thesis emphasizes unit flows, the recycling process itself is not addressed and hence it is assumed that phones are only collected, pre-treated, and finally send to recycling abroad. This is in line with assumptions made by Chancerel (2010), Naoko & Manomaivibool (2011), and Duygan and Meylan (2015).

Mobile phones discarding*.* Although being prohibited by European legislation, as indicated by previous research: between 3-7% of all mobile phones is estimated to be is disposed after entering hibernation, where a Dutch market study indicated this rate to be 6% (Telecompaper, 2016b). UNU (2012) researched Dutch WEEE streams and estimated that 1.8% of the overall weight WEEE recovered from residual household waste in the Netherlands consists of "telephones" with an average weight of 0,256 kg. Probably this is because fixed line telephones are incorporated that include charging docks (which are heavier). The same report states that in 2010 of each 3kg WEEE that was generated in IT & Telecom equipment, approximately 0,54kg is incinerated/landfilled (± 18%). According to a representative of Wecycle, the UNU (2012) report and other UNU reports are generally the best to take as a basis concerning mobile phone WEEE flows for the Netherlands. Therefore a landfill rate of 15% is assumed, which is a weighted average of 18% (3/4) of UNU (2012) and the 6% (1/4) of Telecompaper (2016b) for the IT&T category with a 25% uncertainty interval.

4.2 DISCUSSION

Chapter 4 has given insight in the MFA research methodology and its assumptions. As has been indicated is that mobile phone flows have a greater degree of uncertainty the further down the reverse logistic system one gets, implying large bandwidths that have to be taken into consideration. This must be done in order to account for the uncertainty in these flows since these are less well documented. In line with Naoko & Manomaivibool (2011) and Duygan & Meylan (2015) the bandwidth for flows up to the hibernation stock (P3) are assumed to have a 15% uncertainty bandwidth, and for all flows after this point this is assumed to be a 25%. All of the above will be used to create a MFA for units of mobile phones in the Netherlands for the year 2013, of which the results are shown in **Chapter 6.** The MFA is central in answering the first sub-question: SQ1.

5. CONSUMER BEHAVIOR ANALYSIS RESEARCH METHODOLOGY

Chapter 5 addresses the research methodology of the consumer behavioral analysis, of which the results will be addressed in **Chapter 7**. In **Chapter 5.1** the dependent and independent variables are defined and research hypotheses are developed. In **Chapter 5.2** the questionnaire design will be addressed along with the data collection methodology. In **Chapter 5.3** the variables are operationalized, which is done by taking questions from previous research (**Chapter 3.1 and 3.2),** which have either used the Theory of Planned Behavior (TPB) on recycling intentions or did research addressing mobile phone purchase and disposal behavior.

Note that the methodology addressed in **Chapter 5** only focuses on the consumer behavior analysis and not the material flow analysis. Methodology of the latter is already elaborated in **Chapter 4**.

5.1 CONCEPTUAL MODEL AND HYPOTHESIS DEVELOPMENT

As elaborated in **Chapter 3.2.3**, the Theory of Planned Behavior (TPB) is chosen for modeling and predicting consumer recycling behavior. Besides TPB's fixed components (**Figure 4**), this thesis adds additional factors, highlighted in **Chapter 3.2.1**, to extend the TPB model. The dependent and independent variables in the behavioral analysis addressing SQ2 are defined below. Afterwards the hypotheses are established and a conceptual model is created. SQ3 will be researched based on a descriptive analysis, without the use of extensive statistical analysis, using methodologies from Nixon & Saphores (2007), Ogondo & Williams (2011b), and Song et al (2012).

5.1.1 Dependent Variable SQ2

The behavioral intention to recycle mobile phones is the dependent variable of SQ2, and is defined as *"how hard people are willing to try, or how much of an effort they are planning to exert, in order to perform the behavior."* Intentions are directly linked to the actual behavior itself (Ajzen, 1991). Recycling in this thesis' context is defined as a person's effort to hand in their mobile phones for recovery purposes, including reuse via collection schemes. This is because the interest of this thesis is if people are willing to hand in their old handsets rather than storing them. The intention to recycle is the effort a person is planning to put in handing in their used handsets in the future.

5.1.2 Independent variables SQ2

Attitude *"refers to the degree of which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question"* (Ajzen, 1991). In this study recycling attitude is defined as a person's positive or negative evaluation of recycling. The difference between attitude and the behavioral intention is that the attitude is what a person thinks about pursuing certain behavior, whereas the intention is more an indicator of the likelihood of the behavior taking place.

Subjective norm *"refers to an individual's perception of social pressure to (not) perform behavior"* (Tonglet et al, 2004a) and measures the influence of other people on an individual's behavior.

Perceived behavioral control *"refers to a person's belief of how easy or difficult it is to perform a type of behavior"* (Ajzen, 1991). In this study this factor mainly focuses on a person's perception of how easy they think it is to recycle their mobile phones, if there are enough opportunities to recycle and if a person has the knowledge to properly engage in recycling behavior. Hence the knowledge factor described separately in **Chapter 3.2.1** is included in this factor. This factor is in line with the information mechanism as described by Iyer & Kashyap (2007) and is more internal of nature.

Moral norm *"refers to an individuals perception of the moral correctness or incorrectness of performing a behavior,"* which takes into account personal feelings, and perceived responsibility to perform or not perform certain behavior (Conner & Armitage, 1998). In this thesis, moral norm refers to a person's moral belief towards recycling of e-waste.

Situational factors (Inconvenience) *"refers to physical factors which facilitate or inhibit recycling behavior"* (Tonglet et al (2004a). In this thesis it refers to the belief of a person that that recycling infrastructure is inconvenient, and whether recycling takes much time, money or effort.

Monetary incentives are a form of external facilitators as described by Hornik et al (1995). Monetary compensation has been found to increase recycling in the short-term (Hornik et al, 1995; Iyer & Kashyap, 2007). As illustrated in **Chapter 3.2.2** research on mobile phone disposal behavior indicated that higher monetary incentives are likely to increase a person's intention to return their retired handsets. On the other hand, there are monetary fees that can be levied that aim to let the polluter pay for its own disposal behavior. It is likely that a fee (ARF, PDF, DRS) steers consumer behavioral intentions in the right direction (recycling) just like a Pigouvian tax aims to do by internalizing externalities in prices (Rosen & Gayer, 2010). Therefore a factor for monetary incentives is incorporated in this model.

Past and other recycling behavior influences the possibility of behavior happening in the future if it has happened frequently. Past recycling behavior is defined as whether a person has recycled or handed in their mobile phones in their lives at least once. Other recycling behavior is someone recycles domestic or electronic waste (e.g. glass, paper, plastic), which may influence a person's intention to recycle EoL mobile phones (Ogondo & Williams, 2011b). Therefore recycling behavior is split in past mobile phone recycling behavior and other waste recycling behavior.

Demographics can influence the possibility of recycling to take place. As discussed in **Chapter 3.2.1**, variables like age, gender, and education are highly correlated with recycling behavior (Hornik et al, 1995) and with age, income and education significantly influencing willingness to pay for recycling (Song et al, 2012). In this thesis demographic variables are added which are to be found significant in previous research on e-waste recycling and consumer willingness to pay for recycling. TPB does not factor in demographic variables. These variables can be accounted for if and only if they influence the underlying beliefs that determine the endogenous factors used as predictors (Knabe, 2009). Still, one can check whether sub-groups within a sample have significantly different recycling intentions using ANOVA (Tonglet et al, 2004a), Independent sample T-tests, or Mann-Withney Tests (Field, 2013).

5.1.4 Hypotheses and Model

Using the literature reviewed in **Chapter 3.2**, and the variable definitions above, nine hypotheses are constructed (which are graphically represented in **Figure 6**). These will be tested by means of a logistic regression. This will be elaborated in more detail in **Chapter 7.3**.

Hypothesis 1: Students that have a positive attitude towards recycling are more likely to have the intention to recycle their mobile phones in the future.

Hypothesis 2: Students who perceive a high subjective norm to recycle are more likely to have the intention to recycle their mobile phones in the future.

Hypothesis 3: Students who have a higher perceived behavioral control to recycle are more likely to have the intention to recycle their mobile phones in the future.

Hypothesis 4: Students who perceive a high moral norm to recycle are more likely to have the intention to recycle their mobile phones in the future.

Hypothesis 5: Students who perceive recycling as inconvenient are less likely to have the intention to recycle.

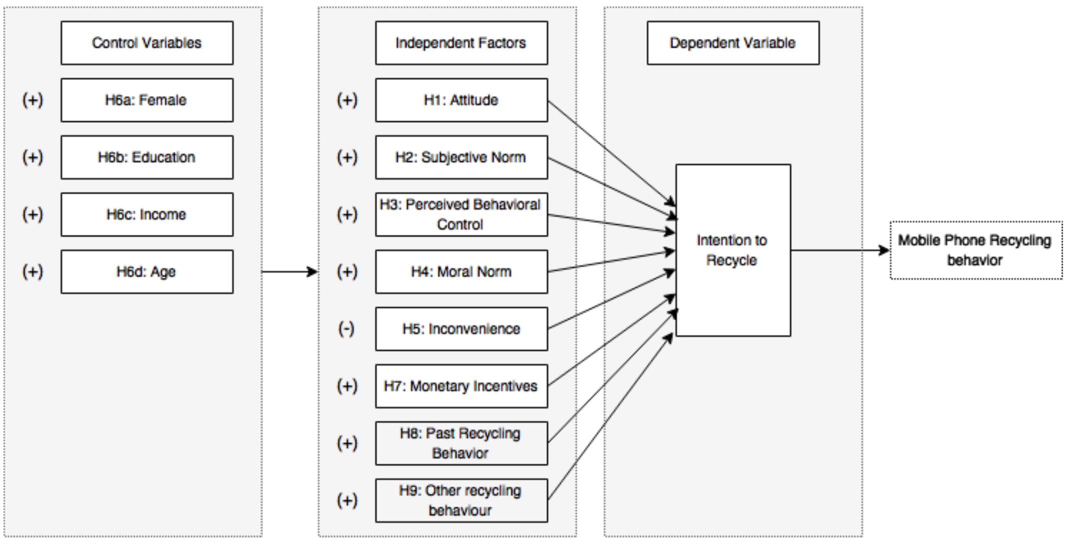
Hypothesis 6: Students who are female, older, and more highly educated are more likely to have the intention to recycle their mobile phones in the future.

Hypothesis 7: Students are being motivated to recycle by monetary incentives

Hypothesis 8: Students who have recycled their mobile phones in the past are more likely to have the intention to recycle their mobile phones in the future.

Hypothesis 9: Students that recycle domestic and electronic wastes more are also more likely to recycle their mobile phones.

Figure 6: Conceptual model



Note that: mobile phone recycling behavior is not observed, only a person's future intention can be observed.

In **Figure 6**, the independent factors are generated by means of a factor analysis, where the factors are created based on questions that are addressed in **Chapter 5.3**. The dependent variable (intention to recycle mobile phones in the future) is a binary variable that is generated based on question INT_3 (**Appendix 5**). The demographic control variables influence the dependent variable via the independent factors, which is a main assumption of the Theory of Planned Behavior. The dependent variable is binary and equals 1 if someone is at least somewhat likely to recycle their mobile phones in the future (=1|INT_3 = 5,6,7) and equals 0 if someone is neutral or less likely to recycle their mobile phones in the future (=0|INT_3 = 1,2,3,4). The binary nature of this dependent variable implies that a binary logistic regression is used in investigating the hypotheses. This is explained in more detail in **Chapter 7.3**.

5.2 RESEARCH DESIGN AND DATA COLLECTION

The main purpose of **Chapter 5** is to investigate which factors explain why students recycle their used mobile phones and why not. As addressed in **Chapter 3.2.1**, the Theory of Planned Behavior (TPB) is proven to be useful to explain such behavior and several additional explanatory factors are added which are described in the conceptual model in the previous paragraph. **Chapter 5.2** addresses the research design (online questionnaire) and data collection methodology.

5.2.1 Research design

The intention to recycle mobile phones is the independent variable in this research and is therefore the main variable interest of the statistical analysis. Willingness to pay for recycling, along with EPR scheme preferences are the center attention of the descriptive analysis. The former is said to directly predict actual behavior if a person can decide at will to perform or not perform the behavior (Ajzen, 1991), which is the case in this research topic of interest. All the independent variables, despite demographics, are assumed to be directly influencing the intention to recycle. To test whether these influences are significant, an online questionnaire is issued to generate a dataset.

5.2.2 Population and sampling technique

The focal unit of analysis in this research is "individual consumers of mobile phones", which basically covers the far majority of the Dutch population. A survey is distributed among Dutch consumers between the age of 18 and 27 since this group has smartphone penetration rates of over 96% (Telecompaper, 2016b) and is the group of people that are most easily reachable by the researcher. Nonprobability sampling is used known as "convenience sampling", where the researcher relies on available subjects. This method is frequently used by university researchers who conduct surveys under students due to the ease and frugality of such a method. However, it has implications for the external validity of the research and therefore outcomes of this study should not be overgeneralized (Babbie, 2013). This is a main reason why findings from foreign studies should not be used to make conclusions about Dutch consumers. Most of the people surveyed, due to their age, will be students.

The research design of the survey[2] (experimental research) is partly descriptive but mainly explanatory. First it aims to describe patterns in student mobile phone use and disposal behavior, like for example handset replacement frequency, replacement motives, and disposal method. Second it aims to explain a respondent's future recycling intention of mobile phones making use of the TPB framework addressed in **Chapter 5.1.** This is done by testing research hypotheses (**Figure 6**) using a logistic regression model. Again because convenience sampling is used, explanations may yield useful insights, but should not be generalized too easily. Still, convenience sampling will be used because there is insufficient data available on the Dutch consumer population level regarding their

[2] Note that research methodology addressing the mobile phone material flow analysis, which is entirely of a descriptive nature, has already been addressed in **Chapter 4**.

mobile phone disposal patterns and their motives. There is some general descriptive information for the Netherlands available from Telecompaper (2016a) and Deloitte (2016b), but both yield no basis to determine underlying causes.

5.2.3 Data collection and questionnaire design

The survey method of conduct is an online survey that is created using the Qualtrics Survey Tool that is supported by the Erasmus University Rotterdam (EUR). The survey is distributed in Facebook "groups" with large amounts of Dutch students and via Whatsapp. The survey can be filled in both on mobile phones and personal computers. The survey contains a brief introduction about the intention of the survey, to put the respondent in the proper frame of mind for answering the questions (Babbie, 2013). However, the introduction is not too detailed in order to avoid biased answers, since typically people tend to fill in what they think researchers want to hear, or what is more socially desirable. People tend to be more honest when there is greater "social distance" between themselves and their interviewers, which is why the survey has to be filled in anonymously (Holbrook et al, 2003). Questions with negative items are avoided as much as possible since people tend to read over words like "not" which affects research outcomes (Babbie, 2013). Previous research has indicated that respondents are more likely to complete the survey if there is a process indicator (Couper et al, 2001), which can be added in Qualtrics. The questionnaire structure is presented in **Table 4**. To be consistent, questions related to SQ2 are asked first (Part 1), and questions related to SQ3 (Part 2) are asked afterwards. Demographic information is asked at last (Part 3) since people are more eager to fill in "sensitive information" when they are stated at the end of the survey and because the already have invested time to fill in the rest of survey (Dobosh, 2017).

Questions are taken from previous/comparable research on recycling, e-waste recycling, and mobile phone disposal behavior. Survey questions and their sources are located in **Appendix 5**. Adopting questions from other research has the benefit that these questions are valid when the research is done correctly and it allows for comparability with results form this research.

Table 4: Overview of factors, variables and question types

Part	Factor/Variable	Abbr.	# Questions	Type of questions
1	Attitude	ATT	6	Likert scale (7 alternatives)
	Subjective norm	SUB	3	Likert scale (7 alternatives)
	Moral norm	MOR	4	Likert scale (7 alternatives)
	Perceived behavioral control	PBC	6	Likert scale (7 alternatives)
	Inconvenience	INC	5	Likert scale (7 alternatives)
	Monetary incentives	MON	3	Likert scale (7 alternatives)
	Other recycling behavior	ORB	2	Likert scale (7 alternatives)
	Past recycling behavior	PRB	2	Likert scale (3 alternatives)
	Behavioral intentions to recycle	INT	4	Likert scale (7 alternatives)
2	Mobile phone consumption	CONS	3	Multiple choice (single answer)
	Mobile phone replacement	REP	4	Multiple choice (single answer and multiple (2) answers)
	Mobile phone recycling WTP	WTP	10	Likert scale (7 alternatives) and Multiple choice (single answer)
3	Demographics	DEM	5	Open Question and Multiple choice (Single answer)

As presented in **Table 4**, the questionnaire consists of 57 questions (41 Likert-scale and 15 multiple choice and 1 open question (age) spread over 13 factors and three parts. Of part one, each question is dedicated to one Factor. Likert scales range from three to eleven options and using a scale anywhere form five to eleven points is recommended and an increased number of point scales is said to increase the reliability of a respondent's answer (Friedman & Amoo, 1999) and therefore decreases the degree of "random guessing". Seven points is then optimal since people differ in weak, moderate and strong feelings both negatively and positively (Alwin & Krosnick, 1991) and they have the option to be neutral. For one Likert-scale question only three points are used indicating whether people ever have recycled multiple phones, one phone or no phones in the past. Studies have also indicated that survey respondents are biased to the left side of the Likert scale, which should be kept in mind (Friedman et al, 1994). Other questions are closed and multiple choice, with some of them offering the option to give two answers (e.g. two main reasons of keeping your old mobile phones).

5.3 OPERATIONALIZATION OF MODEL VARIABLES

Chapter 5.3 explains how the different factors from the TPB model are measured. As explained, questions are based on questions from comparable research and are summarized by factor in **Table 4**. Part 1 is focused on addressing SQ2 and the TPB model. Part 2 emphasizes SQ3 in the form of a descriptive analysis of mobile phone consumption and disposal behavior along with analyzing consumer willingness to pay for recycling via various fee structures (ARF, PDF, DRS).

5.3.1 Part 1

Attitude is measured using six questions. The first three questions measure to what degree people think that e-waste recycling is (1) useful, (2) rewarding, (3) responsible (Tonglet et al, 2004a). Question four (4) measures whether the respondent is interested in e-waste recycling (Knusse & Yule, 2008). The last two measure respondents whether (5) believe that e-waste recycling is good for the environment and whether (6) they make great effort to recycle e-waste (Kelly et al, 2006).

Subjective norm is measured using three questions. The first two questions measure whether respondents are (1) expected to recycle by people in their environment and (2) whether people in their environment would approve it if they would recycle (Tonglet et al, 2004a). The third questions measures whether a person is copying behavior of other people by asking (3) whether the person would recycle if more people would recycle (Knusse & Yule, 2008).

Moral norm is measured before perceived behavioral control because the latter would be asked more specific in the relation to mobile phones, whereas attitude, subjective norm and moral norm are more about recycling in general. Moral norm is measured using questions from Tonglet et al (2004a) which asks respondents (1) whether they think throwing products away when they can be reused is wrong, (2) if not recycling your e-waste is wrong, (3) whether they would feel guilty if they would not recycle their e-waste, and (4) if people must share the responsibility to recycle e-waste.

Perceived behavioral control asks about mobile phone recycling in particular using six questions. Four are from Tonglet et al (2004a) and ask (1) whether a person knows that mobile phones can be recycled, (2) if they know how they can recycle them, (3) if they know where to bring them to be recycled, and (4) whether they think recycling their mobile phones is easy. The last two questions measure (5) if the respondent thinks that they have plenty of opportunities to recycle their mobile phones (Knusse & Yule, 2008) and (6) if they would recycle their mobile phones when they were given more information about the advantages of recycle (Kelly et al, 2006) them.

Inconvenience is measured using five questions. The first three questions are mainly focused on whether a person thinks mobile phone recycling takes too much (1) time, (2) effort, or whether it is (3) too complicated. The latter two questions are more in line with research done towards mobile phone disposal behavior and ask (4) whether people are being motivated to recycle their mobile phones and (5) if they trust current recycling programs for mobile phones (e.g. in terms of safety of personal data) (Mishima & Nishimura, 2016a). If respondents are not being motivated or do not trust these programs, the degree of inconvenience is higher.

Monetary incentives are measured using three questions and are in line with (Kruijs, 216). Each question basically asks if a consumer is willing to recycle if they have to (1) pay for it, (2) if they would do it for free, and (3) whether they would return their phones if they get money for it.

Other recycling behavior is measured using two questions about whether the respondent has (1) recycled ordinary household waste (Philippsen, 2015), or (2) electronic waste in the past year. The second question is based on the first question, but not obtained from a certain source. Since the independent variable concerns the intention to recycle mobile phone, recycling e-waste in general can serve as related recycling behavior considering e-waste other than mobile phones.

Past recycling behavior is measured with two questions asking whether a person has (1) recycled or traded in their mobile phones, or (2) whether they have sold or given away their mobile phone in the past. Basically only question (1) measures the intention to recycle, but question (2) gives an indication whether people keep their old mobile phones or whether they have given it away giving it a second life via reuse on the secondary market. As shown in **Table 4** a Likert scale of three is used indicating if a person has done (1) or (2) multiple times, only once or never for both alternatives.

The behavioral intention to recycle is measured using four questions asking whether respondents are planning to recycle their (1) household waste, or (2) e-waste in the future. The latter two questions identify intentions to do (1) and (2) of the "past recycling behavior" factor in the future.

5.3.2 Part 2

Mobile Phone consumption addresses questions that concern (1) how long people on average use their phone before replacing them, (2) how many phones they have purchased and (3) how many of these still they still have in their possession. These questions are based on **Chapter 3.2.2**.

Mobile Phone replacement addresses questions considering the reasons (1) why people replace their mobile phones, (2) what did they do with their old phones, (3) what incentives would be attractive to them to recycle or hand in their phones and (4) for what reasons people keep their phones. These questions are based on research reviewed in **Chapter 3.2.2**.

Mobile phone recycling WTP addresses the consumer's willingness to pay. First, respondents are asked which stakeholder (Government, mobile phone producers, retailers/telecom service providers, consumers, shared responsibility) they think should bear the recycling costs (Yin et al, 2014). Then, respondents are asked whether they agree with the statement that: consumers are the only end-users of mobile phones and are accountable for at least a part of the recycling costs (Yin et al, 2014).

After these two initial questions the respondents get 6 statements (Likert scale with seven alternatives) based on research done by Yin et al (2014) and Song et al (2012). These statements ask respondents: if an ARF, PDF, or DRS on the sales/disposal of mobile phones is levied, (a) would this make you more aware of the importance of recycling and (b) would this motivate you to recycle your mobile phones. Both (a) and (b) are asked for each method, hence six statements. This way one can see whether consumers have a preference in terms of awareness and incentives.

Question nine addresses consumer willingness to pay via and ARF/PDF as a percentage of a mobile phone's sales price (<1%, 1, 2, 3, 4, 5, 5%>). It is important to note that ARFs should ideally be based on the average weight of each product group, but a percentage-based ARF is chosen in this report, because otherwise it would too complex. Now, support for an ARF can be more easily extended to other products, because consumers answer the question based on the value of their purchases, rather than size (Nixon & Saphores, 2007). According to Nixon & Saphores (2007), almost no consumer in California is willing to pay more than 5% ARF and therefore the alternatives in this survey are restricted to a max of "5%>".

Question ten measures (a) what amount of deposit (DRS) respondents find acceptable to pay on the purchase of mobile phones and (b) if they are motivated to return their old handsets to reclaim their deposit. This is done for deposits ranging from €0 - €5, … , €20 - €25, €25+.

5.3.2 Part 3

The final part "Demographics" asks five questions about the respondent's age, gender, education, study discipline and disposable income (income after all fixed costs). According to Song et al (2012) willingness to pay for e-waste recycling is significantly influenced by age, education and income.

6. RESULTS: MOBILE PHONE MATERIAL ANALYSIS

Chapter 6 discusses the results of the MFA that has been conducted on the focal unit: units of mobile phones, in the Netherlands for the year 2013. Each paragraph in this chapter is dedicated to a certain part of the MFA framework, of which the methodology is discussed in **Chapter 4**. MFA components and definitions used in **Chapter 6** are introduced and explained in **Chapter 4**.

6.1 MOBILE PHONE IMPORTS AND SALES

It is estimated that €8.68 billion worth of mobile phones and smartphones were imported in 2013 in the Netherlands (CBS, 2017). In 2013, the total amount of ICT goods and services imported was €48.2 billion of which €38.6 billion, or 76%, was re-exported (CBS, 2016). Dutch re-exports are very high due to its position as a gateway to Europe. When assuming this percentage to equal Dutch re-exports of mobile phones, this yields that €2.08 billion of mobile phones entered the Dutch System in 2013. Assuming that the average selling price (ASP) of smartphones in Europe was €408[3] in 2014 (GfK, 2015), this implies that ±5.1 million (Mln) units entered the Dutch system. It is estimated that 4.6 Mln Smartphones were sold (Tweakers, 2014). Given that smartphones have an 85% market share (GfK, 2015) ±5.4 Mln mobile phones were sold in 2013. Uncertainty intervals of 15% are assumed for flows up to the obsolescence phase, and 25% in later phases (**Chapter 4.2**). The estimated difference between sales and imports implies a decrease in the distribution stock (P1) equal to 300K.

6.2 MOBILE PHONE IN USE

Dutch mobile phone subscription numbers are shown in **Table 5**. Oneworld (2017) and WorldBank (2017) have similar estimates of subscriptions per 100 inhabitants. Combining these numbers with Dutch population figures from CBS (2017) implies a total of 19.5 Mln mobile phone subscribers to be present in 2013. This is 2 Mln lower than figures stated by CBS (2016) and slightly above figures stated by ACM (2013). Numbers provided by ACM Telecommonitors are in line with CBS (2016) and are remarkably larger than figures from WorldBank and Oneworld. However, figures provided by TNO (2012) are in line with the latter two. Because different sources cover different periods, it is chosen to take the calculated figures (Based on Oneworld and Worldbank) for '06-'09 and figures of the ACM Telecommonitor for '10-'13. Outcomes are corrected with a "SIM per user factor" of 1.2 as explained in **Chapter 4**. **Table 5** indicates that 17.813 Mln mobile phones were in use in 2013.

Table 5: Number of mobile phone subscriptions in the Netherlands

Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Source
Per 100 Inhab.	105	117	124	121	115	118	117	..	117,41*	..	Oneworld (2017)
Per 100 Inhab.	..	..	..	..	115,4	119	118	116,2	116,4	123,5	WorldBank (2017)
Population (x1000)	16.334	16.358	16.405	16.486	16.575	16.656	16.730	16.780	16.829	16.901	CBS (2017)
Total (x1000)	..	..	..	..	20.600	21.800	21.700	21.700	22.600	23.300	CBS (2016)
Total (x1000)	..	..	..	..	19.310	19.648	19.346	19.339	..	..	ACM (2013)
Total (x1000)	..	..	..	..	20.627	21.688	21.859	21.375	21.973	23.199	ACM**
Total (x1000)	17.058	18.453	19.745	19.697	19.243	19.996	..	..	..	..	TNO (2012)
Total (x1000)	17.151	19.139	20.343	19.948	19.061	19.654	19.575	19.498	19.759	20.872	Calculation
Total (x1000)	17.151	19.139	20.343	19.948	20.627	21.688	21.859	21.375	21.973	23.199	Phone Subscriptions
Total (x1000)	14.293	15.949	16.953	16.623	17.189	18.073	18.216	17.813	18.311	19.333	Mobile Phones in Use

** Source: https://www.indexmundi.com/g/r.aspx?v=4010&l=nl* *** Source: ACM Telecommonitor 2012, 2013 and 2016*

[3] It is assumed that import, export and re-export values equals the average product sales value.

6.3 MOBILE PHONE OBSOLESCENCE

First-time sales equal the difference of the "phone in use stock" (P2) at time (t) and time (t-1). In 2009 and 2013 this is a negative value indicating that more mobile phones became obsolete than are purchased (**Table 6**). Total smartphone sales figures by year are obtained from various sources, most of them quoting research done by GfK. Total mobile phone sales equal smartphone sales divided by smartphone market share in the Netherlands. For 2008 global market shares were used as baseline. For 2009, no information is available; hence a 25% market share is assumed, which is higher than 2008 and smaller than 2010. The amount of mobile phones becoming obsolete between 2008-2013 adds up to 28.5 Mln phones (**Table 6**), which is estimated with the time-step method. Of this 28.5 Mln, 5.815 Mln became obsolete in 2013. The replacement period shown is calculated by dividing the amount of phones in use at time (t-1) by replacement sales (obsolete phones) in time (t). Sales data prior to 2008 could not be found and are therefore omitted. When assuming that life-spans follows a Normal Distribution (μ=3, σ=1.25; Duygan & Meylan, 2015; **Chapter 4.1**) it is estimated that 5.35 Mln mobile phones became obsolete in 2013 (**Table 7**), which is ±0.45 Mln lower than the estimation of 5.8 Mln when using the time-step method (**Table 6**)**.** The calculation is made using a cumulative normal distribution, where annual obsolescence equals the difference in cumulative value between year (t) and (t-1) multiplied with the sales of the base year. The amount that has become obsolete in 2013, is the sum of all obsolete estimations based on the normal distribution and purchase data from the years 2008 through 2013. Taking the average value of the two estimations done –the time-step method (5.815 Mln) and the normal distribution method (5.349 Mln) – implies that an average estimated ±5.582 Mln mobile phones became obsolete in 2013. This means that these researched the end-of-life phase for its first owner.

Table 6: Subscriptions, sales and replacement of phones in the Netherlands 2007-2013

Year	Connections/ Inhabitant	Phones/ Inhabitant	Dutch Population (x1000)	Phones in Use (x1000)	Δ Phones in use (x1000)	Total Sales (x1000)	Obsolete (X1000)	Replacement Period
2007	1,17	0,98	16.334	15.949	-	-	-	-
2008	1,24	1,04	16.358	16.953	1.003	3.782[a]	2.778	5,74
2009	1,22	1,01	16.405	16.623	-329	3.600[b]	3.929	4,31
2010	1,25	1,04	16.486	17.189	566	5.833[c]	5.268	3,16
2011	1,31	1,09	16.575	18.073	884	5.930[d]	5.046	3,41
2012	1,31	1,09	16.656	18.216	143	5.864[e]	5.721	3,16
2013	1,28	1,06	16.730	17.813	-403	5.412[f]	5.815	3,13
Total/Average							28.557	3,82

[a] Source: Smartphone sales volume (Marketingfacts, 2012); Smartphone Dutch market share (Gartner, 2009); (Gartner, 2010)
[b] Source: Smartphone sales volume (zdnet, 2010); Smartphone global market share (Gartner, 2011); (Gartner, 2010)
[c] Source: Smartphone sales volume (Marketingfacts, 2012); Smartphone Dutch market share (Marketingfacts, 2012)
[d] Source: Smartphone and cell phone sales volumes (GfK, 2011)
[e] Source: Smartphone sales volume (Tweakers, 2014); Smartphone market Dutch share (calculation based on average market shares of 2011 and 2013)
[f] Source: Smartphone sales volume (Tweakers, 2014); Smartphone market share (GfK, 2015)

Table 7: Obsolete mobile phones estimation in 2013 using a normal distribution

Purchase Year	2008	2009	2010	2011	2012	2013	Obsolete
Total Sales	3.782	3.600	5.833	5.930	5.864	5.412	Cumulative
Obsolete in2008	207	-	-	-	-	-	207
2009	594	197	-	-	-	-	791
2010	1.090	565	320	-	-	-	1.975
2011	1.090	1.037	916	325	-	-	3.368
2012	594	1.037	1.681	931	321	-	4.565
2013	176	565	1.681	1.709	921	297	5.349

Source: Author's own calculations using total sales data from table 5 and a Normal Distribution with (μ=3; σ=1.25)

6.4 MOBILE PHONE COLLECTION

6.4.1 Mobile Phone Collection – Mixed WEEE

The NVMP Association is responsible for WEEE collection, whose operational implementation is done by Wecycle (NVMP, 2017). Dutch WEEE collection information regarding category 3 IT & Telecom Equipment (IT&T)[4] is presented in **Table 8**, which indicates that Dutch collection[5] rates for this are increasing from 31% in 2008 to 51% in 2014, with recovery rates (reuse + recycling + energy recovery) over 95% of which around 85% is recycled (material recovery), 0.0% is reused (refurbished), and 15% is used for energy recovery in 2013. This confirms the assumption made in **Chapter 4** that reuse rates of mobile phones collected with mixed WEEE are negligible (zero).

Table 8: WEEE category IT & Telecom (IT&T) equipment information in the Netherlands

Year	Measure	2008	2009	2010	2011	2012	2013	2014
Products Put on Market (POM)	Tonnes*	73.846	57.161	58.891	60.451	52.913	49.953	57.988
Waste collected	Tonnes	23.070	22.624	20.621	19.444	17.626	14.438	29.701
Collection Rate	%	31,2%	39,6%	35,0%	32,2%	33,3%	28,9%	51,2%
Collection per capita	Kg/Capita	1,37	1,34	1,23	1,09	1,04	0,84	1,72
Recovery	Tonnes	22.458	22.362	19.890	17.091	17.019	14.041	28.270
Recovery Rate	%	97,3%	98,8%	96,5%	87,9%	96,6%	97,3%	95,2%
Reuse	Tonnes	12	13	-	18	-	-	-
Reuse Rate	%	0,1%	0,1%	0,0%	0,1%	0,0%	0,0%	0,0%
Recycling	Tonnes	18.808	19.086	17.370	15.240	14.946	11.968	23.451
Recycling Rate	%	83,7%	85,3%	87,3%	89,2%	87,8%	85,2%	83,0%
Rest	Tonnes	3.638	3.263	2.520	1.833	2.073	2.073	4.818
Energy Recovery Rate	%	16,2%	14,6%	12,7%	10,7%	12,2%	14,8%	17,0%

Source: (Eurostat, 2017)

Table 9: Total WEEE collection figures from Eurostat and Wecycle

Total WEEE Collection	2012	2013	2014	Source
Total WEEE Collected (tonnes)	123.684	117.499	141.805	Eurostat (2017)
WEEE Collected by Wecycle (tonnes)	121.200	114.700	111.200	Wecycle (2017)
WEEE collected by other initiatives (tonnes)	2.484	2.799	30.605	Own Calculation

Wecycle is a Dutch non-profit collecting WEEE via 317 municipalities, 8,500 stores, 1,000 companies, 70 circuit shops, 170 Farms, 2,000 schools and consumers. The majority of WEEE collected comes from municipalities (60%) and the rest from stores (40%) (Wecycle, 2017). The part of NVMP responsible for the collection of WEEE category 3 (IT&T) is Stichting ICT Milieu, which is the compliance scheme for over 300 companies from the IT and telecom sector (NVMP, 2017). As presented in **Table 9,** the Netherlands has collected 117.5K tonnes of WEEE (Eurostat, 2017) of which Wecycle collected 114.7K tonnes (Wecycle, 2017) in 2013. When assuming that Wecycle handled all WEEE collected in 2013, a total of 14.4K tonnes (**Table 9**) of category 3 WEEE is collected, of which approximately 1% can be attributed to mobile phones and tablets (Nederland ICT, 2017). When assuming an average weight of 200 grams per unit (phones weight ± 150 grams, see **Appendix 1**, but tablets can way up to 600 grams (Vera, 2012)), approximately 720K handsets are collected and recycled. This equals a recycling rate of 13% (5.582 Mln = 100%, see **Chapter 6.3**). This is in line with Deloitte (2016) and Telecompaper (2016b), which estimated that ±14% of the Dutch consumers in 2015 sold their mobile phones to recycling companies or traded these in at service operators.

[4] *IT&T composition is shown in **Appendix 6**.*
[5] *For collection, reuse and recovery definitions see **Chapter 4***

However, according to TKSG (2017) – The Dutch government - only 200K mobile phones are recycled via Wecycle in 2013, which is estimated to total 225K handsets when including collection points of competitors. When including mobile phones collected by other recyclers via direct channels with retailers and telecom service providers an estimated 450K handsets are estimated to be recycled (TKSG, 2017). This significantly differs from the estimation using composite IT&T collection figures assuming numbers provided by Eurostat (2017), Nederland ICT (2017), and Wecycle (2017). Because of this discrepancy, an average of both estimations (450K and 720K) is taken, which equals 585K with an assumed 25% uncertainty interval to address for the high degree of uncertainty. It is expected that information provided by TKSG (2017) are more reliable since these have been used by the Dutch government and are specified in number of mobile phones rather than being estimated from an embracing WEEE category (IT&T).

6.4.2 Mobile phone collection – separate collection and landfilling

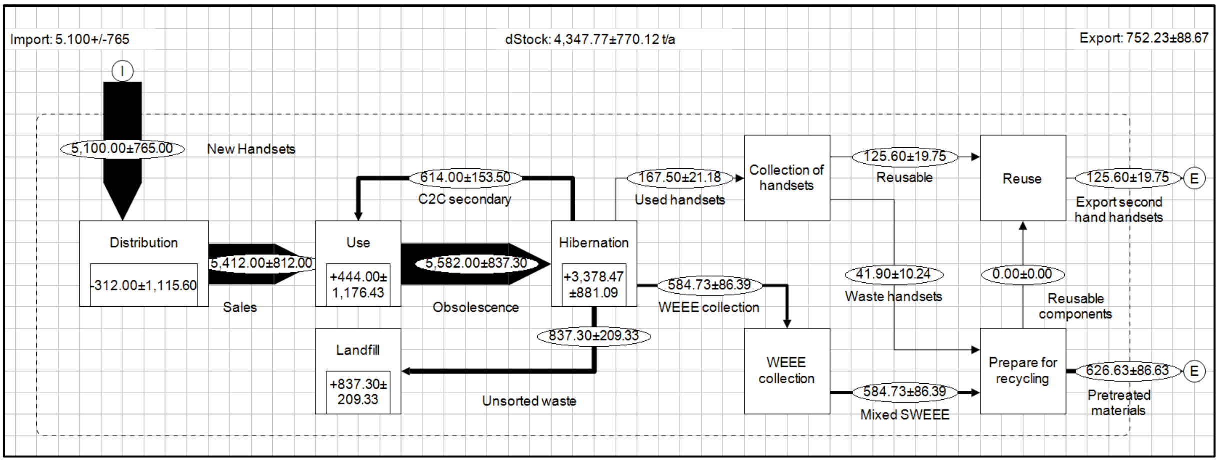
The so-called "re-commerce" market, where refurbished and second hand products are sold, is growing annually where big companies like Ebay, and specialized companies like reBuy and Leapp are operating in. Especially for mobile phones that have high first hand prices, secondary markets can be interesting (Emerce, 2016). Globally, it is estimated that 120 Mln (7% of all smartphone sales) used smartphones were sold in 2016, compared to 80 Mln in 2015 (5% of all smartphone sales) and 4% in 2014 (Deloitte, 2016a). Although more companies sell refurbished phones, it is very difficult to estimate the size of the refurbished market in the Netherlands. Since global estimations of 2014 (4%), 2015 (5%) and 2016 (7%) exist, it is assumed that the business-to-consumer (B2C) secondary market for mobile phones equals 3% of all mobile phone sales in 2013. This is in line with findings from Naoko & Manomaivibool (2011) that showed that 2-3% of EoL mobile phones are separately collected for reuse and reselling purposes in Finland and Germany respectively. Note that Naoko & Manomaivibool (2011) used a 25% uncertainty interval in this assumption. It is also in line with Telecompaper (2016a) that indicated that 3% of the Dutch population sold their used phones directly to a company. For the Netherlands in 2013 this indicates that approximately 167.5K (3% of 5.58 Mln) mobile phones were separately collected (F4). Probably an even larger amount is sold directly in consumer-to-consumer (C2C) markets. As presented by Telecompaper (2016a): 11% of the people surveyed sold their phone via C2C markets. This indicates that approximately 614K (11% of 5.58 Mln) mobile phones have been given a second life in the C2C market in 2013 indicating that the total reuse rate via the secondary market place is approximately 14% per year of all mobile phones that are becoming obsolete. It is assumed that 15% (**Chapter 4**) of all mobile phones becoming obsolete each year are discarded (landfilled), which would be approximately 837.3K units (15% of 5.58 Mln).

6.5 DISCUSSION

6.5.1 Dutch material flow analysis outcomes for the year 2013

The outcomes of the analysis described in **Chapter 6.1-6.4** are summarized in **Figure 7**, which is created using the STAN 2.5 Program (a free MFA software tool). The results show that 5.1±0.765 Mln mobile phones entered the Netherlands and that 5.412±0.812 Mln phones are sold resulting in a decrease of 0.312±1.115 Mln units in the distribution stock. An estimated 5.582±0.837 Mln mobile phones became obsolete in 2013. The difference between sales, C2C secondary markets, and obsolete mobile phones resulted in an increase in the use stock of 0.444±1.176 Mln. The "high" levels of uncertainty in the change in both the distribution and the use stocks are the result of the relatively high (in absolute terms) uncertainty bandwidth of the import, sales and obsolescence flows. Of the discarded 5.582 Mln mobile phones: 0.837±0.209 Mln (15%) are landfilled, 0.614±0.154 Mln (11%) are reused via consumer-to-consumer markets, 0.168±0.021 Mln (3%) are collected separately by retailers and service providers, and 0.585±0.864 Mln (10%) are collected via mixed WEEE streams by recycling companies like Wecycle. This all implies an increase in the hibernation stock of 3.378±0.881 Mln mobile phones (60%). This hibernation stock consists of mobile phones that are stored in households and those that have been given away "informally" by people to for example family and friends. All above indicates that 24% of the mobile phones discarded in 2013 are reused or recycled, which is likely to be higher when incorporating the amount of mobile phones that people give away to someone else for free. However, overall, there is still an annual potential of 40-60% of the discarded mobile phones that can be recovered from households. Which strategy is most suitable to increase the collection rate and reduce hibernation, will be addressed in **Chapter 7**.

Figure 7: Mobile phone material flow analysis 2013 in the Netherlands (X1000 units)



6.5.2 Dutch material flow analysis implications for future years

An estimated 3.4 Mln mobile phones have entered the hibernation stock in 2013. Between 2007 and 2013, an average of 5.1 Mln mobile phones have been sold annually (**Table 7**). Using the same Normal Distribution as in **Table 7** this implies that of this 5.1 Mln, 5 Mln (98%) has reached its end-of-life within the six years, of which ±60% enters the hibernation stock. This equals ± 3 Mln handsets entering the hibernation stock, each year from 2013 onwards, which is a rate that is not likely to decrease anytime soon. Between January 2014 and January 2020 this could lead up to an increase in hibernation stock of 18 Mln obsolete handsets.

6.5.3 Comparing outcomes with comparable research

Some other reports have aimed to estimates some aspects of the system as illustrated in **Figure 7**. Ben, a Dutch telecom-provider, estimated that 6 Mln smartphones are hibernating and around 1.5 Mln used smartphones were handed in at the "milieustraat" or via retailers (NRC, 19/7/2017). With current smartphone replacement and penetration rates a total hibernation estimate of 6 Mln units is a high underestimation, when considering that this thesis estimated that over 5 Mln mobile phones become obsolete every year. According to the Dutch government, which refers to research conducted by GfK, only 900K are "removed from the system" each year of which approximately 50% is recycled (TKSG, 2017). It is unclear what is meant with "removed from the system", but considering the obsolescence scope as used in this thesis it seems like a very low estimate. Probably there is a difference in definition in the measure used by TKSG (2017).

Jaco Huisman, an expert on WEEE flows and the lead author of UNU (2012), has been contacted to comment on the findings of UNU (2012) and collection estimations done by TKSG (2017) (**Chapter 6.4.1**). According to Huisman there isn't much hard data for mobile phone end-of-life flows in the Netherlands making it difficult to estimate the size of return flows. UNU calculations have indicated that around 5 Mln mobile phones (net) are discarded on average each year, which is within the uncertainty interval assumed in this thesis. According to Mr. Huisman it is estimated that Wecycle collects between 5-15% (250K-750K) of the discarded 5 Mln handsets. This interval is very large indicating the high degree of uncertainty in mobile phone end-of-life flows. This thesis' estimation of 585K units collected by all mobile phone recyclers fits in this interval, whereas the collection attributed by TKSG (2017) to Wecycle (200K) on its own falls below this range. Differences in estimates show the high level of uncertainty in flow estimations, especially for the return flows.

6.5.4 Comparing outcomes with mobile phone MFAs conducted in other countries

Table 10 compares MFA outcomes from other countries where mobile phone MFAs have been conducted with outcomes from this MFA. One can conclude that the Netherlands performs relatively average in terms of mobile phone reuse and average in terms of mobile phone recycling. Combining the reuse and recycling rates in the case of Switzerland (37%) and the case of Japan (38%) shows that the Netherlands (24%) still has significant room for improvement. Still as noted previously in the literature review: different studies use different assumptions, methodologies, and focal units, all affecting the MFA outcomes. Hence, one-on-one comparisons should be done with caution.

Table 10: Comparing return flows in the Netherlands with other countries

Source	Country	Year	Measure	Landfilled	Reused	Recycled	Hibernated	Total Obsolete (1)	Total Obsolete (2)
[A]	Switzerland	2011	Weight	63%	21%	15.5%	0%	100%	414 Tonnes
[B]	Japan	2010	Phones	17%	15%	23%	45%	100%	37.4 Mln Units
[C]	Finland	2008	Phones	5%	2%	7%	86%	100%	1.87 Mln Units
[C]	Germany	2007	Phones	5%	1%	4%	90%	100%	23.86 Mln Units
[C]	Sweden	2010	Phones	0%	2%	27%	71%	100%	3.02 Mln Units
[C]	Switzerland	2007	Phones	5%	5%	12%	78%	100%	2.55 Mln Units
[C]	UK	2005	Phones	4%	19%	6%	70%	100%	23.63 Mln Units
[C]	UK	2008	Phones	4%	18%	4%	74%	100%	33.69 Mln Units
Thesis	Netherlands	2013	Phones	15%	14%	10%	60%	100%	5.58 Mln Units

*Source: author's own elaboration on **Table 2** and on **Figure 7***

7. RESULTS CONSUMER BEHAVIORAL ANALYSIS

Chapter 7 analyses the outcomes of the survey on consumer recycling behavior of mobile phones by means of the SPSS statistical software package. As indicated by comparable research that is addressed in **Chapter 3**, there are various reasons why people replace their mobile phones and why people dispose their used mobile phones in different ways. **Chapter 7.1** investigates this and some other descriptive statistics related to mobile purchase and disposal behavior. Key in this descriptive analysis is whether consumers think levying a recycling or deposit fee is beneficial for creating consumer awareness, if it is a motivation for consumers to hand in their old phones, and which tariffs are perceived as acceptable (willingness to pay). This analysis is key in answering SQ3. In **Chapter 7.2** a factor analysis – this is required to create the factors from the extended TPB model (**Table 4**) – is done. This analysis creates the independent variables used in the binary logistic regression (BLR) analysis of **Chapter 7.3**, which are regressed on the dependent variable mobile phone recycling intention. This analysis is key in answering SQ2. Methodology of Field (2013) is used (**Appendix 7**).

7.1 DESCRIPTIVE ANALYSIS

7.1.1 Response rate and sample demographic analysis

Recycling behavior attitude of **211** Dutch students is investigated over the period August 5st - 13th 2017 (See **Chapter 5** for details). Only questionnaires that are completed are considered implying that the sample size of this research equals **206**, out of 538 questionnaires distributed (response rate: **38%)**. The demographic composition is shown in **Table 11.** The sample is slightly biased towards male (**51%**). **71%** of the respondents are between 21 and 24 years, and **70%** has a free disposable income (monthly income after fixed expenses like rent, insurance, subscriptions etc.) of €450 and lower, which can be attributed to the fact that almost all subjects are full-time students.

Table 11: Descriptive demographic statistics

	n	%		n	%
Sex			**Education**		
Male	105	51%	Secondary School	7	3%
Female	101	49%	MBO	1	0%
Total	206	100%	HBO/Polytechnic	38	18%
			University Bachelor	88	43%
Age			University Master	72	35%
18	1	0%	Total	206	100%
19	12	6%			
20	19	9%	**Specialization**		
21	25	12%	Education and Upbringing	5	2%
22	38	18%	Language and Communication	9	4%
23	58	28%	Art and Culture	7	3%
24	26	13%	Law and Public Administration	19	9%
25	15	7%	Economy and Management	97	47%
26	6	3%	Behavior and Society	21	10%
27	6	3%	Healthcare	28	14%
Total	206	100%	Earth and Environment	1	0%
			Exact and IT	6	3%
Free Disposable Income			Technology and Engineering	13	6%
0-150	33	16%	Total	206	100%
151-300	70	34%			
301-450	41	20%			
451-600	26	13%			
601-750	16	8%			
750+	20	10%			
Total	206	100%			

People that have a free disposable income of over €750 are expected to be recent graduates. The majority of the sample has received post-secondary school education (**97%)**, and 78% are enrolled in university programs. When looking at study specialization, it can be concluded that economic, social and behavioral, and healthcare sciences are most popular, accounting for **71%** of all specializations in this sample. As indicated in **Chapter 5.2.2**, the external validity of this research is restricted because of the sampling technique chosen and outcomes are not representative for the Dutch population. However, implications can be made for Dutch Polytechnic (HBO) and Scientific (WO) students, which are 714K persons in total in 2016 (CBS, 2017).

7.1.2 Mobile phone use and disposal behavior

Table 12 presents how many mobile phones each of the respondents have consumed so far and how many of these mobile phones they still have in their possession (including their current main handset). Of the 206 people surveyed, 95% (48+57+90) has consumed 4 or more handsets so far of which only 19% (40) have only their current main handset currently in their possession, implying that the far majority of 81% (206-40) has at least one unused mobile phone stockpiled at home. Correcting total phones in possession (543) with the amount of phones in use (one per respondent), implies that 337 mobile phones are currently in hibernation and are ready for collection, indicating a mobile phone hibernation rate of 1.64 (337/206) per respondent.

Table 12: Number of mobile phones in use and in hibernation

	1	2	3	4	5	6	Total
Number of Mobile Phones Used	0	2	9	48	57	90	206
Number of Mobile Phones in Storage	40	70	50	24	15	7	206
Total Number of phones in Possession	40	140	150	96	75	42	543
Total Number of Phones in Hibernation							337

Table 13 presents mobile phone life span information. A substantial 68% (99+41) of the respondents uses their mobile phones as their primary handset on average between 2 and 2.5 years. 11% of the respondents use their mobile phones, on average, less than 2 years, whereas for 21% this is 3 years or longer. For this sample, this all comes down to an average life span of mobile phones of 2.34 years. This outcome of 2.34 years on average is considerably lower, compared to the obsolescence distribution assumed in **Chapter 6** (μ=3 years, σ=1.25 years). This can imply two things. First, students replace their mobile phones much more regularly compared to other demographic groups. Second, the obsolescence distribution in **Chapter 6** was not accurate for Dutch population. If this second one is true, this implies that the annual obsolescence flow would be larger in reality.

Table 13: Average life spans of mobile phones

Years (A)	0,5	1	1,5	2	2,5	3	3,5	4	4,5	5	5,5	Total
Number of people that reported …. years (B)	2	3	18	99	41	21	7	11	2	1	1	206
(C) = (A) x (B)	1	3	27	198	103	63	25	44	9	5	6	483
Weighted average number of years mobile phones are in use (ΣC/ΣB)												2,34

These respondents offered various reasons for replacing their old handsets (**Figure 8**) of which the most prolific reasons given are technical reasons (37%) followed by the replacement of a broken phone (32%). **Figure 9** summarizes the disposal method respondents used for disposing their most recent replaced handset. Results indicate that the majority of the respondents (60%) stockpiled their most recent replaced phones, while slightly less than a quarter (22%) gave their previous phones to someone else. Most surprisingly, 0% of the respondents have recycled their latest replaced handset.

Approximately 80% of the students reported that they have at least one extra mobile phone (Table 12). According to Figure 9, 60% of the respondents have kept their recently retired phone. Figure 10 summarizes motives for this stockpiling behavior, of which to "use it as a spare" (37%) and "I don't know what to do with it" are the most frequently given reasons. This is equivalent to 61% and 38% respectively of the 124 respondents who stockpiled their latest replaced handsets. Most remarkably, only a small fraction that kept their phones have the prime intention to sell or recycle it in the future.

Figure 8: Reasons for replacing mobile phones (R = 326; N = 206)

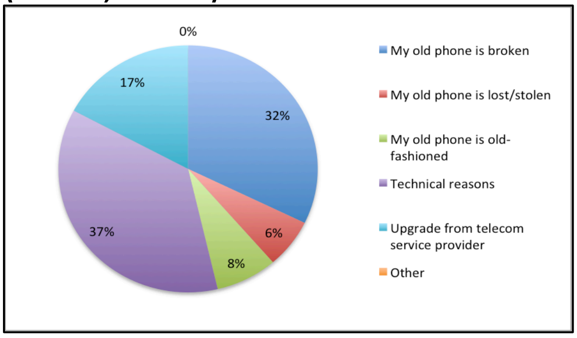


Figure 9: Methods used for disposing most recent mobile phones (R = N = 206)

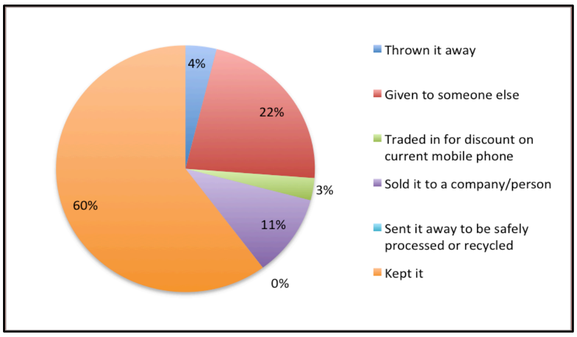


Figure 10: Reasons for stockpiling recently replaced mobile phones (R = 203; N = 124)

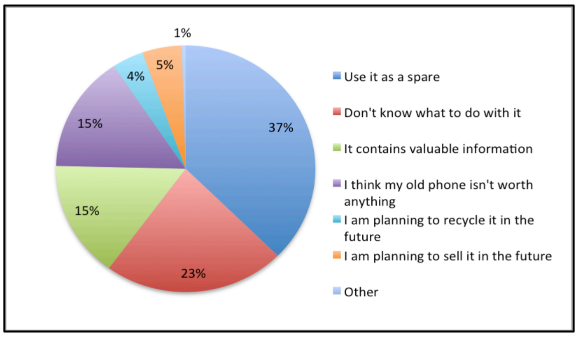
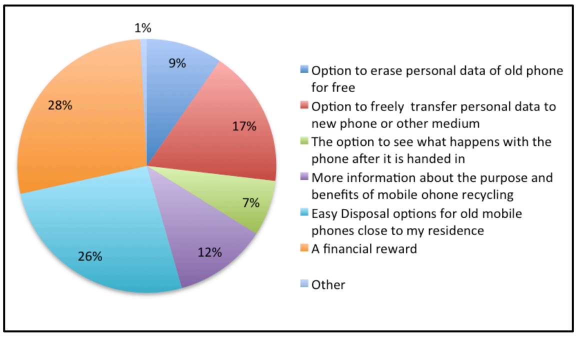


Figure 11: Incentives to increase collection rates of used mobile phones (R = 368, N= 206)



R = the number of reasons/answers given by N respondents. If R>N, respondents could give one or two answers on the specific question. Percentages shown in figures 8-11 are taken from R. Percentages for N are calculated by multiplying the percentage with R and divide it by N.

Figure 11 Suggests that increasing monetary incentives (28%) and a more convenient return infrastructure (26%) can be most successfully used to motivate people to hand in their stockpiled handsets. Providing the option to transfer personal data from the old handsets to other storage devices comes third with 17% of the answers given.

7.1.3 Mobile phone recycling willingness to pay and extended producer responsibility schemes

The survey also addressed the respondent's knowledge about the EPR schemes and WEEE legislation in terms of financial liability of the recycling costs. When asked which parties should bear the recycling costs (Figure 12) the majority thinks these costs must be shared by all stakeholders (40%), followed by mobile phone producers (31%), and the government (20%). Only a small share thinks that retailers, telecom providers (6%), or final consumers (3%) should bear the cost solely.

When asked whether consumers should at least pay some part of the recycling cost because they are the only final user, 46% of the respondents agree, whereas 54% disagree, showing that people are very divided on the matter. Table 14 presents consumer preferences between the three EPR approaches that are central in this thesis: Advanced recycling fees (ARFs), Pre-Disposal Fees (PDFs), and Deposit Refund Systems (DRSs). As showed, there is a slight bias towards the left/positive side of the Likert scale as was expected (**Chapter 5**). For each EPR approach, a weighted average (WA) score on increasing consumer awareness of mobile phone recycling, and its motivational effect is calculated. The WA scores suggest that a DRS has the most promising effect on increasing consumer awareness (5.19) and recycling motivation (5.40).

Figure 12: Who Should Bear the Recycling Costs of End of Life Mobile Phones

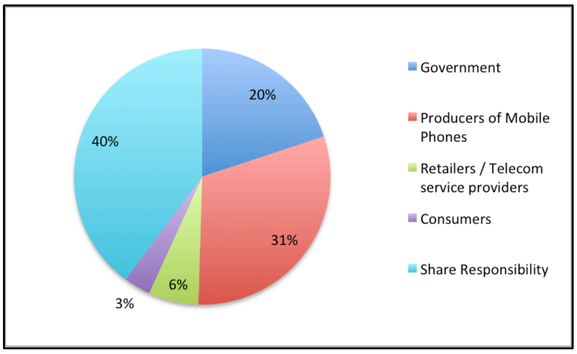


Figure 13: Acceptable recycling fee tariffs for ARF and PDF schemes

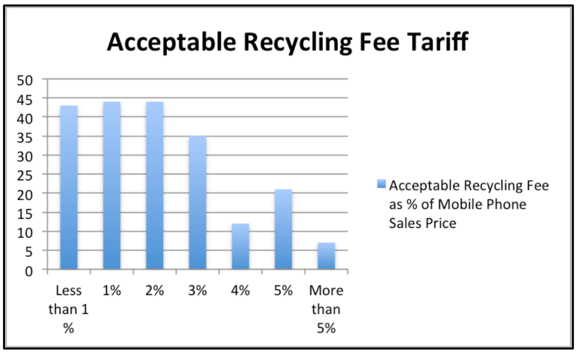


Table 14: EPR schemes as approaches to increase consumer awareness and recycling motivation

	HA	A	SA	N	SD	D	HD	TR	TP	WA
An ARF increases awareness for mobile phone recycling	13	66	55	17	20	22	13	206	947	4,60
An ARF increases motivation for mobile phone recycling	18	52	43	21	30	29	13	206	898	4,36
An PDF increases awareness for mobile phone recycling	12	47	42	31	24	35	15	206	857	4,16
An PDF increases motivation for mobile phone recycling	11	40	37	23	31	41	23	206	792	3,84
An DRS increases awareness for mobile phone recycling	31	80	46	21	10	11	7	206	1070	5,19
An DRS increases motivation for mobile phone recycling	35	87	51	13	5	8	7	206	1112	5,40

ARF = Advanced Recycling Fee, PDF = Pre-Disposal Fee, DRS = Deposit Refund System, HA = Highly Agree (7), A = Agree (6), Somewhat Agree (5), N = Neutral (4), Somewhat Disagree (3), Disagree (2), Highly Disagree (1), TR = # Respondents, S = Score (e.g. HA = 7 points, 7 points times 13 = 91), WA = Weighted Average

Figure 14: Acceptable depository fee tariffs

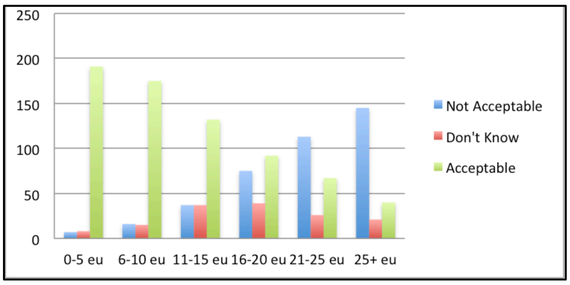


Figure 15: Depository fee as an incentive

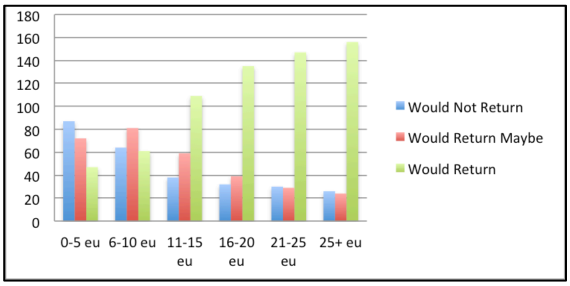


Figure 13 shows that 75 (36%) respondents think a recycling fee of at least 3% is acceptable, 43 people (21%) accept a fee <1%, and the rest (42%) accept a fee of 1-2% on top of the sales price. Interesting, however, is that 79% of the respondents are willing to pay at least 1% extra on the sales price of mobile phones for recycling costs, whereas 54% thinks consumers should not pay at least some part of the recycling costs, which is contradictory. **Figure 14** shows the maximum amount of deposit respondents perceive as acceptable. It indicates that the higher the amount of the fee, the less likely people think it is acceptable. However, **Figure 15** shows that the higher the fee, the more likely people are to return their mobile phones. Overall, 132 students think a DRS of €11-15 is acceptable and 109 respondents would return their used phones to reclaim their deposit. This suggests that some students don't think a deposit fee of €11-15 is a large enough incentive to hand in their used mobile phones, and maybe rather keep their old phones or sell them for a higher price.

7.1.4 Chi-square tests of independence

Chi-square tests of independence[6] are done between the demographic variables and all variables addressed above that are related to mobile phone use, disposal behavior and Willingness to pay (WTP). This test is done because it allows one to compare categorical and ordinal variables with one another (Moore et al, 2011), whereas linear regression requires the dependent variables to be continuous (Field, 2013). This is convenient since all questions are measured on a categorical scale. A Chi-square Statistic determines whether a distribution of observed frequencies differs from the theoretical expected frequencies (Ogondo & Williams, 2011b). Not more than 20% of the cells are allowed to have an expected frequency less than 5, and no cell should have a frequency of less than 1[7]. Variables sub-categories are collapsed in a logical way if this is necessary to satisfy this condition. Outcomes of significant associations are summarized in **Table 15**. This implies that outcomes of tests on other variables turned out to be not significant. Hence, demographic variables did not influence the answers on questions from Part II & III (**Table 4**), unless if shown in **Table 15**. Significant relations that violated assumptions are not taken into consideration. For each interesting outcome it is addressed which cell has the largest contribution[8] to the chi-square statistic.

Table 15: Significant outcomes of chi-Square tests of independence

	Variables		Chi-Square Statistics				Association Strength		Collapsed?	
#	Var 1	Var 2	X^2	df	P-value	Sign.	Phi	Cramer's V	Var 1	Var 2
1	Age	Average replacement frequency	7,301	2	0,026	YES	0,201	0,201	YES	YES
2	Age	Number of mobile phones used	9,964	4	0,041	YES	0,235	0,166	YES	YES
3	Age	Would return if DRS = *€11-15*	16,39	4	0,003	YES	0,302	0,213	YES	NO
4	Education	Average replacement frequency	15,802	2	0,000	YES	0,296	0,296	YES	YES
5	Gender	Number of mobile phones used	7,142	2	0,028	YES	0,199	0,199	NO	YES
6	Gender	ARF increases awareness	18,951	6	0,004	YES	0,324	0,324	NO	NO
7	Gender	PDF Motivation	13,44	6	0,037	YES	0,273	0,273	NO	YES
8	Gender	Intention to recycle mobile phones	23,582	5	0,000	YES	0,362	0,362	NO	NO
9	Gender	Intention to recycle e-waste	11,539	4	0,021	YES	0,253	0,253	NO	YES
10	Gender	Intention to recycle domestic waste	10,963	4	0,027	YES	0,247	0,027	NO	YES
11	Gender	Would return phone if DRS = *€11-15*	8,031	2	0,018	YES	0,211	0,211	NO	YES
12	Income	Average replacement frequency	9,677	4	0,046	YES	0,232	0,232	YES	YES

All relationships are significant at the 5% significance level and each relationship satisfies the cell assumptions for Chi-Square Tests (footnote 6) .

Each conclusion made below indicates the largest positive difference between the expected and the observed cell count in the chi-square crosstab matrix. Significant association (1) indicates that the largest positive observed difference between expected and observed counts was recorded for people older than 24, who replaced their phones more frequently after 2.5 years (X^2 = 4.00), compared to younger people who do this more frequently within 2.5 years. Association (2) indicated that younger people (<21) are more likely to have used 4 or less mobile phones (X^2 = 2.81), and people over 24 are more likely to have used 6+ mobile phones (X^2 = 2.33), which makes sense. Association (3) indicated that people aged over 24 were less willing (X^2 = 2.78), and less sure (X^2 = 6.75), about whether to return their mobile phones (to claim back their €11-15 deposit) than expected. Association (11) indicates that an above expected part of females (X^2 = 3.06), is not motivated to return their mobile phones for €11-15, compared to an above expected part of males that are (X^2 = 3.06) willing to return their phones for this fee range. In association (8) the largest positive observed difference between expected and observed counts was recorded for females (X^2 = 7.15) with an intention of 6 ("likely") to recycle and for males (X^2 = 2.38) with an intention of 3 ("not likely") to recycle. At first glance this seems a little contradicting with association 11, however, for all other deposit fee levels

[6] Tests are done after dataset adjustments in Chapter 7.2-7.3. Therefore N=180 instead of 206. Doing these tests is in line with Ogondo & Williams (2011b).
[7] http://libguides.library.kent.edu/SPSS/ChiSquare
[8] Observation specific Chi-Square Contribution (X^2) is defined as [(observed count – expected count)^2/expected count]

there was no relation between gender and willingness to return. Very interestingly, association (12) indicated that an above expected part of the people in the lowest income category (X^2 = 3.72) use their phone over 2.5 years, suggesting that people with less money replace their phones less often. An association between willingness to pay for recycling by means of an ARF or PDF (from **Figure 13**) and the demographic variables has not been found to be significant: Age ($X^2(8)$ = 15.133, P = 0.057), Gender ($X^2(4)$ = 2.386, P = 0.586), Education ($X^2(8)$ = 7.296, P = 0.505), and Income ($X^2(16)$ = 16.849, df = 30, P = 0.395) all have P-values larger than 5%, indicating that there is no evidence that there is an association between each of the variables and WTP for recycling.

7.2 FACTOR ANALYSIS

Factor analysis *"attempts to achieve parsimony by explaining the maximum amount of common variance in a correlation matrix using the smallest number of explanatory constructs" (Field, 2013)*. These constructs are known as factors or latent variables and represent cluster variables that are highly correlated with each other. Factor analysis aims to reduce the correlation matrix down to a smaller set of dimensions. A factor is essentially a linear combination of variables. In order to conduct a factor analysis, the general procedure as explained in Field (2013) is used, see **Appendix 7**. The factor analysis consists of three phases: initial data screening, the main analysis, and the reliability analysis. All independent variables/questions from **Table 4 Part I** are incorporated. The analysis will be done using SPSS Statistics software, which is in line with Field's (2013) methodology.

7.2.1 Initial data screening – sample size and correlations between variables

Correlations fluctuate from sample to sample, much more so in small samples than in large. Therefore factor analysis reliability depends on the sample size (Field, 2013). A sample size of 206 equals 6.5 times the amount of factor variables (31), which is sufficient as in line with the "Rule of 200" (Guilford, 1954). Sampling adequacy is tested using the Kaiser-Meyer-Olkin (KMO) measure of sample adequacy and the Bartlett's Test. An overall KMO statistic above 0.5 is acceptable, and the closer to 1 the better. Bartlett's Test tests if the correlation matrix significantly differs from the Identity matrix. The KMO statistic of 0.814 (**Table 16**) is "Meritorious" (Field, 2013). Bartlett's Test shows that correlations between variables significantly differ from zero. Since the KMO statistic is close to 1, the pattern of correlations is relatively compact and so factor analysis with the current sample size of 206 observations should yield distinct and reliable factors (Field, 2013). **Table 17** presents variable specific KMOs, for which the same criteria hold as for the overall KMO statistic. As shown all variables have a KMO score that is above the minimum threshold of 0.5. According to Field (2013) variables that have a correlation below 0.3 with many other variables should be reconsidered. Multicollinearity is another problem when variables have a high correlation since this makes it impossible to determine the unique effect of a variable to a factor, which is the case when variables have a correlation coefficient of above 0.8. As presented in **Appendix 8,** four variables have a correlation of above 0.80 (PCB_2 with PCB_3; PCB_4 with PCB_5). According to one simple heuristic: multicollinearity is an issue when the Determinant of the correlation matrix is smaller than 0.00001 (Field, p. 686, 2013), which is the case. The Determinant currently has a value of 5.358E-7, which is smaller than 0.00001 (**Appendix 8**). Therefore PCB_3 ("I know where I can recycle my mobile phones") and PCB_4 ("recycling my mobile phone is easy") are removed, whereas PCB_2 "(I know how to recycle my mobile phone") and PCB_5 ("There are enough opportunities available to me to recycle my mobile phone") are retained. After removing PCB_3 and PCB_4, the overall KMO statistic equals 0.821, the Bartlett's Test is still significant (0.000), and the Determinant of the correlation matrix has increased to 0.00001773, which is larger than the minimum threshold of 0.00001. Hence, multicollinearity is no longer an issue. New variable specific KMO statistics are shown in **Table 18** and are still all above the minimum threshold of 0.5**.**

Table 16: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.814
Bartlett's Test of Sphericity	Approx. Chi-Square	2.667.778
	df	465
	Sig.	.000

Table 17: Variable specific KMO values 1.0 – diagonal of anti-image correlation matrix

ATT_1	ATT_2	ATT_3	ATT_4	ATT_5	ATT_6	SUB_1	SUB_2	SUB_3	MOR_1	MOR_2	MOR_3	MOR_4	PBC_1	PBC_2	PBC_3
0,827	0,882	0,842	0,865	0,844	0,860	0,713	0,742	0,711	0,898	0,899	0,886	0,842	0,798	0,742	0,753

PBC_4	PBC_5	PBC_6	INC_1	INC_2	INC_3	INC_4	INC_5	MON_1	MON_2	MON_3	ORB_1	ORB_2	PRB_1	PRB_2
0,769	0,787	0,791	0,739	0,735	0,873	0,827	0,589	0,856	0,885	0,746	0,901	0,816	0,77	0,534

Table 18: Variable specific KMO values 2.0 – diagonal of anti-image correlation matrix

ATT_1	ATT_2	ATT_3	ATT_4	ATT_5	ATT_6	SUB_1	SUB_2	SUB_3	MOR_1	MOR_2	MOR_3	MOR_4	PBC_1	PBC_2
0,836	0,878	0,857	0,899	0,870	0,863	0,709	0,729	0,645	0,900	0,895	0,889	0,868	0,753	0,734

PBC_5	PBC_6	INC_1	INC_2	INC_3	INC_4	INC_5	MON_1	MON_2	MON_3	ORB_1	ORB_2	PRB_1	PRB_2
0,763	0,774	0,722	0,727	0,804	0,824	0,604	0,848	0,883	0,750	0,914	0,810	0,685	0,527

7.2.2 Main analysis – factor extraction and factor rotation

In doing the factor extraction analysis, a correlation matrix is preferred above a covariance matrix since not all questions are measured on the same Likert scale (3-point or 7-point). The correlation matrix ensures that differences in measurement scales are accounted for (Field, p. 689, 2013). An initial analysis was run to obtain Eigenvalues for each factor in the data. Eight factors have Eigenvalues over Kaiser's Criterion of 1 and in combination explained 62.68% of the variance, see **Table 19. Table 19** is generated using principal axis factoring on 29 items with orthogonal rotation (varimax)**.** Varimax rotation is a good general approach that simplifies the interpretations of factors (Field, p. 681, 2013). The scree plot shown in **Appendix 9** shows an inflexion point (a cut-off point where the slope of the line changes "dramatically") at factor 9, justifying the use of eight factors. Everything at the left side of this cut-off point should be retained (Field, 2013). The factor analysis is done with eight factors, which has a combined variance of 62.68% (best guess) before extraction and 48.8% (in reality) after extraction. The reproduced correlations matrix indicates that 27 of the non-redundant residuals have absolute values greater than 0.05, which is 6% of all residuals. Since this is below 50%, there are no reasons for concern regarding the model's fit (Field, p. 700, 2013). **Table 20** shows the rotated factor matrix: the results of the exploratory factor analysis. Variables highlighted in yellow have factor loadings that are above the minimum threshold of 0.3-0.364 (Stevens, 2002; Field, 2013), for which 0.364 is for sample sizes over 200 (Stevens, 2002). The current sample size is 206. For convenience, 0.3 is chosen since two questions (PBC_6 and SUB_3) have loadings for all factors that between 0.3 and 0.364. The items clustered on the same factor suggests that factor 1 represents the *moral norm* (intrinsic incentives/motivation) since the questions that load high on this factor really concern questions relate to people that recycle because they think it is good, and therefore have an increased effort in recycling. Factor 2 represents the recycling attitude, because this factor has high loadings on questions related solely to attitude (Chapter 5). The same reasoning is done with Factor 3 (inconvenience), Factor 5 (subjective norm), and Factor 6 (monetary incentives), see **Table 19 and Appendix 5**. Factor 4 is a new factor, which consists of "knowledge" and a "past recycling behavior" part, which is similar to perceived behavioral control (PBC) from the Theory of Planned Behavior.

Table 19: Factor communalities and factor Eigenvalues

Part 1b Communalities			Part 1a: Total Variance Explained (Kaiser's Criterion - 7 factors)									
			Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Variable	Initial	Extraction		Total	% of Variance	Cum %	Total	% of Variance	Cum %	Total	% of Variance	Cum %
ATT_1	0,618	0,764	1	6,602	22,766	22,766	6,132	21,146	21,146	3,293	11,356	11,356
ATT_2	0,424	0,461	2	2,938	10,132	32,899	2,526	8,709	29,855	2,859	9,859	21,215
ATT_3	0,545	0,602	3	2,080	7,172	40,071	1,619	5,582	35,437	2,172	7,488	28,703
ATT_4	0,554	0,571	4	1,654	5,702	45,773	1,183	4,080	39,517	2,127	7,335	36,038
ATT_5	0,517	0,501	5	1,461	5,039	50,812	1,011	3,488	43,004	1,317	4,542	40,580
ATT_6	0,537	0,554	6	1,271	4,383	55,196	0,663	2,285	45,290	1,003	3,457	44,037
SUB_1	0,470	0,641	7	1,113	3,838	59,034	0,581	2,004	47,293	0,745	2,569	46,607
SUB_2	0,442	0,556	8	1,057	3,646	62,680	0,437	1,508	48,801	0,636	2,194	48,801
SUB_3	0,259	0,231	9	0,905	3,121	65,800						
MOR_1	0,407	0,419	10	0,875	3,019	68,819						
MOR_2	0,580	0,631	11	0,813	2,803	71,622						
MOR_3	0,492	0,511	12	0,772	2,664	74,285						
MOR_4	0,434	0,374	13	0,744	2,566	76,852						
PBC_1	0,362	0,370	14	0,673	2,322	79,174						
PBC_2	0,562	0,760	15	0,665	2,294	81,468						
PBC_5	0,482	0,522	16	0,605	2,085	83,553						
PBC_6	0,285	0,271	17	0,549	1,894	85,446						
INC_1	0,579	0,622	18	0,527	1,819	87,265						
INC_2	0,661	0,797	19	0,506	1,745	89,011						
INC_3	0,568	0,634	20	0,445	1,533	90,543						
INC_4	0,323	0,377	21	0,419	1,444	91,987						
INC_5	0,220	0,234	22	0,369	1,273	93,259						
MON_1	0,376	0,373	23	0,340	1,174	94,434						
MON_2	0,470	0,665	24	0,330	1,138	95,572						
MON_3	0,284	0,313	25	0,301	1,039	96,610						
ORB_1	0,320	0,331	26	0,276	0,950	97,561						
ORB_2	0,493	0,495	27	0,255	0,881	98,441						
PRB_1	0,335	0,323	28	0,250	0,861	99,302						
PRB_2	0,170	0,251	29	0,202	0,698	100,000						

Extraction Method: Principal Axis Factoring.

Table 20: Rotated factor matrix

Variable	Question	MOR	ATT	INC	PBC	SUB	MON	SOLD	SCHEME
MOR_3	I would feel guilty if I did not recycle my e-waste	0,67	0,18	-0,09	-0,02	0,09	0,06	0,07	0,06
MOR_2	It would be wrong of me not to recycle my e-waste	0,67	0,32	-0,10	0,03	0,21	0,07	-0,01	-0,13
ATT_6	I make great effort to recycle e-waste	0,59	0,25	-0,14	0,30	0,02	-0,00	-0,17	0,01
MON_1	I would recycle my mobile phone, even if I have to pay for it	0,53	0,02	0,00	0,17	0,01	0,20	0,05	0,12
MOR_1	I feel I should not waste anything if it can be used again	0,48	0,25	-0,11	0,01	0,19	0,05	0,28	0,03
MOR_4	Everybody should share the responsibility to recycle e-waste	0,48	0,21	-0,20	-0,01	0,14	0,16	0,05	0,12
ORB_1	I have recycled domestic waste in the past year	0,47	0,19	-0,09	0,13	0,04	0,11	-0,17	0,09
PBC_6	I would recycle my phones if I had more info about recycling adv.	0,33	0,10	0,06	-0,23	-0,01	0,25	0,19	-0,01
ATT_1	E-waste recycling is good/useful	0,15	0,85	-0,02	0,02	-0,01	0,14	-0,03	0,02
ATT_3	E-waste recycling is responsible	0,20	0,69	0,10	-0,00	0,14	0,02	0,23	-0,06
ATT_4	I am interested in the idea of e-waste recycling	0,35	0,65	-0,11	0,10	0,02	0,04	0,06	0,02
ATT_5	I think e-waste recycling has positive effects on the environment	0,26	0,64	-0,00	0,04	0,04	0,09	0,02	0,09
ATT_2	E-waste recycling is rewarding	0,14	0,52	-0,10	0,23	0,12	0,02	0,30	0,11
INC_2	Recycling my mobile phones takes too much effort	-0,22	0,05	0,83	-0,07	-0,06	-0,22	-0,06	0,02
INC_1	Recycling recycle my old mobile phones takes too much time	-0,10	-0,06	0,77	0,02	-0,09	-0,04	0,07	-0,05
INC_3	Recycling my mobile phone is too complicated	-0,02	-0,04	0,71	-0,31	-0,08	-0,02	0,08	-0,13
PBC_2	I know how I can recycle my mobile phones	0,09	-0,05	-0,11	0,84	0,12	-0,06	0,08	-0,03
PRB_1	I have recycled/traded in my mobile phones in the past	0,11	0,05	-0,01	0,52	-0,14	-0,00	0,14	0,01
ORB_2	I have recycled electronic waste in the past year	0,39	0,18	-0,03	0,52	0,07	-0,03	-0,18	-0,04
PBC_1	I know that mobile phones can be recycled	-0,04	0,17	-0,09	0,50	0,23	0,13	-0,10	-0,04
PBC_5	There are plenty of opportunities for me to recycle my mobile phones	0,04	-0,01	-0,36	0,47	0,16	-0,07	0,00	0,37
SUB_1	Most people think I should recycle	0,27	0,03	-0,08	0,09	0,73	-0,09	-0,02	0,11
SUB_2	Most people would approve it if I would recycle	0,08	0,14	-0,14	0,09	0,68	0,14	0,04	0,13
MON_2	I would recycle my mobile phone, even if I don't get money for it	0,39	0,25	-0,06	0,01	0,10	0,64	0,01	0,13
MON_3	I would recycle my mobile phone only when I get money for it	-0,14	-0,04	0,22	-0,02	0,01	-0,48	0,07	-0,07
PRB_2	I have sold or given away my old mobile phone in the past	-0,05	0,10	0,02	0,09	-0,03	-0,10	0,46	0,09
SUB_3	If more would people recycle, I would recycle more too	0,09	0,17	0,10	-0,14	0,07	0,21	0,33	-0,07
INC_4	I am being motivated to recycle my mobile phone	0,39	0,10	0,06	0,07	0,04	0,10	0,06	0,44
INC_5	I trust mobile phones recycling programs	0,10	0,04	-0,11	-0,06	0,14	0,09	0,05	0,42

Extraction Method: Principal Axis Factoring. Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 8 iterations.

Therefore this factor is called a PBC. Factor 7 is hard to assign a latent variable to. However, since it loads high on the question whether someone has sold their old mobile phones in the past it is called "sold". Factor 8 is about trust in recycling programs and also loads high on recycling motivation and perceived opportunities. Therefore this factor is named "recycling schemes" (SCHEME) since each of the questions relates to a person's perception of the quality of mobile phone recycling schemes.

7.2.3 Factor reliability analysis

The eight factors and their corresponding reliability coefficients are shown in **Table 21**. The reliability of the scales used, are tested using Cronbach's alpha (α), the most common measure of scale reliability that takes value between 0 and 1 (Field, 2013). α closer to 1 means a greater internal consistency of items in the scale and a value above 0.7 is acceptable. Values that are much lower indicate that the scale is unreliable (Field, 2013). However, in psychological constructs like the one in this thesis values below 0.7 can be expected because of the diversity of the factors being measured (Field, 2013). The lower α, the higher the degree of cautiousness required in interpreting the factors (Philippsen, 2015). Besides α, **Table 21** indicates what α would be for that factor if variables would be deleted. For none of the variables α significantly increases by omitting the variable from the analysis. Hence all questions are retained. MOR, ATT, INC, PBC, and SUB all exceed the minimum threshold of 0.7, whereas MON, SOLD, and SCHEME do not. Especially SOLD and SCHEME should be interpreted with a high degree of cautiousness. The factor scores are saved as variables (Regression) and are used as independent variables in the binary logistic regression analysis of **Chapter 7.4**.

Table 21: Cronbach's Alpha

Factor	**MOR**	**ATT**	**INC**	**PBC**	**SUB***	**MON***	**SOLD***	**SCHEME***
Items	8	5	3	5	2	2	2	2
Cronbach's Alpha (α) Before Deletion	0,8	0,824	0,829	0,705	0,714	0,578	0,231	0,362
MOR_3	0,757							
MOR_2	0,751							
ATT_6	0,774							
MON_1	0,785							
MOR_1	0,778							
MOR_4	0,775							
ORB_1	0,785							
PBC_6	0,808							
ATT_1		0,763						
ATT_3		0,786						
ATT_4		0,79						
ATT_5		0,787						
ATT_2		0,821						
INC_2			0,698					
INC_1			0,765					
INC_3			0,821					
PBC_2				0,562				
PRB_1				0,696				
ORB_2				0,667				
PBC_1				0,655				
PBC_5				0,669				

* "α when removed" is omitted since these factors only contain the minimum of two underlying variables. So no variables can be removed to improve α.

7.3 BINARY LOGISTIC REGRESSION ANALYSIS

To determine which of the eight factors identified in the factor analysis has the largest effect on recycling intentions of mobile phones a binary logistic regression (BLR) analysis is conducted, with recycling intentions of mobile phones (INT3) as dependent variable, which is converted to a binary limited dependent variable, where the binary variable INT equals 1 when INT3 = somewhat likely (5), likely (6), or very likely (7) and equals 0 when INT3 = not very likely (1), not likely (2), somewhat not likely (3), neutral (4). BLR is preferred over linear regression since using a factor for the INT variable (from the factor analysis) caused the dependent variable not to satisfy the normality assumption, even after several transformations. Even though the sample is “large enough” (>30) according to the Central Limit Theorem, which states that the normality assumption doesn’t matter in “larger” samples (Field, p. 172, 2013) BLR is preferred. BLR, by design, overcomes several restrictive assumptions of linear regression like linearity, normality, equal variances, and normally distributed errors (Statisticssolutions, 2017). Besides, a binary dependent variable creates a more pronounced distinction between people that have or have not the intention to recycle mobile phones.

7.3.1 Binary logistic regression model specification

The Binary logistic regression (BLR) model can be defined as [2] where P(Y) is the probability of Y occurring, (e) is the base of the natural logarithm, and the other coefficients form a linear combination just like in linear regression (Field, 2013) with (b_0) as the intercept and ($b_{0,1,..,x}$) as the parameters associated with independent variables ($X_{1,2..,n}$) (Wooldridge, 2015). Logistic regression is assessed based on log-likelihood (LL) estimation, rather than Pearson correlation as is used in multiple regression models. The deviance statistic (-2LL) follows a chi-square distribution, which makes it easy to calculate the significance of the value. Methodology of Field (P. 775, 2013) is used, see **Appendix 7**, to conduct the binary logistic regression analysis.

$$P(Y) = \frac{1}{1+e^{-(b_0+b_1X_{1i}+b_2X_{2i}+\cdots+b_nX_{ni})}} \qquad [2]$$

7.3.2 Hierarchical regression

All eight variables identified by the factor analysis are added one by one in the BLR model with the binary variable INT as dependent variable. For each addition, the "Omnibus Tests of Model Coefficients” are analyzed to determine whether adding variables has significantly enhanced compared to the baseline model (constant only) and the previous model. Results are shown in **Table 22**. The Block and Model columns show the chi-square statistics of each model. Block shows the improvement of model (n) over model (n-1), which is the most interesting part of this table. The results indicate that adding MOR, ATT, PBC and MON significantly contribute to the change in chi-square of the overall model. Variables that have insignificant Block chi-square statistics virtually have no effect on the fit of the model. Based on this comparison, using a model with only MOR, ATT, PBC and MON is recommended, for which its chi-square statistic equals 70.288 and its Nagelkerke R^2 equals 0.407. Demographic control variables are not added, since this is in conflict with the Theory of Planned Behavior that assumes that such underlying variables are controlled for in the factors.

Table 22: Summary of Omnibus Tests of Model Coefficients

Model	Block	Sig.	df	Model	Sig.	df	Variables								NK R^2
1	36,304	0,000	1	36,304	0,000	1	MOR								0,228
2	19,331	0,000	1	55,635	0,000	2	MOR	ATT							0,333
3	1,262	0,261	1	56,897	0,000	3	MOR	ATT	INC						0,340
4	9,601	0,002	1	66,498	0,000	4	MOR	ATT	INC	PBC					0,388
5	0,140	0,708	1	66,638	0,000	5	MOR	ATT	INC	PBC	SUB				0,389
6	4,748	0,029	1	71,386	0,000	6	MOR	ATT	INC	PBC	SUB	MON			0,412
7	0,034	0,853	1	71,421	0,000	7	MOR	ATT	INC	PBC	SUB	MON	SCHEME		0,412
8	0,446	0,504	1	71,867	0,000	8	MOR	ATT	INC	PBC	SUB	MON	SCHEME	SOLD	0,387
Final	70,288	0,000	4	70,288	0,000	4	MOR	ATT		PBC		MON			0,407

7.3.2 Running and interpreting the regression Model

The final model is estimated and its model diagnostics (Predicted probability values, Predicted group membership values, Standardized residuals, Cook's distance, Leverage values, and DfBeta(s)) are saved as new variables. The first part of **Table 23** (Iteration History) tells the initial -2LL (deviance) of the base model, which is 256.160. The second part of the table shows the model predictions of the dependent variable INT (intentions to recycle a mobile phone in the future), and shows that the model correctly predicted a person's intention to recycle right in 84.4% of the cases compared to 68.3% of the constant only model. Notice that differences between the base model's -2LL (256.104) and the current -2LL (185.815) equals 70.288 (which is the chi-square statistic of the final model (**Table 22**). **Table 24** presents the estimates of the coefficients for the predictors included in the model, and also tells whether these coefficients are significantly different from zero by means of the Wald Statistic. As can be seen, all coefficients are significant at a 5% significance level, which is still the case after bootstrapping. Bootstrapping estimates the properties of the sampling distribution from the sample data, where the data is threated as the population from which smaller samples are taken. This allows one to infer that the sampling distribution is normal at a 95% confidence interval (CI) (Field, 2013). Since the BCa 95% CI doesn't include a zero for any of the variables, it can be concluded that there is a genuine positive relationship between any of the independent variables and the dependent variable INT. Since the model is optimized further, coefficients are interpreted at a later stage. The Hosmer and Lemeshow's Test, which measures whether the model fits the data well (H0), or not (H1), has a chi-square of 5.325, which is not significant (0.722), implying that the model fits the data well. The Nagelkerke's adjusted value of R^2 (a pseudo R^2) has a value of 0.407.

Table 23: Model summary 1a

Iteration History (a,b,c)

Iteration		-2 Log likelihood	Coefficients
			Constant
Step 0	1	256.160	.732
	2	256.104	.867
	3	256.104	.867

a Constant is included in the model.
b Initial -2 Log Likelihood: 219.195
c Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

Classification Table (a)

		Predicted INT		(%) Correct
		0	1	
Observed	0	36 (0)	29(65)	55.4(0.0)
INT	1	16(0)	124(140)	88.6(100.0)
Overall (%)		52	153 (205)	84.4 (68.3)

a The cut value is .500
(#) outcomes from constant only model

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
185,815(a)	0,290	0,407

Table 24: Model summary 1b

Variables in the Equation

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
MOR	1.050	.281	13.959	1	.000	2.859	1.648	4.960
ATT	.848	.228	13.879	1	.000	2.336	1.495	3.650
PBC	.622	.226	7.599	1	.006	1.862	1.197	2.898
MON	.721	.326	4.890	1	.027	2.057	1.085	3.899
Constant	1.118	.205	29.620	1	.000	3.059		

a Variable(s) : MOR, ATT, PBC, MON

Bootstrap for Variables in the Equation

	B	Bias	Std. Error	Bootstrap (a) Sig. (2-tailed)	95% Confidence Interval Lower	Upper
M1_MOR	1.050	.047	.310	.001	.535	1.747
M1_ATT	.848	.027	.257	.001	.407	1.412
M1_PBC	.622	.043	.247	.008	.220	1.156
M2_MON	.721	.035	.315	.015	.191	1.415
Constant	1.118	.048	.221	.001	.789	1.635

a Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

7.3.3 Interpreting residuals

As mentioned, the models' Standardized residuals, Cook's distance[9], Leverages[10], and DfBeta[11](s) have been saved as new variables. These variables are checked per respondent to make sure all minimum conditions are met. As a rule of thumb: Cook's Distance Should be less than 1, only 5% of the Standardized residuals should lie outside ±1.96, and max 1% should lie outside ±2.58, DF Beta's should also all be less than 1. Leverage should be smaller than three times the average leverage (Stevens, 2002), which is defined as (k+1)/N, where (k) is the number of parameters and (N) the number of respondents. **Table 25** shows descriptive statistics of these variables. The maximum values of Cook's Distance (0.25), and all DfBeta's (<0.08) are smaller than the maximum threshold value of 1, which is good. At least some respondents have a Leverage that is too high (0.162>0.0732), which may affect the model. This means that too many respondents have too much influence on the predictive values of the dependent variable (Field, 2013). At least one person has a standardized residual value of -4.6, which is way too high. This is because only 5% of the standardized residuals should lie outside ±1.96, only 1% should lie outside ±2.58, and cases outside ±3.0 are outliers and hence cases for concern (Field, 2013). So both statistics require further inspection. Further inspection of the standardized residuals (SR) shows that five respondents (2.4%) have an absolute SR value higher than ±2.58, which is too much. All observations with an SR value above 3.00 (respondent 11, 173, 176) are omitted and new SR values are generated. Still, too much SR values are too high in absolute terms. Hence, respondents with SR values above 2.58 (respondent: 84 87, 141, 157) are omitted, and new SR values are generated. Now, nine (4.5% of 198) observations are larger than ±1.96, and none are larger than ±2.58. To optimize the Leverage structure, 18 more respondents are dropped that have Leverage scores above three times the average Leverage. 180 observations remain; all conditions of the residual statistics are met Field (2013).

Table 25: Descriptive information of residual statistics

	Cook's Distance	Leverage value	Normalized residual	DFBETA for constant	DFBETA for M1_MOR	DFBETA for M1_ATT	DFBETA for M1_PBC	DFBETA for M2_MON
N	205	205	205	205	205	205	205	205
Mean	0,025	0,024	-0,007	0,000	0,000	0,000	0,000	0,000
Median	0,006	0,018	0,259	0,004	0,003	0,002	0,002	0,002
Std. Deviation	0,043	0,021	0,983	0,015	0,020	0,018	0,016	0,021
Range	0,250	0,159	6,533	0,094	0,149	0,184	0,115	0,160
Minimum	0,000	0,003	-4,607	-0,064	-0,094	-0,108	-0,071	-0,079
Maximum	0,250	0,162	1,926	0,031	0,055	0,076	0,044	0,080

Average Cook's Distance = (4+1)/205 = 0,0244, (2x) 0,0488, (3x), 0,0732

7.3.4 Testing model assumptions

Two assumptions are important in binary logistic regression, which require testing for (1) linearity of the logit, and (2) for multicolinearity. Including interaction terms of the explanatory variables with their own natural logarithm value in the BLR model tests for linearity. Insignificant interaction terms for all independent variables means that the linearity condition is met. Multicollinearity is tested by means of the Variance Inflation Factor (VIF) statistic using normal regression. **Table 26** shows the BLR model including interaction terms[12] and shows that the all interaction terms are not significant indicating that the assumption of linearity in the logit has been met. **Table 26** also shows the VIF statistic, which is problematic if it is less than 0.1 or larger than 10 (Field, 2013). In this case all VIFs are within this bandwidth and hence there is no concern regarding multicollinearity.

[9] A measure of the overall influence of a case on the model as a whole (Field, 2013)
[10] Gauges the influence of the observed value of the outcome value over the predicted values (Field, 2013)
[11] The difference between a parameter estimated using all cases and estimated when one case is excluded (Field, 2013)
[12] In generating the Ln(.) values each variable is added +10 (hence: Ln_MOR = Ln(MOR+10) because of negative values in MOR, in line with (Field, 2013)

7.3.5 Running the final regression model and interpreting the coefficients

Now that all residuals and deviance statistics are examined and the model's linearity and multicollinearity assumptions have been checked one can start interpreting the final results. **Table 27**, shows the decrease in the deviance (-2LL) compared the model estimated before corrections were made regarding the residuals and deviance statistics. The Nagelkerke's R^2 has increased by 0.196 have improved considerably compared to the initial estimated model, and Hosmer and Lemeshow Test is still significant ($X^2(8)$ = 6.915, P = 0,546) at a 5% significance level. In terms of overall accuracy of classification, the model correctly classified 83,9% of the cases (compared to 84,4% in the first model (**Table 23**). This is a decrease in accuracy, however, underlying assumptions regarding residual statistics are being met in this model, whereas this was not the case earlier.

Table 26: Testing the assumptions of linearity and multicollinearity

	Variables in the Equation (a)						Coefficients (b)		
	B	S.E.	Wald	df	Sig.	Exp(B)	Collionearity Statisics		
MOR	-15,557	11,621	1,792	1,000	0,181	0,000			
ATT	-0,547	9,377	0,003	1,000	0,954	0,579			
PBC	-1,961	9,850	0,040	1,000	0,842	0,141	Model	Tolerance	VIF
MON	7,909	19,365	0,167	1,000	0,683	2.720,829	MOR	.564	1.775
LN_MOR by MOR	7,818	5,325	2,156	1,000	0,142	2.485,007	ATT	.913	1.095
LN_ATT by ATT	0,697	4,118	0,029	1,000	0,866	2,008	PBC	.948	1.055
LN_PBC by PBC	1,415	4,354	0,106	1,000	0,745	4,118	MON	.509	1.964
LN_MON by MON	-2,882	8,624	0,112	1,000	0,738	0,056	Model	Tolerance	VIF
Constant	1,665	0,430	14,997	1,000	0,000	5,286			

a Variable(s) entered: MOR, ATT, PBC, MON, LN_MOR * MOR , LN_ATT1* ATT , LN_PBC * PBC , LN_MON * MON . b Dependent Variable: INT

Table 27: Model summary 2a

Model	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
First (N=206)	185,815(a)	0,290	0,407
Final (N=180)	116,651 (a)	0,420	0,603
Difference	- 69,164	+ 0.13	+ 0.196

a Estimation terminated at iteration number 6 because parameter estimates changed by less than .001 for split file $bootstrap_split = 0.

Classification Table (a)

		Predicted INT		
		0	1	% Correct
Observed	0	33(0)	18(65)	64.7(0.0)
INT	1	11(0)	118(140)	91.5(100.0)
Overall %		44	136	83.9 (68.3)

a The cut value is .500
(#) outcomes from constant only model

Table 28 presents the estimates of the coefficients for the independent variables included in the model. According to the Wald Statistic: all coefficients are significantly different from zero at a 5% significance level. This indicates that MOR, ATT, PBC, and MON all are significant predictors of a person's intention to recycle their mobile phones in the future. Since the bootstrapped 95% confidence interval doesn't include a zero for any coefficient, it can be concluded that there is a genuine positive relationship between each of the predictors and the intention to recycle mobile phones. The odds ratio (Exp(B)) of each coefficient (B), states that any of the predictors increase in value, the odds of having a higher intention to recycle increases too. This is because the confidence interval of Exp(B) all lie above 1. For students that score one unit higher on moral norm (MOR), this means that this person has a 5.132 higher odds of having the intention to recycle their phone compared to someone who has not this extra unit of moral norm. Students with a unit more of positive attitude (ATT) towards mobile phone and e-waste recycling have 2.814 times higher odds to have the intention to recycle their mobile phones. Students with a unit more of perceived behavioral control (PBC) have 3.451 times higher odds to have the intention to recycle their mobile phones. Finally, students who do have a higher score on MON, a linear combination with the highest loadings on: recycle phone even if I have to pay for it, even if I don't get money for it, have 1.436 higher odds of having a higher intention to recycle mobile phones.

Table 29 shows a selection of the predicted probabilities including the Beta's of the independent variables. If these values are plugged in [2] one would obtain the predicted probability [3] for respondent (n=1). **Table 29** shows that of the 180 observations, 151 (84%) are correctly and 29 (16%) are wrongly predicted. Assuming that the model is accurate and that the four variables are very significant, then these four variables are the best predictors of having a higher intention to recycle mobile phones. Adding variables like subjective norm (SUB), Inconvenience of recycling (INC), whether someone has sold their mobile phones in the past (SOLD), or whether someone has a positive perception of recycling schemes (SCHEME) did not improve the quality of predicting someone's recycling intention.

$$P(Y_{n=1} = 1) = \frac{1}{1+e^{-(b_0+b_1X_{1i}+b_2X_{2i}+\cdots+b_nX_{ni})}} = \frac{1}{1+e^{-(1{,}80+1{,}64\times0{,}68+1{,}04\times0{,}19+1{,}24\times-0{,}38+1{,}44\times-1{,}03)}} = \frac{1}{1+e^{-1.16}} = 0{,}76 \quad [3]$$

Table 28: Model summary 2b

Variables in the Equation

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
MOR	1,635	0,430	14,465	1	0,000	5,132	2,209	11,920
ATT	1,035	0,419	6,094	1	0,014	2,814	1,238	6,398
PBC	1,239	0,353	12,283	1	0,000	3,451	1,726	6,900
MON	1,436	0,543	6,987	1	0,008	4,206	1,450	12,202
Constant	1,802	0,331	29,659	1	0,000	6,063		

Variable(s) entered: MOR, ATT, PBC, MON.

Bootstrap for Variables in the Equation

	B	Bias	Std. Error	Bootstrap (a) Sig. (2-tailed)	95% C.I. for (B) Lower	95% C.I. for (B) Upper
MOR	1,635	0,118	0,460	0,001	0,962	2,778
ATT	1,035	0,097	0,466	0,010	0,324	2,179
PBC	1,239	0,091	0,396	0,001	0,641	2,176
MON	1,436	0,096	0,579	0,002	0,461	2,732
Constant	1,802	0,116	0,320	0,001	1,365	2,685

a Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

Table 29: Sample of predicted probabilities

Case Summaries

n	MOR (B)	ATT (B)	PBC (B)	MON (B)	Predicted Probability	Predicted INT = 1	Real INT = 1	Predicted Correct	Predicted Wrong
1	0,68	0,19	-0,38	-1,03	0,7621	1	1	1	0
2	-1,28	0,83	0,85	-0,74	0,6373	1	0	0	1
3	-1,55	-0,89	0,93	-0,44	0,2425	0	1	0	1
4	-0,29	-0,90	0,94	-0,74	0,6220	1	1	1	0
5	-0,82	0,79	-1,41	0,14	0,4345	0	1	0	1
6	-1,30	0,49	-0,86	0,21	0,3576	0	1	0	1
7	-1,17	0,29	0,88	-1,03	0,4496	0	0	1	0
8	-0,26	-1,05	0,02	0,21	0,6487	1	1	1	0
9	-0,01	-1,12	-1,28	-0,08	0,2522	0	0	1	0
10	-1,06	0,09	0,60	-1,32	0,2687	0	0	1	0
…	…	…	…	…	…	…	…	…	…
Total (N)	180	180	180	180	180	180	180	151	29

7.3.6 Effect of demographic variables on the intention to recycle mobile phones

The Theory of Planned Behavior states that demographic variables can be included in the theory if (and only if) these variables influence underlying beliefs that determine the attitude toward the act and subjective norms (Ajzen I. , 1988; Knabe, 2009). To investigate whether a relationship exists between demographic variables (exogenous), independent (endogenous), and the dependent variable(s) (exogenous), a correlation matrix is created, see **Table 30**. This table indicates that age is significantly correlated with all other demographic variables (female respondents are younger than male respondents, education is higher when someone is older, and income is higher when someone is older). Furthermore, only gender is significantly (a = 0.01) correlated with some independent variables, and to a lesser degree with the dependent variable (a = 0.05). However, adding demographic variable of them to the model doesn't significantly increase the fit of the model, and is therefore not recommended, in line with the Theory of Planned Behavior (such variables should only be added if and only if these variables have a significant influence on a person's attitude or beliefs, which the correlation matrix already proved to be untrue for al variables despite gender).

Table 30: Pearson Correlation Matrix of Demographic variables with (in)dependent variable(s)

	Age	Gender	Education	Income	MOR	ATT	PBC	MON	INT
Age	1								
Gender	-.203**	1							
Education	.287**	-.013	1						
Income	.269**	-.145	.055	1					
MOR	.090	.279**	.087	-.085	1				
ATT	.027	.044	-.006	-.102	.131	1			
PBC	.130	-.031	-.088	.063	.129	.051	1		
MON	.118	.211**	.055	-.143	.658**	.284**	.226**	1	
INT	.124	.185*	.100	-.062	.503**	.349**	.300**	.515**	1

*** Correlation is significant at the 0.01 level (2-tailed); * Correlation is significant at the 0.05 level (2-tailed).*

The Mann-Whitney Test (allows for not normally distributed ordinal variables, for which the shapes differ per group (Field, 2013)) on the equal distribution of scores has been done on the ordinal variable INT_3 (which is the original dependent variable) grouped on gender. The two groups are equally divided and both contain 90 respondents. This statistic is significant (U = 3222.5, z = -2.45 , P = 0.014) indicating that the distributions and mean ranks of males (81.31) and females (99.69) are significantly different, and that females have a higher intention to recycle their mobile phones. Hence: although adding gender as control variable doesn't enhance the fit of the model, there is evidence that males and females significantly differ in their intention to recycle mobile phones, when both groups are compared. However, doing Mann-Whitney Tests on education (university versus no university), age (<23 years, >=23 years), and income (<€300, >=€300), outcomes are not significant, meaning that for these demographic characteristics people have the same distribution regarding mobile phone recycling intentions. This is in line with the correlation matrix in **Table 30**.

Education (U = 2347.5, z = -1.271, P = 0.204, $N_{no\ university}$ = 38, $N_{university}$ = 143))

Age (U = 4016.5, z = -0.086, P = 0.932, $N_{<23\ years}$ = 87, $N_{>=23\ years}$ = 93)

Income (U = 3863, z = 0.548, P = 0.584, $N_{<€300}$ = 92, $N_{>=€300}$ = 88)

7.4 DISCUSSION

Chapter 7.4 gives an in-depth summary the results from the statistical analysis as done in **Chapter 7**.

7.4.1 Descriptive analysis

The descriptive analysis is done in **Chapter 7.1** and has indicated that the dataset addressed in the statistical analysis part consists mainly of Dutch students, which restricts the generalizability of this study. Within the sample of 206 students an average of 1.64 mobile phones per student are currently hibernating, and mobile phones get replaced on average every 2.34 years, with the majority being replaced in 2-2.5 years. People replace their mobile phones mainly because their old handset is broken or has become technological obsolete. A majority of 60% has stored its most recently replaced handset at home mainly to use it as a spare, or because they do not know what to do with it. The best incentives one can give to students to motivate them to hand in their old phones are monetary incentives and convenient disposal options close to their homes. Most people think that all stakeholders together should be responsible for the recycling costs of mobile phones and 46% thinks that consumers should at least pay some part of it. When comparing the potential of different EPR schemes, the deposit refund system (DRS) seems the most promising both in terms of creating awareness, and as an incentive. The majority (64%) of the respondents thinks a deposit fee of €11-15 is acceptable, and also more than 50% of the respondents have a stated intention to return their phones in this case.

An analysis of independence between demographic variables and mobile phone use/disposal variables indicated that gender is associated with several variables like number of phones used, the intention to recycle e-waste, domestic waste, and mobile phones, and the effectiveness of a DRS fee with a tariff between €11-15. An above expected part of students above the age of 24 tends to use their phones longer than 2.5 years, older people tend have used more phones than younger people. There are some indications that people with less income replace their phones less frequently.

7.4.2 Factor analysis

A principal factor analysis has been conducted in **Chapter 7.2** on 29 out of 31 variables with orthogonal (varimax) rotation the Kaiser-Meyer-Olin measure (KMO = 0.821) verified that sampling adequacy for the analysis (which is "Meritorious"), and all variable specific KMO values are above 0.527, which is above the acceptable limit of 0.5 (Field, 2013). Two variables were deleted due to concerns about multicollinearity. The initial analysis obtained Eigenvalues for each factor, and eight factors had Eigenvalues over Kaiser's criterion of above 1, and explained a combined variance of 62.68%. The scree plot was hard to interpret, but showed an inflexion point at factor 9 that justifies the use of eight factors. Hence, eight factors are retained based on Kaiser's criterion and the scree plot's recommendations. **Table 20** showed the factor loadings after rotation. Variables clustering high on the same factors suggest that factor 1 represents moral norm, factor 2 recycling attitude, factor 3 inconvenience, factor 4 perceived behavioral control, factor 5 subjective norm, factor 6 monetary incentives, and factor 8 perceived quality of recycling schemes. Factor 7 was hard to give a name to, but since the major loading came from the question whether someone has sold a mobile phone in the past, the variable is named after this question: ever sold a mobile phone.

A reliability analysis has been conducted, where moral norm, attitude, inconvenience, perceived behavioral control, and subjective norm all had high reliabilities with Cronbach's alphas above the minimum threshold of 0.7. However, monetary incentives, recycling scheme quality, and "sold a phone in the past" had relatively low reliabilities, with Cronbach's alphas between 0.231 and 0.578.

7.4.3 Binary logistic regression analysis

A binary logistic regression model was estimated in **Chapter 7.3** with the dependent variable INT (=1|INT_3 = 5,6,7; =0|INT_3 = 1,2,3,4) and the dependent variables, which were saved from the factor analysis. According to the Omnibus Tests of Model Coefficient and the Block chi-square statistics, adding inconvenience, subjective norm, perceived recycling scheme quality, and "sold a phone in the past " did not contribute to the fit of the model. Hence, a model is estimated with moral norm, recycling attitude, perceived behavioral control, and monetary incentives as explanatory variables.

In order to enhance the quality of the model, the model is optimized based on the residual statistics (Field, 2013) implying that 26 observations are dropped in order to optimize the structures of the model's leverage and standardized residual values. The model's assumptions of linearity and no multicollinearity (**Table 26**) are both tested and are being met. The model, after dropping the 26 observations, fits the data well (Hosmer and Lemeshow's Test, $X^2(8) = 6.915$, P = 0,546), and the Nagelkerke's Pseudo R^2 has improved from 0.407 (initial mode, N=206), to 0.603 (final model, N=180). It has been concluded that all independent variables have a strictly positive relationship (bootstrapped 95% C.I. >0.00) with the intention to recycle mobile phones. The 95% C.I. of the odds ratio's EXP(B) are all larger than 1 indicating that if all independent variables increase, the odds of having the intention to recycle also increases (assuming that the sample C.I. is true). This indicates that increasing moral norm (MOR), recycling attitude (ATT), perceived behavioral control (PBC), and monetary incentives (MON) with one unit, increases the odds of having the intention to recycle by 5.12, 2.81, 3.45, and 4.21 respectively (**Table 28**) for each predictor variable.

In line with the Theory of Planned Behavior, demographic variables are not included in the model. Therefore, these demographic variables are converted into binary variables representing two independent groups. Based on each grouping, Mann-Whitney Tests on equal distributions have been done, which indicated that there is a significant difference between the distributions of the mobile phone recycling intentions of males and females. This indicated that females have a significantly higher intention to recycle mobile phones (mean =99.69) compared to males (mean = 81.31). For education, income and age no significant differences in distribution have been found.

8. DISCUSSION

In this thesis a material flow analysis (MFA) and a consumer behavioural analysis have been conducted. Of both analyses, outcomes are summarized in **Chapter 6.5** (MFA) and in **Chapter 7.4** (consumer behavioural analysis). **Chapter 8** discusses the methodologies and overall implications of these findings and compares them with other research in **Chapter 8.1**. In doing so, the sub-questions (see **Chapter 1**) are answered. **Chapter 8.2** gives the final conclusion on the research question. **Chapter 8.3** addresses research limitations and gives recommendations for future research.

8.1 DISCUSSION

This thesis aimed to get a better understanding of what consumers (plan to) do with their mobile phones once they have replaced their old handsets with a new one. This thesis has confirmed the conclusions made by comparable research, which was the motive of writing this thesis in the first place: an estimated majority (60%) of all mobile phones that are replaced are hibernating in drawers. The main purpose of this thesis was to identify psychological constructs that can explain a consumer's recycling behavior with respect to used mobile phones and whether an explicit recycling fee on the sale or disposal (the three EPR approaches: ARF, PDF, and DRS) of mobile phones could possibly have a positive impact on mobile phone collection rates. As already indicated in **Chapter 7.1**, the survey is distributed mainly amongst Dutch students and recent graduates limiting the overall generalizability of the research outcomes. Besides, intentions are dynamic and are continuously re-evaluated based on circumstances. This and other limitations will be addressed in **Chapter 8.3**.

The methodology adopted in this thesis was twofold. First, a better picture was constructed of the current performance of national collection flows of mobile phones in the Netherlands, which is done by means of a material flow analysis (MFA). The data for this analysis was collected from the Dutch government, the European Union, the United Nations, and research reports mostly from GfK. Second, a consumer behavior analysis has been conducted, where the Theory of Planned Behavior (TPB) of Ajzen (1991) was used to create a model based on psychological constructs to predict recycling intentions of Dutch students. The dataset for this part of the study was gathered via an online questionnaire, which has been completed by 206 respondents (response rate of 38%). As such, this thesis strived to give more insights in strategies to lower mobile phone hibernation, with the ultimate purpose to formulate an adequate answer on the following research question:

RQ: "Which EPR approach is most effective in reducing mobile phone hibernation in the Netherlands?

The three sub-questions in this research are instrumental to formulate a conclusion; implications and recommendations regarding the research question and are addressed below.

SQ1: What are the current hibernation, landfilling, reuse, and recycling status of mobile phones in the Netherlands?

The material flow analysis analyzed the performance of the mobile phone recovery network for the year 2013 and has shown that an estimated 5.58 million (Mln) mobile phones became obsolete. The far majority of this amount entered the hibernation stock (3.35 Mln - 60%), while others were landfilled (0.84 Mln - 15%), or were collected via reuse and recycling programs (1.34 Mln - 24%).

Assuming that 75% (hibernation + landfill) of all mobile phones (4.2 Mln units) are potentially available for collection, this means a metal recovery potential of 1046kg silver, 100kg gold, 38kg palladium, and 37.6 Mln kg of copper (UNEP, 2009) in 2013. This amounts up to €0.5 Mln[13] worth of silver €3.6 Mln[1] worth of gold, €1 Mln[14] worth of palladium, and €0.25 Mln[15] worth of copper annually. If 50% (this thesis[16]) to 75% (Geyer & Blass, 2010) of the hibernating stock is potential for reuse purposes with, an average second-hand selling price of $91 (€76,59[17]) (Cruz, 2014), this yields a second-hand market potential of €128-192 Mln annually that is currently unused. These (indicative) figures highlight the economic attractiveness of collecting and reselling obsolete mobile phones in secondary markets, as this can be much more profitable than recycling. In order for this to hold, handsets must be collected as soon as possible after replacement since mobile phones may lose 20-30% of their resale value within 8 months of hibernation (Geyer & Blass, 2010). Duygan & Meylan (2015), who did a similar study in Switzerland, made similar conclusions. Compared to Switzerland and Japan, the Netherlands scores below expectations with a recovery (recycling + reuse) rate of only 24% compared to 37% in Switzerland in 2011 (Duygan & Meylan, 2015) and 38% in Japan in 2010 (Mishima et al, 2016b). According to the latter, developing programs to encourage consumers to increase their effort to recycle e-waste products is a clear winner in terms of sustainability and hibernation is even worse than landfilling in terms of sustainability. This is because in landfilling at least some recycling activities are possible. The MFA indicates that there is significant room for improvement in terms of the recovery of obsolete mobile phones in the Netherlands.

The descriptive analysis conducted on the survey results among Dutch students showed that 60% has kept their old handsets after replacement, leading to an average amount of unused mobile phones per student of 1.64 in this sample. With around 714K[18] students studying at a Polytech (HBO) or scientific (WO) university in the Netherlands (in 2016), this implies that this demographic group potentially stockpiles ±1.2 Mln unused mobile phones. On average, mobile phones are replaced once every 2.34 years, with the majority being replaced within 2-2.5 years. At this rate, the number of stockpiled mobile phones is not likely going to shrink anytime soon, which is likely to increase by another 18 Mln obsolete handset until between 2014 and 2020. An average amount of 5.1 Mln mobile phones are estimated to become obsolete every year (**Chapter 6.5.2**) implying that ±3 Mln (60%) is added to the hibernation stock annually. Most commonly, people keep their used mobile phones because they want to use it as a spare, because they do not know what to do with it, or because they think used phones are not worth anything. This indicates the importance of informing people about proper disposal options of used mobile phones. This thesis' survey indicated that financial incentives, and convenient disposal options are the best methodologies to incentivize students to hand in their mobile phones for reuse and recycling.

SQ2: To what extend are a students' intentions to recycle their mobile phones influenced by their attitude to recycle, subjective norm, moral norm, perceived behavioral control, perceived inconvenience, monetary incentives, other recycling behavior, and past recycling behavior?

The results have shown that a student's intention to recycle their mobile phones is positively and significantly (5% significance level) related to their perceived moral obligation to recycle, the degree

[13] *https://goldprice.org/gold-price-euros.html*
[14] *https://www.goldbroker.com/charts/palladium-price/eur*
[15] *https://www.lme.com/Metals/Non-ferrous/Copper#tabIndex=0*
[16] *32% of the reasons of mobile phone replacements is because the old handset is broken. 326 reasons were given by 206 respondents indicating that 0.32x326/206 = 50.6% gave this answer as a primary reason.*
[17] *http://www.x-rates.com/graph/?from=USD&to=EUR&amount=91*
[18] http://statline.cbs.nl/StatWeb/publication/?PA=71450ned

of favorable attitude towards recycling, the perceived behavioral control of performing the recycling behavior, and whether a person is motivated to recycle their mobile phones without getting a monetary reward for it. This means that students are more willing to hand in their mobile phones for reuse and recycling purposes if they think recycling is the right thing to do, if they have the knowledge of how and where mobile phones and e-waste can be recycled (and their actions have reflected this knowledge). It also means that people that are less motivated by monetary rewards – those who would recycle their mobile phones for free or even when they have to pay for it – are more likely to have a higher intention to recycle their mobile phones. Simultaneously, inconvenience of the recycling infrastructure, subjective norms, perceived quality of take-back programs, and whether someone has sold mobile phones in the past do not significantly contribute to explaining recycling behavior. Results indicate that females have a significantly higher intention to recycle their phones in the future compared to males, whereas other education, income and age do not. Therefore, this research rejects the hypothesis stated by the Theory of Planned Behavior that subjective norm significantly influences a person's behavioral intention (to recycle mobile phones in this case), whereas attitude and perceived behavioral control are important factors.

Due to the exploratory factor analysis in **Chapter 7**, hypotheses that were introduced in **Chapter 5** could not be tested on a one-on-one basis because several survey questions loaded high on factors that also included questions related to other factors. Outcomes of the hypothesis tests are located in **Table 31**. From the original hypotheses, hypothesis 1, 3, 4, 7, and 9 could be supported after regressing the adjusted factors on a consumer's recycling intention. Each question that corresponds to the original factors load high (>|0.3|, Field (2013)) on the generated factors, which are found to be significant predictors of recycling intention. Hypothesis 2, 5, 6, and 8 are not supported by the new factors because the questions corresponding to the original intended factors either load high on new insignificant factor (SUB, INC, SCHEME, SOLD) or its effect is ambiguous (e.g. hypothesis 8).

Table 31: Results on hypotheses

H	Relationship with INT	Part of new factor**	Result	Supporting research	Contradicting research
H1	ATT (+) → INT	**ATT***, **MOR**	Sign.	Ajzen (1991), Cheung et al (1999), Tonglet et al (2004a), Tonglet et al (2004b), Botetzagias et al (2015), Bamberg & Moser (2007), Wright (2011)	Davis et al (2006), Philippsen (2015), Xu et al (2017)
H2	SUB (+) → INT	SUB	Not Sign.	Davis et al (2006), Philippsen (2015), Botetzagias et al (2015)	Ajzen (1991), Cheung et al (1999), Xu et al (2017)
H3	PBC (+) → INT	**PBC, MOR**	Sign.	Ajzen (1991), Cheung et al (1999), Tonglet et al (2004b), Botetzagias et al (2015), Bamberg & Moser (2007)	Tonglet et al (2004a), Davis et al (2006), Philippsen (2015), Xu et al (2017)
H4	MOR (+) → INT	**MOR**	Sign.	Beck & Ajzen (1991), Conner & Armitage (1998), Chu & Chiua (2003), Botetzagias et al (2015), Bamberg & Moser (2007)	Davis et al (2006), Philippsen (2015)
H5	INC (-)→ INT	INC, SCHEME	Not Sign.	Tonglet et al (2004a)	Tonglet et al (2004b), Philippsen (2015)
H6a	Female (+)→ INT	…	Sign.	Hornik (1995), Saphores (2012), Botetzagias et al (2015), Kruijs (2016), Iyer & Kashyap (2007)	(Oskamp et al (1991), Gamba & Oskamp (1994), Wright (2011)
H6b	Age (+)→ INT	…	Not Sign.	Botetzagias et al (2015), Oskamp et al (1991)	Hornik et al (1995), Tonglet et al (2004a), Saphores et al (2012), Song et al (2012), Kruijs (2016)
H6c	Education (+)→ INT	…	Not Sign.	Hong et al (1999), Jenkins et al (2003) Botetzagias et al (2015), Kruijs (2016)	Duggal et al (1991), Hong et al (1993), Ferrara & Missios (2004),
H6d	Income (+)→ INT	…	Not Sign.	Hong et al (1993), Botetzagias et al (2015), Kruijs (2016)	Duggal et al (1991, Jenkins et al (2003), Tonglet et al (2004a), Hornik et al (2005), Yoo & Kwak (2009),
H7	MON (+) → INT	**MON**, **MOR**	Sign.	Hornik et al (1991), Iyver & Kashyap (2007), Tanham et al (2014), Amini et al (2014)	Kruijs (2016)
H8	PRB (+) → INT	**PBC**, SOLD	Not Sign.	Tonglet et al (2004a)	Tonglet et al (2004b), Philippsen (2015), Cheung et al (1999), Xu et al (2017)
H9	ORB (+) → INT	**MOR, PCB**	Sign.	Ogondo & Williams (2011b)	

** Each factor in Bold has been found to be significantly influencing a person's behavioral intention to recycle their mobile phones in the future.*

*** new factors are the factors generated from the exploratory factor analysis in **Table 20**. Old factors are those as explained in **Chapter 5** in **Table 4**.*

As shown in **Table 31**, research on factors that influence recycling intentions (of domestic waste and e-waste) is very divided. Many studies generated mixed results regarding the significance and directions of the relationships between endogenous factors and the recycling intention. Note that "Supporting research" in **Table 31** refers to the significance (significant/not significant) of the factor on influencing recycling behavior, and not the direction (positive/negative) of this relationship. Sometimes the sign of the relationship differs too between different research papers.

For hypothesis 6 – the effect of demographic variables on the intention to recycle mobile phones – evidence has been found that females have a significantly different distribution and mean rank (mean $rank_{female}$ = 99.69; mean $rank_{male}$ = 81.31) compared to males implying that females have a higher intention. For age, educational level, and income no such differences have been found indicating that distributions and mean ranks are not significantly different between different age, educational, and income related groups.

For **gender**, this outcome is in line with Hornik (1995), Saphores et al (2012), and Kruijs (2016), and Iyer and Kashyap (2007), which is probably because of the fact that gender (females = 1) is correlation with the factor with the largest coefficient – moral norm (**Table 30**) – suggesting that women are more concerned about the environment than men. For **age**, this outcome is in line with research conducted by Botetzagias et al (2015) and Oskamp et al (1991) that indicated that age doesn't significantly influence recycling behavior. However, Hornik et al (1995), Tonglet et al (2004a), Saphores et al (2012), Song et al (2012), and Kruijs (2016) showed that age plays a significant (but minor) role in e-waste recycling behavior. Since the age range of respondents in this thesis is very restricted (18-27), conducting a similar research on mobile phone recycling intentions for a larger age range is required to get a better understanding of the effect of age. For **education,** this outcome is in line with Kruijs (2016). However, Duggal et al (1991), Hong et al (1993), and Tonglet et al (2004a) support the opposite conclusion that education does influence a person's recycling behavior. Since 78% of the respondents are current students that are involved in a scientific bachelor or master program the variance in this variable is low and a very small amount of data has been collected from lower educational programs, which is a limitation. For **income**, results are supported by Hornik et al (1995) in case of waste recycling and by Saphores et al (2012) and Kruijs (2016) in case of e-waste recycling. Note that range of free-disposable income is small with 70% of the respondents having less than €450 to spend per month (after fixed expenses like rent, insurance and subscriptions).

SQ3: Are students being motivated to recycle their old handsets by imposing a fee-based EPR approach on the sale or disposal of mobile phones and which maximum fee would be accepted?

Based on the respondent's answers addressing willingness to pay the students seem really divided with only 46% of them thinking consumers should be at least partially responsible for the recycling cost of mobile phones. This implies a real lack of awareness of how WEEE legislation works since retailers already implicitly incorporate all such costs in product sales prices. Simultaneously, 79% of the respondents are willing to pay at least 1%, and at least 58% are willing to pay 2% on top of the sales price. This is a contradictory to the previous statement. According to SWICO (a Swiss PRO) recycling fees of €0,08[19] on mobile phones are levied in Switzerland, which is much less than a typical

[19] http://www.swicorecycling.ch/en/administration/arf-tariff

1% of the mobile phone sales price that was used in this thesis. This implies that respondents think that recycling costs per handset are much larger than these can optimally be in reality.
When comparing recycling costs payment systems of advanced recycling fees (ARFs), pre-disposal fees (PDFs), and a deposit refund system (DRS) in this sample a deposit refund system seems the most promising in terms of creating awareness for mobile phone recycling (including reuse) and as a motivational tool for students to return their used handsets. This thesis has indicated that a system based on a deposit refund system (DRS) is the most promising in raising awareness of mobile phone recycling (WA = 5.2), compared to an ARF (WA = 4.6) and a PDF system (WA = 4.16). In terms of a functional incentive, a DRS is the most promising (WA =5.4), compared to an ARF (WA = 4.36), and a PDF (WA = 3.84). However, no significant relationship was found between demographic variables and a person's willingness to return their mobile phones (DRS), or willingness to pay (ARF or PDF system). Still, it was found that an above expected (chi-square test on independence) amount of males would return their used handsets when a deposit fee of €11-15 was levied, whereas the opposite was the case for females. No significant differences between both genders were found for other ranges of deposits. This may indicate that the threshold for a large share of males to return their phones is reached sooner compared to females, which requires further research. Results indicate that a deposit fee of €11-15, €16-20, €21-25, or €25+ are a large enough incentive for respectively 53%, 66%, 71%, and 76% of the respondents to return their mobile phones to claim back their deposits. This implies that 24% of the respondents will never return their old phones regardless of the deposit's tariff. Probably this can be explained by the fact that they think their mobile phones are worth much more than €25 and they rather sell it themselves. Alternatively, safety reasons might play a role. The largest marginal increase in return rate is 23%-point when increasing the deposit refund fee from €6-10 to €11-15. Although these outcomes are only of a descriptive nature, levying a deposit fee of at least €11-15 is enough to incentivize 53% of the respondents from this sample, and is also perceived as acceptable by 64% of the respondents. This equals a "return/accept ratio" of 0.83, compared to 3.9 when the depository fee is €25+. Hence in terms of fee functionality the latter is preferred, but in terms of consensus €11-15 is preferred. Combining a depository fee with more attractive disposal opportunities (convenient return infrastructure) and additional services (e.g. free data removal and data transfer services) likely increases collection rates of used mobile phones.

8.2 CONCLUSION

The primary goal of this study was to identify which type of EPR scheme (ARF, PDF, DRS) is the most effective in reducing mobile phone hibernation by increasing mobile phone collection rates. As already concluded by Silvery & Chang (2010): at least some form of mandatory recycling system should be in place in order to increase the recycling rate. A large fraction (75% - 4.2 Mln units) of obsolete mobile phones is currently not engaging in reuse or recycling activities leading to unsatisfactory recovery rates (24% - 1.34 Mln units). Over 6 out of 10 replaced mobile phones are stockpiling in Dutch households and at Dutch student houses. Stockpiling and landfilling figures together yield a reuse market potential up to €192 Mln annually, which is currently unused. If this behavior continuous, it could be that people will posses substantial amounts of unused mobile phones in the future. This must be prevented. It has been found that moral norms, attitudes towards e-waste recycling, perceived behavioral control, and whether someone is willing to recycle without being compensated for it or when it costs money all positively and significantly influence a student's intention to hand in their mobile phones for reuse and recycling. This must be taken into consideration, when establishing an efficient take-back infrastructure.

These results imply that Dutch students are predominantly motivated by intrinsic (altruistic) factors. So far, however, this thesis' material flow and consumer behavior analysis suggest that intrinsic motivation alone has not lead to a considerable amount of mobile phone reuse and recycling itself. In order to make people more aware of the importance of mobile phone recycling and to provide incentives it is examined which EPR scheme, as an external motivation, is expected to be most successful in doing so. Results have indicated that a DRS is the most promising both in creating awareness for recycling and as an incentive for Dutch students to recycle their phones compared to ARFs and PDFs. Deposit fees of €11-15 are expected to be the most balanced in terms of acceptability and functionality (increasing collection rates), whereas a fee of €25+ has been found to be the most functional in increasing collection rates. However, only 19% of the respondents perceive the latter as acceptable, which is an issue. Levying a recycling fee of €0-5 is perceived as the most acceptable (93%), but, only an unsatisfactory 23% would return their mobile phones in this case.

The practical relevance of these findings is that a DRS on mobile phones is currently under investigation by the Dutch Ministry of Infrastructure and Environment as a potential strategy towards a circular economy (AfvalOnline, 2017). This thesis has compared such a deposit system (DRS) with other recycling fees (ARF and PDF) and has concluded that out of all considered options a DRS approach is the most preferred way to go to reduce mobile phone hibernation. The refundable characteristic of this fee is functioning as an additional motivational tool (Silveira & Chang, 2010). As indicated by (Silveria & Chang (2010): each strategy aimed to increase collection rates can only be successful when it is combined with programs that aim to increased consumer awareness (Silveira & Chang, 2010). This thesis has shown that a DRS potentially satisfies this role to increase consumer awareness (weighted average score of 5.2 out of 7) and simultaneously functions as an incentive (weighted average score of 5.4 out of 7) via the refunds. Combining such an approach with high visible collection points, increased environmental education about what people can do with their used mobile phones, and increased efforts by telecom providers to incentivize consumers to hand in their used phones is likely to increase future collection rates.

8.3 RESEARCH LIMITATIONS AND RECOMMENDATIONS

This thesis has several important limitations, which have to be addressed. First of all, in order to perform the material flow analysis several restricting assumptions had to be made in the calculation of import flows, mobile phones in use, obsolescence flows, and end-of-life disposal options available. Although the current analysis has given some sort of picture about what happens with mobile phones in the Dutch system for a given year, uncertainty intervals are big. According to Wecycle, they are currently focussing on specific sub categories of WEEE that are high in volume, which includes mobile phones. By the end of this year it is therefore more likely to get more accurate information regarding mobile phone landfilling and recycling figures. Future research on this topic should be focussing on decreasing the degree of uncertainty in making such flow estimations.

Secondly, the sample of respondents examined in the behavioral analysis in this thesis is not generated via random probability sampling with the consequence that the sample only gives insights in the behaviour of Dutch students and recent graduates between the age of 18 and 27 in the Rotterdam area. This affects the generalizability of the outcomes to the entire Dutch population. It is recommended to do future research with a different sampling technique that covers a more varied sample of respondents, which is needed to make any implications about the Dutch population. Another method to gain more qualitative data is by means of face-to-face interviews to determine the willingness to recycle and consumer attitudes towards a recycling fee. This likely results in more complete and more comprehensive outcomes that complement the methodology of this thesis.

Thirdly, to overcome issues related to assumptions of linear regression, a binary logistic regression methodology is used to analyse the effect of psychological constructs on the recycling intention. This makes it difficult to compare with comparable research since linear regression (Tonglet et al, 2004ab; Philippsen, 2015), or ordinal regression (Kramer et al, 2014) are more popular in the TPB analytical framework. Ordinal regression is not done due to the lack of knowledge of the author in this specific methodology and because a binary logistic regression is more easily interpreted. Generating a dataset (e.g. by collect more observations) that allows the use of other analysis techniques without violating assumptions is needed to get a better picture between, for example, different gradations of the recycling intention. Ordinal regression can be used to see the significance of each of the 7-point Likert scale levels of the independent variable, rather than the binary outcome where 1 represents at least "somewhat willing to recycle" and 0 represents "neutral" as the most positive answer of not having a recycling intention.

Fourthly, this research uses the Theory of Planned Behavior by Ajzen (1991) as the main analytical framework. However, the predictive ability of the TPB relies on the researcher's ability to identify and measure all attributes that are considered by the consumer in forming their attitudes/beliefs. The theory relies on cognition, which neglects any influence that could result from emotion, spontaneity, habit, or cravings (Bray, 2008). As shown by this thesis: many people have the intention of at least "somewhat willing to recycle my mobile phones in the future", however, no one has recycled their most recently retired mobile phone and only 37% has given their latest handset a second life in the form of reuse. This indicates, even though people have the intention to perform behavior in the future, that past habits may give a different picture.

Besides, an intention is likely to be a dynamic concept, which constantly is re-evaluated by people as circumstances change, making it difficult to predict future behavior (Bray, 2008). It is therefore likely that same survey on the same sample over 10 years yields different outcomes compared to the current outcomes. Examples of alternative methodologies that can be used to assess and predict consumer behaviour are the Theory of Trying, the Model of Goal Directed Behaviour, Utility Theory (Bray, 2008), or the Model of Hornik (1995) (**Table 3**). The same can be said about using the material flow analysis (MFA) as main approach for the life cycle analysis part. Using life cycle assessment (LCA) or multi criteria assessments (MCA) as alternative approaches that complement a material flow analysis can be conducted. Future research could focus on the environmental impact of mobile phone flows in the Netherlands using LCA, or involve more qualitative aspects using MCA.

So far, research on mobile phone has either primarily focussed on mobile phone flows, consumer use and disposal behaviour, and general descriptive statistics concerning incentives and recycling awareness. This thesis attempted to combine each of these areas in one research design in order to get an overall picture of obsolete mobile phones in the Netherlands. Future research could do something similar for a different geographic region than the Netherlands. This thesis placed emphasis on used mobile phones, however, there are many other small WEEE products that share characteristics on which this methodology can be applied. Although mobile phones are the most likely to have the highest replacement frequency and the highest reuse value, the collection of small WEEE overall is still below expectations (Darby & Obara, 2005; Ogondo & Williams, 2011c). One must understand why consumers dispose each particular device in a specific way and how consumers can be incentivised and informed to act pro-environmentally. Future research should also focus on the operational part of creating such a deposit-refund system and whether it is efficient from an operational perspective. For example, do increases in collection rates offset the costs associated with collecting these deposits and how can it be efficiently organized in terms of responsibilities? Finally, this research found no relationship between demographic factors and willingness to pay for the recycling of mobile phones. This is something future research could focus on specifically.

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APPENDIX

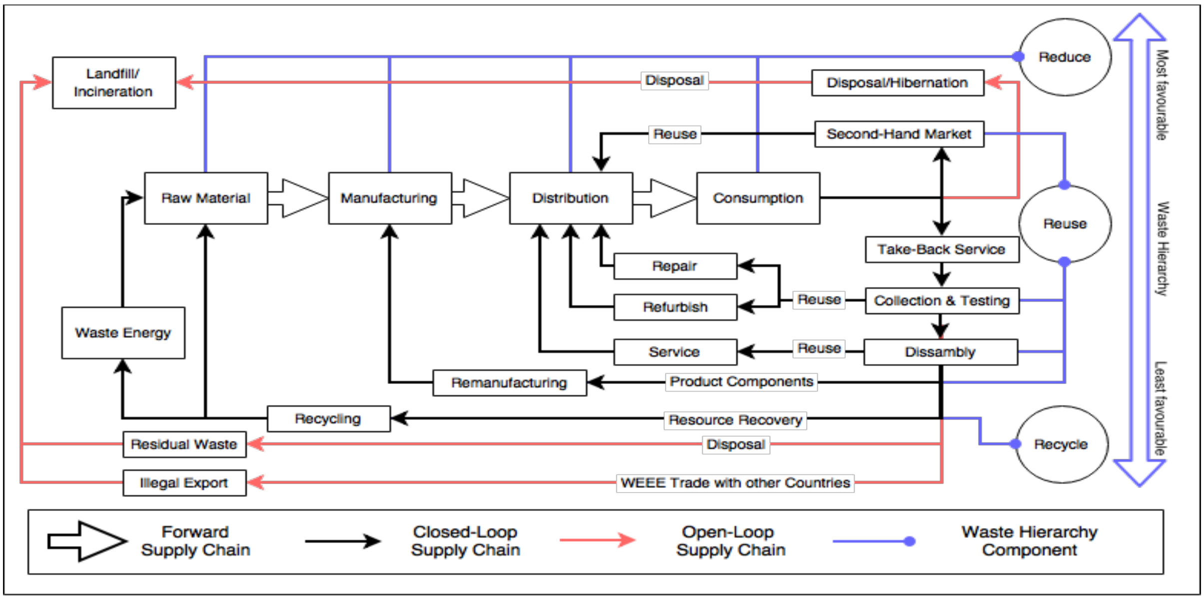
Appendix 1: Mobile Phone Dimensions

Model	Year	Height (mm)	Width (mm)	Depth (mm)	Volume (cm^3)	Weight (g)	Source
Iphone 7 plus	2016	158,2	77,9	7,3	89,96	188	https://support.apple.com
Iphone 7	2016	138,3	67,1	7,1	65,89	138	https://support.apple.com
Iphone 6s plus	2015	158,2	77,9	7,3	89,96	192	https://support.apple.com
Iphone 6s	2015	138,3	67,1	7,1	65,89	143	https://support.apple.com
Iphone se	2016	123,8	58,6	7,6	55,14	113	https://support.apple.com
Iphone 6 plus	2014	158,1	77,8	7,1	87,33	172	https://support.apple.com
Iphone 6	2014	138,1	67	6,9	63,84	129	https://support.apple.com
Iphone 5s	2013	123,8	58,6	7,6	55,14	112	https://support.apple.com
Iphone 5c	2013	124,4	59,2	8,97	66,06	132	https://support.apple.com
Iphone 5	2012	123,8	58,6	7,6	55,14	112	https://support.apple.com
Iphone 4s	2011	115,2	58,6	9,3	62,78	140	https://support.apple.com
Iphone 4	2010	115,2	58,6	9,3	62,78	137	https://support.apple.com
Iphone 3GS	2009	115,5	62,1	12,3	88,22	135	https://support.apple.com
Iphone 3G	2008	115,5	62,1	12,3	88,22	133	https://support.apple.com
Iphone	2007	115	61	11,6	81,37	135	https://support.apple.com
Samsung Galaxy S8	2017	148,9	68,1	8	81,12	155	http://www.gsmarena.com
Samsung Galaxy S7	2016	142,4	69,6	7,9	78,30	152	http://www.gsmarena.com
Samsung Galaxy S6	2015	143,3	70,5	6,8	68,70	138	http://www.gsmarena.com
Samsung Galaxy S5	2014	142	72,5	8,1	83,39	145	http://www.gsmarena.com
Samsung Galaxy S4	2013	136,6	69,8	7,9	75,32	130	http://www.gsmarena.com
Samsung Galaxy S3	2012	136,6	70,7	8,6	83,06	133	http://www.gsmarena.com
Samsung Galaxy S2	2011	125,3	66,1	8,49	70,32	116	http://www.gsmarena.com
Samsung Galaxy S1	2010	122,4	64,2	9,9	77,79	118	http://www.gsmarena.com
Samsung Galaxy S7 Edge	2016	150,9	72,6	7,7	84,36	157	http://www.gsmarena.com
Samsung Galaxy S6 Edge	2015	142,1	70,1	7	69,73	132	http://www.gsmarena.com
Samsung Galaxy S6 Edge+	2015	154,4	75,8	6,9	80,75	153	http://www.gsmarena.com
Samsung Galaxy S8+	2015	159,5	73,4	8,1	94,83	173	http://www.gsmarena.com
Samsung Galaxy S7 Active	2016	148,8	75	9,9	110,48	185	http://www.gsmarena.com
Samsung Galaxy J3	2016	142,3	71	7,9	79,82	138	http://www.gsmarena.com
Samsung Galaxy A3 (2015)	2014	130,1	65,5	6,9	58,80	110,3	http://www.gsmarena.com
Samsung Galaxy A3 (2016)	2015	134,5	65,2	7,3	64,02	132	http://www.gsmarena.com
Samsung Galaxy A3 (2017)	2017	135,4	66,2	7,9	70,81	138	http://www.gsmarena.com
Samsung Galaxy A5 (2015)	2014	139,3	69,7	6,7	65,05	123	http://www.gsmarena.com
Samsung Galaxy A5 (2016)	2015	144,8	71	7,3	75,05	155	http://www.gsmarena.com
Samsung Galaxy A5 (2017)	2017	146,1	71,4	7,9	82,41	157	http://www.gsmarena.com
Samsung Galaxy J	2013	137	70	8,6	82,47	146	http://www.gsmarena.com
Samsung Galaxy J1	2015	129	68,2	8,9	78,30	122	http://www.gsmarena.com
Samsung Galaxy J1 Ace	2015	130,1	67,7	9,5	83,67	131	http://www.gsmarena.com
Samsung Galaxy J1 (2016)	2016	132,6	69,3	8,9	81,78	131	http://www.gsmarena.com
Samsung Galaxy J1 Mini	2016	126,6	63,1	10,8	86,28	123	http://www.gsmarena.com
Samsung Ga. J1 Mini Prime	2016	121,6	63,1	10,8	82,87	126	http://www.gsmarena.com
Samsung Galaxy J2	2015	136,5	69	8,4	79,12	129	http://www.gsmarena.com
Samsung Galaxy J2 (2016)	2016	142,4	71,1	8	81,00	138	http://www.gsmarena.com
Samsung Galaxy J2 Prime	2016	144,8	72,1	8,9	92,92	160	http://www.gsmarena.com
Samsung Galaxy J3 (2016)	2016	142,3	71	7,9	79,82	138	http://www.gsmarena.com
Samsung Galaxy J5	2015	142,1	71,8	7,9	80,60	146	http://www.gsmarena.com
Samsung Galaxy J7	2016	152,2	78,7	7,5	89,84	171	http://www.gsmarena.com
Samsung Galaxy J7 (2016)	2016	151,7	76	7,8	89,93	170	http://www.gsmarena.com

Averages by Year of Samsung and Apple Sample

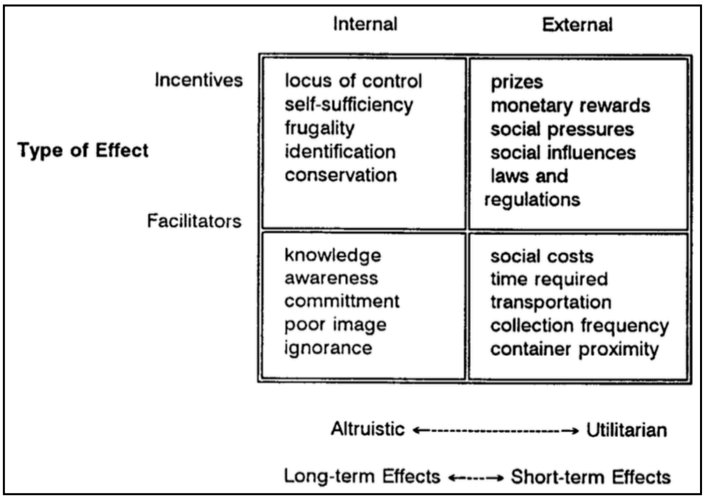
Year	Height (mm)	width (mm)	Depth (mm)	Volume	Weight (g)
2017	143	69	8	78	150
2016	141	70	8	83	149
2015	143	71	8	78	146
2014	142	71	7	72	136
2013	130	64	8	70	130
2012	130	65	8	69	123
2011	120	62	9	67	128
2010	119	61	10	70	128

Appendix 2: A Detailed Abstract of Open-loop and Closed-Loop Supply Chains



Source: Author's own elaboration on (Neto et al, 2010)

Appendix 3: The Altruistic-Utilitarian Framework



Source: (Hornik et al, 1995)

Appendix 4: Empirical Findings on the Theory of Planned Behaviour (Ajzen, 1991)

TABLE 2

PREDICTION OF INTENTION (I) FROM ATTITUDE TOWARD THE BEHAVIOR (A_B), SUBJECTIVE NORM (SN), AND PERCEIVED BEHAVIORAL CONTROL (PBC)

Study	Intention	Correlations			Regression coefficients			
		A_B	SN	PBC	A_B	SN	PBC	R
van Ryn & Vinokur (1990)	Search for a job[a]	.63	.55	.20	.48	.35	.07	.71
Doll & Ajzen (1990)	Play six video games							
	Mean within-subjects	.92	.54	.87	.46	.17	.43	.94
Schlegel *et al.* (1990)	Get drunk[a]	.63	.41	.58	.41	.15	.36	.72
Ajzen & Driver (in press, a)	Five leisure intentions							
	Mean within-subjects	.59	.70	.80	.28	.09*	.62	.85
Watters (1989)	Participate in election	.39	.13*	.30	.32	.03*	.20	.43
	Voting choice	.91	.67	.89	.54	.06*	.39	.94
Netemeyer, Burton,	Participate in election[a]	.33	.34	.62	.10*	.10*	.54	.64
& Johnston (1990)	Lose weight[a]	.33	.14	.51	.24	−.02*	.47	.56
Schifter & Ajzen (1985)	Lose weight	.62	.44	.36	.79	.17	.30	.74
Madden, Ellen, & Ajzen	10 common activities							
(in press)	Mean within-subjects	.52	.36	.37	.43	.22	.26	.63
Ajzen & Madden (1986)	Attend class	.51	.35	.57	.32	.16	.44	.68
	Get an 'A' in a course[b]	.48	.11*	.44	.50	−.09*	.45	.65
Beck & Ajzen (in press)	Cheat, shoplift, lie							
	Mean	.68	.40	.77	.29	.05*	.59	.81
Netemeyer, Andrews,	Give a gift							
& Durvasula (1990)	Mean over five items[a]	.51	.38	.44	.36	.08*	.20	.56
Parker *et al.* (1990)	Commit traffic violations							
	Mean over four violations[a]	.26	.48	.44	.15	.28	.33	.60
Beale & Manstead (1991)	Limit infants' sugar intake[c]	.41	.33	.52	.26	.16*	.40	.60
Godin, Vezina, & Leclerc								
(1989)	Exercise after giving birth[a]	.50	−.01*	.60	.76	−.24	.84	.94
Godin *et al.* (1990)	Exercise after coronary[a]	.42	.13*	.50	.25	.01*	.39	.55
Otis, Godin, & Lambert								
(in press)	Use condoms[a]	.62	.42	.29	.52	.26	.17	.69

* Not significant; all other coefficient's significant at $p < .05$.

[a] Secondary analysis.

[b] Beginning of semester.

[c] Control group, second interview.

Appendix 5: Survey Questions of Part 1

Factor	Question	Source
Attitude (ATT)	1. E-waste recycling is good/useful	Tonglet et al (2004a)
	2. E-waste recycling is rewarding	Tonglet et al (2004a)
	3. E-waste recycling ir responsible	Tonglet et al (2004a)
	4. I am interested in the idea of e-waste recycling	Knussen and Yule (2008)
	5. I think e-waste recycling has many positive effects on the environment	Kelly et al (2006)
	6. I make great effort to recycle e-waste	Kelly et al (2006)
Subjective norm (SUB)	1. Most people think I should recycle	Tonglet et al (2004a)
	2. Most people would approve it if I would recycle	Tonglet et al (2004a)
	3. If more would people recycle, I would recycle more too	Knussen and Yule (2006)
Moral norm (MOR)	1. I feel I should not waste anything if it can be used again	Tonglet et al (2004a)
	2. It would be wrong of me not to recycle recycle my e-waste	Tonglet et al (2004a)
	3. I would feel guilty if I did not recycle my e-waste	Tonglet et al (2004a)
	4. Everybody should share the responsibility to recycle e-waste	Tonglet et al (2004a)
Perceived behavioural control (PCB)	1. I know that mobile phones can be recycled	Tonglet et al (2004a)
	2. I know how I can recycle my mobile phones	Tonglet et al (2004a)
	3. I know where to take my mobile phones to recycle	Tonglet et al (2004a)
	4. Recycling my mobile phones is easy	Tonglet et al (2004a)
	5. There are plenty of opportunities for me to recycle my mobile phones	Knussen and Yule (2008)
	6. I would recycle my mobile phones if I had more information about the advantages of recycling	Mishima & Nishimura, 2016a
Inconvenience (INC)	1. Recycling recycle my old mobile phones takes too much time	Tonglet et al (2004a)
	2. Recycling my mobile phones takes too much effort	Tonglet et al (2004a)
	3. Recycling my mobile phone is too complicated	Tonglet et al (2004a)
	4. I am being motivated to recycle my mobile phone	Ogondo & Williams, 2011b
	5. I trust mobile phones recycling programs	Mishima & Nishimura, 2016a
Monetary Incentives (MON)	1. I would recycle my mobile phone, even if I have to pay for it	Kruijs (2016)
	2. I would recycle my mobile phone, even if I don't get money for it	Kruijs (2016)
	3. I would recycle my mobile phone only when I get money for it	Kruijs (2016)
Other Recycling behaviour (ORB)	1. I have recycled domestic waste in the past year	Philippsen (2015)
	2. I have recycled electronic waste in the past year	Philippsen (2015)
Past recycling behaviour (PRB)	1. I have recycled my old mobile phones or traded it in for a new mobile phone in the past	Philippsen (2015)
	2. I have sold or given away my old mobile phone in the past	Philippsen (2015)
Behavioural intention to recycle (INT)	1. I have the intention to recycle domestic waste in the future	Philippsen (2015)
	2. I have the intention to recycle electronic waste in the future	Philippsen (2015)
	3. I have the intention to recycle my mobile phone or trade it in for a new mobile phone in the future	Philippsen (2015)
	4. I have the intention to sell or give away my mobile phone when I have replaced it with a new mobile phone in the future	Philippsen (2015)

Appendix 6: Components of WEEE IT & Telecom equipment category

3. IT AND TELECOMMUNICATIONS EQUIPMENT

Centralised data processing:

Mainframes

Minicomputers

Printer units

Personal computing:

Personal computers (CPU, mouse, screen and keyboard included)

Laptop computers (CPU, mouse, screen and keyboard included)

Notebook computers

Notepad computers

Printers

Copying equipment

Electrical and electronic typewriters

Pocket and desk calculators

and other products and equipment for the collection, storage, processing, presentation or communication of information by electronic means

User terminals and systems

Facsimile machine (fax)

Telex

Telephones

Pay telephones

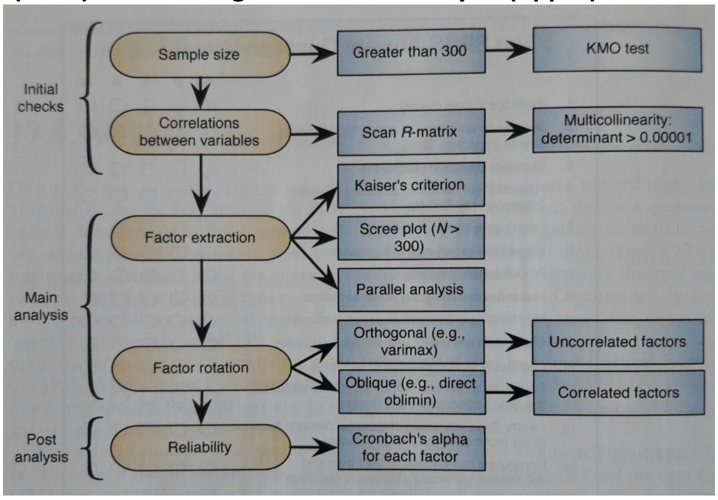
Cordless telephones

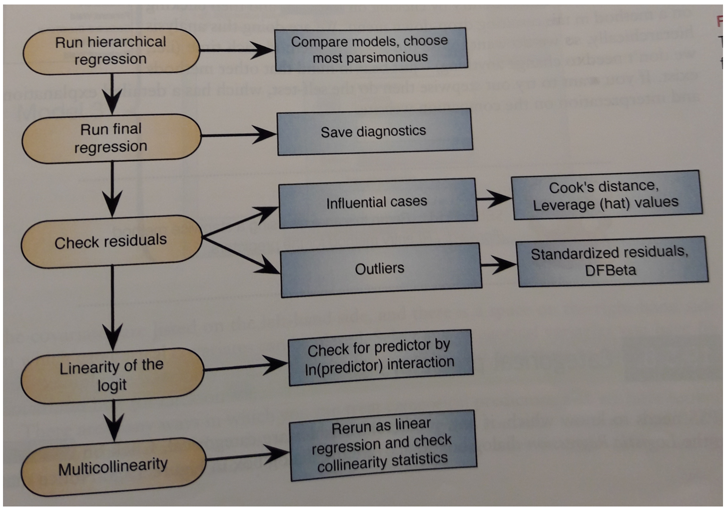
Cellular telephones

Answering systems

and other products or equipment of transmitting sound, images or other information by telecommunications

Appendix 7: Field (2013) methodologies of Factor Analysis (upper) and BLR analysis (bottom)





Appendix 8: Partial Correlation Matrix

Correlation	ATT_1	ATT_2	ATT_3	PBC_2	PBC_3	PBC_4	PBC_5	PBC_6	INC_1	INC_2	INC_3	INC_4
ATT_1	1,00	0,49	0,58	-0,02	-0,04	-0,04	0,02	0,17	-0,09	-0,02	-0,08	0,15
ATT_2	0,49	1,00	0,46	0,24	0,20	0,11	0,19	0,09	-0,14	-0,14	-0,15	0,22
ATT_3	0,58	0,46	1,00	-0,01	-0,02	-0,10	-0,03	0,19	0,01	0,02	0,08	0,22
ATT_4	0,60	0,40	0,55	0,10	0,07	0,11	0,09	0,11	-0,17	-0,15	-0,15	0,23
ATT_5	0,63	0,40	0,49	0,00	0,00	0,02	0,02	0,18	-0,07	-0,04	-0,08	0,17
ATT_6	0,30	0,23	0,22	0,29	0,30	0,23	0,26	0,16	-0,20	-0,25	-0,22	0,30
SUB_1	0,06	0,18	0,12	0,20	0,18	0,17	0,22	0,01	-0,15	-0,16	-0,15	0,15
SUB_2	0,15	0,22	0,21	0,14	0,17	0,20	0,25	0,06	-0,22	-0,20	-0,21	0,18
SUB_3	0,15	0,15	0,22	-0,14	-0,20	-0,27	-0,16	0,24	0,06	0,00	0,16	0,07
MOR_1	0,29	0,31	0,38	0,11	0,16	0,13	0,17	0,26	-0,11	-0,23	-0,11	0,26
MOR_2	0,38	0,32	0,39	0,15	0,12	0,05	0,06	0,30	-0,15	-0,22	-0,12	0,26
MOR_3	0,24	0,23	0,25	0,07	0,08	-0,01	0,04	0,20	-0,14	-0,20	-0,12	0,35
MOR_4	0,30	0,17	0,23	0,06	0,00	0,08	0,18	0,19	-0,26	-0,26	-0,20	0,33
PBC_1	0,14	0,20	0,13	0,45	0,34	0,30	0,26	-0,14	-0,10	-0,12	-0,26	0,05
PBC_2	-0,02	0,24	-0,01	1,00	0,86	0,57	0,49	-0,17	-0,04	-0,15	-0,34	0,07
PBC_3	-0,04	0,20	-0,02	0,86	1,00	0,71	0,64	-0,17	-0,09	-0,17	-0,41	0,12
PBC_4	-0,04	0,11	-0,10	0,57	0,71	1,00	0,81	-0,24	-0,30	-0,35	-0,60	0,05
PBC_5	0,02	0,19	-0,03	0,49	0,64	0,81	1,00	-0,12	-0,29	-0,28	-0,49	0,16
PBC_6	0,17	0,09	0,19	-0,17	-0,17	-0,24	-0,12	1,00	-0,01	-0,04	0,10	0,14
INC_1	-0,09	-0,14	0,01	-0,04	-0,09	-0,30	-0,29	-0,01	1,00	0,70	0,54	-0,01
INC_2	-0,02	-0,14	0,02	-0,15	-0,17	-0,35	-0,28	-0,04	0,70	1,00	0,62	-0,09
INC_3	-0,08	-0,15	0,08	-0,34	-0,41	-0,60	-0,49	0,10	0,54	0,62	1,00	-0,03
INC_4	0,15	0,22	0,22	0,07	0,12	0,05	0,16	0,14	-0,01	-0,09	-0,03	1,00
INC_5	0,03	0,12	0,01	-0,07	0,02	0,09	0,19	0,10	-0,14	-0,15	-0,11	0,23
MON_1	0,16	0,18	0,09	0,19	0,16	0,01	0,06	0,20	-0,10	-0,19	-0,07	0,37
MON_2	0,37	0,24	0,29	0,00	0,01	0,02	0,09	0,34	-0,14	-0,27	-0,10	0,29
MON_3	-0,14	-0,06	0,00	-0,05	-0,06	-0,08	-0,09	-0,08	0,18	0,33	0,19	-0,11
ORB_1	0,26	0,18	0,18	0,13	0,09	0,13	0,15	0,13	-0,17	-0,18	-0,12	0,27
ORB_2	0,22	0,21	0,20	0,41	0,34	0,27	0,22	-0,02	-0,08	-0,18	-0,19	0,19
PRB_1	0,05	0,18	0,04	0,42	0,43	0,22	0,23	-0,05	-0,02	-0,08	-0,12	0,09
PRB_2	0,05	0,22	0,15	0,11	0,09	-0,01	0,06	0,01	0,07	0,03	0,00	0,00

Determinant: 5.358E-7

Appendix 9: Scree plot factor matrix (inflexion point at factor 9)