7-22-2019

Sustainability Implications of Consumer Electronics Adoption in the United States

Shahana Althaf
sa6321@rit.edu

Sustainability Implications of Consumer Electronics Adoption in the United States

by

Shahana Althaf

A DISSERTATION

Submitted in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Sustainability

Department of Sustainability

Golisano Institute of Sustainability

Rochester Institute of Technology

July 22, 2019

Certificate of Approval

Golisano Institute for Sustainability

Rochester Institute of Technology

Rochester, New York

Ph.D. DEGREE DISSERTATION

The Ph.D. Degree Dissertation of Shahana Althaf has been examined and approved by the dissertation committee as satisfactory for the dissertation requirement for the Ph.D. degree in Sustainability.

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Dr. Thomas Trabold, Director of Ph.D. program and Department Chair

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Dr. Gregory Babbitt, Dissertation External Chairperson

____
Dr. Callie Babbitt, Advisor & Committee Chairperson

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Dr. Roger Chen, Committee Member

____
Dr. Gabrielle Gaustad, Committee Member

Date __________________________

ABSTRACT

High rates of technological innovation and consumer adoption in the consumer electronics sector has led to increasing concerns about the potential implications on resource consumption and waste generation. Despite growing public and policy attention on recycling as a strategy to curb resource demand and waste management impacts, less than 50 percent of end-of-life electronics are recovered for recycling in the U.S. A critical barrier to sustainable management of electronics is the lack of data and tools to proactively estimate consumption and waste flows, to create solutions that respond to the dynamic nature of this product sector. For sustainable solutions to keep pace with the rapid rate of innovation, they must be informed by comprehensive and proactive research, that not only quantifies material flows in electronics but also investigates associated economic, environmental and social implications.

This dissertation aims to fill this knowledge gap through three interconnected lines of inquiry. First, a baseline material footprint analysis is conducted to retroactively estimate the material consumption and waste generation associated with household electronic product consumption in the U.S. from 1990 until present. Results from this analysis contradict the long-standing assumption that e-waste is a rapidly growing waste stream in the U.S. In fact, the net material footprint of electronics has begun to decline, mainly due to consumers phasing out large Cathode Ray Tube TVs in favor of lighter flat panel technologies. While the analysis shows decline in potential e-waste toxicity from traditional hazards like lead and mercury, it also raises new issues of concern for e-waste management. Notably, results show high resource potential in the emerging e-waste stream with new opportunities to recover scarce metals not currently recycled.

Second, a predictive material flow model based on historic product adoption behavior was developed, to enable future forecasts of resource and waste flows so that stakeholders can create proactive – rather than reactive – solutions. Adoption forecasts for emerging technologies show increasingly fast windows of product innovation and uptake. In other words, new electronics are likely to have rapid uptake in the market but may be quickly replaced by subsequent product innovations. The forecasts also suggest that waste flows for mature products like CRTs, desktops, monitors and flat panel TVs will continue to be a major issue for the short term, with declining contribution to the U.S. e-waste stream in the future. Material flow estimations predict increasing prevalence of critical materials in e-waste underscoring a need to shift e-waste management mechanisms from 'mass' to 'materials', or in other words, from an emphasis on 'waste diversion' to a new focus on 'resource retention'.

Finally, a comprehensive set of sustainability metrics were created and applied to assess the economic, environmental and social impacts for the wide spectrum of materials used in electronics. Material metrics help identify key material hotspots and prioritize new solutions for reducing resource demand and waste management challenges. This dissertation contributes novel data and modeling tools that can aid stakeholders across the electronics industry in making informed decisions in product design, policy planning and material recovery in electronics.

ACKNOWLEDGEMENT

Let me begin by thanking god almighty for blessing me with the opportunity to return to college and continue my education after being a mother.

Next, I would like to dedicate my sincere gratitude to my PhD advisor Dr. Callie Babbitt for this great research opportunity. Her continuous support and guidance have helped me grow as a person and as a researcher. I will always be grateful to her for all her great mentoring. Her hardworking nature and dedication to research will always be an inspiration to me.

A sincere thanks to Dr. Roger Chen for his guidance throughout my PhD. Thanks to him for being so approachable and patient with me during the MATLAB training days. He is my MATLAB guru and I will always be thankful to him for my coding skills. Thanks to Dr. Gabrielle Gaustad for all her help and guidance in my research, especially in my material sustainability chapter. Thanks for being such a great inspiration, Dean. Gabby! Thanks to Dr. Gregory Babbitt for taking time from his busy schedule to be on my dissertation committee. Next, I would like to thank my funding agencies- National Science Foundation, Consumer Technology Association and Staples Sustainable Innovation Lab for making this research possible. I also want to thank my MS thesis advisor Dr. Drew Maywar for leading me to the world of research and inspiring me to apply for a PhD.

Last but not the least, I would like to thank my family and friends for their continuous support. My friends in GIS especially Swati and Hema, my sister, my brother-in-law, my sister-in-law - 'Thanks to all of you, you all have played a great part in my PhD journey and my success'. My parents, for instilling the importance of education in me at a very early age and for doing everything they could to support my studies. And to my husband, without whose support none of this would have been possible, 'Ikka, thank you for being who you are, thank you for being my mentor, my best friend and the best partner anyone could ever ask for. I know you are most proud of my accomplishments and you will do absolutely anything to help me achieve my dreams'.

Finally, my son, 'I am sorry if I did not spend enough time with you these four years when I was busy with my research and writing. I want you to know that no matter what I achieve in my career, I will be most proud of being your mother. Thank you for coming into my life, for being my life, you are my inspiration, and this is for you'.

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GLOSSORY OF TERMS

EPR	Extended Producer Responsibility
EPA	Environmental Protection Agency
CRT	Cathode Ray Tube
CTA	Consumer Technology Association
REE	Rare earth Elements
PGM	Platinum Group Metals
LED	Light Emitting Diode
LCD	Liquid Crystal Diode
CCFL	Cold Cathode Fluorescent Lamp
PCB	Printed Circuit Board
LIB	Lithium Ion Battery
CE	Circular Economy
GWP	Global Warming Potential
MRD	Mineral Resource Demand
CED	Cumulative Energy Demand
ITO	Indium Tin Oxide
MFA	Material Flow Analysis
LCA	Life Cycle Assessment

CHAPTER 1: Introduction

Consumer electronic products have fundamentally changed the way society communicates, accesses information, and entertains. Electronic product sales generated over US$225,000 Million in the United States in 2017 (CEA, 2017). Electronics owned in US households have become increasingly diverse since 2000 (Ryen et al., 2014) with each household owning more than 11 devices, of which at least four are connected to the internet (Mars et al., 2016). This growth and diversification in electronics consumption has led to both public and scientific concerns about the potential implications on material demand for product manufacturing and end-of-life product management. (Lundgren,2012).

E-waste management has been predominantly deemed as a waste diversion mechanism in the U.S., since traditional electronics were assessed to contain hazardous materials like lead, mercury and cadmium (Chen et al., 2011; Kiddee et al., 2013), which have the potential to cause environmental as well as human health hazards if not managed properly at end-of-life. However, modern electronics also contain valuable metals such as gold, silver, platinum and rare earth elements (Christian et al., 2014; Friege, 2012), the recycling of which can bring economic benefits while offsetting the environmental impacts of virgin metal mining. In recent years, circular economy has introduced an alternative model to the traditional take-make-waste flow model of resources (Kirchherr et al., 2017; Korhonen et al., 2018) and brought attention to the potential for urban mining in the electronics sector (Zeng et al., 2018a). Urban mining, which is the process of retrieving valuable materials from end-of-life products, has been evaluated as a strategy to mitigate resource demand and e-waste (Brunner, 2011; Eygen et al., 2016; Zeng et al., 2018a), but the current e-waste management system is far from realizing these benefits.

E-waste Management System in the US

The U.S. does not currently have a federal mandate to recycle electronic waste. However, some states have enacted legislation mandating the collection and recycling of a select category of products (Figure 1.1). Among the 25 states and District of Columbia that have implemented some type of e-waste legislation in US, only 15 have imposed landfill bans which prohibit the disposal of electronic devices at solid waste landfills (EPA, 2016; Westgate, 2017). Most states follow the extended producer responsibility (EPR) model, where the financial obligation of the product recovery and recycling is passed on to manufacturers who sell products into that state. California is the exception, as it uses the advanced recycling fee model in which consumers pay retailers a small fee at the time of product purchase that is deposited into a fund intended to pay for statewide recycling.

Under the EPR financial model, the state defines a set of devices to be collected for recycling and sets mass-based collection targets for each manufacturer, to reflect their market share in the state (Kang and Schoenung, 2005a). Common product categories 'covered' under state laws include TVs, monitors, laptops, desktops and printers. While the product categories covered for recycling in different states differ, they mostly reflect mature electronics – devices which have already saturated the market, and which may have begun to decline or even be no longer sold, omitting emerging products whose material opportunities and risks are unknown. As with 'covered products' states also differ in the list of 'covered entities' which refers to the consumer groups who can bring back their used products for recycling under that state EPR system. All the state level programs collect e-waste from households, while some include small business and non-profits (ERCC, 2017). Large businesses are usually not included for end-of-life product recovery in state programs. However, industry experts suspect that even the recovered devices are generally shipped overseas to developing countries (Lee et al., 2018) by recyclers for cheap labor, where the products are disassembled in informal settings with no safety standards, placing the workers at risk of hazardous material exposure (Drayton, 2007; Grant et al., n.d.; Perkins et al., 2014). Due to this lack of effective e-waste management policies and recycling infrastructure, the end-of-life product recovery rate for recycling in U.S., is still less than 50% (U. S. Environmental Protection Agency, 2016), while the remaining share of end-of-life electronics continue to stay in landfills or in storage in households.

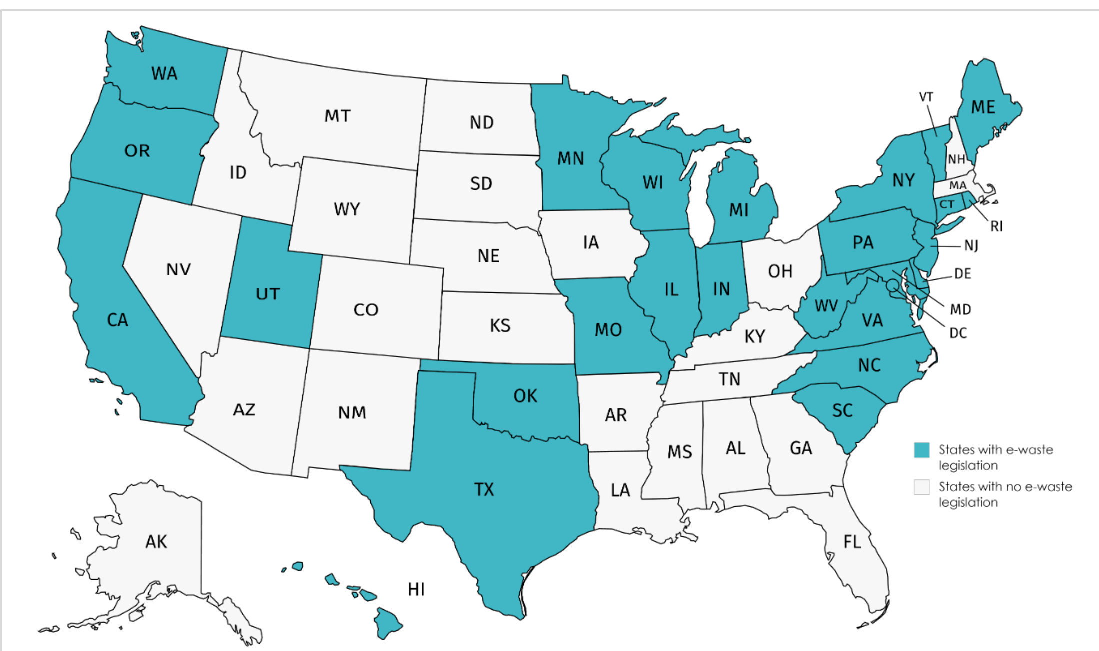


Figure 1.1. States in the U.S. with e-waste legislation

Owing to the variability in product scope and covered entities, it is difficult to compare state level collection rates. However, e-waste collection per capita of a few states (Table 1.1) for which e-waste collection data was publicly available for the latest years show that even though huge variability exists in collection rates, there is a general decline in e-waste collection in the recent years (ERCC, 2018). As state e-waste departments comment that the decline in collection rates is due to changes in TV waste (Connecticut Department of Energy and Environmental Protection, 2017) as light flat panel TVs replace large Cathode Ray Tube (CRT) in the waste stream, the implications of this observed trend on e-waste management is huge as CRTs have been the focus of e-waste polices due to its toxic lead content. As traditional products targeted by e-waste policies start to decline, and new technologies with unknown sustainability implications enter the waste stream, there is need to re-evaluate the waste management strategies.

States in the U.S.	E-waste collection rate (lb /capita) from year 2009-2016								
	2009	2010	2011	2012	2013	2014	2015	2016	2017
Minnesota	5.79	6.59	6.27	6.6	6.01	6.52	7.29	6.58	5.63
North Carolina	0.83	0.96	2.5	4.39	3.63	3.83	3.84	2.85	
Oregon	4.96	6.31	6.69	6.84	7.06	6.91	7.41	6.51	5.81
Washington	5.78	5.92	6.18	6.3	6.48	6.28	6.03	5.14	4.17
Michigan		0.8	1.95	2.79	3.05	2.6	2.58	2.08	1.62
Wisconsin		3.66	6.15	6.83	6.75	6.48	5.16	5.48	5.42

Table 1.1. Trends in annual e-waste collection rates (per capita) in U.S. States.

Shifting perspectives in e-waste management: Waste diversion to Sustainable Material Management (SMM)

Historically, e-waste management represented diversion of toxic waste from landfill and recycling large components for economic benefits. However, the implications of e-waste management are bound to change, as newer consumer technologies enter the waste stream. In contrast to the products currently making up most of the U.S. e-waste, modern electronics are characterized by high functionality in sleek product designs, which is enabled by diverse suite of metals that includes metals such as gallium, tantalum and REEs. Portability is another key feature of newer electronics, which is realized using lithium ion batteries (LIBs) that rely on critical metals like cobalt and lithium. Adding to the demand of these metals in electronics is the growing adoption of clean energy technologies such as electric vehicles which employ LIBs and wind turbines which use REEs. Risk to supply disruptions of these metals, as clean energy technologies are deployed significantly within the global clean energy economy, has resulted in many countries designating these metals to be 'critical' (Lusty and Gunn, 2014). The geographical concentration of production of critical metals is another factor that adds to the significance of mineral security or supply security. Given that consumer electronics are a major consumer of these 'critical metals', electronics recycling benefits gain an added dimension- as a path to mineral security. These emerging material trends call for sustainability material management strategies not just at product end-of-life, but throughout the material lifecycle in a product, including sourcing and production (U.S. EPA, 2009).

To facilitate sustainable materials management in the electronics sector, e-waste policy implementation can become more effective, if it is informed by present and near-term forecasts of e-waste flows and composition. Similarly, product design and manufacturing would benefit from better predictive capacity about which materials may be available from recycled and which materials may be in high demand due to consumption in other competing technologies. Development of recycling technologies and infrastructure would also benefit from near term forecasts of waste flows and its sustainability implications. In any of these cases, proactive insight is necessary, but fundamentally limited by a lack of data or even the predictive tools that can forecast resource use and waste generation in the electronics sector.

While there is considerable amount of literature on product and component level material flows (Babbitt, 2009; Kahhat and Williams, 2012; Yu et al., 2010) and associated environmental impacts (Boyd and Hernandez, n.d.; Duan et al., 2008; Heller, 2002; Kahhat and Williams, 2011; Meyer and Katz, 2016; Teehan and Kandlikar, 2013; Tukker and Jansen, 2006), a comprehensive analysis that involves the whole community of products in electronics is lacking. A key challenge in modelling product and material flows in electronics, is the evolving nature of electronics, where new products are continuously added to the product community and subsequently into the waste stream. This lack of material flow data is a key barrier in evaluating and employing sustainability strategies in the sector. However, planning holistic sustainable material management strategies not only requires up-to-date data on material demand and waste flows in electronics sector, but also knowledge about the potential environmental and economic challenges and opportunities, associated with the use of primary and secondary materials in product manufacturing.

Dissertation Objective

This dissertation aims to answer the overarching research questions of 1) 'How does the dynamic nature of technological progress and consumer trends affect the material consumption and waste generation in the consumer electronics sector and 2) How can sustainable material management strategies effectively respond to these changes. Through the compilation and analysis of historical product adoption data, product material profiles and material specific sustainability metrics, this research creates quality data and novel modeling tools, that lays the foundation for sustainable materials management in electronics, by informing key stakeholders about potential sustainability risks and opportunities. The novelty of this research is that, it improves the state of knowledge on material implications of electronics use in the US, by presenting the most up-date and comprehensive material flow analysis for electronics and by quantifying associated sustainability risks and potential solutions. This dissertation will also be the first to explore the implications of electronics material flow on e-waste policies in the US.

The research was carried out through three interconnected investigations, which are detailed below and shown schematically in Figure 1.2.

Research Question 1: What is the current material footprint of electronics in United States?

Approach: Conduct a comprehensive material flow analysis for all common electronics owned in US in the last 28 years; Understand the trends in the overall mass and material profile of electronics consumption and waste generation; and identify key sustainability challenges and opportunities.

Research Question 2: How can we enable future material flow forecasts in electronics?

Approach: Use characteristics of historic electronic adoption behavior to forecast future product scenarios; Develop parametrized MFA (material flow analysis) models with predictive capability built on historic trends in product adoption or sales.

Research Question 3: How can we minimize sustainability impacts of materials used in consumer electronics?

Approach: Develop a comprehensive set of sustainability metrics for materials contained within electronic products; evaluate the evolving demand and waste of these materials from economic, environmental and social perspectives; Explore potential solutions to minimize sustainability risks associated with material use in electronics.

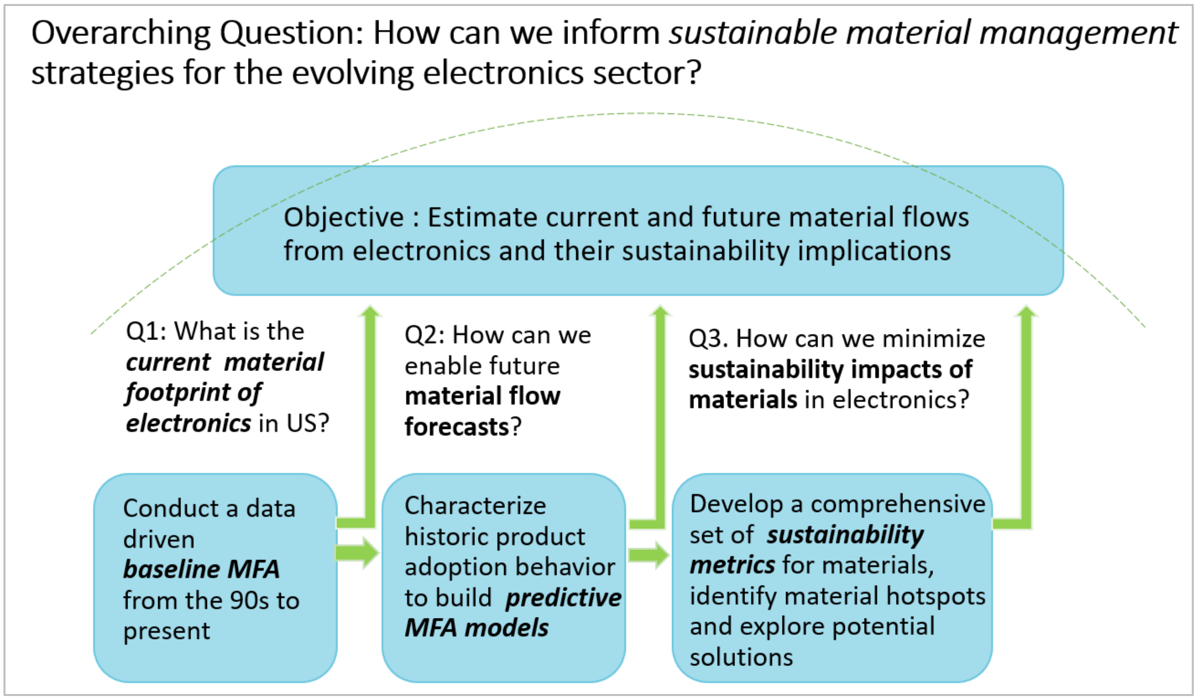


Figure 1.2. Overview of Research Structure

CHAPTER 2: A baseline material footprint analysis for the consumer electronic sector in the U.S.

1. Introduction

Over the last decade, scientific studies (Charles et al., 2017; Cucchiella et al., 2015; Eygen et al., 2016; Herat, 2007; Kaya, 2016; Kumar et al., 2017; Ogunseitan et al., 2009; Perkins et al., 2014; Wang et al., 2013; Zeng et al., 2018b) and media reports have claimed electronic waste to be one of the 'fastest growing waste streams'. While it is intuitive to expect that "e-waste" will grow in parallel with expanding electronic product consumption and decreasing product lifespans, this assertion has not been rigorously analyzed, particularly over a time scale that would reflect nascent electronic consumption trends. Material studies on electronic waste are important to the sustainability field (Zhang et al., 2017, Kiddee et al., 2013; Robinson, 2009), since the products making up electronic waste may contain scarce metals such as cobalt and rare earth elements (Christian et al., 2014; Cucchiella et al., 2015; Işıldar et al., 2017,Dutta et al., 2016), alongside hazardous materials like lead, mercury and brominated flame retardants (Adeyi and Oyeleke, 2017; Chen et al., 2011; Kiddee et al., 2013). Sustainable solutions for consumer electronics do exist, including material substitution (Boks and Stevels, 2014), recycling (Cucchiella et al., 2015; Kang and Schoenung, 2005b; Kaya, 2016; Zeng et al., 2018a), and refurbishment (Bakker et al., 2014; Zlamparet et al., 2017); but are challenged by the system's dynamic nature, wherein waste management is fundamentally "backwards looking," focused on products coming out of use, rather than the new products and evolving suite of materials being added to households over time.

While academic literature has begun to focus more on broad consumer trends (Borthakur and Govind, 2017; Pérez-Belis et al., 2015), most studies have focused on single products such as mobile phones (Golev et al., 2016; Guo and Yan, 2017; Li et al., 2015; Pengwei et al., 2018), computers (Kahhat and Williams, 2012; Petridis et al., 2016; Steubing et al., 2010; Streicher-porte et al., 2005; Yang and Williams, 2009; Yu et al., 2010) and televisions (Gusukuma and Kahhat, 2018), to evaluate product-level consumption trends and end-of-life management strategies. In reality, consumers do not purchase and use individual devices in isolation, rather adopting these products into an ecosystem of devices that collectively meet their needs for communication, productivity, and entertainment (Ryen et al., 2014). Capturing the resource and waste implications of this complex, interacting system requires a detailed understanding of how technological innovation and consumer product adoption change over time (Kasulaitis et al., 2018a; Ryen et al., 2014). Existing literature is largely focused outside the US

(Cucchiella et al., 2015; Habuer et al., 2014; Hagelüken and Corti, 2010; Liu et al., 2006; Parajuly et al., 2017; Wang et al., 2013; Zeng et al., 2016), has a narrow product scope (Miller et al., 2016), and/or has become outdated due to lack of data (Duan et al., 2013; Kasulaitis et al., 2018b; Mars et al., 2016; Miller et al., 2016). For example, e-waste reports by the U.S. Environmental Protection Agency (U. S. Environmental Protection Agency, 2016) stop in 2014 and eventhough another report by National Center for Electronics Recycling (Mars et al., 2016) projected e-wasteflows till year 2020, attendant material impacts were not analyzed. While the need for updated, systematic material studies on electronics was pointed out by past research, (Kasulaitis et al., 2018a) which analyzed the influence of dematerialization on e-waste until 2010, literature has not kept up with real changes in product consumption.

Without up-to-date, holistic analyses of resource use and waste generation in the electronic product sector, proposed interventions and management strategies may not result in the intended sustainability benefits. For example, state e-waste policies in the U.S. historically have been motivated by the goal of keeping hazardous materials like lead and mercury out of landfills (Williams et al., 2008). As a result, these policies focus on large TVs and computers, which can contain hazardous substances in elevated concentrations, but which are predicted to actually decline in the waste stream going forward, as consumers move towards lightweight mobile devices (Althaf et al. 2019). Without a rigorous empirical basis for regulatory coverage, policy instruments are not typically responsive to the changing mix of products or the shifting focus away from toxicity and towards material scarcity, carbon footprint, and economic value. To fill this knowledge gap, we aim here to evaluate the material consumption and e-waste generation associated with changing product consumption trends, with the goal of identifying emerging sustainability challenges and opportunities for science-based solutions.

2. Methods

2.1. MFA Model

To model the material flows from common electronics in US, we applied the methodology of Material Flow Analysis (MFA), which applies mass balance principles to estimate yearly waste flows of products from annual sales and lifespan probability of products. A key innovation here is the application of material flow modeling to the entire portfolio of electronic products consumed in U.S. households over an almost 30-year period. The MFA model estimates product waste flows in each year as follows:

$$W_{p,t} = \sum_{i=1}^{n} L_{p,i} \times S_{p,t-1} \qquad Eq. 1$$

where $W_{p,t}$ is the waste flow of product p in year t, L is the probability that a product p will reach its end-of-life after a lifespan of i years, S is the annual product sales into US households for each year, and n is the maximum lifespan.

Product lifespan probabilities were modelled using the Weibull distribution since it is the most widely used approach for capturing product obsolescence rates (Gu et al., 2018; Habuer et al., 2014; Miller et al., 2016; Oguchi et al., 2008). The probability density function of a Weibull distribution is represented as

$$f(t, a, b) = \frac{a}{b}\left(\frac{t}{b}\right)^{(a-1)} e^{-\left(\frac{t}{b}\right)^{a}} \qquad Eq. 2$$

where a is shape parameter and b is the scale parameter. Here we define product lifespan as the total time it resides in a household, whether in use or in storage, until it becomes available for end-of-life management by reuse, recycling, or discarding. Mean and maximum product lifespan estimates from literature (refer to Appendix A, Table 2) were used to compute the shape parameter a and scale parameter b. The model estimates product waste flows by units based on annual sales units; unit sales are then converted to mass sales by applying average mass of each product sold in each year. Flows of interest in this study are product consumption or inflow to US households (in sales units or sales mass), and annual product waste flows from households in units and mass. To disaggregate total product mass into specific materials and components, material composition data were obtained by extensive product disassembly (n>80 products) and literature search.

2.2. Data Collection

The MFA model study scope included 20 common products sold in US households from 1980 to 2018, which includes TVs, monitors, audio-visual products and mobile products (refer to Appendix A Table 1 for product scope). The products were chosen to represent the typical product ecosystem owned in average US households. The model inputs included annual sales data of all products from 1980 to 2018, average mass and mean and maximum lifespan of products sold each year. Refer to Appendix file Table S8 for annual sales data of all 20 products included in the study scope. These data included compilations of manufacturer reported sales and shipment data and consumer purchase surveys provided by the Consumer Technology Association (CTA) and collaborators (e.g., IDC product sales data provided courtesy of the National Center for Electronics Recycling).

Product mass: Average product mass in each year was estimated through a combination of data from literature, direct weighing of sample products in the lab, and data compilations provided by the National Center for Electronics Recycling, who monitor product weight as part of e-waste compliance efforts in several U.S. states. Since product mass may change over time for some products, mass averages were calculated to reflect the weighted averages reflecting consumption of given size products, mass of different sizes, and averages across multiple products measured. For smaller products such as cameras and phones, product mass was held constant over time due to a lack of observed temporal trends and some data limitations. For larger products which represent major contribution to waste flow mass and underwent significant change in average mass due to expanding screen sizes and technology driven dematerialization, such as TVs, monitors and laptops, a dynamic mass estimate was applied. Refer to Appendix A, Table 3 for the average mass of products for which static mass estimate was applied and the associated data sources. For products with yearly mass data from multiple data sources, a fitted trend was used to estimate the dynamic mass input while for products which lacked data from multiple source, mass trend was built on the single reliable data source. Refer Appendix A, Table 4 for dynamic mass estimates for CRT displays, flat panel displays and laptops.

Average material profile of products: Average material composition of products was determined empirically to assess base materials (e.g., copper, plastics, steel, plastics) and components (e.g., batteries, printed circuit board, display glass) via disassembly of representative products in each of the 20 product categories. Due to lack of product availability and safety concerns, material composition for CRTs is adopted from published literature (Townsend et al., 2004) (Refer to Appendix file, Table. 5 for product material profiles). While the composition of lithium ion batteries was characterized by lab scale disaggregation study, composition of components such as PCB, LCD and CRT modules were adopted from literature to estimate the flows of key materials of value and concern, like gold, indium, cobalt, lead and mercury.

Indium content in flat panel glass (0.023175%) (Boundy et al., 2017) and lead content in CRT glass (9.82%) (Monchamp et al., 2001) are adopted from literature, while average lithium (2.14%) and cobalt content (12.5%) in LIBs are estimated from lab scale battery disassembly. Average lead content in printed circuit boards is assumed to be 1.7% till year 2008, reducing to zero by 2010. The average gold content in PCBs (0.06%) was estimated through compilation of over 50 data points from over 25 published studies. Mercury content in LCD displays with CCFL backlights was calculated based on average mass percentage of mercury per kg of CCFL lamp (0.04%) (McDonnell and Williams, 2010) and the weight of CCFL lamps in LCD displays estimated from a combination of lab scale product disassembly data and published literature. E-waste concentration of other metals such as REEs, Ta, Sn, Ga, Pd and Ag as estimated based on their mass contribution per product reported in literature (Cucchiella et al., 2015). Refer to Appendix A, Tables 6 and 7 for calculations for mercury content in LCD TVs and monitors.

Uncertainty Analysis: Variability exists in key model inputs such as product lifespan and average product mass. Uncertainty analysis was used to capture the uncertainty in study results associated with assumptions in lifespan probability, average mass of products sold yearly, and choice of products included in the study. Parameters to generate Weibull and lognormal distributions were calculated from mean lifespan and standard deviation lifespan inputs of products. For mass uncertainty analysis, the minimum and maximum data points from the available mass range was used for products with static mass assumptions (Refer to Appendix A, Table 3). For dynamic mass products the uncertainty range was estimated by calculating the average percent difference of different data points to the estimated average trend. These maximum and minimum mass values estimated encompass typical changes in product size over time and variability in product model and design. Product scope uncertainty analysis was carried out by including six additional products not initially included in the study due to their recent emergence in the electronics ecosystem (and lack of detailed material composition data). Refer to Appendix A, Table 8 and 9 for sales and mass data, respectively, for the additional products).

3. Results

The results presented here are determined using high quality electronic product adoption and material composition data, providing the most up to date and comprehensive material footprint analysis of electronics.

3.1. The net material footprint of e-waste in the U.S. has begun to decline

Residential e-waste in the US is shown here to be in decline, with a net mass reduction of 16% since its peak in 2015 (Figure 2.1). The dominant contribution to e-waste is from display technologies, including legacy and modern TV and monitors, which collectively make up to two-third of the total e-waste mass. The observed decline in e-waste is attributed mainly to technological substitution of heavy CRT (cathode ray tube) displays by lighter LCD (liquid crystal display) and LED (light emitting diode) technologies, which provide an approximately 75% mass reduction per product. CRT displays in the waste stream peaked in 2010, just a few years after the digital transition in television broadcast signals and the rapid switch to digitally enabled flat panel TVs. While CRT displays have declined in the waste stream since their peak, these devices still make up almost one third of the total mass of e-waste coming out of U.S.

households. It is expected that CRTs will persist as an e-waste management challenge in the near future, as consumers indicate that they keep them as secondary TVs in basements and guest bedrooms and often do not know how or where CRTs should be recycled (CTA, 2016).

However, the contribution of flat panel display devices to total e-waste is becoming increasingly significant, even surpassing CRTs with about 38% contribution to the total waste stream mass (Figure 2.1). Flat panels often have higher failure rates and shorter lifespans (Kalmykova et al., 2015), leading to more frequent replacement cycles. These findings highlight the need for proactive implementation of waste strategies that can effectively reclaim materials contained in new products while still safely managing legacy devices. CRT displays in e-waste emerged as a critical waste management problem due to the potential release and toxicity of the lead they contain, leading to policy and technology solutions aimed at keeping them in productive use. However, reuse and recycling pathways diminished along with consumer demand for these TVs, and the lack of economic incentive for recycling coupled with ban on waste exports created a disruption to the e-waste industry, including criminal cases associated with stockpiling or illegally exporting CRT waste (Singh et al., 2016). With nearly half a million metric tons of CRT devices estimated here to enter the consumer e-waste stream in 2018, there remains a pressing need for open-loop recycling and end of life management strategies.

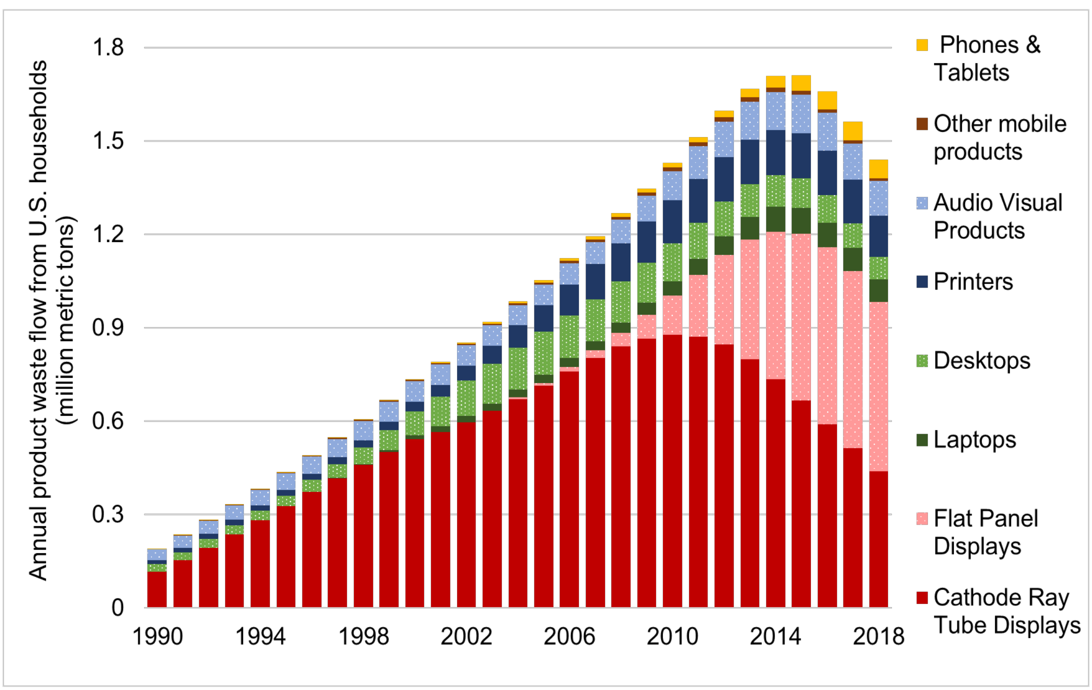


Figure 2.1. Declining trend observed in annual waste flow (in metric tons) of commonly owned products in U.S. households. It is to be noted that MFA scope includes only 20 common product categories (Appendix A, Table 1) which represent product ecosystem in an average U.S. household.

These recent trends in e-waste flows can be attributed to a combination of natural technological progress and consumer shifts in product adoption behavior. Figure 2.2 shows the underlying consumption trends over the last few decades as annual product inflows to U.S. households in terms of in terms of sales or inflow units (top) and mass of each product categories sold (bottom).These time series reflect a dramatic dematerialization of the consumer electronics 'ecosystem' in U.S. households. Until the early 2000s, consumers were buying fewer products, but the dominant technologies were large, heavy, and made sizable contributions to total resource consumption. This trend then reversed after the technological transition to digital display devices in 2008, which completely replaced CRT displays from the market. Even after flat panel TV prices fell and device adoption resurged to previous levels, the product sector never matched the resource consumption in the CRT era.

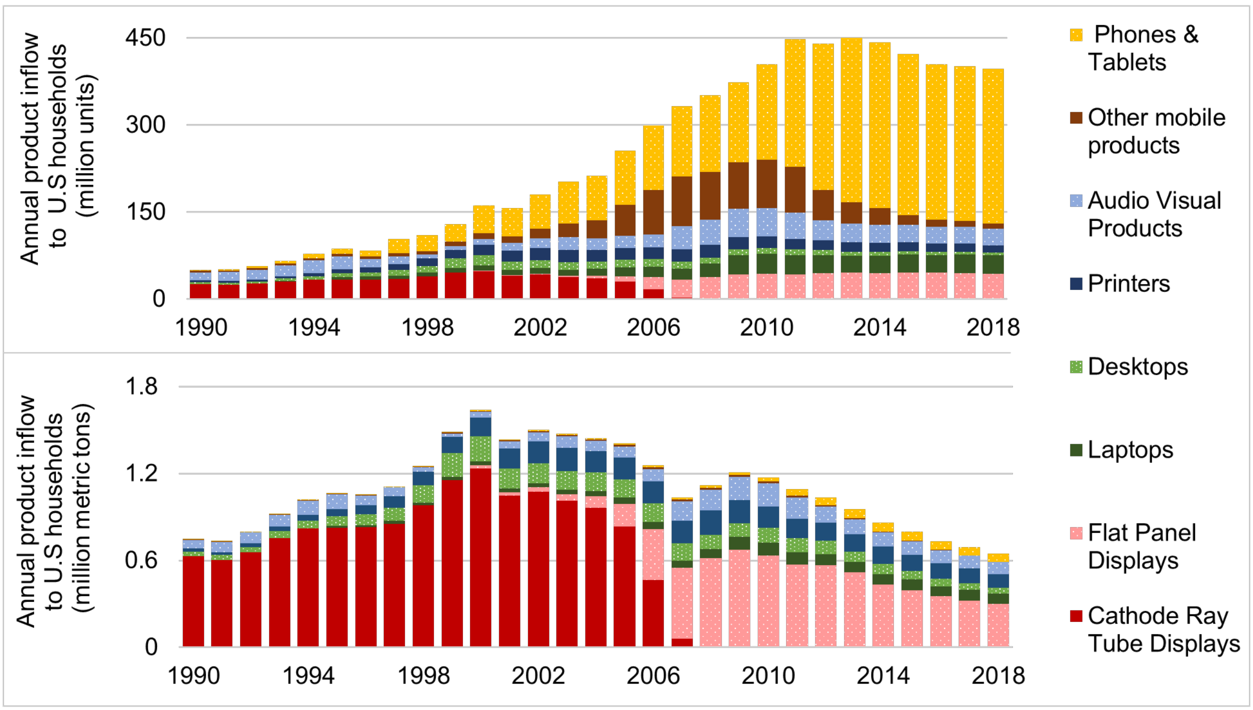


Figure 2.2. Electronics consumption trends in the U.S. in the last 28 years (stacked bar charts), represented by annual product sales or inflow units (top) and annual product sales mass or inflow mass to households (bottom).

Other recent trends in dematerialization and product light weighting also contributed to declining electronic product material intensity. Light metals such as aluminum and magnesium together with plastic replaced heavier steel product casings and structural components. In addition, overall product consumption by unit also began to plateau and decline, largely due to device convergence, wherein multifunctional mobile devices, like smart phones, have replaced many products consumers would have owned separately before, like MP3 players or digital cameras included in the category ‘other mobile products’. Figure 2.2 shows the effect of this device convergence on disaggregated product consumption flows, where the declining trend in product sales coincides with the increase in phone and tablet adoption, which made up to one-third of total sales in recent years. Even though smart phones now make up 48% of the total annual product consumption by sales, their relatively low mass compared to larger devices leads to a mass contribution of less than 5%.

These findings, which highlight the changing product mix in e-waste, have implications for e-waste policy development and implementation in the U.S. At present in the U.S., 25 states and the District of Columbia has laws mandating residential e-waste collection and recycling and almost every state e-waste policy are mass-based targeting larger products in the system for recovery (Electronics TakeBack Coalition, 2015). While a mass-based end-of-life product recovery mechanism can be effective in waste diversion, the decreasing dominance of larger products and increasing prevalence of lighter multifunctional products with critical metal content in the waste stream, indicates the need to reconsider the established e-waste management strategies. For example, if we consider the most common products covered by state policies for recovery such as TVs, monitors and computers, they reflected 48% of the total e-waste product unit flows in year 2000 but only 25% of the flows in 2018. Even though the decline in mass contribution of these products are not as steep (around 5%), the changing e-waste product mix imply new material management opportunities and challenges in the sector.

3.2. Complexity and resource potential are high in the emerging e-waste stream, while toxicity from traditional materials of concern is on the decline.

While declining resource consumption and waste generation are positive sustainability outcomes, these trends are not without economic, environmental, and social tradeoffs. The innovations responsible for device convergence and product light weighting have been achieved by increased use of designs and components that may limit recycling, and technologies that rely on potentially scarce minerals that are often mined in socially and geopolitically regions (Mars et al., 2016).

Figure 2.3 illustrates how the changes in product flows have affected the material profile of e-waste over the last 28 years. E-waste materials are disaggregated into broad categories that include base metals like Fe, Al and Cu, plastics and complex components such as lithium-ion batteries, display modules, and PCBs (printed circuit boards). E-waste material profile shows decreasing dominance of CRT glass and increasing presence of components like batteries and flat panel display glass which are key constituents of portable electronics and flat panel TVs respectively. These complex components present barriers to sustainable waste management, as there are limited recycling infrastructure and commercial-scale technologies in the US for recovering materials from these components. Increase in product complexity imparted by high functionality, portability and miniaturization in newer products in the waste stream, in turn restricts the economic feasibility of material recovery due to reduced ease of disassembly (Vanegas et al., 2018). End-of-life management of lithium ion batteries, which now constitute 24 thousand metric tons in the residential e-waste stream are especially challenging due to their hazardous characteristics from use of flammable liquid electrolytes (Winslow et al., 2018). However, the importance of recycling these components will continue to grow, as they contain metals such as cobalt and indium, which have been categorized as critical resources, due to their physical scarcity and their importance for numerous economic activities, including clean energy, electronics, medical, and defense sectors.

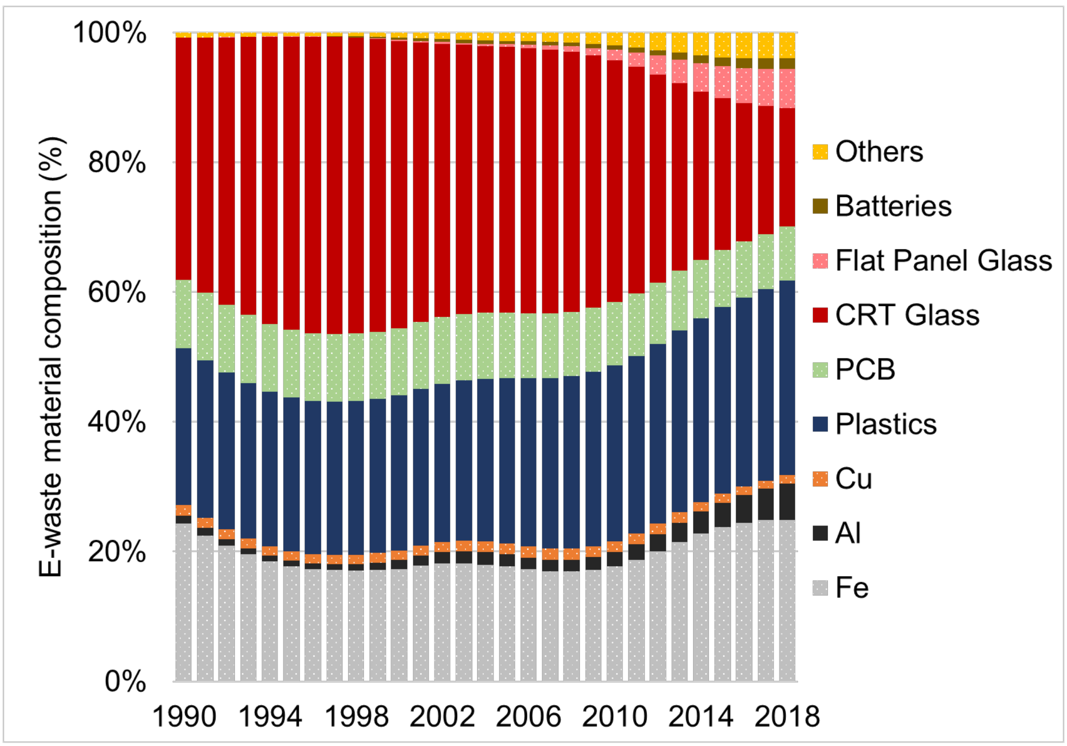


Figure 2.3. Changes in e-waste material profile from US households over the last 28 years. Figure shows decreasing dominance of CRT glass and increasing presence of complex components like batteries and flat panel display modules.

One sustainability concern surrounding e-waste management is the potential for hazardous materials contained in these products to impact human and environmental health if managed improperly during recycling or disposal. Lead contained in printed circuit boards and CRT glass and the mercury found in LCD displays with CCFL (Cold Cathode Fluorescent Lamp) backlighting are two key hazards. As TV technology has shifted to LED-lit flat panels, both products, and the materials they contain, have begun to decline. As a result, lead content in e-waste has undergone significant reduction in the last 10 years (Figure 2.4), while mercury content has only recently started to decline, particularly after 2016 when LCD TVs peaked in the waste stream. Over 95% of the lead in e-waste was attributed to CRT glass, and the declining presence in the waste stream is due to technological progress and natural substitution by newer products as discussed earlier. The remaining fraction was attributed to lead solders previously used in PCB components. This fraction has largely been eliminated due to policy intervention, such as the RoHS (Restriction of Hazardous Substances) directive, which mandated lead-free PCB fabrication since 2010.

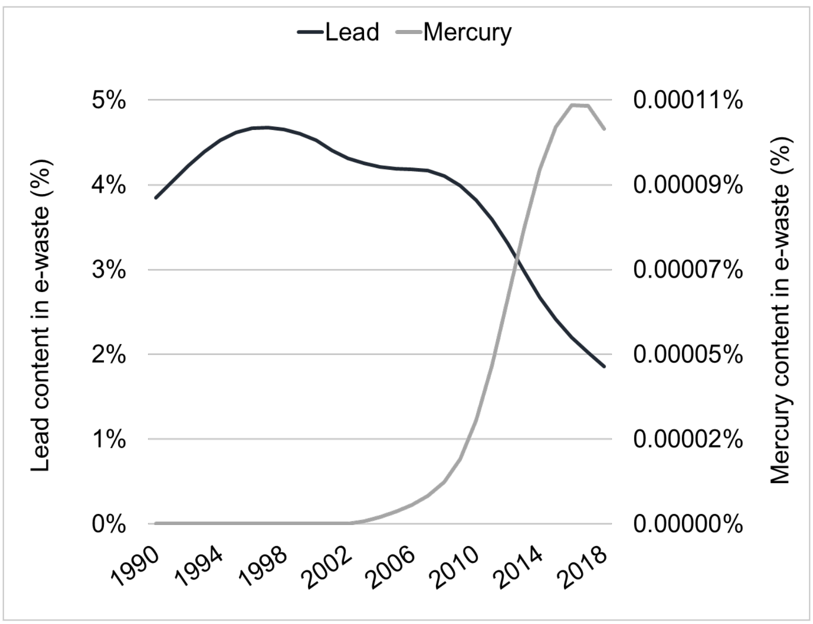


Figure 2.4. Declining in e-waste toxicity from lead and mercury. Lead flows represents waste flows from PCBs (printed circuit boards) and CRT glass. Mercury flows represent waste flows from CCFL lighting in LCD TVs and monitors.

The e-waste stream also represents a potential source for obtaining materials that are critical to modern technology. Due to increased adoption and reduced lifespans of mobile technologies like laptops, tablets, and smartphones that use lithium ion batteries (LIBs), cobalt concentration in the waste stream has steadily increased (Figure 2.5). Cobalt is a key component of LIB cathodes, both for electronics, and for many electric vehicle battery chemistries. As both sectors grow, secondary sources will be an increasingly important input for lithium ion battery manufacturing (Singh et al., 2016), particularly to alleviate social concerns over cobalt extraction in vulnerable regions including the Democratic Republic of the Congo (Olivetti et al., 2017). As the electronics ecosystem is increasingly dominated by products with flat panel and touch screens, there is also increased demand for indium (as indium tin oxide, used as a transparent conductive coating). While it is only present in small concentrations within a given product, its overall concentration in the e-waste stream has steadily risen (Figure 2.5). Indium has been a recent target for sustainability due to its physical scarcity, high cost, and widespread use in growing applications of transparent electrodes, as used by photovoltaic panels and high efficiency windows (Laurenti et al., 2016). The concentration of cobalt (0.21%) and indium (0.001%) in e-waste in 2018 is still lower than observed ore concentration (Sverdrup et al., 2017) (5% and 0.005%, respectively at the high end), but these materials are potential future priorities for recycling, particularly to create a domestic supply in the U.S., as geographical concentration and fluctuating commodity value of these metals may lead to economic uncertainty in the electronics industry.

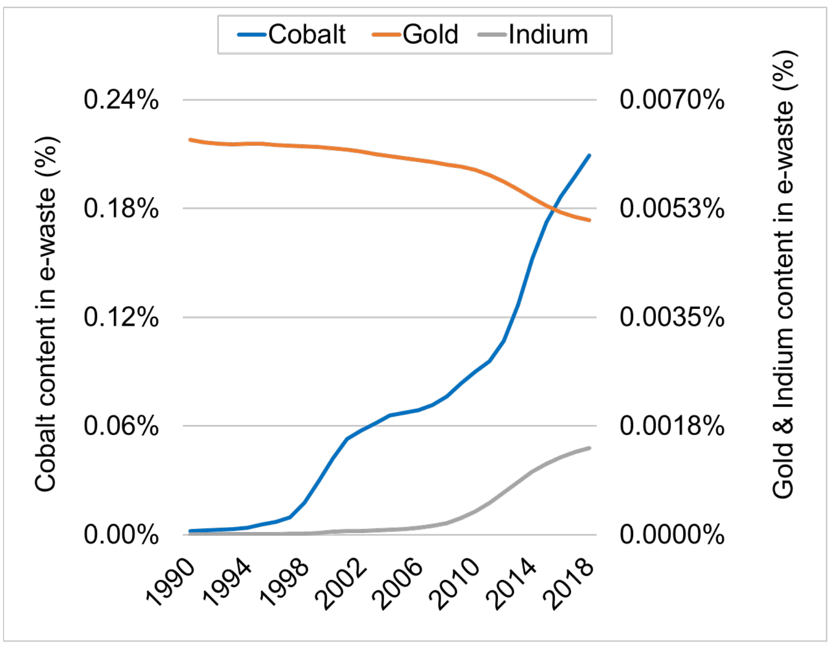


Figure 2.5. Increasing resource potential in the waste stream. Critical (cobalt, indium) and precious (gold) metal flows highlight potential for material recovery in the emerging waste stream.

On the other hand, gold content in the aggregate e-waste stream (0.0051%) is over ten times higher than its ore concentration (Sverdrup et al., 2017) (0.0003%). Historically, the global e-waste recycling system has relied on the economic value of gold, which is typically recovered through PCB smelting. However, gold in e-waste has begun to decline in concert with to the overall dematerialization trends observed, from a peak of 93 metric tons in 2014 to current estimates of 73 metric tons in 2018 for the U.S. residential sector. Gold is also becoming more dilute and dispersed across products, which increases the labor and processing costs associated with managing e-waste (Kasulaitis et al., 2018b).

Similar to gold, higher concentration in e-waste than their ores are observed for other precious metals such as silver and palladium, which are mostly found in PCBs in electronic products (Figure 2.6). However, as in the case of cobalt and indium, e-waste content of other critical metals in electronics such as rare earths elements (REEs), lithium, tin, tantalum and gallium are lower when compared to their ores. But since many of these metals are identified to be critical materials by the U.S. Department of Energy (Energy, 2011), it is necessary to plan for policy instruments, recycling technologies and infrastructure that can effectively reclaim these resources from end-of-life electronics.

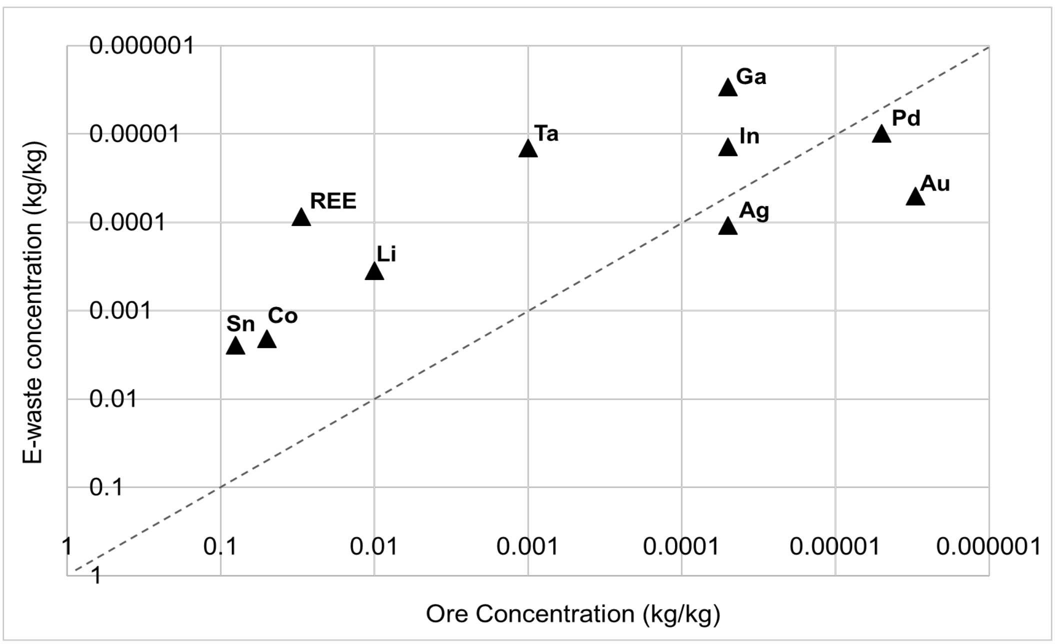


Figure 2.6. Concentration of materials of interest in emerging electronic waste (results for year 2018) in comparison with their average concentration in ore deposits (Sverdrup et al., 2017). For most materials except precious metals (Pd, Ag and Au), e-waste concentration is much lower compared that in their respective ores.

3.3. Theoretical potential to close the loop on critical materials is high

The implications of the changes in e-waste material footprint on the viability for closed loop recycling or circular economy is tested theoretically by matching the mass of key materials contained in new products sold and used products entering the waste stream within the same years (2008 and 2018) as shown in Figure 2.7. In 2008, the demand for most raw materials far exceeded the amount of the same materials contained in the waste stream, meaning that even with aggressive recycling initiatives, the electronics industry would still be reliant on extracting virgin raw materials. In 2018, however, the total mass of indium, cobalt, gold, and plastics contained in e-waste far surpassed the cumulative demand for each of those materials contained in new products being sold. Thus, the potential exists for a closed-loop circular economy through material recovery.

However, just because theoretical circularity potential exists does not guarantee that a closed-loop material recovery pathway will be viable. Critical metals like cobalt and indium are characterized by low recycling rates, due to a lack of policies that target the products that contain these materials, absence of widespread commercial recycling technologies and infrastructure, complexity in product design, and material dilution and dispersion in the e-waste stream. Technologies do exist to recover these materials but face a challenging pathway to achieve full scale deployment. In addition, electronic product designs are optimized to meet consumer demands for low cost products with maximum functionality while maintaining ease of assembly and manufacturing. To meet resource demand through circular economy, product designs need to be revisited to facilitate ease of material recovery. One goal of the extended producer responsibility model underlying e-waste policies in the U.S. is to shift waste management costs back to producers, thus creating motivation for design and material selection that leads to enhanced recycling. This outcome has not been realized however, outside niche markets (e.g., Fairphone (Reuter et al., 2018)). In the case of plastics, the potential for recovery has increased over the years as the plastic content in e-waste grew from 24% to 30% since year 2000 (Figure 2.3). At present, around half a million metric tons of plastic is available for recovery from e-waste generated annually from U.S. households. However, there are many challenges in e-plastic recycling, the main being contamination in the waste stream due to the wide range of plastics used in electronics and the use of brominated flame retardants which are added to e-plastics to enhance their resistance to fires. Nonetheless, the recent bans and subsequent disruption in e-plastic export market to Southeast Asian countries, stresses the need to develop domestic recycling systems.

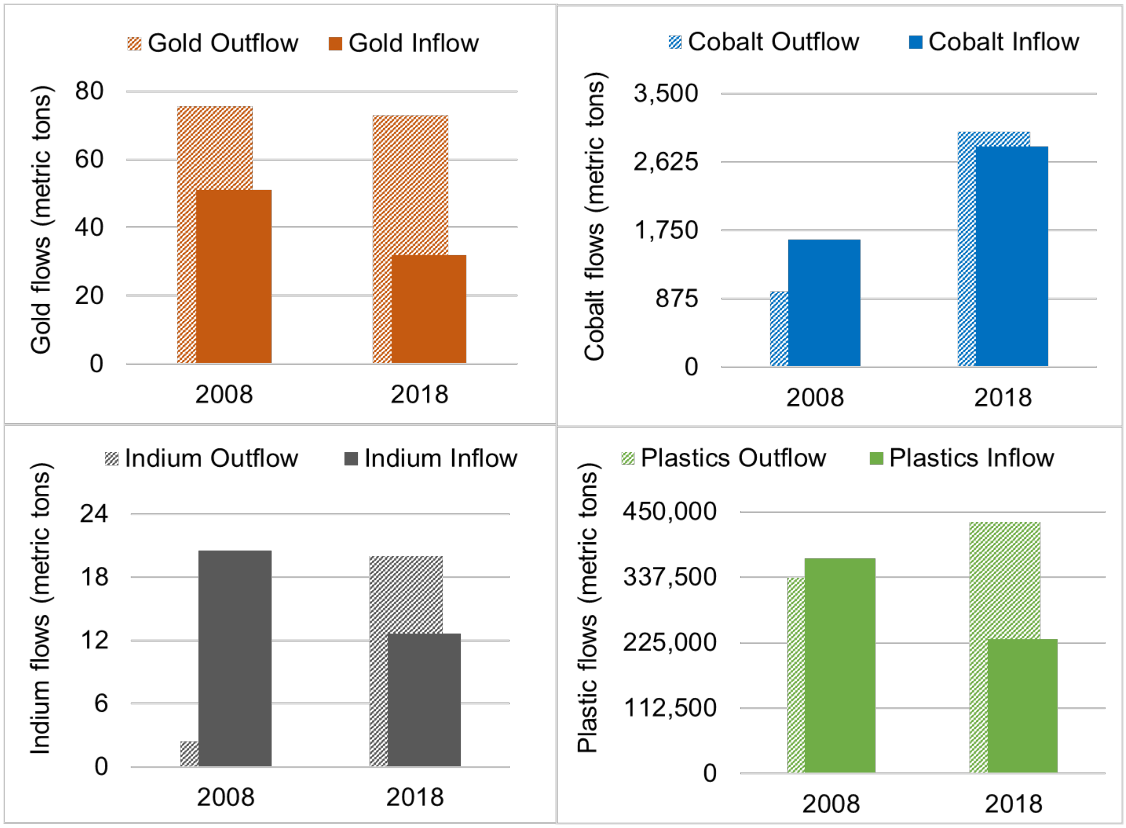


Figure 2.7. Comparing annual material inflow or demand with waste flows show that potential to close the loop exists at least theoretically for all materials (gold, cobalt, indium and e-plastics) tested.

3.4. Uncertainty Analysis

This study benefited from high quality product sales data and the largest database available on electronic product composition. However, additional sources of uncertainty in this analysis may stem from data limitations around product mass and lifespan values. Lifespan uncertainty was assessed by comparing waste flows calculated using both Weibull and lognormal lifespan distributions , both of which are commonly used to assess e-waste flows (Babbitt et al., 2009; Petridis et al., 2016). Uncertainty around product mass values were assessed via ranges reflecting maximum and minimum observed product masses and sensitivity to products included in the study scope were tested by including six newer devices to the 20 baseline products. None of these sensitivity analyses showed any fundamental difference to the trends shown here for material consumption and e-waste generation (Appendix A, Figures 1a, 1b, and 1c). However, the trends reported here will certainly continue to change in the future. Related research has shown that electronic product adoption and replacement cycles are consistent over time, and that these patterns can be used to predict future waste challenges for emerging products (Althaf et al., 2019). In addition, the underlying material flow model can be adapted to include new products as the electronic product ecosystem evolves over time.

4. Discussion

The current e-waste management system in the US is backwards looking, optimized for large legacy products with a focus on diverting wastes from landfill. However, technological innovation has fundamentally changed the products purchased and discarded, along with the materials they contain. Given the evolving nature of the electronic product ecosystem, up-to-date estimation of resource consumption and e-waste generation is necessary to make informed decisions for sustainable resource management. Such comprehensive analysis is rare, mainly due to the need for exhaustive data collection on product adoption that are required. Through the application of product material profiles studied and characterized through lab disassembly of over 80 different products and highly resolved product sales and lifespan data, this study reports the most current material footprint analysis for electronics in the U.S., enabling the identification of immediate challenges and opportunities for integrating sustainable materials management and circular economy approaches in electronics.

Analysis results break the long-standing assumptions about e-waste, by reporting a declining trend in overall mass and hazardous material concentration. At the same time, there is increased product complexity and material diversity in the emerging electronics system, imparted by the high adoption of multifunctional light weight products that employ a wide spectrum of materials from the periodic table. Most of these materials (such as REEs, Co and In) embedded in the complex designs of modern-day consumer electronics are considered to be critical mineral resources by global economies. As smaller complex products start dominating the waste stream, the relative dilution and dissipation of the materials in the waste stream also increase, creating new challenges in the retrieval of valuable materials. For example, more than 150 smartphones will need to be processed to recover the same amount of gold (from PCBs) that can be recycled from a single CRT TV. Product design complexities will further add to the difficulty of material recovery, negatively affecting the economics of recycling if appropriate technologies are not employed. Product and material diversity, and the dynamic nature of the emerging e-waste stream uncovered in this study highlights the need to invest in recycling technologies that are not only efficient enough to reclaim the valuable materials contained in small amounts per product, but also resilient to the changes in the system.

Given the changing dynamics in mineral commodity markets due to import policies and other market forces, this study is timely, as e-waste management based on recycling could expand opportunities to ensure domestic supply of many scarce materials such as Co, In and rare earth elements, which are currently sourced mostly from China, a geopolitical competitor of the U.S (Habib et al., 2016). These findings point to a needed shift in focus in our e-waste management mechanism from '*mass to materials*' and from '*waste diversion to resource retention*'. Such a paradigm shift can only be enabled through joint effort from all stakeholders, where policy makers change incentive structures and collection targets; recyclers create and scale-up adaptive material recovery technology; and manufacturers adopt product designs that maximize recycled content and facilitate easy product disassembly and recycling. While the baseline MFA in this chapter advances the knowledge on material footprint of electronics, the analysis is mostly retrospective. To plan for material management systems that are resilient to the changes in electronics landscape, proactive insights about material flows in the system are necessary. The next chapter addresses this need for predictive capability in material flow models for electronics.

CHAPTER 3: Predictive material flow models for the consumer electronic system

1. Introduction

Baseline MFA for electronics in chapter 1 showed that unprecedented innovation and increased consumer demand for faster, sleeker, and smaller devices have drastically changed the electronics landscape in the last decade. Large, single function products have been replaced with multifunctional portable products (Erinn G. Ryen et al., 2014) and electronic components are increasingly integrated into accessories, clothing, appliances, and fitness products (Perera et al., 2015). Industry groups predict that consumers will increasingly adopt smart home technology products including thermostats and security systems, while at the same time maintaining high ownership levels of traditional products like smart phones and televisions (Consumer Technology Association, 2017).

While the evolution and expansion of consumer electronics has enabled social, education, and communication advances, it has also created new sustainability challenges (Balde et al., 2017). Electronic products are characterized by environmental impacts across all life cycle stages, from raw material extraction to end-of-life product management (Kohler and Erdmann, 2004). The functionality of modern electronics is realized through a mix of complex components composed of precious, scarce and base metals (Cucchiella et al., 2015; Tansel, 2017), which are extracted through energy intense processes leading to significant upstream emissions (Dutta et al., 2016). MFA results in chapter 2 showed that there is increased prevalence of critical materials such as cobalt and rare earth elements in the e-waste stream, which are in high demand in electronics and other sectors such as electric vehicle manufacturing and clean energy technologies, indicating huge potential for material recovery in the emerging e-waste stream. Given rapid innovation cycles, increasing consumer adoption, and declining product lifespans in the electronics sector (Bakker et al., 2014), critical material consumption and waste generation is bound to increase in future. Therefore, consumer electronics are ripe for a transformation via the circular economy, to minimize resource consumption, extend product lifespan through reuse, repair and remanufacturing (Bakker et al., 2014; Reike et al., 2018; Zlamparet et al., 2017), and close the loop on material supply chains (Işıldar et al., 2017a; Zeng et al., 2018a).

Circular solutions may offer sustainability benefits for electronics, but they also face obstacles to widespread adoption (Mars et al., 2016). As the electronic product "ecosystem" grows, the number, type, and diversity of devices requiring circular management also expand (Erinn G. Ryen et al., 2014). This complexity can confound product repair, upgrade, disassembly, and material identification and segregation, all of which are labor-intense processes further slowed by product heterogeneity and lack of standardization (Cucchiella et al., 2015). Where materials are recovered, recycling economics often hinge on a few low-volume, high-value materials, such as gold, which are increasingly diluted in the e-waste stream due to product light-weighting trends (Kasulaitis et al., 2018a). The presence of hazardous materials like lead and mercury in complex components like older printed circuit boards and display units, also can limit recovery efforts (Chen et al., 2011; Kiddee et al., 2013). In addition, shrinking product lifespans (Babbitt et al., 2009) are effectively narrowing the window in which circular innovation can be deployed, leaving our e-waste management system to be "backwards looking" - focusing on legacy devices that have been in the market for a long time, even while new products are emerging in the waste stream (Babbitt et al., 2017).

These factors underscore the importance of creating circular economy (CE) strategies that are agile and responsive to the evolving demand for and waste from consumer electronics consumption. CE interventions in electronics should respond to key leverage points that maximize resource efficiency and minimize environmental burden, through green product design, creation of reuse markets, development of material recovery technologies to improve use of recycled materials in products, and policies to effectively engage multiple stakeholders in resource conservation and recovery activities (Bocken et al., 2016; Gaustad et al., 2018; O'Connor et al., 2016). Green product design strategies include design for longevity (Bakker et al., 2014), ease of disassembly (Vanegas et al., 2018) and reduced use of critical and environmentally intense materials (Boks and Stevels, 2014). However, for most of these CE interventions to create proactive - rather than reactive - solutions, they must be attuned to future resource demand and waste generation.

Take for example the case of current U.S. e-waste policy implementation. The product categories that are most commonly covered under each state's policy mostly reflect mature product categories that have already saturated the market, omitting emerging products whose material opportunities and risks are unknown (Electronics TakeBack Coalition, 2015). Near term forecasts of consumer discards can inform e-waste policies, especially in setting the scope of products to be covered under the policies and establishing realistic annual e-waste collection targets. Similarly, new product design would benefit from better predictive capacity about which materials may be available from secondary sources (e.g., used electronics in a closed-loop scenario) and which materials may be scarce due to consumption in other competing industries. In any of these cases, proactive insight is necessary, but fundamentally limited by a lack of the predictive tools and data needed to forecast physical flows in the evolving electronics sector, which is key in circular economy implementation (Kalmykova et al., 2018).

Therefore, this paper addresses the question: How do we proactively plan and deploy CE strategies for the rapidly evolving electronic product sector? This challenge is addressed by creating and validating models to forecast product sales and e-waste generation and then using these models to identify issues and opportunities for circular economy in the electronics sector. To this end, historic product adoption data is studied to generalize the factors that govern product adoption trajectories and then applied to the model based on established e-waste estimation methods from literature, to generate near term forecasts for both mature and emerging products. The paper is organized as follows: Section 2 reviews forecasting literature that guided the development of the model. Section 3 describes the methodology, including model development, validation, and application to inform CE planning. Subsequent sections discuss results and broader implications.

2. Literature Review

E-waste estimation methods in the literature include input-output models, factor models, time series, econometric analysis, and direct waste analysis (Li et al., 2015; Wang et al., 2013). Among these, material flow analysis (MFA), which is an extension of input-output modeling, is widely used and an appropriate choice for CE planning, as it enables estimation of the product and material demand and management of secondary resources (Kalmykova et al., 2018). MFA estimates the stocks and flows of materials within a defined temporal and spatial system, commonly using data on commodity flows into the system and their discard rates (Brunner and Rechberger, 2004). In most e-waste literature, MFA applications are typically static or retrospective (Kasulaitis et al., 2018; Li et al., 2015, Miller et al., 2016, Wang et al., 2013), due to the nature of available data. However, CE planning requires a more proactive approach, thus requiring forecasts of product adoption and obsolescence. Such information is not commonly available, but potentially can be approximated according to models of product adoption cycles.

Forecasting product adoption is commonly achieved using the “S-shaped” logistic curve, or sigmoid curve, to describe a product market adoption cycle (Fisher and Pry, 1971; Kucharavy and Guio, 2015, 2011; Marchetti and Nakicenovic, 1979; Meyer et al., 1999; Yang and Williams, 2009). The three parameter logistic curve commonly used in socio-technical systems (Kucharavy and Guio, 2011), has its roots in ecology, where it was originally used to model population growth of biological species

(Lefkovitch, 2018). While the logistic curve describes a product's growth until it reaches market saturation, it does not capture the entire market life cycle, which includes an inevitable decline due to substitution by competing technologies. The Norton-Bass model, which includes logistic distribution as a special case, captures both adoption and substitution leading to a product's decline (Norton and Bass, 1987). This approach has been applied to forecasting consumer electronics, including LCD TVs (Tsai (2013), mobile phones, computers (Islam and Meade (1997), and desktop displays (Lu et al. 2015). However, as pointed out by Tseng et al. (2009), the Norton-Bass model is mostly suited for modeling direct substitutions by successive generations of technology, which is not always observed in consumer electronics, particularly in the case of disruptive innovation. The Fisher-Pry model (1971) has also been applied in electronics forecasting, an approach that uses a two-parameter logistic model to describe technology substitution (Cho and Daim (2016). The logistic Fisher-Pry model was extended by Marchetti and Nakicenovic (1979) to include mutliple generations of energy technologies, based on the assumption that technologies grow and decline at logistic rates. This model has been used to study adoption of music media (Meyer et al., (1999) and OLED TVs (Tseng et al., 2009). While these studies show that logistic growth-decline is an apt approximation to describe product adoption cycles, these models are again reliant on knowledge of subsequent generational replacements.

In reality, replacement cycles and product innovation in consumer electronics are challenging to predict, as decline of one technology generation is not always predicated solely on substitution by the next generation. In many cases, functional convergence leads to decline of many single function devices due to simultaneous substitution by a single new multifunctional product. For example, the decline of digital cameras, camcorders, and MP3 players was driven by the advent of smartphones, which would not be otherwise predicted as a successive generation of those products. Similarly, in the case of AV (audio-visual) media, the decline of Blu-rays and DVD players was triggered by the advent of new streaming media services, rather than a new product generation (Figure 1 in Appendix B illustrates the technological shifts and substitution in AV products). Therefore, to integrate product adoption cycles in electronics forecasting, it is necessary to develop modeling capability that can capture adoption trends on a product-by-product basis, even in the absence of information about subsequent generations of technology.

The methods applied in this chapter build on the foundation of models described above, through use of the logistic growth and decay curves that have been applied to technology adoption broadly and e-waste forecasts specifically. One new contribution is the construction of these curves independently, without the specification of an unknown successive replacement technology required to trigger product decline. Another contribution is the focus on emerging electronic technologies that are not yet widely adopted. Literature examples have provided several demonstrations of forecasting waste flow from specific product categories that already comprise a major part of the e-waste stream, such as computers (Kahhat and Williams, 2012; Petridis et al., 2017; Rahmani et al., 2014; Yang and Williams, 2009; Yu et al., 2010), or on products with known hazards, such as cathode ray tube (CRT) TVs (Gusukuma and Kahhat, 2018). However, for CE planning, it is equally important to forecast adoption for newer technologies, requiring modeling advances in data-scarce cases.

3. Methodology

Baseline MFA in Chapter 2 indicated that the material footprint of consumer electronics is changing due phasing out of Cathode Ray Tube (CRT) TVs and increased adoption of mobile technologies. This chapter's objective is to present an MFA model developed to proactively inform key leverage points that can enable CE solutions for electronics. For example, for mature products that are declining or no longer sold in the market, a critical circular economy challenge is how to recover and manage these products over the remainder of their life cycle, particularly if no demand exists for their reuse or for their component materials. Another challenge is to understand how e-waste policy implementation might be affected by the decline of these products in the waste stream. For emerging products, which may have unforeseen sustainability risks, but that are not typically covered by e-waste policies or prioritized for greener product design, projections are essential to model timing and magnitude of potential resource demand or the extent to which circular material systems can provide these resources with secondary or closed-loop supply. In addition, it is necessary to understand how CE planning might address the interactions of mature and emerging products in scenarios of technology substitution. Thus, the predictive MFA model was developed with the aforementioned CE challenges in mind. The overarching approach was to use historical sales data to construct logistic curves of product adoption and decline, and then apply these curves to project future product consumption and waste flows (Figure 3.1), as explained in more detail in the following subsections.

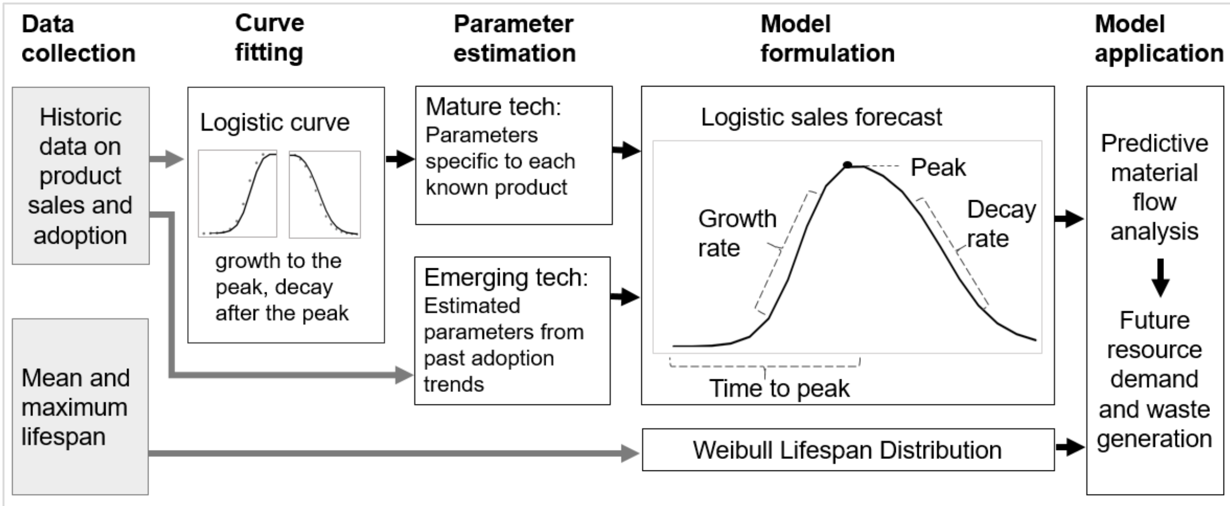


Figure 3.1. Conceptual framework of the methodology adopted in this study to enable proactive CE planning in electronics sector. Gray boxes and arrows represent data inputs collected from literature and electronics industry sources. All other boxes and arrows represent model calculations and outputs.

3.1. MFA Model Framework

The MFA model (Equation 1) estimates annual waste flows using product sales and lifespan probability distributions.

$$W_{p,t} = \sum_{i=1}^{n} L_{p,i} \times S_{p,t-1} \qquad Eq. 1$$

where $W_{p,t}$ is the waste flow of product p in year t, L is the probability that a product p will reach its end-of-life after a lifespan of i years, S is the annual product sales into US households for each year, and n is the maximum lifespan.

Product Sales: Based on findings from the literature review described above, product sales ($S_{p,t}$) were approximated by a three-parameter logistic curve (Equation 2), which includes phases of product growth, saturation, and then decline in the market, similar to the approach of Marchetti and Nakicenovic (1979) and Meyer et al., (1999).

$$S_{p,t} = \begin{cases} \frac{a}{1+exp(-b_1(t-c_1))} & t \leq t_{peak} \\ \frac{a}{1+exp(+b_2(t-c_2))} & t > t_{peak} \end{cases} \qquad Eq. 2$$

Here, a product's sales over its entire market cycle can be described by the time it takes to reach peak adoption (t_{peak}), the maximum adoption level or peak sales units (a), growth and decay rates (b_1 and b_2), and growth and decay midpoints, which are the times at which the curve reaches the inflection point of $a/2$ (c_1 and c_2). For simplicity, the parameter b is replaced by the equation $ln(81)/\Delta t$, where Δt is the time required for the logistic curve to grow from 10% to 90% of the carrying capacity (for b_1) or decay from 90% to 10% (for b_2), a simplification demonstrated by Meyer et al. (1999). Additional information on the estimation of parameters a, Δt, and c is provided in section 3.2.

The choice of logistic curve was verified by testing Equation 2 against real product sales data Ten products were selected that had high quality sales data spanning the entire period between the product's entry into the market to present (or to the point at which it was no longer sold). These data were provided by the Consumer Technology Association as reported in chapter 1 Appendix. The growth and decline curve for each product was tested against candidate distributions using a least squares estimation approach as implemented in MATLAB. Goodness of fit parameters, including R-squared, SSE (sum of squared errors) and BIC (Bayesian Information Criterion- a popular criterion for model selection among a finite set of models, using maximum likelihood estimation) were used to confirm that logistic curves were the best distribution to represent adoption cycle of electronics (See Appendix Table 7).

<u>Lifespan Probability Distribution:</u> The other key input to the forecasting MFA model according to Equation 1 is the lifespan probability distribution for each product. A Weibull distribution is applied here, as it is the most commonly used distribution to model lifespan of electronics in literature (Bakker et al., 2014; Gu et al., 2018; Habuer et al., 2014; Oguchi et al., 2008). The Weibull PDF (probability density function) is given below:

$$f(t,\gamma,\alpha) = \frac{\gamma}{\alpha}\left(\frac{t}{\alpha}\right)^{(\gamma-1)} e^{-\left(\frac{t}{\alpha}\right)^{\gamma}} \qquad Eq. 3$$

where γ is the shape parameter, α is the scale parameter and t is the time. The shape and scale parameters describing the distribution are computed from mean and maximum product lifespan estimates from literature (see Appendix B, Table 1). In this study, lifespan is defined as the total time that a product resides within a household during its first life, after which it becomes available for end-of-life management, which may include reuse, recycling for material recovery, or discarding.

3.2. MFA model parameters for mature products

Parameterizing the model described in Equations 1 and 2 is relatively straightforward for mature products, because past sales data are readily available. The 11 products considered in the mature product category are: CRT (Cathode Ray Tube) monitors, CRT TVs, desktop computers, printers, laptop computers, LCD (liquid crystal display) monitors, LCD TVs, Plasma TVs, LED (light emitting diode) monitors, LED TVs, and tablets. For these products, parameter estimation was carried out by fitting the three-parameter logistic curve to each product's unit sales over time. Depending on the product, different degrees of the market life cycle are covered by the available sales data, ranging from only a few years (for LED displays) to a full life cycle (for CRT TVs). In all cases, parameters were extracted from the product-specific logistic curve based on least squares estimation. (See Appendix B Table 2 for logistic parameters extracted for each product in the mature category).

The application of the MFA model to mature products is particularly important from the standpoint of assessing e-waste policy in relation to CE planning. The mature products analyzed here are those that are most commonly covered by e-waste legislation in U.S. states. The MFA results describe waste flows in units of products, which were then translated to overall waste stream magnitude based on each product's average mass. Mass results help relate the waste projections to mass-based collection or recycling targets used by most states in the U.S. Product mass estimations were determined using literature and disassembly as described in Babbitt et al. (2017) and are summarized in Appendix B Table 3.

3.3. MFA model parameters for emerging products

In the case of emerging products, for which historic adoption data is scarce, the guiding approach in estimating parameters for logistic forecasting was to analyze how past products behaved in the market, identify trends in the underlying logistic curve size and shape, and then extend these trends to products recently introduced. The historic sales data of over 15 products (Table 3.1), which entered the market between 1962 and 2009 were compiled, and the key parameters that describe their logistic market trajectory (time to peak, sigmoid midpoint and Δt) were extracted. One of the clear relationships revealed was that these parameters were inversely related to year of market entry. In other words, innovation cycles, or the time between a product entering the market and reaching saturation at peak sales, are shrinking in a steady and predicable way. Curve fitting to this temporal trend was tested to determine if year of market entry could effectively predict time to peak and growth rate, resulting in an exponential curve (R^2 = 0.82) as shown in Figure 3.2, where T_p is the time until a product reaches its peak sales and

Y_m is the year the product enters the market. To validate this trend, the predicted exponential curve was compared against a different set of 10 products (also shown in Table 3.1) that were not part of the original curve formulation. This strong agreement was consistent for exponential curves relating year of market entry to other necessary logistic parameters, including growth rate and sigmoid midpoint (See Appendix B Table 4 and Appendix B Figures 2 and 3). Thus, most of the parameters required to construct the logistic sales curve (Equation 2) for emerging products can be predicted by specifying only the year in which that product first is sold in the market.

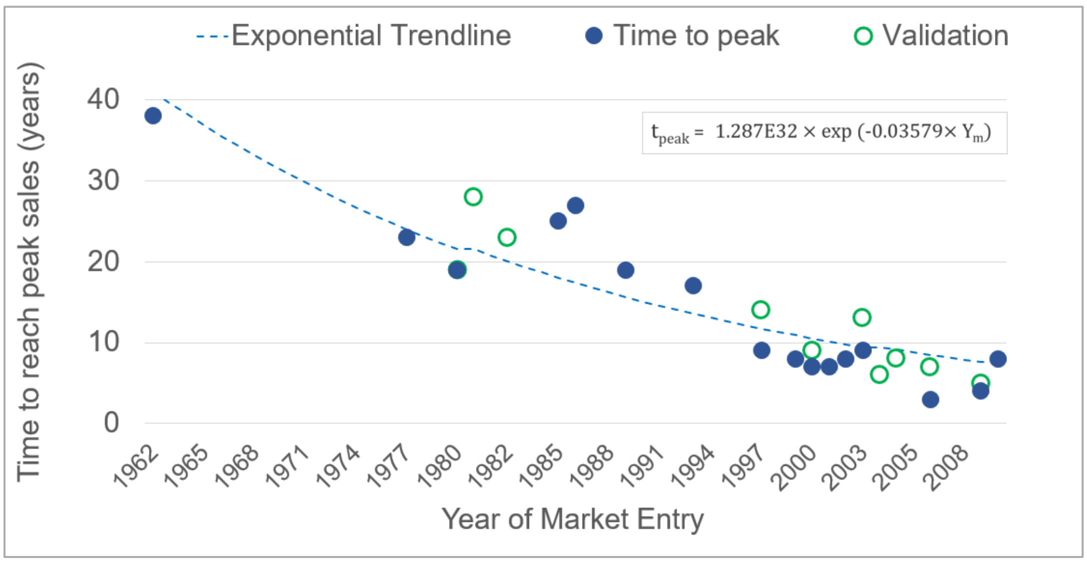


Figure 3.2. The time between a product entering the market and reaching its peak sales volume is shown here to clearly decline over time. A predictive relationship is built using filled circles and then validated by comparison against additional products (open circles).

The other parameter required to apply the logistic model (Equation 2) is *a*, the carrying capacity, or in terms of electronic products, the maximum level of product sales. For emerging technologies, this parameter is difficult to anticipate, given the unpredictable nature of technological progress and the rate at which consumer attention flickers from one gadget to the next. However, past product behavior can again inform projections of future product trends. In this case, the type of product (and the functions it provides) was observed in historical sales data to be strongly related to the maximum peak sales. Some products, like phones, are owned by individuals, rather than households, and are seen to be commonplace in modern work and life, which is supported by high sales rates (over 1.5 smartphones were purchased per average U.S. household in 2018). On the other hand, stationary, home-based AV equipment is shared among members of a household and the saturation point for ownership will be lower (about 0.2 VCR or DVD players purchased per household in the year that each of these products' sales peaked).

Products	Year of market entry	Time to peak
CRT TV	1962	38
VCR	1977	23
Desktop CPU	1980	19
CRT monitor	1980	19
Printer	1980	28
Telephone Answering Devices	1982	23
Digital camcorders	1985	25
Satellite Set-Top Boxes	1986	27
Basic mobile phone	1989	19
Laptops	1994	17
DVD player	1997	9
Digital cameras	1997	14
MP3 player	1999	8
LCD monitor	2000	7
LCD TV	2000	9
Portable Navigation Devices	2001	7
Plasma TV	2002	8
Cable Set-Top Boxes	2003	9
Smart phone	2003	13
VoIP Adapters	2003	6
IPTV	2004	8
Blu-ray player	2006	7
Digital Photo Frames	2006	3
Tablet	2009	4
LED TV	2009	8
LED Monitor	2009	5

Table 3.1. Products used to identify temporal trends in parameters describing logistic product adoption curves. Products shaded in gray were used to construct predictive trends while remaining products were used to validate the resulting curves.

To determine the carrying capacity of a logistic curve for an emerging product, the peak sales per household was tabulated for all products listed in Table 3.1, and grouped under categories that describe a product's form or function: Computing (including computers, monitors, and printers); TVs (including multiple technologies of CRT, LCD, LED, and plasma); Home media (VCR, gaming consoles, etc.); Small mobile devices (MP3 players, digital cameras, portable navigation systems, etc.); and Phones (including basic and smartphones and tablets). A full list of products assigned to each category and their peak sales is provided in the Appendix B Table 5. These data are summarized in Figure 3.3, which visually illustrates the ranges in peak sales observed. Most product categories demonstrated consistent ranges of adoption peaks. One exception was for those products that were ultimately only adopted to a limited degree (maximum sales of only about 0.05 – 0.1 products per household even in the highest sales year). These products, which represent a scenario of "limited adoption," included devices like Plasma TVs and e-readers, both of which were quickly outcompeted by products seeing "mainstream adoption," such as LCD TVs and tablets, respectively. The limited and mainstream adoption ranges assigned to each product category is presented in Appendix B Table 6.

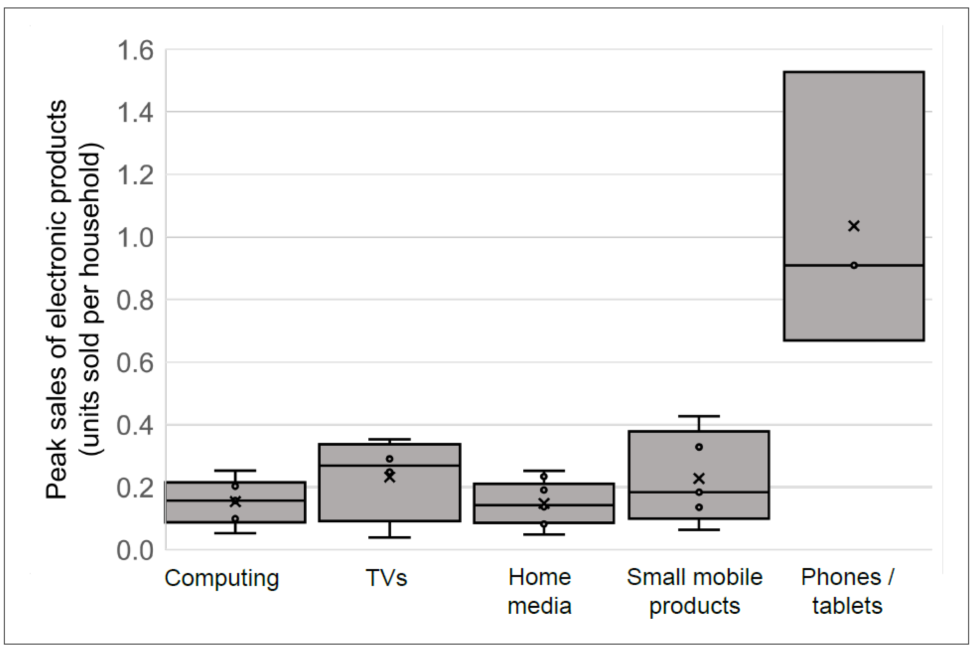


Figure 3.3. Ranges of peak sales (in units sold per U.S. Household) for products according to functional categories. Median values are shown as a line across each box.

Using the approximations described above, the logistic adoption parameters for an emerging product could be generated by using only two pieces of information: 1) the year of market entry, which was estimating by extrapolating the curve shown in Figure 3.2 to determine time to peak; and 2) the type of product it was (as best represented by product categories listed above), which would establish ranges of the curve's maximum sales in either a trajectory of mainstream or limited adoption.

To demonstrate the MFA model's applicability in forecasting resource demand from emerging products, it was applied to four case study products that represent a spectrum of new electronic technologies: 1) fitness trackers; 2) smart thermostats; 3) drones; and 4) OLED (organic light emitting diode) TVs. Fitness trackers were modeled as small mobile devices; smart thermostats and drones as home media products; and OLED TVs within the TV category. While fitness trackers and drones are fundamentally new products, smart thermostats represent a case such that a "non-smart" alternative already exists, and adoption would be related to replacement of legacy systems. Based on these observations, emerging products were modeled under both potential trajectories: limited adoption, which constrained a, or peak sales, to between 0.05 - 0.1 products sold per household; and mainstream adoption, which set peak sales to be equivalent to the mean value observed for the product category to which each of these devices is categorized, including an uncertainty range of +/- 10%.

3.4. MFA model application to study interactions of mature and emerging technologies

Finally, the potential usefulness of the predictive model to study interactions of mature and emerging technologies for CE planning in situations where technology substitutions occur, was demonstrated using the case of TV technologies. TVs are the most commonly covered device across all U.S. state e-waste policies and have historically been a primary focus of hazard-based e-waste management, due to lead contained in CRT glass and the mercury contained in fluorescent-lit LCD displays. OLED TVs represent a natural innovation in display technology that has been progressing over multiple generations, and therefore the forecasts of OLED TV adoption were coupled with logistic models of past TV technology, and the potential evolution of e-waste in the TV category was projected for the next 15 years, a time period selected to reflect the long lifespans of these products within the household. Perfect substitution of OLED for LED technology was assumed, based on similar observation of each past TV technology generation.

4. Results

The key outcome of this study is the development of an MFA model based on logistic forecasting that can be used to predict flows of products with abundant historic data and for those with scarce adoption data, to inform proactive CE strategies. The following sections detail the results for model validation and then demonstrates the model's applicability in addressing key data challenges in circular economy planning in electronics.

4.1. Model Validation

The use of a three-parameter logistic curve in modelling adoption cycle (growth and decline) of products was tested against real sales curves of existing electronics products. Logistic was the best distribution of those compared, based on goodness of fit parameters such as SSE, R square and BIC. The full list of curve fitting statistics is reported in Appendix B Table 7. The forecasting capability of the MFA model is validated by comparing model generated e-waste flows of CRT monitors, Desktops, Printers, LED monitors, LCD TVs and Laptops with waste flows estimated using actual annual sales data from 2000 to 2018. Results (Figure 3.4) shows that forecast results are in strong agreement with those generated from real data, with less than 5% error in cumulative flows across products. Waste flows forecasted five years forward show how the models capture the effect of product market decline on e-waste estimations.

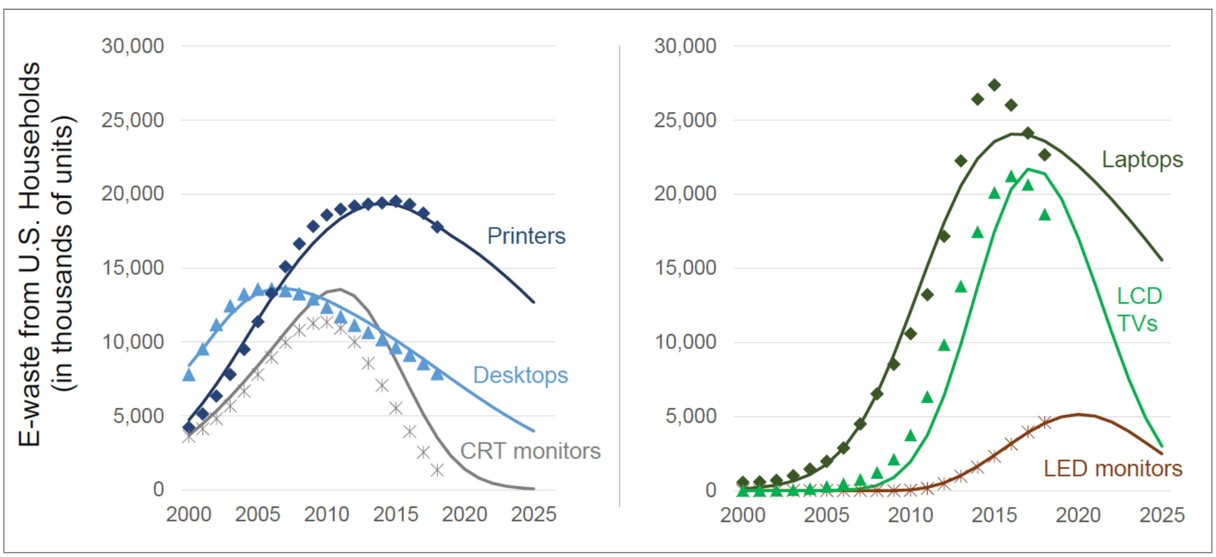


Figure 3.4. Comparison of e-waste flows estimated using the three-parameter model of logistic sales to e-waste flows calculated directly from real sales data of the products. E-waste flows reflect annual outflows from U.S. households in thousands of units. Line plots indicate forecasting model results while scatter plots indicate waste flows estimated from real sales data.

Waste flow forecasts in Figure 3.4 predict that CRT monitor units in the residential e-waste stream will soon be insignificant, which should help alleviate concerns about lead exposure during their downstream management. However, in the short term, few opportunities exist for closing the loop on these materials, as no demand exists for product reuse or CRT glass recovery. Waste flow forecasts for computing and display technologies like laptops and LCD TVs and monitors show that these products have likely reached their peak and will start slowly declining in the waste stream. In five years, laptops and printers are forecasted to decrease 20% from their current waste flow while LCD TVs are predicted to decline to more 50% from their current waste flow. Desktop computers are expected to sharply decline (40%) in the waste stream in the next five years, which is expected to have interactive effects on monitors, which are typically purchased to use with desktop computing. A comparison with waste flow forecasts by past studies (Mars et al., 2016) show that while our model results deviate more for some products such as laptops and printers (MFA results are -38%), results are close to past estimations for desktops (-14%), flat panel monitors (+7%), and TVs (-7%). While desktop waste flows estimated by the MFA model for year 2010 differed by less than 1% (-0.03% from low adoption scenario) from those reported by Miller et al (2016), monitor waste flows deviated by more than 20% (-26% for flat panel monitors and -20% for CRT monitors) from the study which applied the same sales-lifespan MFA method. Here the difference in estimations for monitor waste flows is likely due to our underlying assumption that monitor adoption follows a 1:1 ratio with desktop sales, based on input from consumer technology industry experts (Babbitt et al. 2017) rather than using real monitor sales data, which is available to a limited degree but does not account for monitors sold with desktops as a package. Other deviations in waste flow units from past estimations could be attributed to uncertainties associated with lifespan assumptions, as definition of product lifespans vary in different studies (Babbitt et al. 2009).

While model forecasts are impacted by lifespan uncertainties, the trends of this and other studies are consistent, and the downward trend in forecast e-waste flows is unlikely to change, as it is primarily driven by inflows to households in the way of new sales, which have begun to decline for all mature products studied. These results have significant implications to e-waste policy planning, as the products analyzed here fall under the commonly covered devices in U.S. state e-waste policies.

4.2. Forecasting implications to U.S. e-waste policy

Under extended producer responsibility (EPR) policies adopted for end-of-life management of electronics in most US states, collection targets are set based on manufacturers' share of covered products in the waste stream, as determined by sales-adjusted mass estimates (Electronics TakeBack Coalition, 2015). The process of setting collection targets often relies on observed trends in past years' product collection rates as the main factor in determining the next year's recovery goals (Oregon E-Cycles Program, 2018). Neither states nor manufacturers typically have the modeling capability to predict future waste flows, limiting their ability to set appropriate targets or plan for end-of-life management. Therefore, the predictive MFA model offers significant utility for these stakeholders in its ability to project e-waste flows over a near-term time horizon. To assess how this model might be used by policy stakeholders, it is applied to commonly covered devices in U.S. state policies, which include mature products such as TVs, monitors, computers and printers, to estimate their cumulative waste flows in the U.S. (Figure 3.5). These estimates were generated using the logistic forecasting model for a 15-year period, which includes recent past and six years beyond the present. Note that the model predicts the total mass of products coming out of households, which may then go into reuse, recycling, or discard pathways.

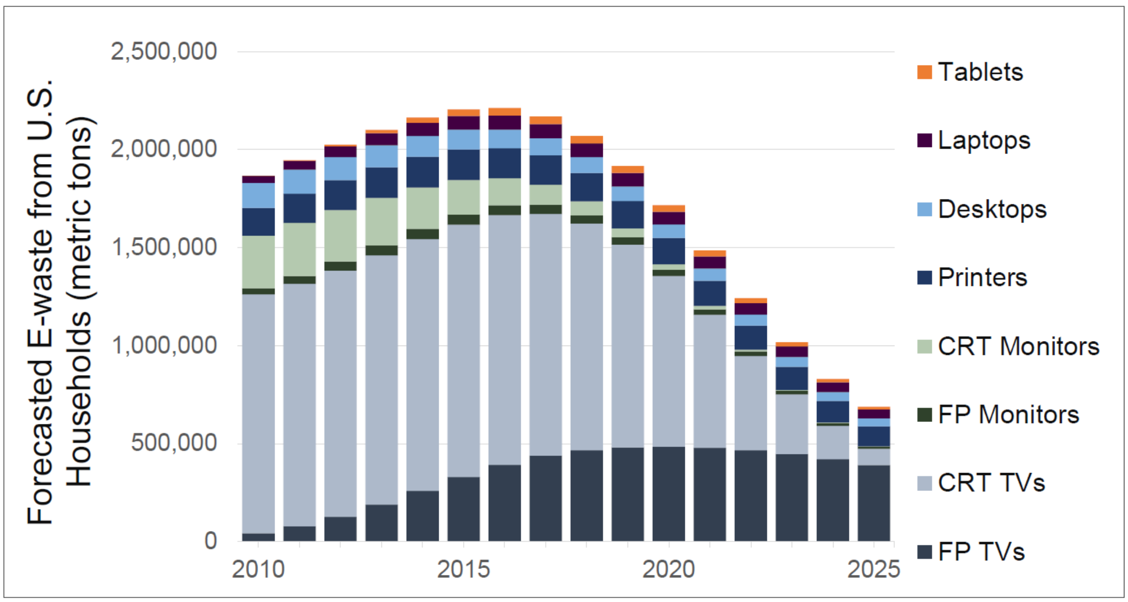


Figure 3.5. Application of predictive model to inform e-waste policies, demonstrated through estimation of cumulative waste flows of devices commonly covered for recovery under state e-waste legislations. Chart shows the decline in mass flows of commonly covered devices. (FP: Flat Panel, which includes LCD and LED displays; CRT: Cathode Ray Tube).

E-waste flow forecasts in Figure 3.5 suggest that the mature products that are currently the focus of state e-waste policies are beginning to decline in the waste stream, a trend expected to continue in the next several years. This trend is largely attributable to the changing mix of display technologies, where heavy CRT TVs and monitors are no longer sold and slowly empty from consumers' households, while being replaced with lighter products such as flat panel displays and tablets. These results point to potential sustainability benefits of reducing the overall amount of e-waste requiring management, particularly devices which contain hazardous materials such as CRT (lead) and LCD displays (mercury). On the other hand, the shift introduces new uncertainties for the recycling industry, which has long been established around processing large products with high potential for disassembly and component and material recovery. Further, the decline of mature products will be offset to a degree by other products that are now emerging or growing, but that are not covered under such policies. For example, smartphones, which are a small contribution to e-waste by mass, contain a high concentration of valuable materials including gold, cobalt, and lithium (Cucchiella et al., 2015). In addition, TVs, which show significant dynamism within this policy case, contain indium, a scarce material for which very limited recycling is currently possible (Buchert et al., 2012).

As policy is a key enabler of the circular economy, e-waste regulations are expected to increase the ability to repair and reuse products or recover materials that can be returned to functional use in new devices. However, the forecasted decreasing trends in cumulative waste flow suggest that states will need to fundamentally shift from product collection and recovery targets based on mass alone. Already, states have informally reported declining collection rates (Rubinstein 2018), and at least one state, Illinois, is moving away from mass targets to convenience-based systems, which emphasize consumer access to e-waste collection points. It is challenging to benchmark these forecasts to other studies, as most literature applies a retrospective rather than prospective approach. Comparison of e-waste flow estimates with past studies (Powell and Chertow, 2018; U. S. Environmental Protection Agency, 2016b) show comparable trends in the lead-up to peak waste flows (estimated in Figure 3.5 to be 2016-2017). However, it should be noted that results presented here are for the U.S. residential/consumer sector only, and so the magnitude of flows will naturally be smaller than the above-mentioned studies, which include residential and commercial sectors together. A direct comparison of results to a U.S. Environmental Protection Agency (2011) study, which applied the same sales-lifespan method for e-waste estimations from 1990 to 2010, is provided in Appendix B Figure 4, confirming consistency in trends for the overlapping period.

4.3. Forecasting implications of emerging technologies

The predictive MFA model was applied to four case study products that represent a wide array of emerging technologies for which data are scarce and near-term forecasting is necessary to identify potential opportunities and risks for CE planning. For each of the emerging technologies (fitness trackers, smart thermostats, drones, and OLED TVs) both mainstream and limited adoption trajectories were projected based on the peak sales ranges for the product categories to which these technologies most closely align. The forecasts, shown in Figure 3.6, were generated using only the year of market entry (as predictor of logistic parameters associated with growth rate and time to peak sales) and the product category (as predictor of the maximum sales).

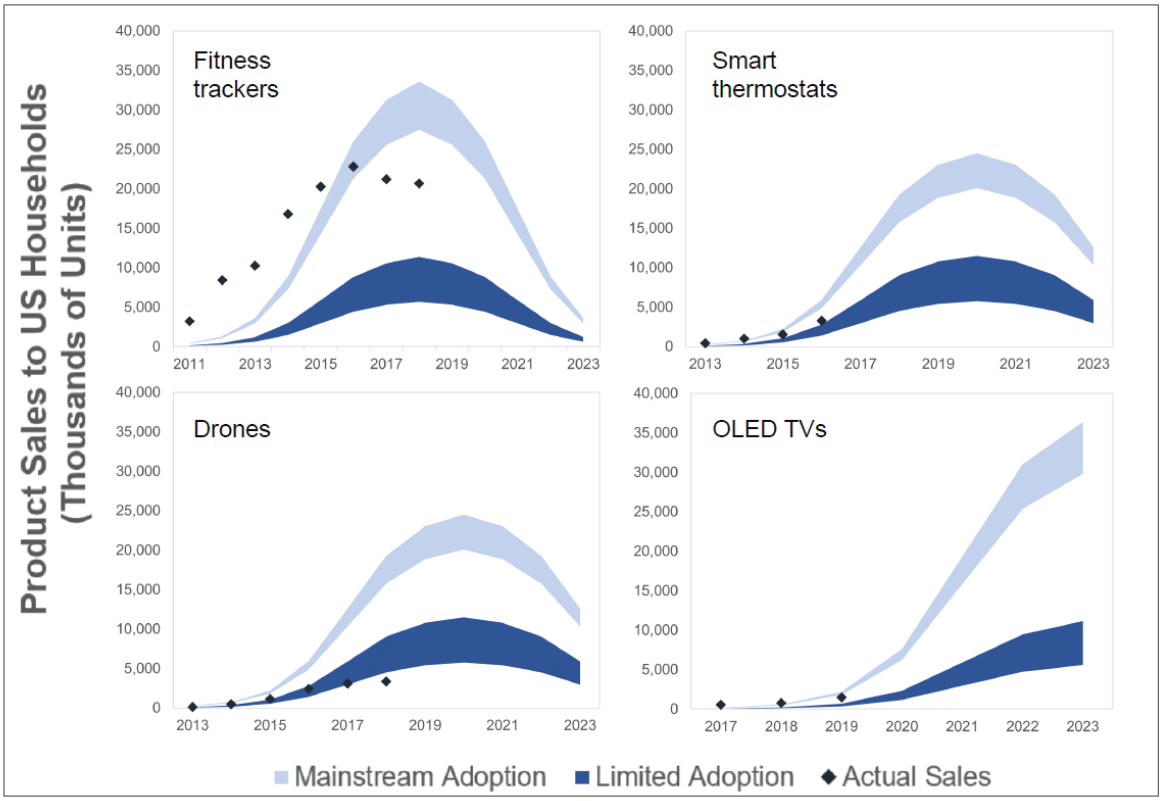


Figure 3.6. Forecast sales of emerging products: fitness trackers, smart thermostats, drones and OLED TVs. Comparison of possible mainstream and limited adoption scenarios (which include a range of peak sales) with the actual available sales data suggests which of the two adoption trajectories each product may follow.

Forecast results, compared against the limited real sales data that are available (See Appendix B Table 13), show that among the products studied, drones and fitness trackers have reached or may soon approach their peak. As per the adoption forecasts, fitness trackers have entered mainstream adoption in a manner consistent with other small mobile products and have reached the maximum carrying capacity or peak sales to households. On the other hand, drones appear to be unlikely to enter mainstream adoption as a household product. Annual sales of fitness trackers, which are currently around 22 million units, are unlikely to go above 35 million units, while maximum annual sales of drones are unlikely to go above 10 million units, if these products follow the trends of past products in their respective categories. The smart thermostat results suggest that they are still in the growth phase, but as a home product, the annual sales will likely peak at less than 25 million units, even if they enter mainstream adoption. Even though it is too early to confirm which adoption scenario OLED TVs will follow, the mainstream ranges are more likely, given past TV turnover and a recent peak of LED TV sales, which is usually a harbinger that a substitute product is beginning to invade the market niche.

These case study findings, which can easily be extended to any electronic product with limited amount of information, have significant implications for circular resource management. Many of these products contain complex components like lithium-ion batteries, which contain critical materials that are in high demand in other sectors, including electric vehicle manufacturing. In the case of emerging display technology OLEDs, which contains display units that employ thin, organic carbon-based films for lighting (Bagher, 2017), the implications on resource consumption and end-of-life management are unknown. This uncertainty underscores the need for forecasts that predict likely material implications. As discussed before, whether a technology will achieve mainstream adoption depends on similar competing technologies in the market. In the case of TVs, another emerging technology is also beginning to grow: QLEDs (Quantum Dot LEDs) are a variation of display technology recently introduced that may ultimately compete for market share with OLEDs. QLED displays are typically constructed using indium or cadmium-based nano-structured materials, for which additional environmental risks are unknown (Bagher, 2017).

4.4. Forecasting interactions between mature and emerging products

TV technology evolution is a unique case because it allows for a direct assessment of how product interactions, technological shifts, and substitution cycles ultimately influence e-waste flows and resource demand. From a circular economy standpoint, this information is critical to understand the capacity for closed-loop systems, in which materials are recovered from one type of product and returned to another of the same type. Such an approach may be most useful in products containing unique materials, such as the cobalt contained in mobile products' batteries, or the rare earth phosphors used in LED-lit flat panel TVs. As technology shifts, gaps open between increasing secondary material supply from products that have peaked and the demand for secondary materials by the product starting to emerge (Kasulaitis et al. 2018). This dynamic is illustrated in Figure 3.7 by coupling the waste flow forecasts of OLED TV with those of mature TV technologies presented in section 4.1.

TV technology forecasts are important to CE planning because these products are characterized by high mass, contain materials of interest, and form a significant part of the e-waste targeted for collection by state e-waste policies. The technology shifts in this product category have historically created challenges in their waste management, due to changing material profiles. Currently, CRT displays continue to persist in the waste stream, but no closed-loop solutions exist. As these products are no longer on the market, there is no demand in the electronics sector for the materials or components they contain. LCD TVs, which contain mercury in the cold-cathode fluorescent lamps used for backlights, have also peaked in the waste stream and are beginning to decline. The forecasts suggest that these TV technologies (LCD and CRT) will become insignificant in the waste stream in five-to-ten years, whereas LED TVs will make up a significant fraction of the waste flow. These forecasts highlight the need to prepare for end-of-life management of LED and OLED TVs to recover critical materials like indium (contained in flat panel displays) back into the manufacturing pipeline. It is to be noted that we have assumed maximum adoption scenario of OLED TVs in this analysis and have not considered influence of a competing technology like QLED in the market, which may bring its own challenges in end-of-life management of TVs as their displays are based on cadmium and indium nanostructured materials (Bagher, 2017; Chopra and Theis, 2017; Scalbi et al., 2017). These results emphasize the utility of the forecasting MFA model in understanding the implications of interactions between mature and emerging products in the material profile of the waste stream and associated circular economy strategies.

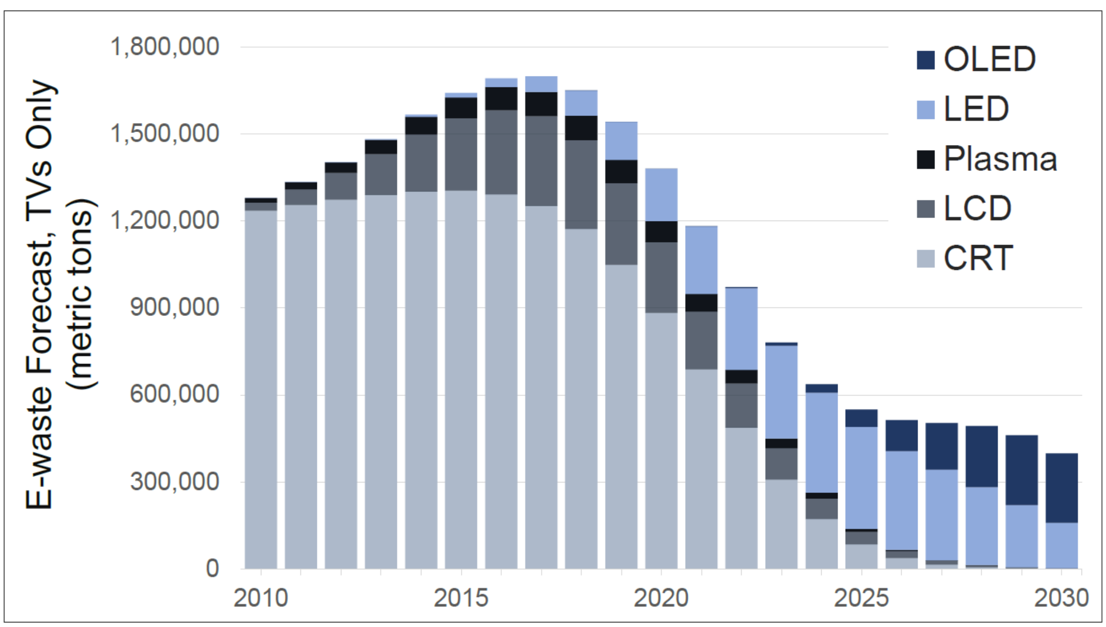


Figure 3.7. The evolving U.S. TV waste flow, reflecting multiple generations of new technology substitution, and its implication on reducing the e-waste stream due to light weighting over time.

5. Implications to CE planning

Applying the forecasting MFA to mature and emerging electronic products provides insights on key factors for effective CE planning, given the evolving nature of the e-waste stream and rapid pace of technological innovations. For example, the e-waste stream undergoes dematerialization when new technologies have significantly lower mass than products they substitute, especially in the case of TVs. The mass contribution of TVs in e-waste is forecasted to diminish 50% in the next five years, mainly due to dematerialization trends (Babbitt et al. 2017). Another key trend is the decline in TV technologies that contain hazardous materials like lead and mercury, where lead from CRTs is forecasted to reduce to less than 5 thousand metric tons by 2025, from the current level of 70 thousand metric tons in the e-waste stream. On the other hand, increased demand is expected for potentially scarce materials like indium due to continued growth of flat panel display technologies. However, combining the TV forecasts with literature estimates of indium content per TV (Buchert et al., 2012) suggest that indium in the waste stream from LCD and LED TVs may actually exceed its demand in these technologies by more than 30% within 5 years, due to increased adoption of lighter TV technologies. These trends suggest great potential for circular strategies that would close the loop on scarce materials in flat panel TVs.

Similar potential for circularity is observed in critical metals like cobalt and lithium, found in lithium-ion batteries that are key components of mobile electronics. For example, adoption and waste flow estimates of laptops show that cobalt contained in laptop batteries in the U.S. e-waste stream outweighs its demand in batteries for new laptop computers, a product where sales are slowing while batteries are also becoming lighter and more material efficient. In fact, the projected cobalt waste flow from laptops (> 1,000 metric tons in year 2021) is likely to soon exceed the combined cobalt demand for batteries in laptops and drones (< 900 metric tons in 2021). (See Appendix B Tables 8-12 for the data and calculations used in these informal estimates). While these trends in material flows where material content in e-waste exceeds its demand, indicate theoretical potential to close the material loop in electronics, it is limited at present by lack of effective recycling technologies and infrastructure. This highlights the need to enable other circular economy strategies that extend product and component lifespan, such as product reuse, repair, refurbishment and remanufacturing. The methods developed in the present study can support these CE strategies through estimations of product waste-flows which represent the products available after primary use, for life span extension or material recovery measures. However, consumer education and implementation of effective e-waste policies and collection systems are key in ensuring circular end-of-life pathways to recover used products from consumers, for enabling all aspects of CE including reuse, repair, remanufacturing and recycling (Gaustad et al., 2018).

The study findings also imply the need to shift the focus of end-of-life management of electronics away from mass-based diversion mechanisms and towards a broader perspective on sustainable materials management. The projected trends in e-waste generation emphasize the need to move away from the use of policy where all materials are treated equally, to explore alternate methods for setting collection targets, such as those based on environmental or economic savings associated with the circular economy. However, planning for such policy targets requires product level sustainability analysis, the key barrier being the lack of comprehensive knowledge on environmental and economics tradeoffs associated with material use and material recovery, topics that will be addressed in the next chapter.

6. Conclusions

For material management strategies to keep pace with the rapid pace of innovation in the electronics sector, proactive tools are needed to generate near term forecasts of resource demand and e-waste flows. This study contributes a novel method for informing circular economy planning in the electronics sector. The key contribution of this model is the use of historic sales data for over 25 products to create future-oriented sales curves that can then be used to forecast demand and waste flow of products irrespective of their historic data availability. While material flow forecasts for emerging products based on generalized trends can be burdened with uncertainty, this study takes the view that we cannot wait until data are perfected, or otherwise, proactive opportunities to implement material management strategies will be lost.

This model is flexible, and with appropriate validation, can be used to study any new product category, since only the year of market entry and the functionality category of the product is required to estimate peak sales range and forecast the adoption curve. For example, to forecast adoption scenarios of an upcoming consumer technology such as a smart mirror or smart shades, the peak sales range of 'Home Media' functional category and the potential market introduction year could be applied to the MFA model. However, the high rate of innovation and demand for multifunctionality in electronics may eventually create a need to develop newer functional groups, to accommodate the consumer adoption patterns of future technologies that may not fall in the existing 5 categories. The MFA model also provides a scaffold on which other material management metrics can be built, coupling product flows with material profile data and sustainability impacts associated with specific materials. However, there is lack of comprehensive data on sustainability implications of material use in electronics, a key knowledge barrier in prioritizing material management strategies in the sector. Chapter 4 addresses this exact data gap.

CHAPTER 4: Modeling and minimizing sustainability impacts of materials used in consumer electronics

1. Introduction

Consumer electronics are made up of a broad spectrum of materials that includes base metals like copper and steel, precious metals like gold and PGMs (platinum group metals), as well as many critical metals (Cucchiella et al., 2015). In addition to these valuable metals, complex components in electronics are known to contain toxic materials like lead, mercury and cadmium (Chen et al., 2011; Kiddee et al., 2013). Historically, sustainability concerns have focused on these materials' potential toxicity, due to the presence of lead in Cathode Ray Tube (CRT) displays and potential value at end-of-life, primarily associated with gold in printed circuit boards (Perkins et al., 2014) Cucchiella et al., 2015). Therefore, significant effort has been aimed at reduced use of toxic substances as well as recovery of materials of high economic value. For example, e-waste policies in most U.S. states set mass-based targets that are related to the market share of product manufacturers within a given state (Electronics TakeBack Coalition, 2011). Such a system ends up targeting high mass products like TVs, monitors, and desktop computers, which are where most hazardous and valuable materials are concentrated, and which help meet the collection targets. Mass-based e-waste management systems serve their purpose when the goal is waste diversion and economic material recovery. However, new material concerns are emerging in the electronics sector due to rapid rate of technological innovations and consumer adoption, which continue to add new products with unknown material implications to the waste stream.

Material flow analyses in Chapter 2 and 3 showed that the traditional electronic products targeted by e-waste policies in the U.S. are declining in the waste stream, and there is increased prevalence of newer technologies not yet covered by regulation. Newer electronics are characterized by compact size, multifunctionality, and complex and difficult-to-recycle product designs, which introduce new uncertainties for the recycling industry which has long been established around processing large products with high potential for disassembly and material recovery. The multifunctional capabilities of these modern-day electronics are enabled through a broad spectrum of materials (Christian et al., 2014), which include rare earth elements (REEs) and many critical metals. The touch enabled displays of modern mobile electronics rely on potentially scarce materials like indium, while the lithium-ion batteries that power these products contain critical metals like cobalt and lithium (Christian et al., 2014; Pengwei et al., 2018). Materials like cobalt and REEs, are not only key enablers of modern electronics, but are also in high demand for a wide array of applications in defense and clean energy technologies such as electric vehicles and wind turbines (Dutta et al., 2016). Global demand for these materials is expected to continue strong growth, as the emerging clean technology market enters mainstream adoption.

Due to their economic importance and supply risk, most raw materials in electronics are increasingly added to the growing list of 'strategic minerals' or 'critical materials' by global economies. For example, cobalt, a key ingredient in lithium ion batteries used for energy storage in electronics and other applications, is included in the U.S. Department Of Energy critical mineral list (USGS, 2018) and the European Union' Critical Raw Material list, and was recently categorized as a strategic mineral by the DRC (Democratic Republic of the Congo), the leading cobalt producing country. Similarly, REEs such as neodymium, dysprosium and europium which are key constituents of permanent magnets and electronic displays (Buchert et al., 2012) have been included in the U.S. DOE critical mineral list due to their importance in clean energy technologies and increasing supply risk due to production concentration in China (U.S. Department of Energy, 2011). Compounding the metal supply risks are the supply chain vulnerabilities due to geopolitical competition (Gemechu et al., 2017) and social-political situations in the countries that are leading producers of critical materials (Young, 2018). In addition to supply risk due to increased demand and geographically concentrated production, the environmental implications of material use in electronics has also emerged to be a key concern, as mining sector employs energy intense processes and are a significant contributor to global warming (Tost et al., 2018).

These emerging material concerns in electronics highlight the need for holistic sustainable material management (SMM) in the sector, rather than narrow focus on a few materials for end-of-life recovery. SMM approach seeks most productive use of resources to reduce environmental impacts, conserve resources, and reduce costs, for overall long-term system sustainability (U.S. EPA, 2009). Holistic SMM strategies would divert toxic waste from landfills, bring economic benefits through recycling, and minimize environmental impacts, while ensuring domestic supply security of materials that have been recognized to be critical to national security and economic growth. SMM strategies that have been explored in the literature include material substitution (Graedel et al., 2015b), dematerialization (Petrides et al., 2018) and recycling (Cucchiella et al., 2015; Friege, 2012; Zeng et al., 2018a). However, it is important to make informed choices in prioritizing these sustainability strategies and the materials to target in electronics, as they involve tradeoffs in economic and environmental benefits. For example, in product design choosing a material substitute for environmental benefits without considering its scarcity aspects may minimize environmental impacts at the expense of supply security. Therefore, it is necessary to quantify every potential material sustainability risk and opportunity using measurable metrics, to identify hotspots in the system, from material sourcing to end-of-life management so that potential solutions can be explored.

A wide body literature exists on material criticality (Erdmann and Graedel, 2011; Jin et al., 2016), which includes a study by Graedel et al., (2015), which estimated metal criticality based on supply risk, vulnerability to supply restriction and environmental implications (Graedel et al., 2012), and an Oko-Institute report (Buchert et al., 2009) which performed material criticality assessments based on supply risks, recycling restrictions, and demand growth. Past research has explored the criticality of specific materials such as rare earth elements (Nassar et al., 2015a), indium (Ylä-mella and Pongrácz, 2016), copper (Nassar et al., 2012), and iron (Nuss et al., 2014), and has looked into the implications of metal use in specific applications such as clean energy technologies (Elshkaki and Graedel, 2013; Grandell et al., 2016; Månberger and Stenqvist, 2018; Nassar et al., 2016), photovoltaics (Goe and Gaustad, 2014), and lithium ion batteries (Olivetti et al., 2017).

While the scientific literature is rich in data on diverse aspects of material sustainability such as geological scarcity (Henckens et al., 2016; Sverdrup et al., 2017), price (Leader et al., 2019), environmental impacts of production (Nuss and Eckelman, 2014; Weng et al., 2016; Zaimes et al., 2015), potential for material substitution (Graedel et al., 2015b), and recycling rates (Graedel et al., 2011), these data are spread across many different studies and have not yet been synthesized specifically for the electronic product sector. To prioritize material specific sustainability efforts for consumer electronics, there is the need for comprehensive data on material sustainability that can answer key questions such as: Which materials are used in electronics and in what quantities? How and where are these materials obtained? Which materials pose the highest sustainability risks? And, what is the potential for material recovery through recycling?

To answer these questions, this study for the first time compiles, analyzes, and interprets the social, economic, and environmental implications of materials in consumer electronics. This research involved a multi-step process, from characterizing common materials used in electronic product manufacturing and identifying key metrics to quantify sustainability risks of materials use in products, to collecting data to parameterize these and synthesizing the findings to identify key areas of concern and explore potential solutions. In terms of investigating alternate solutions, one objective was to understand the degree to which recycling, which is a central part of most e-waste policy, can minimize sustainability concerns relative to other strategies that have different levels of technical feasibility. The key contribution of this research is the compilation and contextualization of material specific sustainability information for electronics and the evaluation of SMM strategies.

2. Methods

The goal of the study was to develop and apply a comprehensive set of sustainability metrics for materials used in consumer electronics, to enable the identification of key materials of concern and evaluation of potential solutions. The methodology adopted to achieve the research goal involved multiple steps.

1) Characterizing common materials in electronics to include in study scope.
2) Identifying key metrics that can capture economic, environmental and social sustainability risks across the life cycle of materials used in electronics and collecting data to parameterize these metrics.
3) Analyzing and synthesizing the material metrics data to identify hotspots (key materials of concern) in each sustainability dimension.
4) Evaluating the potential for recycling and other sustainability solutions for their potential to minimize these impacts.

The following subsections describe each of the steps in the methodology in detail.

2.1. Characterizing common materials in electronics

Common materials contained in consumer electronics was characterized through review of published studies on materials in electronics. Primarily, a literature search on recycling potential of electronics, especially complex components in electronics such as printed circuit boards, display units and batteries, was used to narrow down the list of key materials to be included in the study scope (Buchert et al., 2012; Cucchiella et al., 2015; Işıldar et al., 2017b; Wang and Gaustad, 2012). A similar approach of literature search on reuse potential of e-plastics was used to identify different types of polymers found in electronics (Mills and Tatara, 2016). Consumer electronics materials included in this study scope are presented in Table 4.1. Materials are grouped into base metals, precious metals, critical metals, rare earths, hazardous materials and different types of polymers.

Base metals	Precious metals	Critical metals	REEs	Polymers
Al	Au	Sb	La	ABS
Cu	Ag	Ba	Ce	HIPS
Mg	Pd	Co	Pr	PA
Fe	Pt	Ga	Nd	PS
Ni	Rh	Gr	Sm	PC
Zn	Ru	In	Eu	PVC
Ti	Rh	Li	Gd	PMMA
Hazardous metals		Mn	Y	
Pb		Ta	Tb	
Hg		Te	Dy	
Cr		Sn	Ho	
Cd		V	Tm	
			Yb	
			Lu	

Table 4.1. Material list included in study scope. Precious metals ruthenium (Ru), iridium (Ir) and Osmium (Os) belong to platinum group metals, and rare earth elements (REEs)- scandium (Sc), erbium (Er) and promethium (Pm) are omitted from the study due to lack of data availability.

2.2. Identifying key metrics to measure sustainability risks of materials in electronics

To develop material sustainability metrics, economic, environmental and social implications of material use were considered. Table 4.2 summarizes the sustainability aspects considered in the study and the metrics used to quantify each one of them. A wide array of data sources such as journal articles, reports, data from government websites, and results from the application of modeling tools such as Simapro LCA software and MFA model developed in Chapter 2 were used to parametrize the sustainability metrics. Additional detail on the selection and definition of each metric, units of measurement, and data sources are given in Appendix C Table 1.

Sustainability aspects	Metrics to measure sustainability
Economic	Global reserves Ore concentration Annual mine production Static index of depletion Production % as byproduct Geographical concentration of production (HHI) Price Price volatility Import Reliance Electronics sector consumption
Environmental	Global Warming Potential Cumulative Energy Demand Mineral Resource Demand Toxicity
Social	Socio-Political Index of Producer Countries

Table 4.2. Metrics used to measure economic, environmental and social sustainability risks associated with material use in electronics.

The economic implications of material use in electronics are quantified considering both the direct economic costs of material choice and indirect issues that may have an influence on material cost. Direct economic metrics include material price, fluctuations in price (measured as 5-year coefficient of variation), annual production, and material consumption in electronic sector. Indirect economic metrics capture factors that affect the economics of materials more broadly, such as material scarcity, geographical concentration of material production, and import reliance in the U.S. Material scarcity metrics are key in economic assessment of materials, since price fluctuations are dependent on supply risks and disruptions. Material scarcity is quantified using five different metrics: global reserves, ore concentration, annual production, static index of depletion, and the extent to which a material is only produced as a by-product. Global reserve is the working inventory of supply of economically extractable mineral commodity (U. S. Geological Survey). The static index of depletion of a material is calculated as the ratio of its global reserves to annual production. The index of depletion is subject to change, as new material reserves are discovered over time and annual production or demand of materials also may increase or decrease. However, the metric gives an indication about near-term supply risk due to its geological scarcity.

Another scarcity metric that has economic implications is the byproduct production percentage. When materials are recovered only as byproducts, it is challenging for production to keep up with demand since the byproduct material production is driven by the demand and production of its parent or host metal (Nassar et al., 2015b). This may lead to supply scarcity and price fluctuations of byproduct materials. Geographical concentration of production is another factor that presents economic risks as material production concentrated in a few countries increases the risk of supply disruptions and price hikes. In this study geographical concentration of production is quantified using the 'Herfindahl-Hirschman Index (HHI)', a statistical measure of market concentration (Brown, 2018). Import reliance in the U.S., expressed as the percentage of total consumption., is used to evaluate material economics from the U.S. perspective, as high reliance on imports of a material implies potential for supply risk and price fluctuations in the country. The consumption by the electronics sector is measured as the percentage of total material produced annually that is used in electronics sector. It should be noted that, due to the level of aggregation in the source data, this estimate includes products like appliance and commercial electronics, and not consumer electronics alone.

The environmental implications of material production are quantified through five metrics that reflect a cradle-to-gate life cycle perspective: global warming potential (GWP), mineral resource demand (MRD), cumulative energy demand (CED) to produce per kg of each material, and potential eco-toxicity (supply chain and direct freshwater ecotoxicity). GWP quantifies the supply chain greenhouse gas impact, while CED measures the net energy and fuel resources associated with extracting and producing a material. MRD analyzes the life cycle input of mineral resources associated with extracting and producing a material. Supply chain ecotoxicity quantifies the potential toxicity of a wide array of chemicals emitted into freshwater systems in a materials' production chain, while direct toxicity represents the potential toxic effect of a metal if it were to be directly released to a freshwater ecosystem. Data were obtained from the eco-invent database in Simapro 8 LCA software and from literature sources.

Social implications of material production are evaluated using quantitative and qualitative measurements. Quantitative measurement of social aspects of material sustainability is performed by extending the previously presented assessment of geographical production concentration (HHI) to factor in the potential for political instability in the producing countries. Social sustainability is estimated by weighting the HHI of materials using the World Governance Indicator of Socio-Political Stability and Absence of Violence (WGI-PSAV) index, which is a method used in literature to measure the risk to supply disruption of materials due to the socio-political instability in producer countries (Goe and Gaustad, 2014).WGI PSAV index score which rates political stability of countries on a scale from poor (-2.5) to good (+2.5) is collected from World Bank website. Another consideration to identify social hotspots is whether materials in electronics belong or are similar to a class of materials called 'conflict minerals' due to social conflicts associated with their production.

2.3. Identifying material hotspots (key materials of sustainability concern) in electronics

A combination of quantitative and qualitative assessments was used to identify key areas of concern in each aspect of sustainability. The first step was to identify materials that presented highest risk in each metric by creating heat maps color coded through conditional formatting as: darkest blue color for top 90th percentile and lightest blue color for the bottom 10th percentile, in terms of sustainability risks. The next step was to narrow down key materials of concern in each aspect of sustainability- economic, environmental and social. Material hotspots were identified by qualitative evaluation by considering three factors: the risk level of materials in each metric, its consumption in electronics sector and its relevance to U.S. economy as understood from import reliance.

2.4. Evaluating the potential for sustainability solutions

Once sustainability data were compiled, alternate sustainability strategies were assessed for their ability to minimize the identified risks. Recycling was a key opportunity considered here, given its central place in e-waste policy in the U.S. and globally. Quantitatively evaluating recycling potential is challenging, as there is limited and inconsistent data about material-specific recycling rates. The recycling rate of a material depends on its properties and its content in waste, in addition to many systems-level factors such as waste management policy, waste recovery infrastructure, consumer collection rates, and performance of available recycling technologies. Publicly available 'recycling rate' data do not often consider all these factors and therefore may not always reflect the actual recycling rate of a material that enters its end-of-life. Data on recycling rate of materials from used electronics is even more limited.

Here, the range of metrics used to evaluate recycling potential are recycling efficiency in the U.S., secondary material use in the U.S., the concentration of dilution of a given material in the e-waste stream, and the potential for material circularity in electronics. Recycling efficiency (referred to as 'end-of-life recycling rate' or EOL-RR in Graedel et al., (2011)) is defined here as the amount of old scrap recovered and reused, relative to the amount available to be recovered and reused (after collection), or the percentage of total waste generated (not specific to electronics sector) that is recycled in the U.S.

Recycling efficiency represents the existing technology and infrastructure in the US to recycle a material, though not specific to electronics sector. Secondary material use (referred to as recycled content or RC in

Graedel et al., (2011)) is the percentage of recycled material that makes up the total material consumed in the U.S. annually. This metric represents the market potential for recycled material in the U.S. (not electronic specific) and include both post-consumer scrap and prompt scrap that is recovered during material extraction and processing steps. USGS data as reported by Graedel et al., (2011) is used for recycling efficiency and secondary material use for most materials except REEs, gallium, indium, lithium, mercury, tellurium, rhodium, ruthenium , iridium and osmium. For these materials, consensus recycling statistics from expert knowledge as reported by Gradeal et al (2011) is used for the study.

Material dilution is calculated as the ratio of the mass of a material in the e-waste stream relative to the total mass of electronic waste flow in the same year. Material dilution is estimated from MFA results for year 2018 as described in Chapter 2 and represents the potential challenge extracting a material from the waste stream due to its concentration relative all other materials and products in the waste stream. Theoretical circularity potential is also calculated using MFA results from Chapter 2 for year 2018, as the ratio of end-of-life waste material relative to material demand in the same year for new electronics. Circularity potential reflects the theoretical ability to achieve ‘closed-loop’ circularity in electronics through recycling. Appendix C Table 2 reports definitions of metrics used to define recycling potential and the data sources.

However, recycling is not the only sustainable solution available, and may not be the optimal choice for some materials. Functional substitution of scarce materials with other suitable materials has been discussed in literature, as a strategy to deal with material availability constraints in a high demand scenario (Graedel et al., 2015b). Material substitution and dematerialization can be a potential solution for environmental and social risks as well. Therefore, substitutability of key materials of concern in electronics is investigated as a potential sustainability solution. Supply chain diversification is another strategy that can minimize potential supply disruptions due to production concentration. However, the potential to enable alternate supply chain for a given material depends on its geological availability in other geographic locations. Therefore, metrics such as global reserves and geographical production concentration are used to analyze the potential for alternate supply chains for key material hotspots.

The results of the study are organized as six subsections. Sections 3.1, 3.2 and 3.3 present the key findings of economic, environmental and social assessment of electronic material sustainability, especially metals. Section 3.4 analyzes the potential for recycling as a sustainability solution for material hotspots while section 3.5 discusses alternate solutions such as material substitution and alternate supply chains for key materials of concern among metals. It is to be noted that the sustainability analysis of plastics used in electronics is conducted using a limited set of metrics due to data unavailability and therefore study findings for different types of plastics used in electronics is presented in a separate section. Section 3.6 presents the sustainability analysis of plastic use in electronics as a case study. For plastics, price and annual production are included as economic metrics while and GWP, CED and MRD are included as environmental metrics. Data for environmental metrics for plastics is extracted from Eco invent database in Simapro LCA software while data for other metrics are adopted from Ashby (2013).

3. Results

The sustainability profiles of consumer electronic materials assessed through economic, environmental and social aspects, the key hotspots identified, and potential solutions are discussed in detail in subsections below. Results for metric measurement for each sustainability aspect are presented as heat maps where the darkest blue represents the greatest risk, and the lightest blue represents lowest risk. Gray indicates that no reliable data were available or included. This representation is used throughout the results sections (absolute results in Appendix C Tables 3 to 6) Metric data for individual rare earths is provided when data is available, otherwise represented in general as REEs. Platinum group metals such as Ir, Ru and Os are not included in most tables due to data unavailability.

3.1. Economic aspects of material sustainability

The economic aspects of material sustainability measured using 10 different metrics is presented as two heat maps in Table 4.3a and Table 4.3b. Table 4.3a presents metrics measuring scarcity or physical availability of materials while Table 4.3b represents metrics that directly measures material economics such as price and price volatility, in addition to material consumption in electronics sector as well as the reliance of U.S. economy on imports of each material.

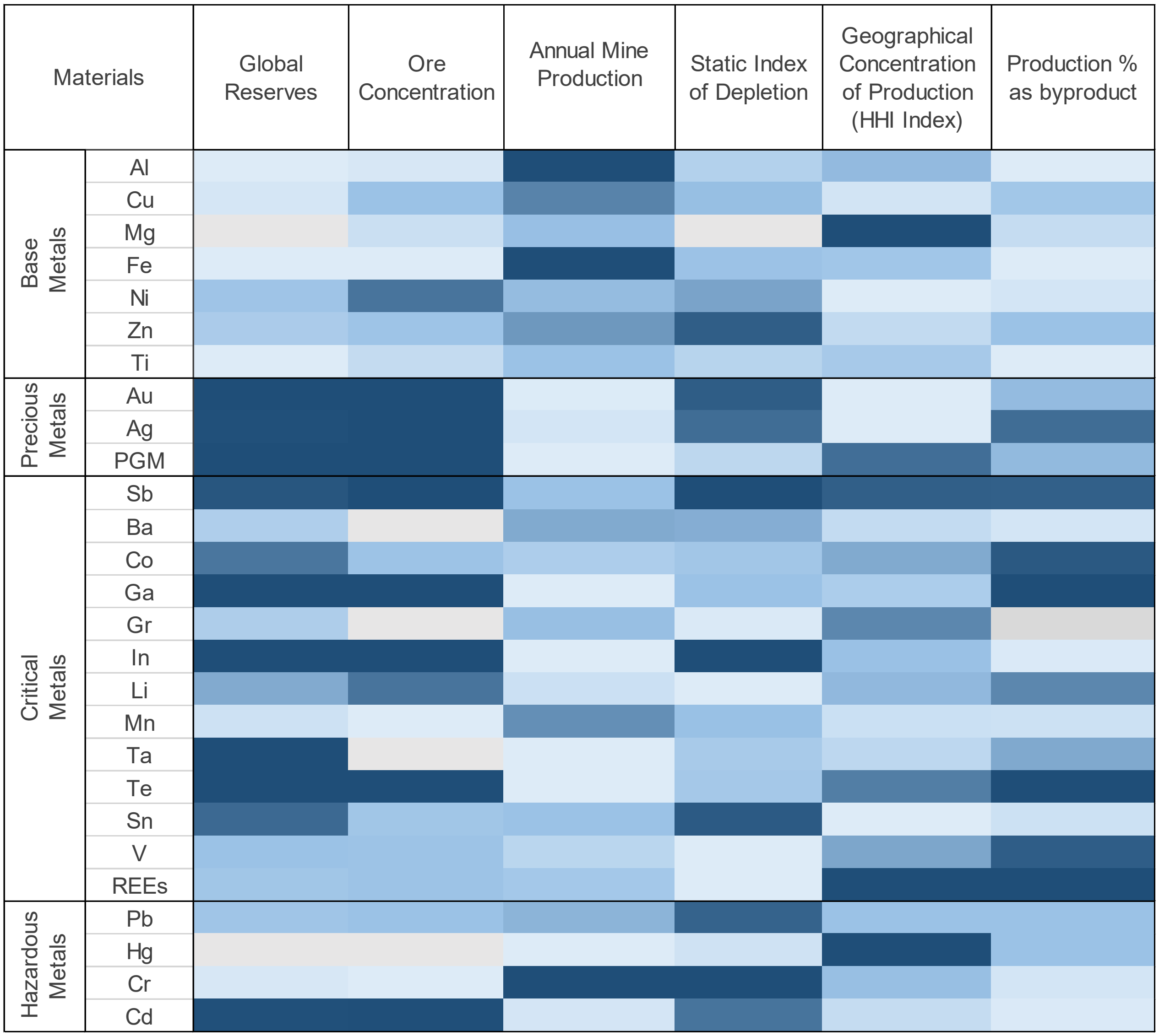


Table 4.3a. Measuring economic aspects of sustainability measuring using metrics: global reserves (metric tons), ore concentration (%), annual mine production (metric tons), static index of depletion (years), geographical concentration of production (HHI) and material production percentage as byproduct (%). Annual mine production is for year 2017. Data sources: USGS Mineral Commodity Summaries; Henckens et al (2016), Sverdrup et al (2017), Goe & Gaustad (2014), Nassar et al., (2015b).

Materials		Price	Price Volatility	Import Reliance: US Perspective	Electronics Sector Consumption
Base Metals	Al				
	Cu				
	Mg				
	Fe				
	Ni				
	Zn				
	Ti				
Precious Metals	Au				
	Ag				
	Pd				
	Pt				
	Rh				
Critical metals	Sb				
	Ba				
	Co				
	Ga				
	Gr				
	In				
	Li				
	Mn				
	Ta				
	Te				
	Sn				
	V				
REEs	La				
	Ce				
	Pr				
	Nd				
	Eu				
	Sm				
	Gd				
	Y				
	Tb				
	Dy				
Hazardous Metals	Pb				
	Hg				
	Cr				
	Cd				

Table 4.3b. Measuring economic aspects of sustainability using metrics: price, price volatility (5 year coefficient of variation), import reliance in U.S. in 2017 (% of material consumption in U.S.) and material consumption in electronics sector (% of total material consumed in a year; electronics sector includes

both electrical and electronics applications). Data sources: USGS Mineral Commodity Summaries, Graedel et al (2015b).

The key materials of concern identified through the synthesis of economic sustainability profiles of materials presented in Table 4.3a and 4.3b are REEs (rare earth elements), indium, and gallium. Indium and gallium emerged to be a concern due to geological scarcity and price, while REEs emerged to be an issue due to price volatility and geographical concentration of production. The geographic concentration metric HHI calculated using production contribution of different countries is always positive, with higher values indicating a more concentrated production. Table 4.3a highlights REEs to pose highest risk in production concentration, indicating high positive HHI. Another factor that compounds the economic sustainability risks of REE and gallium production is that they are produced only as byproducts during the processing of the major metals (REEs- Iron Ore, Gallium- Aluminum), making it difficult to increase their supply in response to rapid changes in demand (Nassar et al., 2015b). See Appendix C Table 4 for details on material production as by-product. A material with high positive HHI value and high % production as byproduct, represents high risk to supply and therefore can be considered as a material of high concern in economic sustainability, which is the case for REEs. Even though many other materials such as gold, platinum group metals (PGMs), cobalt, and antimony showed potential risks in terms of price, scarcity and production concentration, REEs, indium and gallium are highlighted as economic hotspots since in addition to their high risks in other metrics, they represent high rate of consumption in electronics sector and high import reliance in U.S., both factors indicating the importance of these materials in electronics industry and in the U.S. economy.

Nearly 85% of indium produced globally is used in the ITO (indium tin oxide) layer of flat panel displays, primarily for electrically conductive purposes (USGS, 2018). The global production of REEs are also mainly driven by the electronics sector, especially REEs such as Nd (neodymium), Dy (dysprosium) and Eu (europium). Nearly two-thirds of total Nd and Dy produced is used in permanent magnets, whereas nearly 100% consumption of Eu which has exhibited high price volatility among materials in electronics, can be attributed to its use in lamp phosphors (See Appendix C Table 8 for major use sectors of materials). Gallium production is also significantly connected to electronics as 67% of gallium produced is used in integrated chips in electronics.

The geographical concentration of material production is an important aspect that presents economic risks to sustainability for all the material hotspots. Figure 4.1 which presents production distribution of materials in electronics, highlights the dominance of China in material sourcing especially in the case of REEs, a group of metals identified to be an economic risk. The geographical distribution of mine production shows that more than 50% of most of the materials is produced in less than two countries, with

China being the primary producer in most cases. This high production concentration introduces supply chain risk due to excessive control that the producing countries exert on material production. In the event of political instability, policy barriers, or natural disaster, the supply chain is more vulnerable to disruptions that may present sustainability risks by increasing material price or decreasing availability. The HHI (geographic concentration of production) column in economic metric heat map (Table 4.3a) quantifies the production concentration of materials and helps identify materials with high supply risk due to lack of supply diversity. REEs with a high HH Index have emerged to be key materials of concern while PGM (platinum group metals), critical metals such as antimony, vanadium, tellurium, magnesium and battery materials such as cobalt, lithium and graphite also present economic risks to sustainability from supply chain vulnerabilities due to their production concentration.

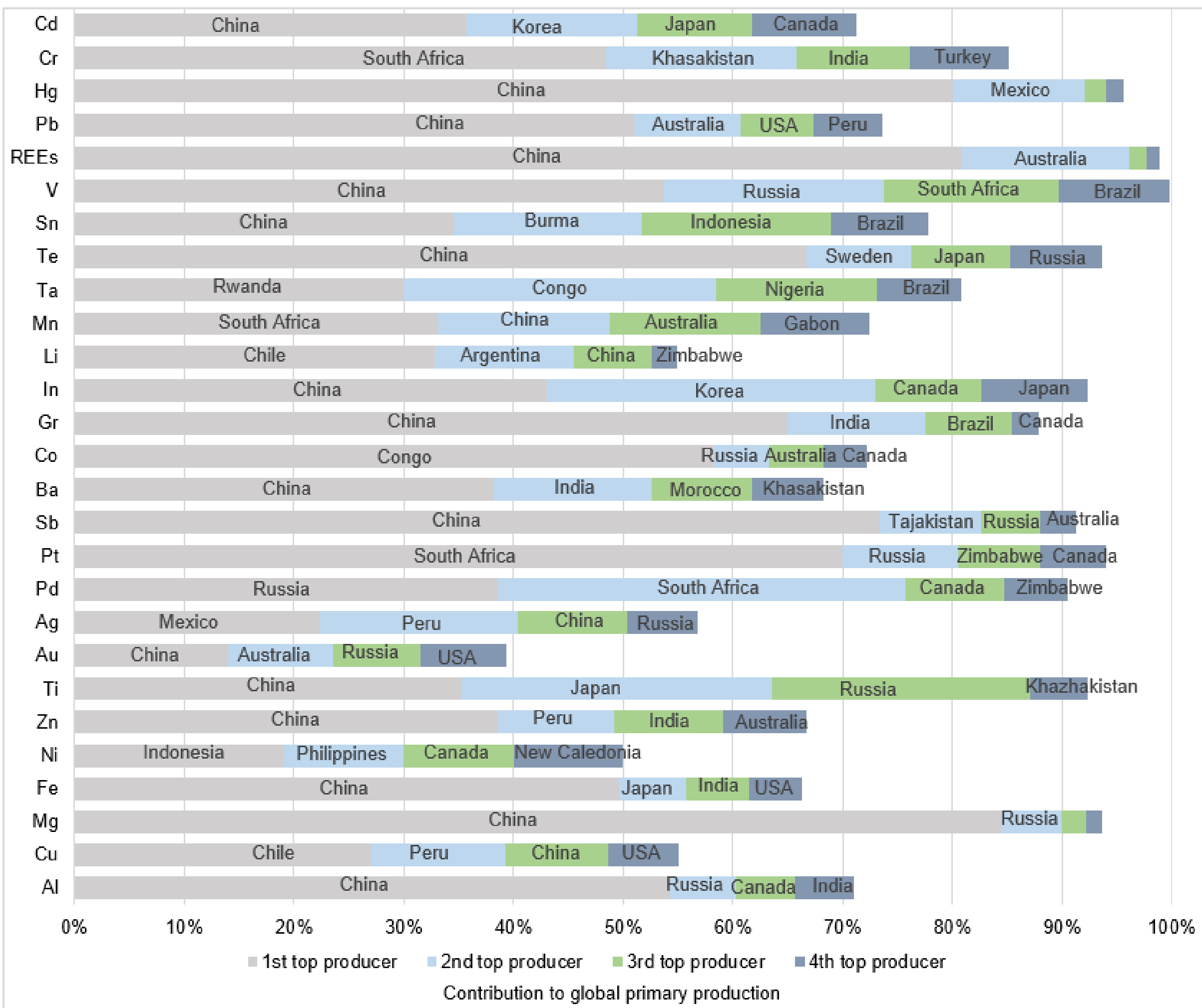


Figure 4.1. Geographical distributions of mine production of common materials in electronics, showing top four producing countries in 2017. Data Source: USGS, Mineral Commodity Summaries, 2018.

Quantifying economic sustainability aspects for the broad range of materials used in electronics, shows that different materials present risks in different factors of material economics. However, holistic evaluation of economic sustainability profiles of materials highlights a few hotspots that need consideration in evaluation of sustainability strategies in electronics. Table below (Table 4.4) summarizes the key findings of economic sustainability assessment of materials.

Economic Hotspots	**High Risk Factors**
REEs	Production concentration, High price volatility, Byproduct (100%- Fe) High consumption in electronic sector: (Dy-100%; Nd-76%- magnets), (Eu-100%-phosphors), (Sm-73%-battery alloy)
Indium	Geological Scarcity Price High consumption in electronic sector (84%- Flat panel displays)
Gallium	Geological Scarcity Price Byproduct (100%-Al, Zn) High Consumption in electronic sector (67%-IC chips)

Table 4.4. Economic hotspots in electronics.

3.2. Environmental aspects of material sustainability

The environmental aspects of material sustainability measured using 4 different metrics: global warming potential (GWP), cumulative energy demand (CED), mineral resource demand (MRD) and freshwater ecotoxicity is presented as a heat map in Table 4.5. The heat map highlights materials with potentially high resource demand and environmental impact due to extraction and refining stages. The key materials of concern identified to be environmental hotspots are precious metals, REEs and critical metals indium, gallium, lithium and tantalum.

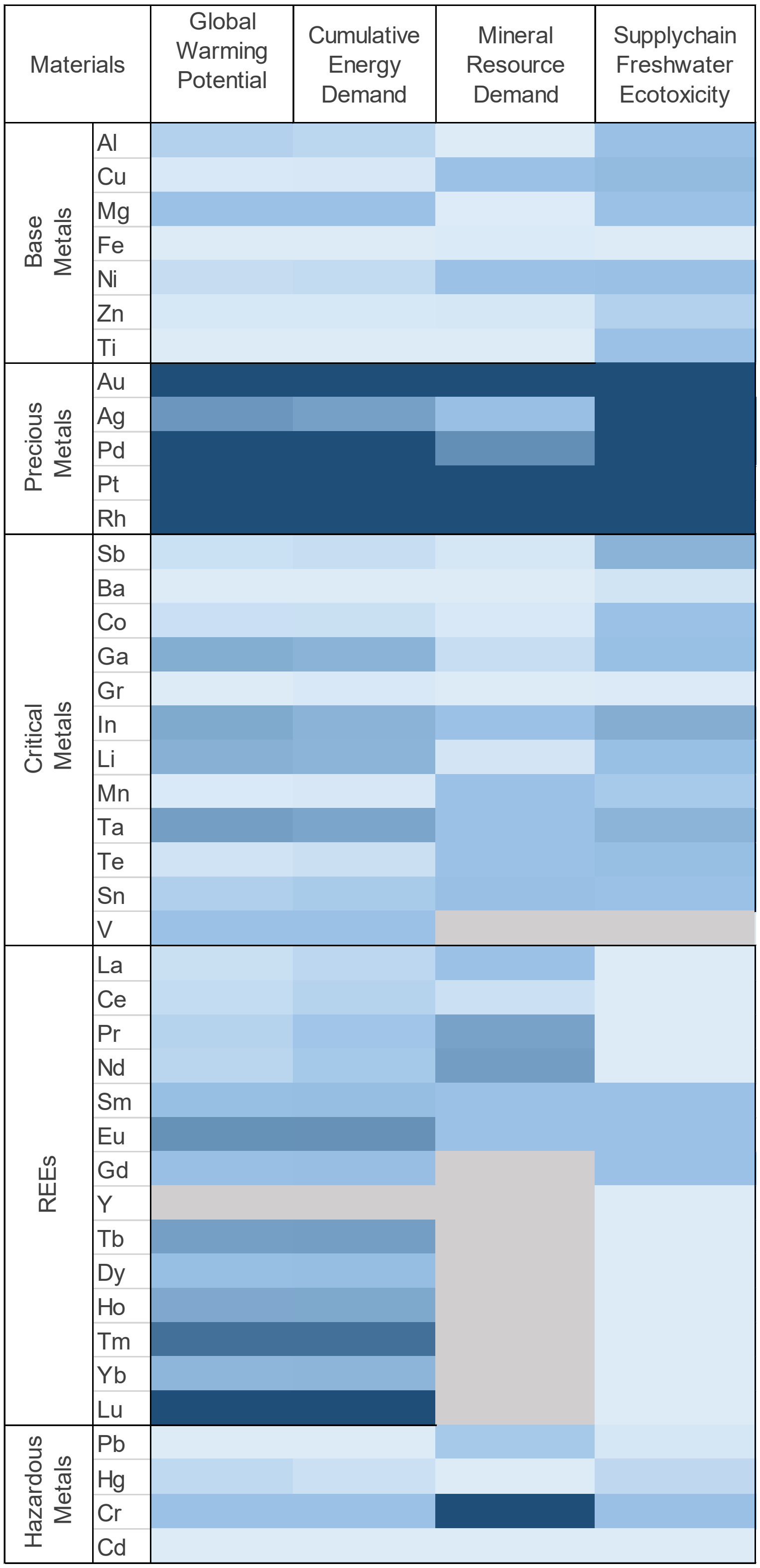


Table 4.5. Measuring environmental aspects of sustainability using metrics- GWP, CED, MRD and freshwater ecotoxicity. Data Source: Simapro Eco invent database.

Precious metals such as gold, palladium, platinum and rhodium are clearly the materials with highest environmental impact when considering impacts per unit mass of material produced. REEs and the critical metals such as indium, gallium, lithium and tantalum also have significant impact on the environment, while most base metals, which are used in large quantities in electronic products have lower impact to the environment. REEs and critical metals are identified to be environmental hotspots in electronics despite their impact being much lower than precious metals, since the production of these metals are largely driven by electronics sector. Precious metals are also considered as hotspots as their environmental impacts are almost 50 times more than other high impact materials in electronics (See Appendix C Table 6 for data on environmental metrics), indicating that even though there are used in small amounts in products they may have higher contribution to total environmental impact of most products. This also means that sustainability strategies in precious metal use in electronics have the potential to bring huge environmental benefits to the sector.

For example, a single product may only contain trace amount of precious metals, but their individual impacts may be high enough to be significant at the product scale. See Appendix C Figure 1, where this effect is demonstrated by comparing where the relative contribution of materials to total mass as well as total carbon footprint of a typical laptop. Figure 1 in Appendix C shows that in an average laptop, even though the mass contribution of precious metals such as Au, Pt and Pd is insignificant when compared to base metals like aluminum and plastics, their contribution to total carbon footprint of the product is high. Lithium used in batteries also stands as a hotspot as its impact is high while mass contribution is insignificant. These results indicate need to explore sustainability strategies to minimize the environmental risks associated with these material challenges.

The high global warming potential and cumulative energy demand of the material hotspots are mostly due to the high energy intensity of extraction processes used to recover these materials from the earth's crust. The environmental impacts of energy use are directly related to the carbon intensity of the energy sources used for the processes in the major producer countries of materials. This implies that the average carbon intensity or global warming potential per unit of electricity produced in major material producer countries plays a key role in overall environmental impacts of material extraction. Figure 4.2 shows a country-level heat map reflecting the global warming potential per kWh of electricity generated in countries that produce consumer electronics material, and their share of specific material production. We can see that a major share of precious metals, REEs and critical metals of concern are produced in countries with a high carbon grid or an electricity grid powered majorly by non-renewable energy sources such as coal power plants (China, Australia, South Africa). These results show that carbon intensity of the electricity grid of a country should be a major consideration in evaluating alternate supply chains for materials as part of holistic SMM strategies.

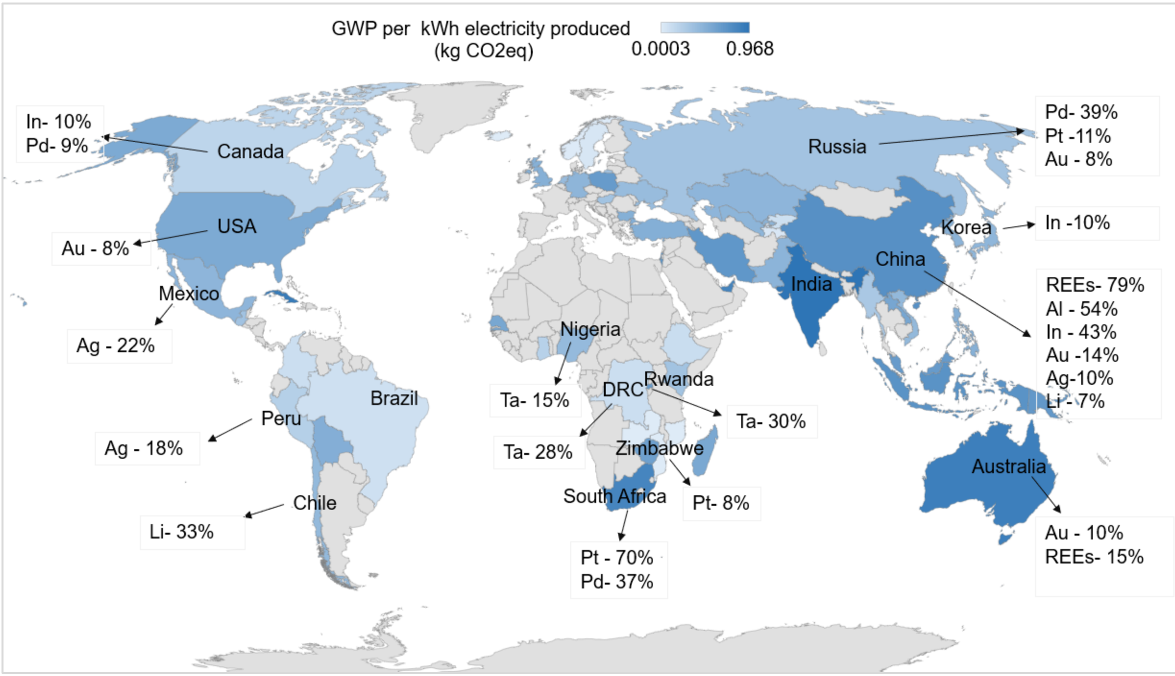


Figure 4.2. Global warming potential per kWh of electricity generated in consumer electronics material producing countries and their production contribution of materials identified to pose environmental risks. Dark blue color indicates high carbon intensity of the grid while light blue color indicates cleaner grid (low carbon).

Environmental Hotspots	**High Risk Factors**
Precious Metals	Highest GWP, CED, MRD, Supply chain toxicity
REEs	GWP, CED
Indium	GWP, CED, MRD
Gallium	GWP, CED
Lithium	GWP, CED
Tantalum	GWP, CED, MRD

Table 4.6. Environmental hotspots in electronics.

Table 4.6 summarizes the key findings of environmental sustainability assessment of materials. Environmental evaluation highlighted precious metals to pose highest risk. However, when the material consumption in electronics sector is considered, a few more material hotspots that needs consideration in evaluation of sustainability strategies in electronics emerge such as REEs, indium, gallium, lithium and tantalum.

3.3. Social aspects of material sustainability

The sustainability risks to material production due to socio-political factors is evaluated by considering quantitative as well as qualitative measurements. Quantitative measurement is performed by using WGI-PSAV weighted HHI to identify the hotspots. Another consideration is whether materials significant in electronics sector belongs to a class of materials called 'conflict minerals' due to social conflicts associated with their production.

The results from quantitative estimation of social aspects of material sustainability are presented in Figure 4.3 which presents a comparison of metrics of geographical concentration with and without the weighting socio-political factors of the material producer countries, to identify social hotspots due to supply chain concentration. In this analysis, cobalt has emerged to be the material of highest concern. Cobalt has a high negative value for the social metric (representing significant political instability in regions where material production is concentrated), largely due to the dominant production of cobalt in the Democratic Republic of the Congo (DRC), which is a country known for its socio-political issues and has a high negative PSAV index. Even though Hg and Mg are highlighted to pose high social risks, REEs are identified to be the next social hotspot due their significance in electronics manufacturing. REEs such as neodymium and dysprosium are key ingredients of permanent magnets used in electronics, while other rare earths are used in in flat panel displays (Buchert et al., 2012).

Regarding qualitative estimation of social hotspots, cobalt is increasingly considered to be similar to '*conflict minerals*' which are categorized so because they are sourced from a geographical location (DRC) characterized by socio-political conflicts. The materials classified as *conflict minerals* are tungsten, tantalum, tin and gold (3TG), as economic activities associated with their production and trade have contributed to armed conflicts and widespread violence in the eastern DRC (Young, 2018). It is to be noted that except tantalum, DRC is not a leading producer of other 3TG metals. However, illegal mineral trade worth millions of dollars happen in DRC which forms substantial source of finance for armed groups in the country. Conflict mineral regulations are established in countries across the world. In the U.S., regulations (Dodd-Frank financial reforms) require that companies that use conflict minerals in their products should report on the mineral use and disclose country of origin on the sources of metals. Among *conflict minerals*, tantalum, tin and gold are identified to be social hotspots in electronics, as tantalum and tin production is moderately driven by electronics sector (48% of tantalum and tin produced is used in electronics in capacitors and solder respectively), and gold is a key raw material in electronics (gold is a constituent of PCBs) even though major use sector of gold is not electronics. See Appendix C Table 8 for major use sectors of metals.

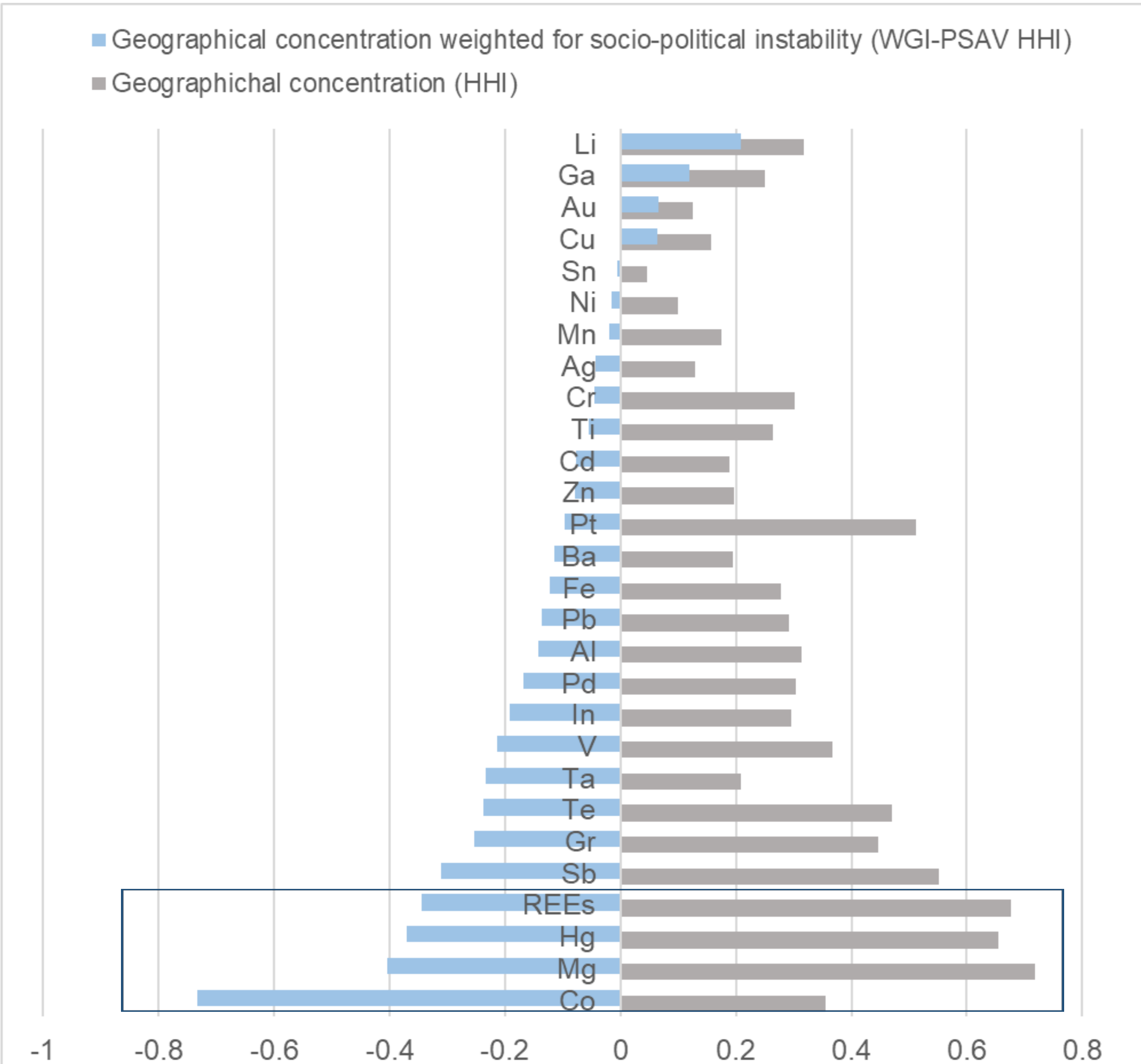


Figure 4.3. Comparison of the HHI with and without socio-political weighting factors. Materials with high positive HHI have greatest risks due to supply chain concentration in a few countries. Materials with highly negative WGI-PSAV HHI have greatest risks because the supply chain concentration aligns with politically unstable regions.

Figure 4.4 shows the socio-political instability of producer countries assessed by the World Governance Indicators on Political Stability and the Absence of Violence (PSAV) and their production contribution of materials that are chosen to be social hotspots. We can see that cobalt and tantalum, two key material enablers of consumer electronics, pose the highest sustainability risks in social aspects as they are sourced mainly from DRC and neighboring countries with high negative socio-political stability score (WGI-PSAV). Results indicate need to explore alternate supply chains for these materials of highest social concern in electronics manufacturing. Table 4.7 summarizes the findings of social sustainability analysis of materials in consumer electronics. The key materials of concern identified in the analysis of social aspects of sustainability are cobalt, tantalum, gold and tin.

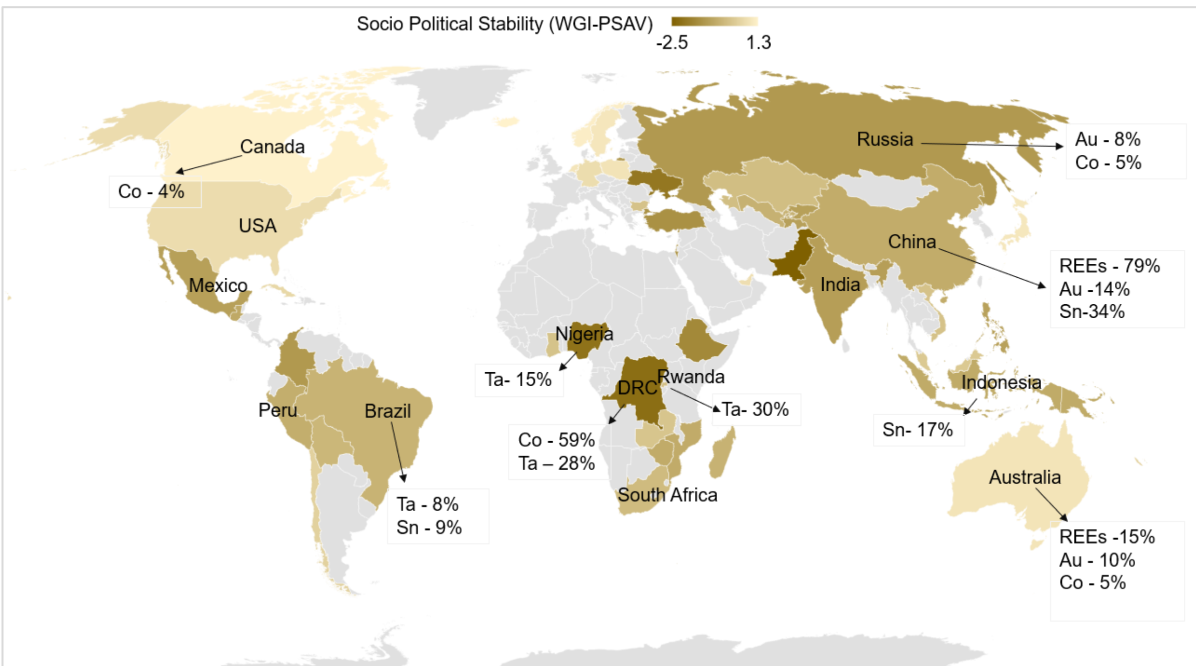


Figure 4.4. Socio-political instability of producer countries assessed by the World Governance Indicators on Political Stability and the Absence of Violence (WGI-PSAV) and their production contribution of materials identified to pose sustainability risks from social aspects. Dark color indicates high risk (low socio-political score) while light color indicates low risk (high socio-political score)

Social Hotspots	High Risk Factors
Cobalt	Highest negative value for social metric (PSAV-HHI)
REEs	Negative value for social metric (PSAV-HHI)
Tantalum	Conflict mineral
Tin	Conflict mineral
Gold	Conflict mineral

Table 4.7. Social hotspots in electronics.

The next sections of the chapter explore potential sustainability solutions for the material hotspots.

3.4. Potential for recycling for material sustainability

Material flow analysis in Chapter 2 and 3 showed changing trends in electronics consumption and waste flows, with increased prevalence of mobile multifunctional products containing critical metals. Recycling is considered as a primary sustainability solution as it can solve both material demand and waste management challenges. In this chapter, the material sustainability evaluation from three different dimensions of sustainability-economic, environmental and social, helped identify the materials hotspots or key materials of sustainability concern in electronics. They are REEs, PGMs, indium, gallium, gold, cobalt, tin, lithium and tantalum. Even though each of these metals pose risks in different aspects, recycling can be considered as a universal solution for all the materials due to a couple of reasons; First, a major share of these high impact materials produced (except gold) is consumed in electronics sector, which means that electronics recycling can bring back majority of the end-of-life materials back to production pipeline, offsetting the need for their virgin mining. Second, the import reliance in U.S. for each of these materials (except gold) is high which indicates the economic potential of recycling these metals which will not only ensure domestic supply security but will also mitigate other sustainability risks associated with the materials.

Even though recycling is a promising sustainability solution, the current state of e-waste management is far from meeting this objective. There are many factors affecting the current state of recycling in the U.S., including lack of effective e-waste policies and collection systems that can ensure end-of-life pathways to recover used products from consumers, lack of efficient recycling technologies and infrastructure, that can economically recover effective technology and the absence of sufficient markets for recycled materials from electronics. At present in the U.S., the lack of financial motivation in recycling is resulting in most of the end-of-life products recovered being shipped to developing countries for cheap labor.

Given the changing material profile of e-waste and its implications on the economy, environment and society, it is important to make use of every opportunity for sustainability, especially in the management of the resourceful e-waste stream. Here, the potential for recycling as a sustainability solution is explored for the key materials of concern using four different metrics- recycling efficiency in U.S., current use of recycled material, circularity potential (waste to demand ratio) and material dilution in e-waste. Quantification of potential for recycling of materials using the metrics, captures the present-day challenges and opportunities in considering recycling as an immediate sustainability solution for most material hotspots identified in the study.

Recycling efficiency in Table 4.8 is the ratio of waste material available to material recovered in the U.S (not specific to electronics sector) and therefore it represents the existing recycling technology and infrastructure in the U.S. to reclaim used materials. Secondary material use is another metric that represents the recycling market as it is the recycled material content in total material consumed in the U.S. Circularity and dilution metrics are used to assess the potential for recycling in the electronics sector specifically, based on the material content in the emerging e-waste stream as calculated from MFA results in Chapter 2.

Recycling potential assessment of the material hotspots based on the above metrics presented as a heat map in Table 4.8 shows that, in the case of precious metals, considerable amount of recycling and secondary material use is taking place in the U.S. The recycling efficiency and secondary material use of precious metals indicates that the recycling infrastructure and market for recycled material is in place in the U.S., though not specifically for electronic sector. However, high circularity potential and low dilution level in e-waste indicates that there is huge potential for recycling precious metals in electronics sector. Similar potential for recycling is observed for critical metals tantalum and tin. Recycling efficiency and secondary material use in U.S. indicate considerable amount of recycling is taking place in U.S, for tantalum and tin, while low dilution levels and high circularity levels indicate potential for recycling to improve in electronics sector.

However, this is not the case for other materials, especially REEs. Recycling efficiency and secondary material use metrics indicate the glaring lack of capacity for REE recycling in the U.S. At present there is almost no commercial REE recycling happening in the U.S., even though research on the same is progressing. (See Appendix C Table 7 for recycling data in absolute numbers for all materials). While circularity potential metric which compares waste flow to material demand indicate that recovering REEs from electronics can help meet their demand in the sector, dilution levels of REEs in e-waste represents the key challenge in recovering them from used electronics. REE dilution levels in e-waste is high since they are present only in small quantities per electronic product. Since REEs are the group of materials that emerged to be a concern in all three aspects of sustainability, identifying potential solutions for REE sustainability is key in ensuring material sustainability in electronics. In the U.S., around 12,000 metric tons of imported REEs is consumed annually, majority of which is imported from China a geopolitical competitor of the U.S.(See Table 4.9 for details about the consumption of material hotspots in the U.S.).This high import reliance indicates the economic potential for REE recycling in the U.S. All these factors highlight the need to invest in research and development of recycling technologies for REEs. Prioritizing recycling as the key sustainability solution for REEs will not only mitigate their sustainability risks in electronics sector but will also reduce United States' foreign dependency for this material group.

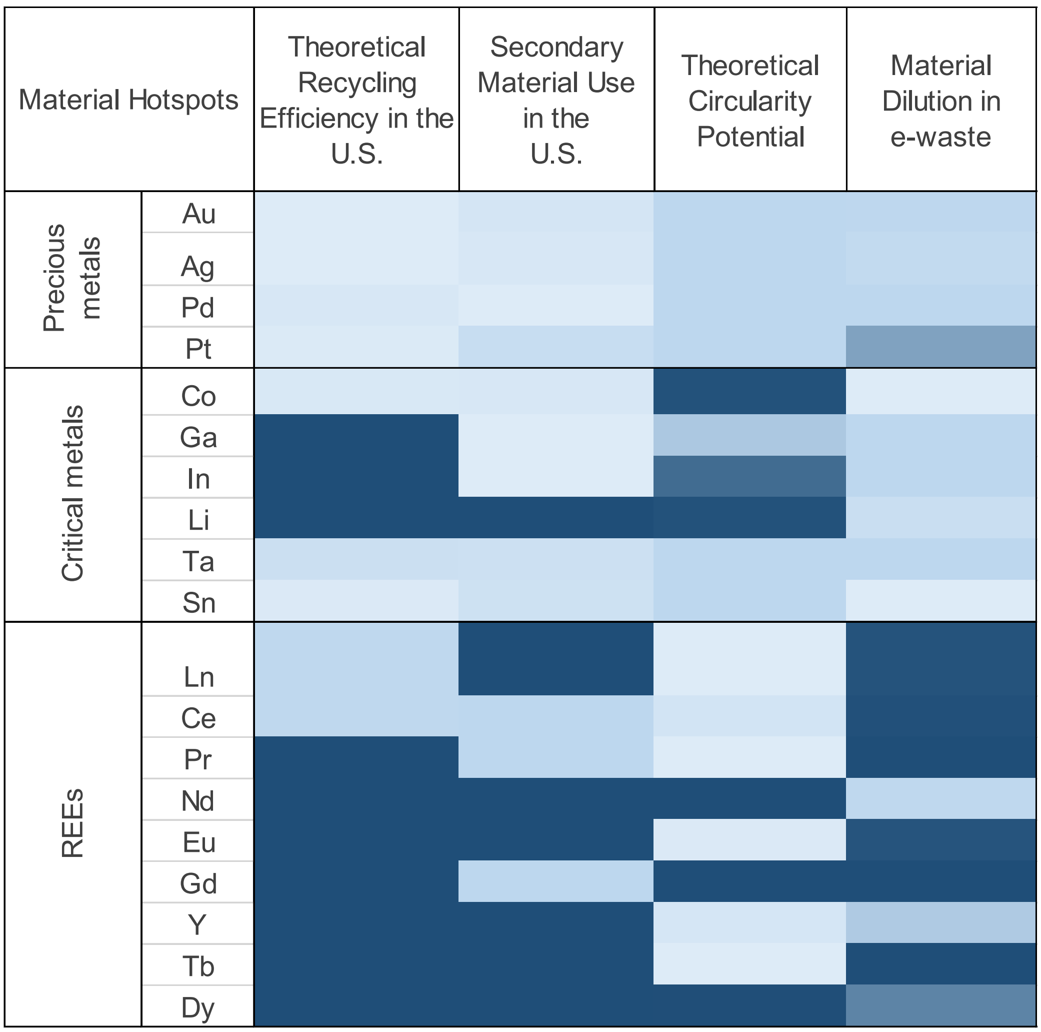


Table 4.8. Assessing the potential for recycling as a sustainability solution for material hotspots. See Appendix C Table 7 for absolute values of the recycling metrics for all materials in the study.

The other materials among the hotspots for which recycling efficiency emerged to be a concern are gallium, indium and battery material lithium, indicating lack of recycling technology and infrastructure to recover them. However, high secondary material uses for indium and gallium in the U.S. shows that market for recycled material already exists, which can be a motivation for developing recycling technology to recover them from e-waste. Low dilution levels in the e-waste stream also shows that there is potential for recovery of both indium and gallium from e-waste if proper recycling infrastructure is in place, which is lacking at this point. In the U.S around 23,000 metric tons of gallium is consumed for integrated chip manufacturing and the country is completely reliant on imports especially from China for the metal (Table 4.9). Import reliance is extremely high for indium as well, asserting the need to ensure domestic supply of the materials through recycling.

Material Hotspots		Annual Consumption (metric tons)	Import Reliance	Major Import Source	Main Use Sector in the U. S.
Precious metals	**Au**	145	0%	-	Jewelry
	Ag	5500	62%	Mexico	Electrical and electronics
	Pd	42	45%	South Africa	Auto catalysts
	Pt	45	68%	South Africa	Auto catalysts
Critical metals	**Co**	7200	72%	China	Superalloys in aircraft engines
	Ga	23000	100%	China	Integrated Chips
	In	170	100%	China	ITO layer in flat panel displays
	Li	2000	50%	Argentina	Batteries
	Ta	1170	100%	Brazil, Rwanda	Tantalum capacitors
	Sn	46000	75%	Indonesia	Tinplate, solder
	REEs	12200	100%	China	Catalysts

Table 4.9. Consumption of material hotspots in the US. It is to be noted that the U.S. import reliance data reported here is the net import reliance (import -export) as percentage of apparent consumption. A zero percent import reliance for gold indicates that U.S was a net exporter of gold in year 2018 (USGS mineral commodity summaries).

In the case of lithium, both recycling efficiency and secondary material use highlight lack of recycling infrastructure in the U.S. However, the low dilution levels in e-waste is a motivator for developing recycling technology to recover lithium from used batteries in e-waste. In the case of cobalt, another battery material the recycling efficiency and secondary material use metrics indicate that considerable amount of recycling is taking place in the U.S., though not in the electronics sector. Cobalt contained in purchased scrap constituted around 33% of total consumption in US in 2017 (USGS, 2018). Even though cobalt recycling from scrap is economically viable, LIB recycling is still not at full capacity. As in the case of lithium, dilution levels in e-waste is not a huge issue for cobalt compared to other materials hotspots, as they are concentrated in spent LIBs. While two-thirds of cobalt is mined in DRC, most is ultimately refined in China, and in the U.S. most of the cobalt consumed is imported from China. Therefore, recovering cobalt from end-of-life batteries in electronics is important not only to ensure supply security but also to diversify cobalt supply chain. While current recycling rates of lithium from batteries is almost zero, there is considerable effort aiming to recover cobalt from batteries. However, lab scale recycling yields prove that ongoing research is on the right path in developing better recycling technologies for material recovery from spent batteries (see Appendix C Table 9).

Given the importance of the material hotspots in ensuring material sustainability in electronics as well as in ensuring mineral security in the U.S., there is a compelling need to invest in the development effective recycling technologies to recover them economically from the e-waste stream. Meanwhile, it is important to explore alternate solutions to mitigate the material sustainability risks identified in the study.

3.5. Alternate solutions for material sustainability

3.5.1. Material substitution

While recycling is a potential sustainability solution implemented at product end-of-life, material substitution is a solution that is applied in product design where materials of high economic, environmental or social risk is functionally replaced with materials with better sustainability profiles. Figure 4.5 demonstrates how product level environmental impact (carbon footprint) reduction can be achieved through material substitution, by applying material level global warming potential metric to average laptop material composition compiled for MFA in Chapter 1 for three different potential casing materials-plastic, Al and recycled Al. In this example, Al use led to a higher impact when only obtained from primary sources, but also opened up a greater potential for recycling and selection of recycled content, which, when combined with material substitution, provided the most effective integrated solution of the three options.

While material substitution is practical for base metals like Al, as demonstrated in the example, it is challenging for most of the material hotspots in this study, as their high demand in electronics is due to their distinctive physical and chemical properties. In the case of REEs, they are used in consumer electronics and other defense and clean energy technologies applications due to their unique magnetic, luminescent, and catalytic properties, which makes their replacement in these technologies not effective. Similarly, in the case of indium, which is a key ingredient of ITO layer in flat screen displays even though antimony tin oxide coatings, carbon nanotube coatings, organic light-emitting diodes and copper or silver nanowires, have been explored as a substitute for ITO layer to reduce dependency on indium, none of these technologies have attained mainstream adoption. In the case of cobalt use in LIBs, using iron-phosphorous, manganese, nickel-cobalt-aluminum, or nickel-cobalt-manganese chemistries can reduce cobalt dependency, but may result in altered performance.

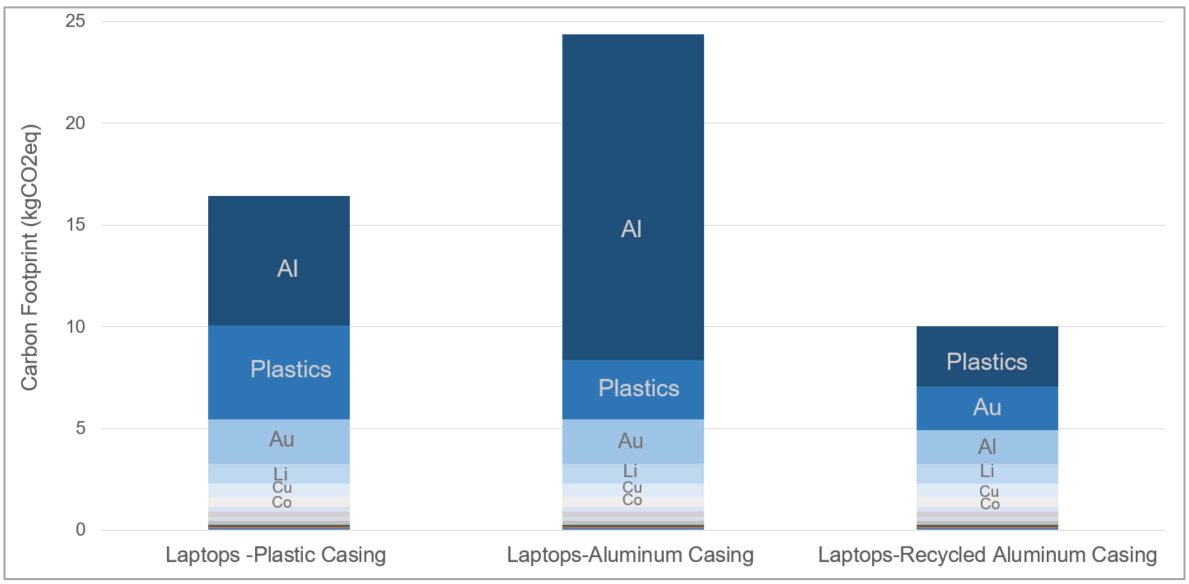


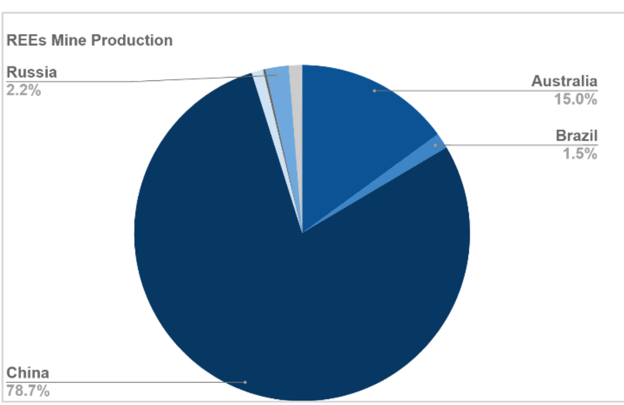
Figure 4.5. Comparing carbon footprint of laptops (cumulative carbon footprint of all materials in laptop; product manufacturing and use phase emissions not included) with different casing materials: plastic, aluminum, and recycled aluminum to demonstrate the applicability of material substitution as a sustainability solution.

3.5.2. Supply chain diversification

Another potential sustainability solution for material hotspots is to explore alternate supply chains to minimize risks associated with geographical concentration of production, based on their global reserves.

Here, the potential to diversify supply chain for two key material hotspots-REEs and cobalt are explored by comparing their geographical distribution of production with their global reserve distribution. Figure 4.6a shows production distribution of REEs side by side with the distribution of global reserves. While reserves distribution of REEs show that extractable REEs are present in many countries, presently over 79% of REE mine production occurs in China, a country which holds only 36% of global reserves. Similarly, Australia which holds only 3% of global REE reserves contributes over 15% to total REE production. With recoverable reserves throughout the world as seen in Brazil, Vietnam and Russia, there is good potential to explore alternate supply chains for REEs, if economics permit.

Cobalt is also a good candidate for exploring alternate supply chains. Currently DRC dominates mine production with around 60% contribution to global production of cobalt. But DRC holds only 25% of the cobalt reserves while the remaining is distributed among many countries which may have fewer supply chain risks (Figure 6b). For example, Australia has around 1.2 million metric tons of identified cobalt reserves (USGS), which indicates a potential to explore alternate supply chains. However, other factors affecting the feasibility of changing supply chain would need to be addressed in parallel. For example, even though Co mine production is concentrated in DRC, as the Refined Metal Production pie chart in Figure 6b shows, most of the processing and refining of the metal takes place in China. This indicates that in addition to exploiting existing reserves around the world, developing technology and infrastructure to process metals to refined form is also important to achieve supply chain diversification of material hotspots. While the REEs and cobalt shows good potential for supply diversification, it may not be the case for other material hotspots. In the case of indium, there is limited potential for supply chain diversity as nearly 70% of known global reserves is in China, indium's leading producer country (USGS mineral commodity summaries).



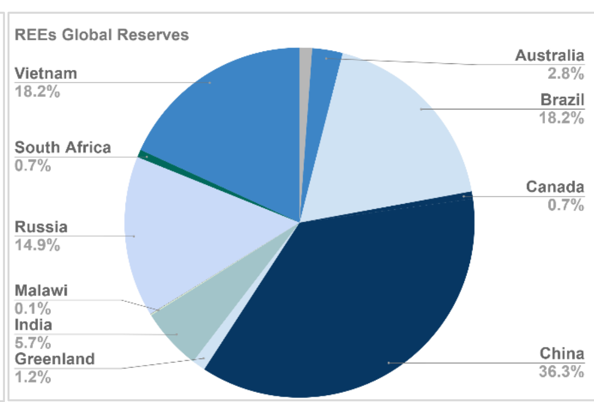


Figure 4.6a. Current REE production distribution versus REE global reserve distribution.

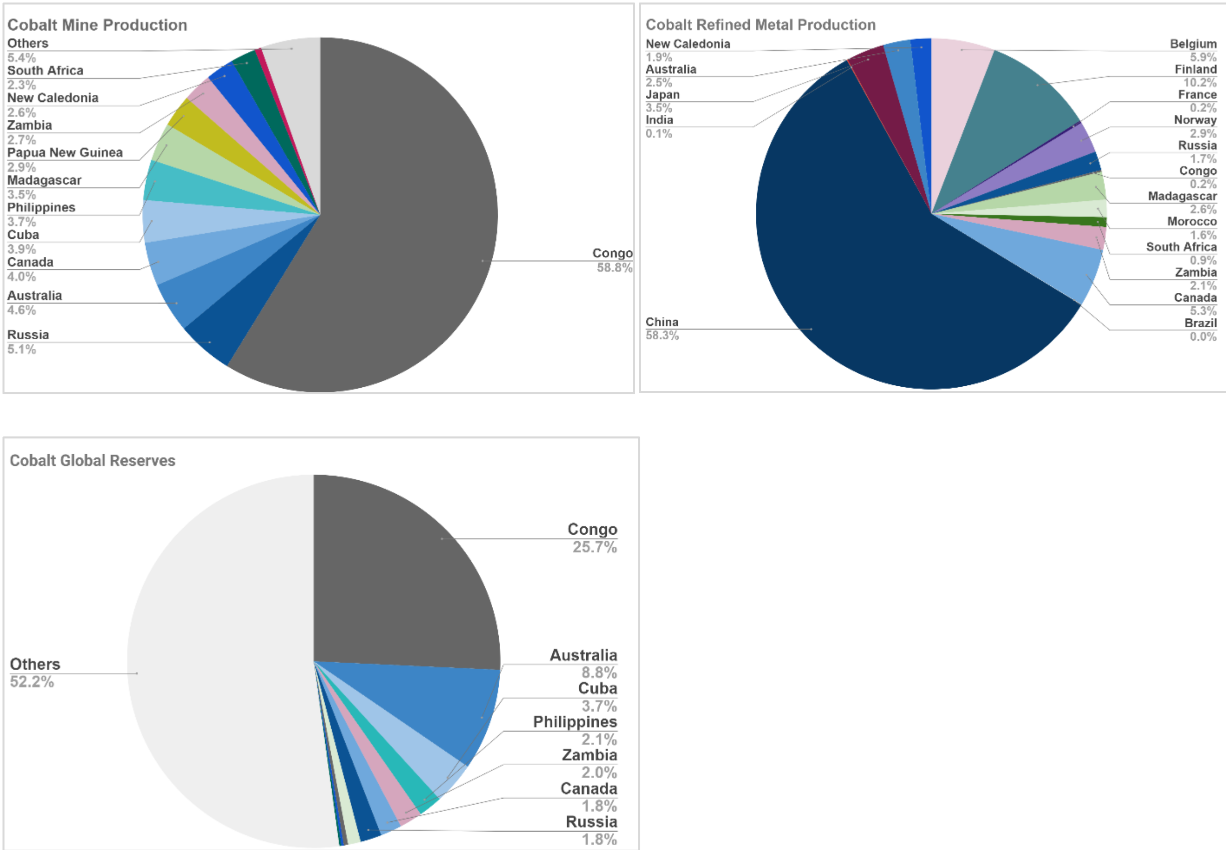


Figure 4.6b. Current cobalt mine production and refined metal production distribution, versus global reserve distribution of cobalt.

3.6. Case Study: Sustainability analysis of plastic use in electronics

In addition to metals, plastics are also key raw materials used in consumer electronics manufacturing. Consumer electronics represent an annual consumption of over 200,000 metric tons of plastics, which ultimately make up 25% of the e-waste flow. While around 12 types of polymers are found in electronics, some are more common including ABS (Acrylonitrile-butadiene-styrene copolymer), HIPS (Polystyrene, high impact), PA-(Polyamide), PS (Polystyrene) and PC (Polycarbonate) (Mills and Tatara, 2016). In this study, the potential sustainability issues with 7 different types of plastics used in electronics are analyzed. Table 4.10 presents a heat map with comparisons of annual production, price and environmental issues associated with production of different types of plastics used in consumer electronics.

Polymers in electronics	Annual Production	Price	Carbon Footprint	Energy Demand	Mineral Resource Demand
ABS					
HIPS					
PA					
PS					
PC					
PVC					
PMMA					

Table 4.10. Measuring economic and environmental sustainability of polymers commonly used in electronics

The sustainability profiles of different polymers used in electronics estimated using the economic and environmental metrics show that among the polymers considered, ABS, HIPS, and PS have the lowest environmental risk. Among those polymers, ABS seem to present minimum economic risk as assessed by annual production and price, making it a suitable choice in electronics product manufacturing. It is to be noted that even though the heat map shows price variation among different plastics (PVC and PS having relatively lower price), the actual price difference between types of plastics is minimal. The average price per pound of plastic is 1$ per pound (Ashby, 2013). As with metals in electronics, recycling is a potential solution to minimize sustainability impacts of plastic use in electronics, which is explore below.

Recycling as a sustainability solution for plastic use in electronics

Even though electronic products have become smaller and lighter with ongoing dematerialization trends, as per Chapter 2 MFA results, the plastic content in the e-waste stream has not decreased. In fact, the plastic content relative to other e-waste materials has been slightly increasing, underscoring the need for e-plastics recovery and recycling. Around half a million metric tons of plastic is available for recovery from electronic waste generated annually from U.S. households. The average environmental savings achievable through recycling of different plastics as reported by Ashby (2013) is given in Table 4.11. The low values of recycled fraction in current supply also highlights the limited availability of recycled plastics in the US, indicating need for proper recycling infrastructure.

There are many challenges in plastic recycling from electronics, the main being contamination in the waste stream due to the wide range of plastics used in electronics. The mixed stream is challenging to sort and identify, and mixed plastics have low economic value. Another roadblock to e-plastic recycling is the use of brominated flame retardants which are added to e-plastics to enhance their resistance to fires (Mills and Tatara, 2016). However, the recent bans and subsequent disruption in e-plastic export market to China, Vietnam and other Southeast Asian countries, stresses the need to develop domestic recycling systems which would solve the waste management problem and reduce environmental impacts, while generating revenue.

Plastics	Energy demand for primary production (MJ)	Energy savings from recycling (%)	Carbon footprint for primary production (kgCO2eq)	Carbon savings from recycling (%)	Recycled fraction in current supply
ABS	95	51%	4	26%	4%
PA	123	65%	8	68%	1%
PP	79	37%	3	-	6%
PE	81	38%	3	7%	9%
PC	109	61%	6	58%	1%
PET	85	54%	4	40%	21%
PVC	59	39%	3	14%	2%
PS	97	51%	4	25%	6%
PLA	52	29%	4	39%	1%

Table 4.11. Environmental benefits of recycling plastics.

4. Data Uncertainty

The goal of this research was to model sustainability risks associated with material use in electronics, through a range of quantifiable metrics. Even though data from the best available sources were used (see Appendix C Table 1), quantifying economic, environmental and social risks for the whole spectrum of materials in electronics involved assumptions and aggregations, which introduces uncertainty in the potential sustainability impacts quantified. For example, to quantify ‘electronics sector consumption’, a key metric in identifying material hotspots, aggregated data for material use in both electrical and electronic applications was used, due to lack of sector specific data. Even though such aggregated data may overestimate use level of materials in electronics sector, it gives a good indication on whether the production of a material is driven by the electronics industry and if sustainability strategies in the sector will offset a major share of the material impacts.

Another metric which was a major consideration in the determination of material hotspots was the import reliance of materials in the U.S. To model this, the net import reliance (import -export) as percentage of apparent consumption (as reported by USGS) was used, which yielded a negative import reliance for some materials such as gold, for which U.S is a net exporter. Economic metrics such as global reserve, annual mine production and annual price were directly adopted from USGS mineral commodity summaries for year 2018, while index of depletion, HH index and price volatility, were calculated based on the same data. For many of the economic metrics such as reserves, ore concentration, mine production, index of depletion, HH Index, PSAV-HHI and production ratio as by product, due to lack of availability of disaggregated data for each REE, available aggregated data for REEs (REE oxide production data in most cases) was used. Even for metrics such as price, import reliance and electronics sector consumption, for which published data was available for individual REEs, scandium (Sc), erbium (Er) and promethium (Pm) were omitted due to lack of data availability.

To model environmental impacts, global average data for global warming potential (GWP), cumulative energy demand (CED) and mineral resource demand, per kg production of each material was extracted from Ecoinvent database (using Simapro LCA software). For energy use related environmental impacts such as GWP and CED, the use of global average data results in uncertainty, as GWP and CED impacts are directly related to the carbon intensity of the electricity used in mining and processing materials, and global average data may not always reflect the exact carbon intensity of the electricity grid in mining locations of producer countries. Nonetheless, these uncertainties are not expected to affect the environmental impact ranking and identification of material hotspots in this study. The evaluation of potential for recycling is another topic that required reliance on assumptions and approximations due to unavailability of accurate recycling statistics, especially in the electronics industry. Lack of a consistent approach in defining recycling rates in literature, is a key factor contributing to the uncertainty in evaluating recycling status in the sector. The term ‘recycling rate’ is used in different contexts in literature where sometimes it refers to recycling efficiency of the system (including end-of-life product collection rates) or recycled material use, while sometimes the term is used to denote the recycling process efficiency. This lack of accurate data itself calls for research and development initiatives in the recycling sector.

Even in the presence of all this data uncertainty, the analysis performed, and conclusions drawn in this chapter are well grounded on best available theoretical data and can serve as the groundwork in planning for sustainability efforts in electronics.

5. Conclusions

Material use in the electronics sector is becoming a significant sustainability challenge, as many material enablers of modern electronics are also widely demanded for diverse applications such as clean energy technology. While the industry has started to implement material sustainability strategies, such as recycling and material substitution, there is still a need for holistic SMM data and evaluation of strategies that engages multiple stakeholders in creating solutions. This study is the first to compile traditionally disparate sustainability data on electronics materials and synthesize this information to identify key material hotspots and discuss potential solutions.

REEs were shown to have significant impacts in all dimensions of sustainability, while critical metals like In, Co, Ta, Tin, Li and precious metals (gold and PGMs) are also materials of concern needing sustainability solutions. Cobalt is identified as the key social hotspot, largely due to its spatially concentrated supply chain in politically unstable regions. Recycling emerged as a critical but challenging opportunity for making major material improvements. Many of the materials analyzed have high demand (in electronics and other sectors) and high reliance on imports due to lack of US reserves or production volume. Thus, developing recycling for low volume, high value materials, like REEs and gallium, can alleviate these supply chain pressures while also reducing environmental impact. Supply chain diversification also presented a potential solution for REEs and cobalt. However, implementing these solutions will require both fundamental technology advances as well as joint effort from all stakeholders in the electronics system, including recyclers, product manufacturers and e-waste policy makers.

CHAPTER 5: Conclusions

There is increased emphasis on sustainable material management in the electronics sector, as the key material enablers of modern electronics are critical to the growing clean energy economy. The evolution and expansion of electronics from traditional single-function products to multifunctional devices, and the increased integration of electronics in new products as seen in 'wearable' electronics and 'smart' home systems, has changed the material profile of the electronics system. However, the e-waste management system in the U.S. remains backwards looking, optimized to recover legacy products, while new products with unknown material implications are entering the waste stream with no strategies in place for their end-of-life management. To be able to respond to the dynamic nature of the sector, sustainability strategies need to be informed by proactive estimates of material use and waste generation as well as their sustainability implications in the system. But academic as well as industrial research has not kept pace with evolution in the sector, limiting the data and insight available to evaluate sustainable material management strategies in electronics. Therefore, this research aimed to close this knowledge gap by contributing novel data and modeling tools, estimating current and future materials flows, and quantifying social, economic, and environmental sustainability implications.

This research first generated a baseline material footprint analysis for consumer electronics (Chapter 2), by compiling and analyzing sales, lifespan and material profile data of over 20 different product categories in the U.S. Through the application of highly resolved sales and lab scale material composition data of common electronics, on a material flow model, the 2nd chapter reports the most comprehensive and up-to-date material footprint analysis for electronics in the U.S. Once the material baseline for the electronics system was established, the model was expanded to include predictive capability in material flow analysis for emerging electronics (Chapter 3). This study characterized historic product adoption behavior in electronics and used these trends to create near-term projections of product adoption and waste generation scenarios. The modeling framework demonstrated in Chapter 3 can be used to inform proactive material management strategies in electronics by identifying opportunities and risks for both emerging products as well as mature products in the market. The final goal of the research (Chapter 4) was to investigate the sustainability implications associated with material demand and flows in electronics that were estimated in Chapters 2 and 3. A comprehensive set of sustainability metrics was developed and applied to the broad spectrum of materials in electronics to identify economic, environmental and social hotspots. The findings represent the first comprehensive compilation of sustainability metrics applied to electronics materials, which were used to explore solutions including recycling, material substitution, and changing material supply chains.

Key Takeaways

Through application of highly resolved data and modeling tools, this research advances the state of knowledge on sustainability implications of consumer electronics adoption in the United States. Major findings of this research are summarized below.

- The electronics landscape in US is undergoing a major change on material footprint with increased prevalence of light weight multifunctional products in the market. E-waste in the US has begun to decline. Complexity and resource potential are high in the emerging e-waste stream, while toxicity from traditional materials of concern is on the decline. Waste flow forecasts for mature products like CRTs and desktops, show their declining contribution to the U.S. e-waste stream.

- A key trend observed in historic product adoption behavior across current and legacy electronics is the steadily shrinking innovation cycle; emerging technologies are likely to have rapid uptake in the market but may be quickly replaced by subsequent product innovations.

- REEs are identified to be key materials of sustainability concern in electronics due to their heavy use in the sector, high geographic production concentration and environmental impacts, and high production ratio as byproduct. Cobalt is also associated with economic as well as social sustainability risks due to its production concentration in DRC and high production ratio as by-product. Gallium, tantalum, tin, lithium, gold and platinum group metals (PGMs) are other material hotspots in electronics requiring sustainability solutions.

- Recycling and supply chain diversification are both promising avenues for reducing material risks, especially for REEs and cobalt. There is a critical need for expansion of recycling technology and infrastructure for efficient material recovery from e-waste, but achieving this promise will require significant policy, economic, and technology advances.

Research Implications & Recommendations for Stakeholders

The emerging trends in electronic material footprint highlighted by this research underscore a need to shift the focus of e-waste management mechanisms from 'mass' to 'materials', or in other words, from an emphasis on 'waste diversion' to a new focus on 'resource retention'. This study identified three 3 key leverage points: policy, product design and recycling technology, to intervene and facilitate sustainability in the overall electronics system. To use e-waste policies as an instrument to initiate sustainability material management, it is necessary to move away from the mass-based policy targets where all materials are treated equally, to explore alternate methods for setting collection targets such as those based on environmental or economic savings through recycling. Anshassi et al., (2017) in their study about solid waste management in Florida has described an approach where lifecycle thinking is incorporated in material management by developing LCI-normalized collection targets. An identical approach to prioritize economic value, energy saving potentials, and eco-toxicity in recovering different materials from printed circuit boards was proposed by Wang and Gaustad, (2012). Similar waste management mechanisms are worth exploring in the electronics sector, as they will bring the focus on materials in a product rather than mere mass. The same holds for sustainable product design and recycling technology development; they must be informed by economic, environmental and social tradeoffs associated with material use and material recovery. Company-oriented raw material selection models for component manufacturing that take into account material criticality assessments, life cycle impact assessment (LCIA) and social life cycle assessment (SLA) have been proposed in literature (Kolotzek et al., 2018). Adoption of approaches that incorporate sustainability thinking in product design can result in elimination or minimization of materials with potential environmental, social, or supply risk in electronics.

However, to enable these leverage points to establish holistic SMM in electronics, it is necessary for greater coordination among stakeholders in the electronic system, including e-waste policy makers, product manufacturers and recyclers. Product designs that incorporate more recycled material content can increase the viability of secondary material markets and promote recycling, while establishment of recycling technology and infrastructure that are resilient to changes in the e-waste material profile can in turn increase secondary material supply and aid green-product design. In either case, effective e-waste policies are needed to ensure end-of-life pathways for the whole range of products owned in households, by broadening the scope of products covered by e-waste laws and creating flexible recycling targets. However, a key policy barrier in establishing a material management mechanism in the US, is the lack of a uniform federal policy for e-waste management. In the absence of a federal e-waste law, the lack of uniformity in the state-by state approach represents a significant compliance burden to the electronics manufacturers, as they are responsible for financing, collecting and recycling these products in the widely adopted EPR model (NCER, 2006). Consumer awareness is another barrier to the effectiveness of e-waste management system. At present, the variations in product scope of e-waste laws and landfill bans across states can confuse consumers about what products can be recycled in their home state, potentially reducing the per-capita e-waste recovery rates (Drayton, 2007). The economies of scale that can be achieved through a national level recycling system should be the motivation for establishing federal e-waste recycling laws as a key instrument for achieving sustainable material management in electronics.

Limitations and extensions

A key contribution of this research is the high-quality product adoption data that enabled the quantification of product flows and associated sustainability implications in the system. However, there are uncertainties associated with data on average product lifespan, which were based on published literature. Consumer survey-based data on electronics use that reflect recent product use patterns in U.S. would help bring in more accuracy in e-waste estimations. However, as reported in the uncertainty analysis in Chapter 2, the key finding of the study, which is the declining trend observed in e-waste in U.S., is not expected to change with more resolved lifespan data. This decline in e-waste mass is mainly due to a product light weighting trends as well as higher product disposal rates in the U.S, that resulted in fast replacement of large electronics in the system. While these trends may hold true for many developed economies with high rate of technology diffusion, it may not be the case for economies in transition. As past studies have shown, product lifespans and technology diffusion rates are dependent on socio-economic environment of a country (Petridis et al., 2015; Yu et al., 2010) and in some regions, technology difusion may be slow and product lifespans longer as consumers hold on to expensive electronics for longer times, which in turn may create a longer lag before reaching the e-waste decline phase. However, technological leapfrogging may also occur, where developing economies may skip intermediate technologies, resulting in faster adoption of newer, smaller multifunctional devices and therefore replacing large legacy products from the system sooner than expected. These factors again highlight the importance of data driven analysis in evaluating strategies for managing the resource-intense and fast changing electronics waste stream in different regions of the world.

This research analyzed the sustainability implications of consumer electronics adoption in the U.S from a materials perspective. Material sourcing, production, consumption and waste flows in electronics were the primary foci of this research. However, there are other life cycle aspects of sustainability, particularly associated with manufacturing and end-of-life management that are not explored here but key for future study. In addition, expanding sustainability analyses to include new methods, like Social LCA, can also provide greater insight into social impacts, which are traditionally challenging to quantify. Even though this research discussed the implications of material flows and material sustainability on e-waste policies, applying the SMM metrics to specific analyses of e-waste policy is also a priority for detailed study, particularly as state policies continue to evolve. These models can also be expanded to consider material interactions across sectors, given the wide use of electronic materials in other emerging technologies, such as electric vehicles. The possible research extensions from this work are vast, as this study provides a knowledge base on product and material flows and impacts, and lays the groundwork for effective sustainable material management in electronics. While this future-oriented study may be burdened with uncertainty, the research findings demonstrate the importance of a proactive approach for electronics, rather than reacting to sustainability issues after they have resulted in social, economic, or environmental impacts.

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APPENDIX A

Products included in the MFA

Products included in the material flow analysis are grouped into five categories: computing products, CRT displays, Flat panel displays, Audio visual products, other mobile products and phones. Table below shows the products included in each category.

Table 1: Product scope

Computing	CRT Displays	Flat Panel Displays	Audio Visual Products	Other Mobile Products	Phones
Laptops	CRT Monitors	Plasma TVs	Blu-Ray Players	Digital Cameras	Smart Phones
Tablets	CRT TVs	LCD TVs (CCFL)	DVD Players	Digital camcorders	Basic mobile phones
Desktops		LCD monitors (CCFL)	VCR	MP3 Players	
Printers		LCD (LED) TVs	Gaming Consoles		
		LCD (LED) monitors			

Uncertainty analysis results

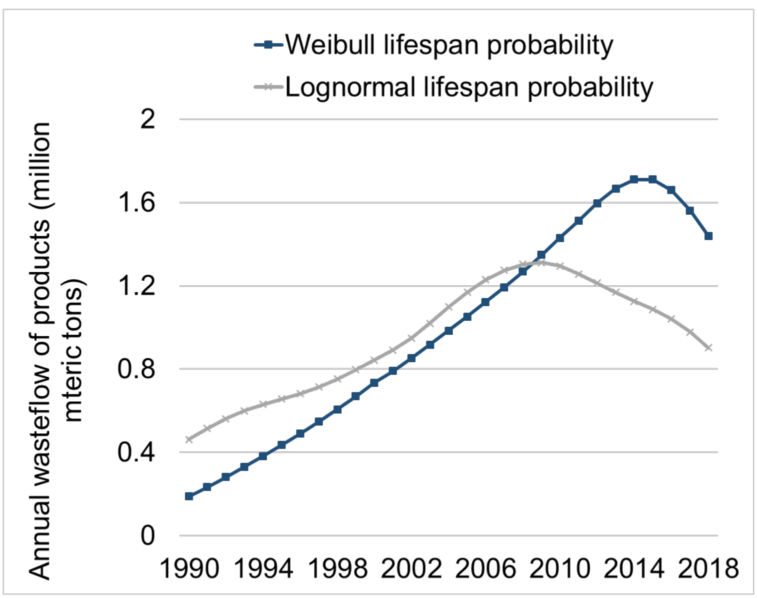

Figure 1a. Sensitivity to lifespan probability assumption (Weibull vs lognormal). Figure shows that the declining trend in e-waste holds true, irrespective of the lifespan distribution assumption. However, under lognormal distribution assumption of product lifespans, net mass of e-waste peaks early compared to Weibull distribution.

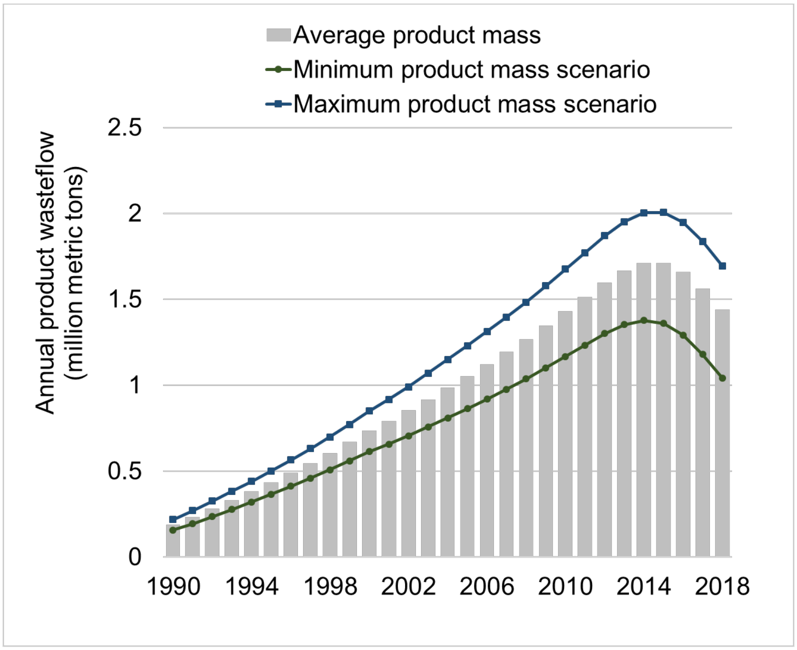

Figure 1b. Sensitivity to product mass assumptions (min, max scenarios). Figure shows that the declining trend in e-waste holds true, for both minimum and maximum product mass scenarios.

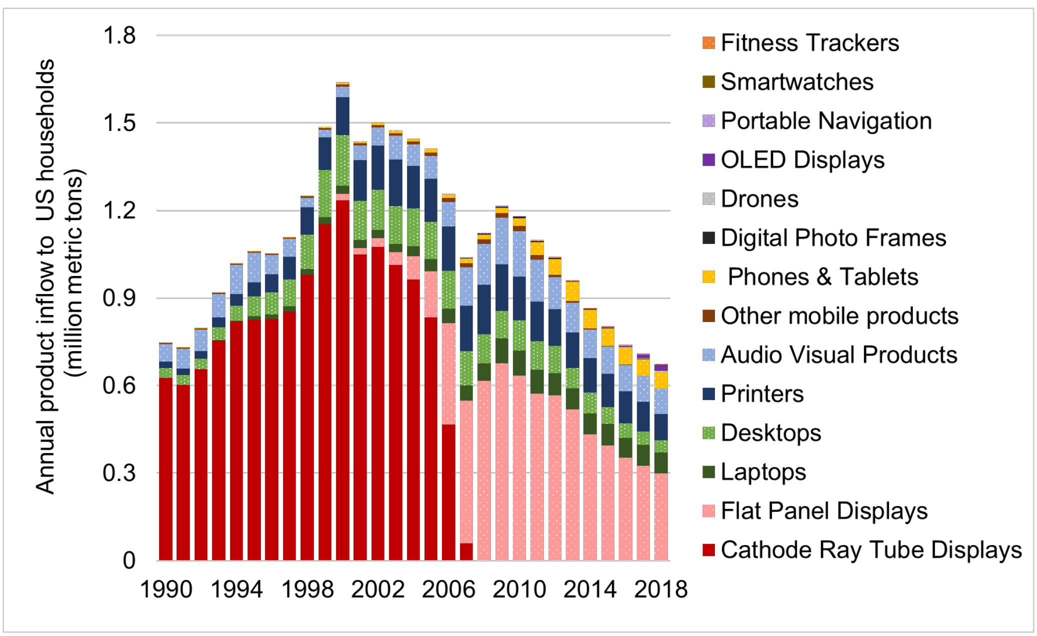

Figure 1c. Sensitivity to product scope. Figure shows that there is no fundamental change in the trends observed in e-waste mass even when 6 additional products (fitness trackers, smart watches, portable navigation, OLED displays, drones and digital photo frames) are included in the baseline product scope.

Parameters for product lifespan distribution

Table 2: Mean and maximum lifespan values used to estimate Weibull parameters.

Products	Maximum	Minimum	Mean	Std Dev
Basic mobile phone	7	1	2	2
Blu ray Player	10	1	6	2
CRT Monitor	13	1	9	3
CRT TV	20	1	14	5
Desktop CPU	10	1	4	2
Digital Camcorder	14	1	6	3
Digital Camera	14	1	5	3
DVD Player	10	1	6	2
Gaming Consoles	10	1	4	2
Laptops	9	1	4	2
LED Monitor	10	1	4	2
LED TV	10	1	6	2
LCD Monitor	10	1	4	2
LCD TV	10	1	6	2
MP3 Player	7	1	4	2
Plasma TV	10	1	7	2
Printer	10	1	7	2
Smart Phone	7	1	2	2
Tablets	5	1	3	1
VCR	15	1	8	4

Average product mass estimations

For smaller products such as cameras and phones, mass was assumed to be static over time, while for larger products which represent major contribution to waste flow mass and underwent significant dematerialization over years, such as TVs, monitors and laptops, average mass of products sold was considered to be dynamic over the years. A combination of data from lab, literature and data compilations from NCER were used for both static and dynamic product mass estimations.

Static Mass: For mass uncertainty analysis, minimum and maximum from the range of available data was used. Table below shows average, minimum and maximum mass assumptions for static mass products.

Table 3: Static mass assumptions of products

Products	Average mass (kg)	Minimum mass (kg)	Maximum mass (kg)
Basic mobile phone	0.114	0.095	0.149
Blu-ray player	3.15	0.983	4.46
Desktop CPU	9.89	6.71	12.7
Digital camcorders	1.14	0.848	1.31
Digital cameras	0.132	0.096	0.150
DVD player	3.69	2.34	5.16
Gaming consoles	2.81	1.18	4.23
MP3 player	0.093	0.052	0.128
Printer	7.45	5.31	8.90
Smart phone	0.137	0.091	0.180
Tablet	0.441	0.222	0.726
VCR	4.43	3.86	5.00

Data Sources: Lab disassembly data, U.S EPA waste management, NCER and literature.

Dynamic mass: For products with yearly mass data from multiple data sources (laptops, LCD monitors, LCD TVs, Plasma TVs), a fitted trend was used to estimate the dynamic mass input while for products which lacked data from multiple sources (CRT TVs and monitors), mass trend was built on the single reliable data source. Dynamic mass estimates for LED TVs and monitors were generated by assuming a LED displays to be 35% lighter compared to LCD displays, based on lab disassembly data which was also corroborated in literature. For mass uncertainty analysis, in the case of products with mass data points from multiple data sources (laptops, LCD monitors, LCD TVs, Plasma TVs), the uncertainty range was estimated by calculating the average percent difference of different data points to the fitted trend. In the case of products which relied on a single reliable data source for estimating dynamic mass trends (CRT TVs and monitors), the average difference of any additional data point to the trend was used to estimate the uncertainty range. These calculations yielded a 14% mass uncertainty range (yearly average mass ±14%) for CRT monitors, CRT TVs and LCD monitors, a 12% LCD TVs and 5% for plasma TVs. For LED TVs and monitors, the same uncertainty range for LCD TVs and monitors were applied due to lack data.

Table 4: Dynamic mass assumptions of products.

Year	Average product mass (kg)							
	CRT monitor	CRT TV	Laptops	LCD monitor	LCD TV	LED Monitor	LED TV	Plasma TV
1990	11	26	0.0					
1991	11	27	0.0					
1992	11	27	3.4					
1993	11	27	3.4					
1994	13	27	3.3					
1995	15	27	3.3					
1996	17	27	3.2					
1997	18	27	3.2					
1998	20	28	3.1					
1999	22	27	3.1	3.4	0			45
2000	24	27	3.0	3.6	25			44
2001	23	27	3.0	3.8	24			42
2002	23	27	2.9	3.9	24			41
2003	23	28	2.9	4.1	23			39
2004	23	29	2.8	4.3	22			37
2005	23	30	2.8	4.5	21			36
2006	23	30	2.7	4.7	20			34
2007	23	30	2.7	4.8	20			33
2008			2.7	5.0	19			31
2009			2.6	5.2	18	3.4	12	29
2010			2.6	5.4	17	3.5	11	28
2011			2.5	5.6	17	3.6	11	26
2012			2.5	5.7	16	3.7	10	24
2013			2.4	5.9	15	3.8	10	23
2014			2.4	6.1	14	4.0	9.2	21
2015			2.3	6.3	13	4.1	8.7	
2016			2.3	6.5	13	4.2	8.2	
2017			2.2			4.3	7.7	
2018			2.2			4.4	7.1	

Product Material Profile Estimations

Table 5: Average material profile of products

Product Category	Fe	Al	Cu	Other metals	Plastic	PCB	Flat Panel Glass	CRT glass	Battery	Others
Basic Phones	1.0%	5.6%	2.1%		33%	18%	8.8%		25%	6.1%
Blu Ray Disc	60%	0.2%	3.5%		18%	18%				1.4%
CRT Monitor	3.0%		2.0%	1.0%	20%	12%		62%		
CRT TV	6.0%		1.0%		23%	10%		60%		
DVD Players	49%	1.1%	4.1%		33%	13%				0.2%
Traditional Desktop	54%	9.6%	4.4%	1.1%	19%	10%	0.0%			1.7%
Digital Camcorders/Cameras	16%	12%	1.4%		41%	16%	4.2%		0.9%	8.3%
Gaming Consoles	31%	9.1%	2.2%	0.0%	34%	17%			0.02%	6.2%
Laptops	12%	15%	1.8%	5.8%	28%	12%	8.2%		14%	2.4%
LCD monitors	36%	6.2%	5.3%		28%	6.2%	18%			0.2%
LCD TV	43%	2.5%	0.9%	4.7%	28%	5.8%	13%			2.5%
LED monitors	38%	0.3%	0.04%		44%	2.6%	15%			0.4%
LED TV	18%	27%			35%	5.7%	14%			0.2%
MP3 Player	14%	26%	0.7%		17%	14%	7.7%		12%	8.9%
Plasma TV	32%	11%	0.5%	1.9%	30%	5.9%	12%			6.7%
Printer	30%	0.2%	0.5%		61%	3.1%	0.1%			5.2%
Smart Phone	6.3%	9.4%	1.2%	2.5%	23%	14%	9.6%		23%	12%
Tablet	3.6%	9.3%	0.4%		32%	7.2%	15%		23%	9.7%
VCR	65%		1.5%		19%	15%				

Data Source: A combination of product disassembly and literature data for most products. For CRTs, the material composition is adopted from Townsend et al (2004).

Mercury content in LCD displays

Mercury content in LCD TVs and monitors with CCFL backlights was calculated based on average mass percentage of mercury per kg of CCFL lamp (0.04%) from literature and weight contribution of CCFL lamps in LCD displays. The CCFL lamp weight in LCD displays were estimated through a combination of lab scale product disassembly data and published literature, to be 0.11% in monitors and 1.2 % in TVs.

Table 6: CCFL lamp weight estimation for LCD TVs.

LCD TV screen size (inches)	Total TV weight (kg)	Total CCFL lamp weight (kg)	Lamp weight per kg TV (%)	Data Sources
40 inches	14.236	0.1666	1.2%	Lab Disassembly
37 inches	20.66	0.24	1.2%	Wrap 2010
Average CCFL lamp weight per kg TV=			**1.2%**	

Table 7: CCFL lamp weight estimation for LCD monitors.

LCD Monitors	**Total Monitor weight (kg)**	**Total CCFL lamp weight (kg)**	**Lamp weight per kg monitor (%)**	**Data Source**
Dell 2015	2.84	0.004	0.14%	Lab Disassembly
HP	4.97	0.0062	0.12%	Lab Disassembly
Model Unknown	5.279	0.00194	0.04%	Huisman 2007
NEC Multi Sync LCD 1810	5.165	0.009	0.17%	California 2004
Mitsubishi LXA565W	4.731	0.0034	0.07%	California 2004
Mitsubishi LXA565W	4.997	0.0033	0.07%	California 2004
Sony SDM-M81	6.892	0.0125	0.18%	California 2004
Sony CPD-M151	4.956	0.0046	0.09%	California 2004
Sony SOM-X52	4.576	0.0045	0.10%	California 2004
Sony SOM-HJ53	3.596	0.0044	0.12%	California 2004
Average CCFL lamp weight per kg monitor=			**0.11%**	

Historic product adoption data

Table 8: Annual sales data of products in units sold to residential sector. Data were provided by the Consumer Technology Association. 2018 and 2019 values are projections made by CTA.

Year	LCD Monitors	LED Monitors	LCD TVs	Plasma TVs	Portable Navigation	Smart Phones	Tablets & E-readers
1999	1,122			2,000			
2000	399,850		832,000	8,000	107,000		
2001	419,827		845,000	16,000	162,000		
2002	495,530		935,000	106,000	221,000		
2003	764,570		1,253,000	342,000	300,000	2,306,000	
2004	1,351,645		1,842,000	870,000	550,000	3,627,000	
2005	2,801,727		4,077,000	1,639,000	707,000	7,920,000	
2006	7,312,696		10,325,000	3,028,000	2,284,000	11,282,000	20,000
2007	11,095,043		16,843,000	3,166,000	8,751,000	19,500,000	147,000
2008	9,977,497		24,116,000	3,572,000	15,320,414	28,555,000	580,000
2009	9,097,128	478,796	28,239,700	3,366,000	14,870,000	41,163,000	2,290,000
2010	8,364,245	2,091,061	22,815,200	4,416,000	13,683,650	54,136,000	18,570,000
2011	6,983,869	2,883,996	20,230,000	3,807,000	12,315,285	87,431,000	52,960,000
2012	6,163,915	3,348,273	20,981,649	2,982,000	9,325,000	114,061,000	70,827,375
2013	3,343,581	3,829,659	16,861,378	1,995,000	7,274,000	151,000,000	86,466,279
2014	2,415,051	6,081,601	10,133,000	1,063,000	6,401,000	160,221,000	84,527,842
2015	1,082,980	6,036,373	5,982,641		4,600,000	174,640,890	73,848,551
2016	119,211	5,841,332	800,560		4,140,000	179,880,117	68,302,475
2017	0	4,623,094	0		3,767,400	174,650,293	64,475,481
2018	0	4,379,760	0		3,483,338	169,420,468	61,249,750

Table 8. Annual sales data of products, continued.

Year	CRT TVs	Desktops	VCRs	Printers	CRT Monitors	Basic Mobile Phones	Digital camcorders
1980	17,581,000	343,225	11,336,000	369,000	343,226		
1981	16,811,000	686,451	12,005,000	738,000	686,452		
1982	17,058,000	1,064,000	11,702,000	1,145,000	1,064,000		
1983	19,721,000	1,907,500	10,748,000	2,769,000	1,907,500		
1984	21,328,000	2,331,000	9,760,000	2,935,000	2,331,000	22,750	
1985	20,779,000	2,016,000	10,119,000	2,363,000	2,016,000	68,250	517,000
1986	22,461,000	2,397,850	10,718,000	2,178,000	2,397,850	259,350	1,169,000
1987	23,170,000	2,870,700	12,329,000	2,308,000	2,870,700	514,150	1,604,000
1988	23,092,000	3,053,400	12,448,000	2,585,000	3,053,400	809,900	2,044,000
1989	23,627,000	3,117,030	13,087,000	2,880,000	3,117,030	1,365,000	2,286,000
1990	22,570,000	3,319,935	13,562,000	2,954,000	3,319,935	1,665,300	2,962,000
1991	21,300,000	3,333,317	15,641,000	2,880,000	3,333,317	2,174,900	2,864,000
1992	23,029,000	3,468,850	16,673,000	3,600,000	3,468,850	3,480,750	2,815,000
1993	25,649,000	4,557,707	18,113,000	4,320,000	4,557,707	5,086,900	3,088,000
1994	27,908,000	5,353,664	22,809,000	5,160,000	5,353,664	8,030,750	3,209,000
1995	26,736,000	6,912,069	23,072,000	6,480,000	6,912,069	9,368,450	3,560,000
1996	25,895,000	7,567,312	14,910,000	8,400,000	7,567,312	10,524,150	3,634,000
1997	24,921,000	9,314,468	13,538,000	10,400,000	9,314,468	24,570,000	3,650,000
1998	26,768,000	11,980,924	6,416,000	12,500,000	11,980,924	27,300,000	3,829,000
1999	29,188,000	16,375,290	2,267,000	15,000,000	16,374,168	30,667,000	4,790,000
2000	30,620,000	14,975,336	1,365,000	17,400,000	14,575,486	47,866,000	5,848,000
2001	26,980,000	13,575,382	759,000	18,800,000	13,155,555	48,594,000	5,284,000
2002	28,245,000	13,940,539	53,000	20,300,000	13,445,009	59,140,900	5,790,000
2003	25,640,000	13,055,206	6,000	21,518,000	12,290,636	69,945,330	5,262,000
2004	23,824,000	13,225,393		19,581,000	11,873,747	72,690,000	5,559,000
2005	20,427,000	12,814,129		19,973,000	10,012,402	86,042,000	5,242,000
2006	10,904,000	13,284,211		20,273,000	5,971,515	99,472,000	5,320,000
2007	1,400,000	11,871,347		21,001,000	776,304	101,500,000	5,558,000
2008		9,977,497		22,944,000	0	102,775,000	5,608,000
2009		9,575,925		21,499,076	0	94,239,000	6,267,000
2010		10,455,307		20,054,153	0	91,225,000	7,246,000
2011		9,867,865		18,022,000	0	79,000,000	5,459,000
2012		9,512,188		16,950,000	0	66,602,000	2,663,000
2013		7,173,240		16,285,000	0	51,950,000	1,633,000
2014		8,496,653		15,990,877	0	41,560,000	1,195,000
2015		7,119,353		15,240,323	0	29,092,000	776,750
2016		5,960,542		14,489,769	0	20,364,400	512,618
2017		4,623,094		13,820,492	0	12,696,000	460,403
2018		4,379,760		13,275,000	0	10,005,000	305,437

Table 8. Annual sales data of products, continued.

Year	Laptops	LED TVs	DVD Players	Blu-Ray Players	Gaming Consoles	MP3 Players	Digital Cameras
1992	222,000						
1993	303,358						
1994	384,056						
1995	581,574						
1996	609,733						300,000
1997	516,546		349,000				863,000
1998	571,983		1,079,000				1,180,000
1999	1,319,101		4,072,000			500,000	2,114,000
2000	1,739,930		8,499,000			587,000	4,234,000
2001	1,835,910		12,707,000			724,000	5,556,000
2002	2,941,318		17,090,000			1,737,000	9,267,000
2003	5,900,451		21,994,000			3,031,000	14,786,000
2004	7,323,092		19,990,000			7,126,000	18,852,000
2005	9,728,855		21,148,000			24,812,000	23,249,000
2006	11,059,675		22,306,000	130,000		38,124,000	32,947,000
2007	14,159,632		20,919,000	1,136,000	17,981,150	48,020,000	32,220,000
2008	17,996,965		18,970,000	2,773,000	21,603,534	43,731,000	33,168,000
2009	27,969,324	1,486,300	21,026,000	7,088,000	21,187,590	40,101,000	32,932,000
2010	28,843,486	5,703,800	18,268,500	9,301,000	21,479,500	39,686,000	36,545,000
2011	27,359,802	8,354,000	15,511,000	9,991,000	20,031,168	36,263,000	37,697,000
2012	24,920,728	11,397,351	10,540,000	10,769,000	12,790,400	26,472,000	23,202,000
2013	22,738,676	19,312,622	8,936,000	11,088,000	12,428,000	19,503,000	15,341,000
2014	21,765,793	25,517,000	7,570,000	9,088,000	14,292,200	15,272,000	11,532,000
2015	22,046,317	33,346,359	7,363,000	7,727,000	15,149,732	7,788,720	8,336,000
2016	20,457,000	39,227,440	6,419,526	7,298,777	14,082,485	5,841,540	5,170,531
2017	19,778,474	41,706,600	5,640,766	5,556,436	14,121,693	5,666,294	5,488,813
2018	18,780,985	40,505,173	4,768,125	5,523,795	14,477,159	5,892,946	5,548,325

Table 8. Annual sales data of products, continued

Year	Drones	OLED Displays	Digital photo frames	Smart watches	Fitness Trackers
2006			1,450,000		
2007			5,262,000		
2008			7,472,040		
2009			9,319,000		
2010			9,133,000		
2011			7,970,000		3200000
2012			6,535,000	5000	8415000
2013	127,500	9000	5,118,000	6000000	10267000
2014	449,700	38000	3,275,520	2355000	16800000
2015	1,145,000	72200	2,075,000	10597500	20254000
2016	2,425,000	181000	1,524,500	9007875	22824000
2017	3,400,000	532972	1,189,110	8106888	21217000
2018	4,448,000	971279	986,149	7944890	20656000

Table 9. Average mass of additional products in uncertainty analysis.

Product Category	Size	Model	Mass (kg)	Data Source
OLED TVs	55"	LG C9 55-inch Class 4K Smart OLED TV	19	Manufacturer website
	65"	LG C9 65-inch Class 4K Smart OLED TV	25	
	77"	LG C9 77-inch Class 4K Smart OLED TV	30	
	65"	LG E9 Glass 65-inch Class 4K Smart OLED TV	20	
	55"	LG E9 Glass 55-inch Class 4K Smart OLED TV	16	
	55"	LG B8PUA 4K HDR Smart OLED	16	
	55"	SONY 55" Class - OLED - A9G MASTER Series	19	Seller Website -Best Buy
	65"	Sony - 65" Class - OLED - A9G MASTER Series	21	
	77"	Sony - 77" Class - OLED - A9G MASTER Series	35	
		OLED TVs average mass =	**22**	
Smart Watches	38 mm	Apple Watch Series 3 (38mm)	0.05	consumerreports.org
	40 mm	Apple Watch Series 4 (40mm)	0.07	
	1.1"	Samsung Galaxy Watch Active smartwatch	0.05	
	1.3"	Samsung Gear S2 smartwatch	0.06	
	1.3"	Samsung Gear S3 Frontier smartwatch	0.09	
		Smart watches average mass =	0.06	
Portable GPS Navigation	5"	Magellan RoadMate 5375T-LMB GPS	0.17	consumerreports.org
	6 "	Magellan RoadMate 5330T-LM GPS	0.17	
	6.1"	Garmin nuvi 68LMT GPS	0.24	
	5"	Garmin nuvi 57LMT GPS	0.18	
		Portable navigation system average mass =	**0.19**	
Digital Photo Frames	10”	Insignia - 10" Widescreen LCD Digital Photo Frame	0.91	Seller Website -Best Buy
	8”	Aluratek - 8" LCD Digital Photo Frame	0.64	
	7”	Polaroid Digital Photo Frame 7" Screen	0.32	
		Digital photo frame average mass =	**0.62**	

For drones (0.947 kg) and fitness trackers (0.025 kg), lab scale average mass data was available. Average mass of other products was collected from alternate sources (Table above).

APPENDIX B

Product Adoption Cycle

The case of audio-visual (AV) media is used to demonstrate that decline of one technology generation is not always predicated solely on substitution by the next generation. Figure 1 shows historic market adoption data of audio-visual media technologies -VCRs, DVD Players, Blu-rays and Streaming media players. It can be observed that the beginning of decline phase of all incumbent technologies coincides with that of the entry of a new competing technology, and in the case of Blu-rays and DVD Players market decline is triggered by the advent of new streaming media services, rather than a new product generation.

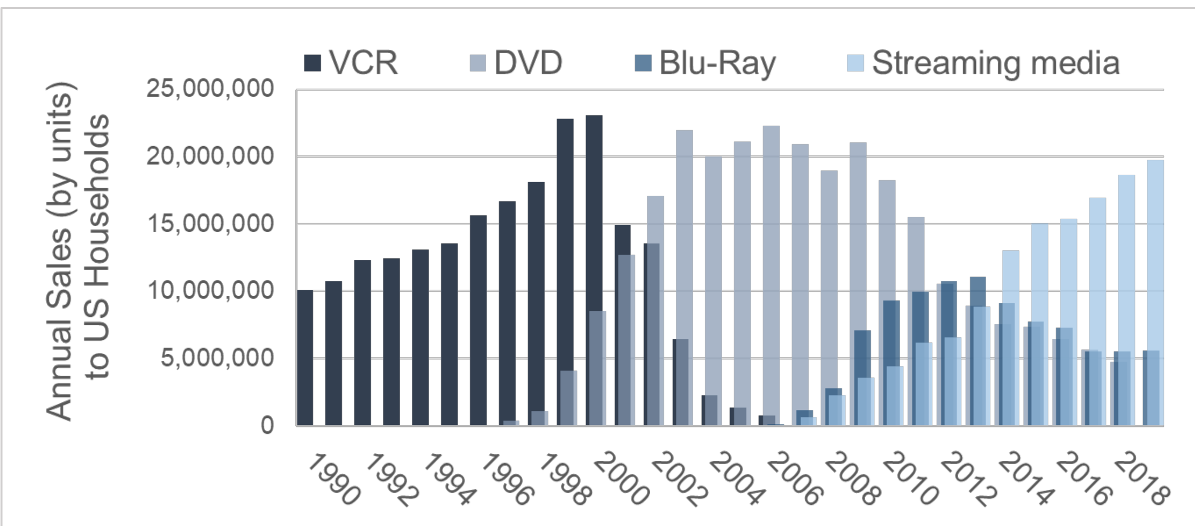

Figure 1. Technological shifts and substitution phenomena in the historic adoption of audio-visual (AV) media technologies in US (Data from CTA 2017, as reported in Babbitt et al. 2017).

Product Lifespan Assumptions

To characterize product lifespan, literature and data sources, including values provided by the consumer technology association were reviewed and compiled. Here, we define lifespan to be total time a product spends in a household before being discarded (to reuse, recycling, or ultimate disposal) and potentially including both in-use and storage times. These values are summarized in table below and converted to Weibull parameters for the predictive MFA model.

Table 1: Lifespan estimates assumed:

Products	Maximum	Minimum	Mean	Standard Deviation
Basic mobile phone	7	1	2	2
Blu ray Player	10	1	6	2
CRT Monitor	13	1	9	3
CRT TV	20	1	14	5
Desktop CPU	10	1	4	2
Digital Camcorder	14	1	6	3
Digital Camera	14	1	5	3
DVD Player	10	1	6	2
E reader	5	1	3	1
Gaming Consoles	10	1	4	2
Laptops	9	1	4	2
LED Monitor	10	1	4	2
LED TV	10	1	6	2
LCD Monitor	10	1	4	2
LCD TV	10	1	6	2
MP3 Player	7	1	4	2
Plasma TV	10	1	7	2
Printer	10	1	7	2
Smart Phone	7	1	2	2
Tablet	5	1	3	1
VCR	15	1	8	4
Drone	7	1	4	2
Fitness Tracker	7	1	3	2
Smart Thermostat	10	1	5	2

MFA model parameters for mature products

Table 2: Logistic parameters from data and from curve fitting for mature products.

	Data			Logistic Curve Fitting			
Products	**Start Year**	**Time to peak**	**Peak Sales**	**Growth rate**	**Growth midpoint**	**Decay rate**	**Decay midpoint**
CRT TV	1962	38	30620000	0.14	20	1	6.3
CRT Monitor	1980	19	16374168	0.27	16	0.63	7
Desktop CPU	1980	19	16375290	0.27	16	0.17	15
Laptops	1993	17	28843486	0.55	14	0.22	12
LED Monitor	2009	5	6081601	0.7	3.4	0.81	6
LED TV	2009	8	41706600	0.75	5.2	0.91	5.1
LCD Monitor	2000	7	11095043	1.7	6.6	0.64	5.9
LCD TV	2000	9	28239700	1.1	7.5	0.69	5.1
Plasma TV	2002	9	4416000	0.73	4.7	1	3.8
Printer	1980	28	22944000	0.31	18	0.19	12
Tablet	2009	4	86466279	1.6	2.8	0.45	7.2

Average Product Mass

To translate product flows into cumulative mass flows, average mass data were collected from literature, direct weighing of sample products in the lab, and data compilations provided by the National Center for Electronics Recycling, who monitor product weight as part of e-waste compliance efforts in several U.S. states. Since product mass may change over time for some products, mass averages were calculated to reflect the weighted averages reflecting consumption of given size products, mass of different sizes, and averages across multiple products measured. Product mass was held constant over time, to minimize variability attributed to factors other than product adoption, as the focus of the study. Additional detail about all product mass sources was given in Babbitt et al. 2017.

Table 3: Product mass assumptions

Product	Average Mass (kg)
CRT TV	46
CRT Monitor	20
Desktop CPU	10
Laptops	3
LED Monitor	4
LED TV	10
LCD Monitor	5
LCD TV	14
Plasma TV	23
Printer	8
Tablet	0.6

Estimating MFA model parameters for emerging products

Table 4: Logistic parameters extracted for 15 products to identify temporal trends (Δt is used to calculate growth rate as growth rate=ln (81)/ Δt

Products	Market Entry Year	10%	90%	Δt	50%	Time to peak
CRT TV	1962	4.5	37.5	33	18.5	38
VCR	1977	6.5	22.5	16	15.5	23
Desktop CPU	1980	3.5	19.5	16	17.5	19
Digital camcorders	1985	1.5	25.5	24	11.5	25
Satellite Set-Top Boxes	1986	9.5	27.5	18	17.5	27
Basic mobile phone	1989	7.5	17.5	10	13.5	19
Laptops	1993	9.5	16.5	7	15.5	17
DVD player	1997	2.5	8.5	6	4.5	9
MP3 player	1999	5.5	8.5	3	6.5	8
LCD monitor	2000	4.5	7.5	3	6.5	7
Portable Navigation Devices	2001	5.5	7.5	2	6.5	7
Plasma TV	2002	2.5	8.5	6	4.5	8
Cable Set-Top Boxes	2003	1	9.5	8.5	2.5	9
Digital Photo Frames	2006	1	1.5	0.5	3.5	3
Tablet	2009	1.5	4.5	3	2.5	4
LED TV	2009	1.5	7.5	6	5.5	8

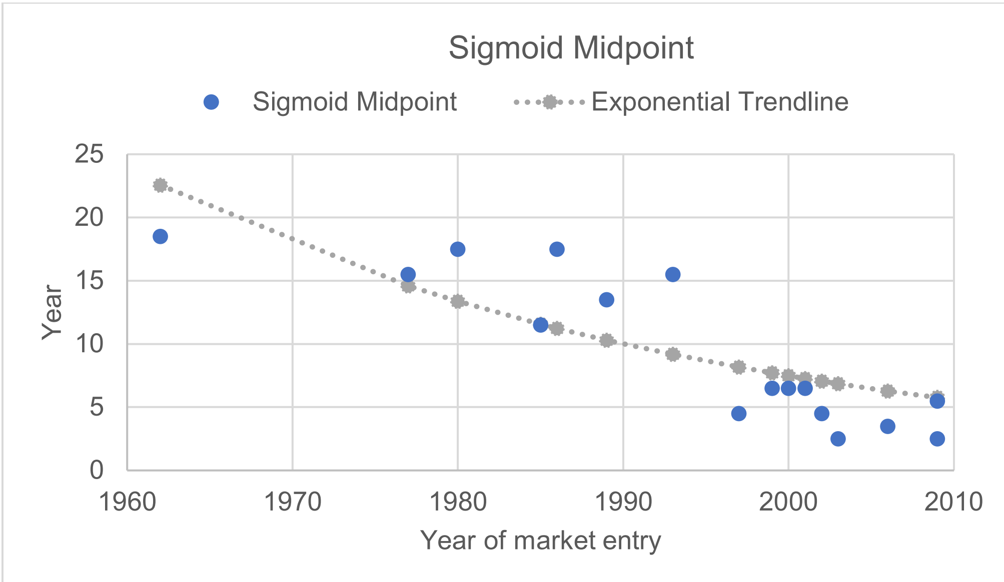

Figure 2: Exponential trend line for sigmoid midpoint of logistic adoption curve

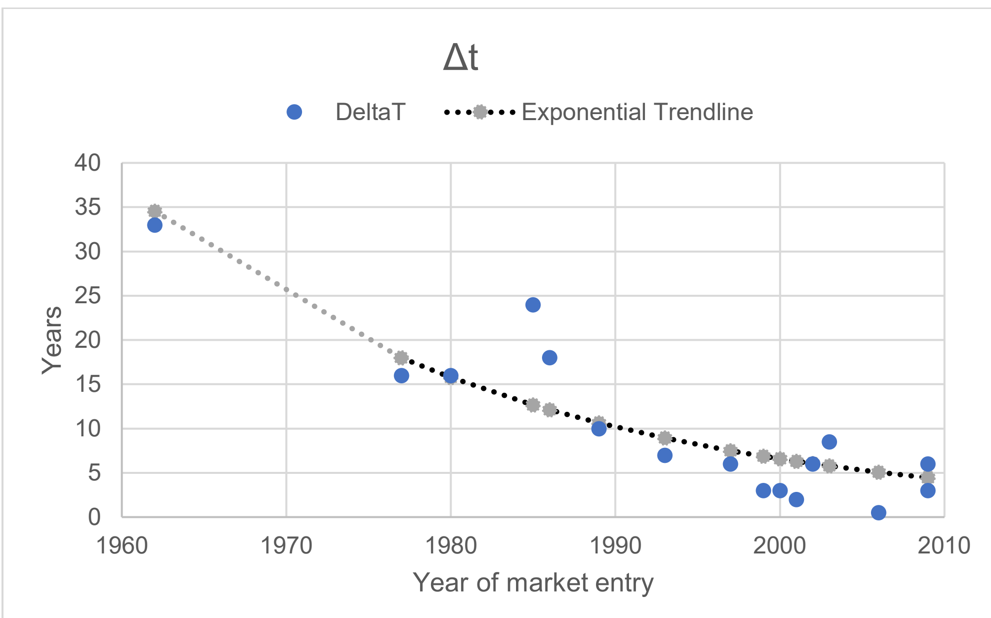

Figure 3: Exponential trend line growth rate of logistic adoption curve (represented by Δt)

Table 5. Products and peak sales units to households.

Product Category	Products	Peak sales per household
Computing	LED Monitor	0.05
	LCD Monitor	0.10
	CRT Monitor	0.16
	Desktop	0.16
	Printer	0.20
	Laptop	0.25
TV	Plasma TV	0.04
	LCD TV	0.25
	CRT TV	0.29
	LED TV	0.35
Audio-Visual	IPTV	0.05
	Digital photo frames	0.08
	VOIP	0.09
	Blu-Ray	0.10
	Cable set top boxes	0.14
	Satellite Set top boxes	0.15
	Gaming	0.19
	DVD	0.20
	VCR	0.23
	Answering Devices	0.25
Small Mobile	Camcorder	0.06
	Portable Navigation	0.14
	E reader	0.18
	Digital Camera	0.33
	MP3	0.43
Phones	Tablet	0.67
	Basic Phone	0.91
	Smart Phone	1.53

Table 6. Limited adoption and mainstream adoption ranges assigned to product categories

Computing	**Min**	**Max**	**Average**
Limited adoption range	0.05	0.10	
Mainstream adoption range	0.17	0.21	0.19
TV			
Limited adoption range	0.05	0.10	
Mainstream adoption range	0.27	0.33	0.30
Audio-Visual			
Limited adoption range	0.05	0.10	
Mainstream adoption range	0.17	0.21	0.19
Small Mobile			
Limited adoption range	0.05	0.10	
Mainstream adoption range	0.24	0.30	0.27
Phones			
Limited adoption range	0.05	0.10	
Mainstream adoption range	0.93	1.14	1.04

Logistic MFA Model Validation

To confirm the logistic assumption of product adoption curves, growth and decline curve for each product was tested against candidate distributions using a ‘least squares’ approach as implemented in MATLAB. Goodness of fit parameters such as SSE (sum of squared errors), R-squared, Root Mean Squared Error (RMSE), AIC (Akaike information criterion) and BIC (Bayesian Information Criterion) were used to confirm that logistic curves were the best distribution to represent adoption cycle of electronics. AIC and BIC were calculated from parameters estimated through ‘least squares’ approach using the equations given below.

$$AIC = n + n \log(2\pi) + n \log(RSS/n) + 2(p+1) \qquad \text{Eq (1)}$$

$$BIC = n + n \log(2\pi) + n \log(RSS/n) + (\log n)(p+1) \qquad \text{Eq (2)}$$

Where RSS is the residual sum of errors, n is the number of observations and p is the number of parameters.

Table 7: Best Curve results

For most products that have matured in the market, a logistic curve emerged to be the best fit curve, which was selected to represent all products.

Products		Curves Tested	Goodness of fit					
			SSE	R square	Adjusted R Square	RMSE	AIC	BIC
CRT TV	growth	linear	1.7E+14	9.5E-01	9.5E-01	2.1E+06	5.7E+02	5.7E+02
		logistic	1.3E+14	9.6E-01	9.6E-01	1.9E+06	5.7E+02	5.6E+02
		exponential	4.1E+14	8.8E-01	8.7E-01	3.3E+06	5.8E+02	5.8E+02
	decay	linear	1.2E+14	8.2E-01	7.9E-01	4.5E+06	1.3E+02	1.2E+02
		logistic	3.7E+13	9.5E-01	9.4E-01	2.5E+06	1.2E+02	1.2E+02
		exponential	2.1E+14	7.0E-01	6.5E-01	5.9E+06	1.3E+02	1.2E+02
CRT monitor	growth	linear	7.5E+13	7.6E-01	7.5E-01	2.0E+06	2.9E+02	2.9E+02
		logistic	3.9E+13	8.7E-01	8.6E-01	1.5E+06	2.9E+02	2.9E+02
		exponential	1.4E+13	9.6E-01	9.5E-01	8.7E+05	2.8E+02	2.8E+02
	decay	linear	3.2E+13	8.3E-01	8.0E-01	2.1E+06	1.4E+02	1.3E+02
		logistic	1.9E+13	9.0E-01	8.6E-01	1.8E+06	1.4E+02	1.3E+02
		exponential	5.0E+13	7.3E-01	6.9E-01	2.7E+06	1.4E+02	1.3E+02
Desktop CPU	growth	linear	7.5E+13	7.6E-01	7.5E-01	2.0E+06	2.9E+02	2.9E+02
		logistic	3.9E+13	8.7E-01	8.7E-01	1.5E+06	2.9E+02	2.9E+02
		exponential	1.4E+13	9.6E-01	9.5E-01	8.7E+05	2.8E+02	2.8E+02
	decay	linear	1.1E+13	9.5E-01	9.5E-01	8.0E+05	2.8E+02	2.7E+02
		logistic	1.1E+13	9.5E-01	9.5E-01	7.9E+05	2.8E+02	2.8E+02
		exponential	2.0E+13	9.1E-01	9.1E-01	1.1E+06	2.8E+02	2.8E+02
Printer	growth	linear	2.0E+14	8.9E-01	8.9E-01	2.7E+06	4.3E+02	4.3E+03
		logistic	4.4E+13	9.8E-01	9.8E-01	1.3E+06	4.1E+02	4.1E+02
		exponential	1.8E+14	9.0E-01	9.0E-01	2.6E+06	4.3E+02	4.3E+02
	decay	linear	6.5E+12	9.4E-01	9.4E-01	8.1E+05	1.7E+02	1.7E+02
		logistic	1.5E+13	8.7E-01	8.6E-01	1.2E+06	1.7E+02	1.7E+02
		exponential	3.2E+12	9.7E-01	9.7E-01	5.7E+05	1.6E+02	1.6E+02
Laptops	growth	linear	3.4E+14	7.7E-01	7.5E-01	4.6E+06	2.8E+02	2.8E+02
		logistic	5.9E+13	9.6E-01	9.6E-01	1.9E+06	2.7E+02	2.6E+02
		exponential	2.7E+13	9.8E-01	9.8E-01	1.3E+06	2.6E+02	2.6E+02
	decay	linear	6.9E+12	9.4E-01	9.3E-01	9.3E+05	1.4E+02	1.4E+02
		logistic	1.6E+13	8.6E-01	8.5E-01	4.1E+05	1.5E+02	1.4E+02
		exponential	4.4E+12	9.6E-01	9.6E-01	7.4E+05	1.4E+02	1.4E+02

Table 7: Best Curve results, continued

Products		Curves Tested	Goodness of fit					
			SSE	R square	Adjusted R Square	RMSE	AIC	BIC
LCD monitor	growth	linear	3.0E+13	7.3E-01	6.8E-01	2.2E+06	1.2E+02	1.2E+02
		logistic	2.2E+12	9.8E-01	9.8E-01	6.1E+05	1.1E+02	1.1E+02
		exponential	2.0E+12	9.8E-01	9.8E-01	5.8E+05	1.1E+02	1.1E+02
	decay	linear	2.4E+12	9.8E-01	9.8E-01	5.5E+05	1.4E+02	1.3E+02
		logistic	1.8E+12	9.9E-01	9.9E-01	4.7E+05	1.4E+02	1.3E+02
		exponential	5.5E+12	8.9E-01	8.7E-01	1.4E+06	1.5E+02	1.4E+02
LCD TV	growth	linear	1.8E+14	8.2E-01	8.0E-01	4.8E+06	1.6E+02	1.5E+02
		logistic	6.3E+12	9.9E-01	9.9E-01	8.9E+05	1.4E+02	1.4E+02
		exponential	4.2E+13	9.6E-01	9.5E-01	2.3E+06	1.5E+02	1.5E+02
	decay	linear	3.1E+13	9.5E-01	9.4E-01	2.3E+06	1.2E+02	1.2E+02
		logistic	3.0E+13	9.5E-01	9.4E-01	2.2E+06	1.2E+02	1.2E+02
		exponential	9.0E+13	8.5E-01	8.3E-01	3.9E+06	1.2E+02	1.2E+02
Plasma TV	growth	linear	1.2E+12	9.4E-01	9.3E-01	4.2E+05	1.2E+02	1.2E+02
		logistic	9.4E+11	9.5E-01	9.5E-01	3.7E+05	1.2E+02	1.2E+02
		exponential	3.3E+12	8.3E-01	8.1E-01	6.9E+05	1.3E+02	1.2E+02
	decay	linear	5.4E+10	9.9E-01	9.9E-01	1.3E+05	6.5E+01	6.1E+01
		logistic	6.7E+10	9.9E-01	9.9E-01	1.5E+05	6.8E+01	6.2E+01
		exponential	4.5E+11	9.4E-01	9.2E-01	3.9E+05	7.0E+01	6.6E+01
LED Monitor	growth	linear	1.2E+12	9.3E-01	9.1E-01	5.5E+05	8.5E+01	8.0E+01
		logistic	1.9E+12	8.9E-01	8.7E-01	6.8E+05	8.8E+01	8.2E+01
		exponential	1.4E+12	9.2E-01	9.0E-01	5.8E+05	8.5E+01	8.1E+01
	decay	linear	3.9E+11	8.6E-01	8.1E-01	3.6E+05	6.9E+01	6.6E+01
		logistic	3.4E+11	8.7E-01	8.3E-01	3.4E+05	7.1E+01	6.6E+01
		exponential	4.6E+11	8.3E-01	7.8E-01	3.9E+05	7.0E+01	6.6E+01
LED TV	growth	linear	3.6E+13	9.8E-01	9.8E-01	2.3E+06	1.4E+02	1.3E+02
		logistic	1.9E+13	9.9E-01	9.9E-01	1.7E+06	1.4E+02	1.3E+02
		exponential	1.1E+14	9.4E-01	9.3E-01	4.0E+06	1.4E+02	1.4E+02
	decay	No Data						
Tablet	growth	linear	9.8E+13	9.8E-01	9.7E-01	5.7E+06	8.1E+01	7.7E+01
		logistic	4.1E+13	9.9E-01	9.9E-01	3.7E+06	8.2E+01	7.6E+01
		exponential	5.9E+14	8.8E-01	8.4E-01	1.4E+07	8.5E+01	8.1E+01
	decay	linear	3.2E+13	9.8E-01	9.7E-01	2.5E+06	1.1E+02	1.0E+02
		logistic	1.1E+14	9.1E-01	8.9E-01	4.8E+06	1.1E+02	1.1E+02
		exponential	3.3E+13	9.7E-01	9.7E-01	2.6E+06	1.1E+02	1.0E+02

The forecasting capability of the MFA model is validated by comparing e-waste flow forecasts generated by the model with past e-waste flow estimations in literature**.**

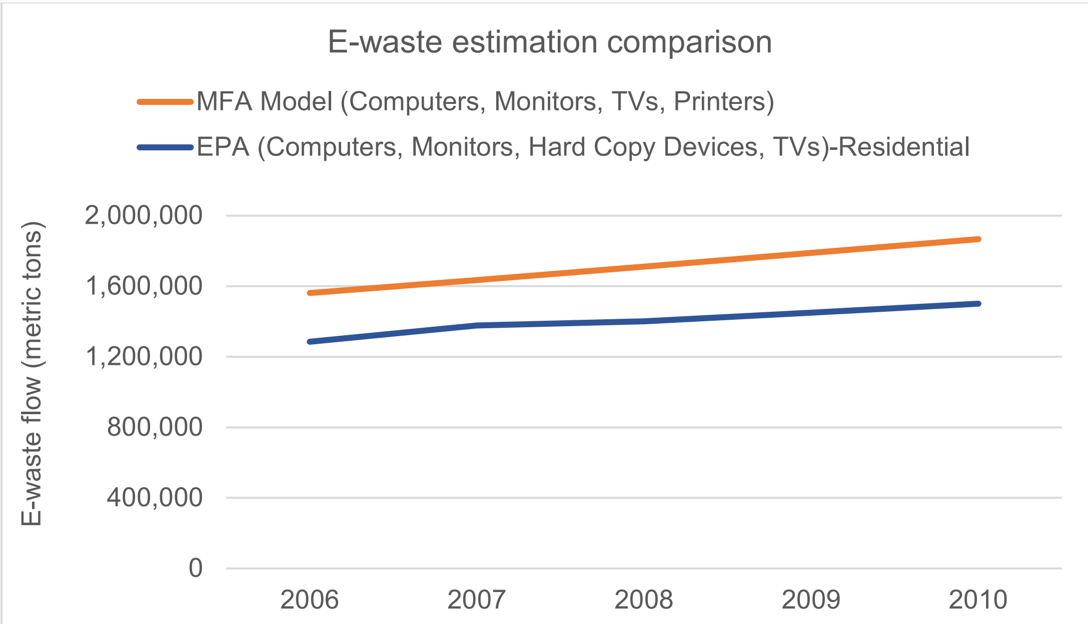

Figure 4: Comparing MFA results to a U.S. Environmental Protection Agency (2011) study.

<u>Material flow calculations to understand implications of MFA results to CE planning.</u>

Product flow forecasts are applied to material profile of products to gain insights on key implications of MFA forecasts on circular economy planning.

Table 8: Forecasting near term lead outflows from Cathode Ray Tube (CRT) devices

Year	CRT TV waste flow forecasts (metric tons)	CRT Monitor waste flow forecasts (metric tons)	Total CRT waste flows (metric tons)	Forecasted Lead waste flow from CRTs (metric tons)
2018	1.2E+06	7.1E+04	1.2E+06	7.4E+04
2019	1.0E+06	4.6E+04	1.1E+06	6.5E+04
2020	8.7E+05	2.8E+04	9.0E+05	5.4E+04
2021	6.8E+05	1.6E+04	6.9E+05	4.2E+04
2022	4.8E+05	9.1E+03	4.9E+05	2.9E+04
2023	3.0E+05	5.0E+03	3.1E+05	1.9E+04
2024	1.7E+05	2.7E+03	1.7E+05	1.0E+04
2025	8.4E+04	1.4E+03	8.5E+04	5.1E+03

Lead waste flow forecasts assume 6% lead content per ton of CRT device as reported by Babbitt et al (2017).

Table 9: Forecasting near term indium flows from Flat panel TVs (LCD and LED).

Year	LCD TV waste flow forecast (units)	LED TV waste flow forecast (units)	Total Flat panel TV waste flow forecast (units)	LED TV sales forecast (units)	LCD TV sales forecast (units)	Total Flat panel TV sales forecast (units)	Forecasted Indium waste flows (metric tons)	Forecasted Indium demand (metric tons)
2018	2.1E+07	8.4E+06	3.0E+07	4.1E+07	1.8E+06	4.3E+07	7.7E+00	1.1E+01
2019	2.0E+07	1.3E+07	3.2E+07	3.9E+07	9.5E+05	4.0E+07	8.4E+00	1.0E+01
2020	1.7E+07	1.7E+07	3.4E+07	3.6E+07	4.9E+05	3.7E+07	8.9E+00	9.6E+00
2021	1.4E+07	2.2E+07	3.6E+07	3.0E+07	2.5E+05	3.1E+07	9.4E+00	8.0E+00
2022	1.1E+07	2.7E+07	3.8E+07	2.2E+07	1.2E+05	2.2E+07	9.8E+00	5.7E+00
2023	7.6E+06	3.1E+07	3.8E+07	1.3E+07	6.2E+04	1.3E+07	1.0E+01	3.3E+00
2024	4.9E+06	3.3E+07	3.8E+07	6.2E+06	3.1E+04	6.3E+06	9.9E+00	1.6E+00
2025	3.0E+06	3.4E+07	3.7E+07	2.7E+06	1.6E+04	2.8E+06	9.6E+00	7.2E-01

Indium flow forecasts assume 260 mg indium content per flat panel TV as reported by Babbitt et al (2017).

Table 10: Forecasting near term cobalt flows from laptops.

Year	Laptop waste flow forecasts (metric tons)	Laptop sales forecasts (metric tons)	Forecasted LIB demand (metric tons)	Forecasted LIB waste flow (metric tons)	Forecasted cobalt waste flows (metric tons)	Forecasted cobalt demand (metric tons)
2018	7.1E+04	6.0E+04	8.4E+03	9.9E+03	1.3E+03	1.1E+03
2019	6.9E+04	5.5E+04	7.8E+03	9.6E+03	1.2E+03	1.0E+03
2020	6.6E+04	5.1E+04	7.1E+03	9.2E+03	1.2E+03	9.3E+02
2021	6.3E+04	4.6E+04	6.5E+03	8.8E+03	1.1E+03	8.4E+02
2022	5.9E+04	4.2E+04	5.8E+03	8.3E+03	1.1E+03	7.6E+02
2023	5.5E+04	3.7E+04	5.2E+03	7.7E+03	1.0E+03	6.7E+02
2024	5.1E+04	3.2E+04	4.5E+03	7.1E+03	9.3E+02	5.9E+02
2025	4.7E+04	2.8E+04	3.9E+03	6.5E+03	8.5E+02	5.1E+02

Cobalt flow forecasts assume 14% LIB (Lithium ion battery) content in laptops and 13% cobalt content in LIBs as reported by Buchert et al (2012).

Table 11: Average material profile of drones

Aluminum	Copper	Steel	Plastic	PCB	LIB	Flat Panel Glass	Others	Total mass (g)
3%	3%	15%	54%	10%	14%	1%	3%	947

Data Source: Product disassembly data

Table 12: Cobalt demand forecast for drones.

Year	Drone sales forecasts (units)	Drone sales forecasts (metric tons)	Forecasted LIB demand for drones (metric tons)	Forecasted cobalt demand for drones (metric tons)
2013	5.3E+04	5.0E+01	7.2E+00	9.4E-01
2014	1.7E+05	1.6E+02	2.3E+01	3.0E+00
2015	5.1E+05	4.9E+02	7.0E+01	9.1E+00
2016	1.4E+06	1.3E+03	1.9E+02	2.5E+01
2017	3.0E+06	2.8E+03	4.0E+02	5.2E+01
2018	4.5E+06	4.3E+03	6.2E+02	8.0E+01
2019	5.4E+06	5.1E+03	7.4E+02	9.6E+01
2020	5.7E+06	5.4E+03	7.8E+02	1.0E+02
2021	5.4E+06	5.1E+03	7.4E+02	9.6E+01
2022	4.5E+06	4.3E+03	6.2E+02	8.0E+01
2023	3.0E+06	2.8E+03	4.0E+02	5.2E+01
2024	1.4E+06	1.3E+03	1.9E+02	2.5E+01
2025	5.1E+05	4.9E+02	7.0E+01	9.1E+00

Cobalt demand forecasts as based on most likely adoption scenario of drones.

Table 13: Annual sales data of emerging products in units sold to residential sector. Data were provided by the Consumer Technology Association. 2018 and 2019 values are projections made by CTA.

Year	Fitness Trackers	Drones	Smart Thermostats	OLED TVs
2011	32,00,000			
2012	8,415,000			
2013	10,267,000	127,500	425,000	
2014	16,800,000	449,700	1,020,000	
2015	20,254,000	1,144,670	1,550,000	
2016	22,824,000	2,425,000	3,256,000	
2017	21,217,000	3,109,000		532,140
2018	20,656,000	3,363,260		771,603
2019		3,544,854		1,234,565

APPENDIX C

Table 1. Sustainability Metrics Definition

Sustainability Aspects	Metric	Unit	Definition	DataSource
Environmental	**Global Warming Potential (GWP)**	kg CO2 eq	Quantifies the supply chain emissions from processes required to extract and product materials for use in CT products.	Ecoinvent database, Simapro LCA Software
	Cumulative Energy Demand (CED)	MJ	Quantifies the net energy and fuel resources associated with extracting and producing a material for use in a CT product.	Ecoinvent database, Simapro LCA Software
	Mineral Resource Demand (MRD)	kg Fe eq	Analyzes the life cycle input of mineral resources associated with extracting and producing a material for use in a CT product.	Ecoinvent database, Simapro LCA Software
	Supply Chain Ecotoxicity	PAF.m3.day	Quantifies the potential toxicity of a wide array of chemicals emitted into freshwater systems in a materials' production chain.	USEtox Characterization Factors
	Direct Ecotoxicity	species·yr/kg 1,4-DBC emitted to freshwater eq	Represents the potential toxic effect of a metal on freshwater eco system, if is emitted into freshwaters.	ReCiPe Method, Characterization factors

Table 1. Sustainability Metrics Definition- Continued

Sustainability Aspects	Metric	Unit	Definition	DataSource
Economic	**Global reserves**	metric tons	Reserve is the working inventory of supply of economically extractable mineral commodity.	USGS Mineral Commodity Summaries 2018
	Ore concentration	%	Percentage of material content in its ore	Sverdrup et al (2017)
	Annual Production	metric tons	Mine production of a metal in year 2017.	USGS Mineral Commodity Summaries 2018
	Static Index of Depletion	year	Ratio of global reserve of a material to the annual demand or production of the material. Reserve is the working inventory of supply of economically extractable mineral commodity.	Calculated
	Herfindahl-Hirschman Index (HHI)	-	Measures the geographical concentration of material production. The HHI value is always positive with higher values indicating a more concentrated production (undesirable).	Calculated based on producer countries information from USGS
	Price	$/pound	Metal price in year 2017	USGS Mineral Commodity Summaries 2018
	Price Volatility		Annual change in material price expressed as 5 year (2014-2018) coefficient of variation	Calculated price information from USGS
	Import Reliance-US Perspective		Percentage of total material consumed in the US annually that is imported.	USGS Mineral Commodity Summaries 2018
	Electronics Sector Demand	%	Measures material use in electronic sector, as the percentage of annual mine production of a material.	Gradeal et al (2015)

Table 1. Sustainability Metrics Definition- Continued

Sustainability Aspects	Metric	Unit	Definition	DataSource
Social	**PSAV-Herfindahl-Hirschman index (PSAV-HHI)**	-	PSAV-Herfindahl-Hirschman index-In addition to considering how concentrated the production of a given material is, this metric also considers the socio-political stability of the producer countries to evaluate risk to business continuity. The WGI-PSAV weighting metric can be positive or negative, with negative indicating less stability and more violence.	Calculated based on country level PSAV Data from World Bank and HHI

Table 2. Recycling Potential Metrics Definition.

Sustainability Aspects	Metric	Unit	Definition	DataSource
Recycling Potential	**Theoretical Recycling Efficiency in US**	%	Represents amount of old scrap recovered and reused relative to the amount available to be recovered and reused.	Graedel et al (2011)
	Secondary Material Use in US	%	Represents the fraction of the apparent metal supply that is scrap on an annual basis.	Graedel et al (2011)
	Theoretical Circularity Potential	-	Calculated as ratio of material waste to material demand in electronics in year 2018, from Chapter 1 MFA results	Calculated based on e-waste estimation from Chapter 1
	Material Dilution in E-waste	%	Calculated as ratio of material waste mass to total e-waste mass estimated for 2018, based on from Chapter 1 MFA results.	Calculated based on e-waste estimation from Chapter 1

Table 3. Economic aspects of sustainability associated with material sourcing represented using metrics such as global reserves, ore concentration, annual mine production, rate of depletion (static index of depletion) and HHI (geographical concentration of production.

Materials		Global Reserves (metric tons)	Ore concentration (%)	Annual Mine Production (metric tons)	Static Index of depletion based on reserve (years)	Geographical Concentration of Production (HHI Index)	Production % as byproduct
Base Metals	Al	7,000,000,000	50%	60,000,000	117	0.31	0%
	Cu	790,000,000	3%	19,700,000	42	0.16	9%
	Mg		40%	1,100,000		0.72	4%
	Fe	80,000,000,000	55%	1,700,000,000	47	0.28	0%
	Ni	74,000,000	1%	2,100,000	35	0.10	2%
	Zn	230,000,000	6%	13,200,000	17	0.20	10%
	Ti	930,000,000	35%	170,000	130	0.26	0%
Precious Metals	Au	54,000	0%	3,150	17	0.13	15%
	Ag	530,000	0%	25,000	21	0.13	71%
	PGM	69,000	0%	474	146	0.51	16%
Critical Metals	Sb	1,500,000	0%	150,000	10	0.55	80%
	Ba	290,000,000		7,700,000	38	0.19	2%
	Co	7,100,000	5%	110,000	65	0.36	85%
	Ga	50,000	0%	292	43	0.25	100%
	Gr	270,000,000		1,160,000	233	0.45	
	In	1,000	0%	720	2	0.30	1%
	Li	16,000,000	1%	43,000	372	0.32	52%
	Mn	680,000,000	55%	16,000,000	43	0.18	3%
	Ta	110,000		1,300	85	0.21	28%
	Te	31,000	0%	420	74	0.47	100%
	Sn	4,800,000	8%	290,000	17	0.05	3%
	V	20,000,000	5%	80,000	250	0.37	82%
	REEs	110,000,000	5%	130,000	846	0.68	100%
Hazardous Metals	Pb	88,000,000	3%	4,700,000	19	0.29	10%
	Hg			2,500	200	0.66	10%
	Cr	810,000,000	55%	310,000,000	3	0.30	2%
	Cd	500,000	0%	23,000	23	0.19	1%

Table 4. Economic aspects of sustainability associated with material production as by product.

Materials		Production % as byproduct	Parent Metal
Base Metals	Al	0%	-
	Cu	9%	Ni (5%), Au (2%), Pb/Zn (2%), Ag, Pt
	Mg	4%	K(Potash)
	Fe	0%	-
	Ni	2%	Pt, Pd
	Zn	10%	Cu
	Ti	0%	-
Precious Metals	Au	15%	Cu (12%), Zn, Ag
	Ag	71%	Zn/Pb (36.5%), Cu (23.5%), Au (10.4%), Other (0.5%)
	PGM*	16%	16% represents Pt production from Ni.
Critical Metals	Sb	80%	Pb (40%), Ag (16%), W (12%), Sn (8%), Au (4%)
	Ba	2%	Cu, Au, Pb, Ag, Zn and fluorite
	Co	85%	Ni (50%), Cu (35%), Pt, Pd, As
	Ga	100%	Al, Zn
	Gr		
	In	1%	Zn (80%), Sn (15%), Cu (5%)
	Li	52%	K(Potash)
	Mn	3%	Fe
	Ta	28%	Sn slag (15%), Nb (13%)
	Te	100%	Cu (>90%), Pb and Bi (<10%)
	Sn	3%	Zn (2%), Ta (0.4%), Cu (0.1%)
	V	82%	Fe (62%), Alumina (12%)
	REEs	100%	Fe
Hazardous Metals	Pb	10%	Zn, Cu
	Hg	10%	Au-Ag
	Cr	2%	Pt
	Cd	1%	Zn

Note: Only 16% of Pt is produced as by-product while 100% of Ru, Rh, Pd, Os and Ir are produced as by-products of Pt.

Table 5. Economic aspects of sustainability associated with material availability represented using metrics such as price, price volatility, electronic sector consumption and import reliance in the US.

Materials		Price ($/lb)	Price Volatility (5 year coefficient of variation)	Import Reliance: US Perspective (% of total consumption)	Electronics Sector Consumption (% of total production)
Base Metals	Al	0.99	0.1	61%	7%
	Cu	2.85	0.2	33%	4%
	Mg	2.15	0.0	25%	6%
	Fe	0.28	0.3	18%	6%
	Ni	4.60	0.2	59%	11%
	Zn	0.34	0.1	85%	17%
	Ti	0.09	0.1	53%	12%
Precious Metals	Au	18261	0.1	0%	6%
	Ag	249	0.2	62%	25%
	Pd	12464	0.1	45%	10%
	Pt	13913	0.2	68%	3%
	Rh	15217	0.2		1%
Critical metals	Sb	4.01	0.1	85%	26%
	Ba	0.08	0.1	75%	16%
	Co	26.6	0.4	72%	22%
	Ga	202	0.3	100%	67%
	Gr	0.64		100%	25%
	In	164	0.3	100%	84%
	Li	6.95	0.4	50%	46%
	Mn	0.00	0.1	100%	2%
	Ta	87.7	0.1	100%	48%
	Te	16.4	0.5	75%	6%
	Sn	9.50	0.1	75%	48%
	V	5.20	0.2	100%	9%

Table 5. Economic aspects of sustainability associated with material availability represented using metrics such as price, price volatility, electronic sector consumption and import reliance in the US. Continued

Materials		Price ($/lb)	Price Volatility (5 year coefficient of variation)	Import Reliance: US Perspective (% of total consumption)	Electronics Sector Consumption (% of total production)
REEs	La	1.36	0.5	100%	16%
	Ce	1.36	0.5	100%	10%
	Pr	52.3	0.2	100%	5%
	Nd	26.1	0.2	100%	76%
	Eu	35.2	1.1	100%	100%
	Sm				73%
	Gd	48.26	0.0	100%	21%
	Y	3.64	0.5	100%	
	Tb	215.91	0.3	100%	
	Dy	84.09	0.4	100%	100%
Hazardous Metals	Pb	1.12	0.1	40%	80%
	Hg	13.16	0.5	0%	10%
	Cr	4.75	0.1	69%	5%
	Cd	0.77	0.2	25%	66%

Table 6. Environmental aspects of sustainability using metrics such as global warming potential (GWP), cumulative energy demand (CED) and mineral resource demand (MRD).

Materials		GWP (kg $CO2_{eq}$)	CED (kgCO2 $_{eq}$)	MRD (kgFe_{eq})	Supply Chain Ecotoxicity (PAF.m3.day)	Direct EcoToxicity (species·yr/kg 1,4-DBC emitted to freshwater eq)
Base Metals	Al	20	222	0.4	338,003	-
	Cu	4.1	61	53	1,375,377	162
	Mg	32	401	1	217,045	-
	Fe	2	21	1	6,080	-
	Ni	12	177	45	392,609	46
	Zn	5	62	4	79,350	211
	Ti	0	4	0.05	222,666	-
Precious Metals	Au	17083	256403	81312	5,438,507,700	-
	Ag	360	5492	1424	19,497,900	485
	Pd	6117	84645	32322	143,142,550	-
	Pt	29145	368365	140481	1,040,594,500	-
	Rh	26849	344844	130323	912,131,180	-
Critical Metals	Sb	10	149	4	2,730,766	-
	Ba	0	1	0	31,400	3
	Co	10	137	2	118,931	6
	Ga	195	2737	10	624,480	-
	Gr	2	55	0	14,000	-
	In	223	2715	118	3,707,743	-
	Li	168	2514	5	616,750	-
	Mn	4	62	179	96,481	-
	Ta	305	4748	46	2,612,227	-
	Te	8	135	28	782,272	-
	Sn	22	327	1486	186,181	5
	V	33	516			178

Table 6. Environmental aspects of sustainability using metrics such as global warming potential (GWP), cumulative energy demand (CED) and mineral resource demand (MRD). Continued

Materials		GWP (kg $CO2_{eq}$)	CED (kgCO2 $_{eq}$)	MRD (kgFe_{eq})	Supply Chain Ecotoxicity (PAF.m3.day)	Direct EcoToxicity (species·yr/kg 1,4-DBC emitted to freshwater eq)
REEs	La	11	215	2	11,223	-
	Ce	13	252	1	11,223	-
	Pr	19	376	4	11,223	-
	Nd	18	344	4	11,223	-
	Sm	59	1160	2	116,552	-
	Eu	395	7750	2	116,552	-
	Gd	47	914		116,552	-
	Y				11,223	-
	Tb	297	5820		11,223	-
	Dy	60	1170		11,223	-
	Ho	226	4400		11,223	-
	Tm	649	12700		11,223	-
	Yb	125	2450		11,223	-
	Lu	896	17600		11,223	-
Hazardous Metals	Pb	1	17	2	24,978	1
	Hg	15	126	0	60,101	50
	Cr	31	538	36	352,895	87
	Cd	1	17	0	10,766	17

Table 7. Potential for recycling as a sustainability solution quantified using metrics such as theoretical recycling efficiency, secondary material availability, theoretical potential for circularity and material dilution in e-waste.

Materials		Theoretical Recycling Efficiency in US	Secondary Material Use in US	Theoretical Circularity Potential	Material Dilution in E-waste
Base Metals	Al	42%	36%	1.97	4.656%
	Cu	43%	30%	2.52	3.935%
	Mg	39%	33%	2.37	0.015%
	Fe	52%	41%	1.49	24.170%
	Ni	57%	41%	2.29	0.130%
	Zn	19%	27%	3.42	0.173%
	Ti	91%	52%	1.80	0.000%
Precious Metals	Au	96%	29%	2.37	0.004%
	Ag	97%	32%	2.37	0.013%
	Pd	65%	50%	2.37	0.001%
	Pt	76%	16%	2.37	0.000%
	Rh	65%	40%		
	Ru	10%	55%		
	Ir	25%	18%		
	Os	0%	0%		
Critical metals	Sb	89%	20%	2.37	0.033%
	Ba	0%	0%		0.926%
	Co	68%	32%	1.31	0.249%
	Ga	0%	38%	2.26	0.000%
	Gr	0%	0%	1.31	0.214%
	In	0%	38%	1.52	0.001%
	Li	0%	0%	1.31	0.029%
	Mn	53%	37%	2.37	0.012%
	Ta	35%	21%	2.37	0.002%
	Te	0%	0%		0.000%
	Sn	75%	22%	2.37	0.288%
	V	0%	0%		0.000%

Table 7. Potential for recycling as a sustainability solution quantified using metrics such as theoretical recycling efficiency, secondary material availability, theoretical potential for circularity and material dilution in e-waste. Continued

Materials		Theoretical Recycling Efficiency in US	Secondary Material Use in US	Theoretical Circularity Potential	Material Dilution in E-waste
REEs	Ln	5%	0%	5.42	0.000%
	Ce	5%	5%	4.47	0.000%
	Pr	0%	5%	5.42	0.000%
	Nd	0%	0%	1.25	0.005%
	Eu	0%	0%	5.23	0.0000%
	Gd	0%	5%	0.77	0.0000%
	Y	0%	0%	4.75	0.0003%
	Tb	0%	0%	5.42	0.0000%
	Dy	0%	0%	1.29	0.0001%
Hazardous Metals	Pb	95%	63%	2.37	3.373%
	Hg	5%	38%	2.37	0.000%
	Cr	87%	20%	2.37	0.003%
	Cd	15%	14%		0.002%

Table 8. Major use sectors.

Materials	Major Use Sector	Use (%)
Cd	Batteries	66%
Cr	Infrastructure Steel	25%
Hg	Gold Mining	21%
Pb	Batteries	80%
Dy	Neodymium magnets	100%
Gd	Neodymium magnets	69%
Eu	Phosphors	100%
Sm	Battery alloy	73%
Nd	Neodymium magnets	76%
Pr	Neodymium magnets	70%
Ce	Glass Polishing	25%
La	Fluid cracking catalysts	46%
V	Steel Alloy	43%
Sn	Solder	54%
Te	Metallurgy	48%
Ta	Capacitors	100%
Mn	Metallurgy	90%
Li	Batteries	46%
In	Flat Panel Displays	84%
Gr	Refractories	35%
Ga	Integrated Chips	67%
Co	Batteries	80%
Ba	Oil Industry	54%
Sb	Flame Retardants	51%
Rh	Auto catalyst	86%

	Major Use Sector	Use %
Pt	Auto catalyst	33%
Pd	Auto catalyst	54%
Ag	Electrical	23%
Au	Jewelry	62%
Ti	Pigments	88%
Zn	Galvanizing	50%
Ni	Industrial machinery	31%
Fe	Construction	48%
Mg	Refractories	86%
Cu	Electrical	26%
Al	Automotive applications	28%

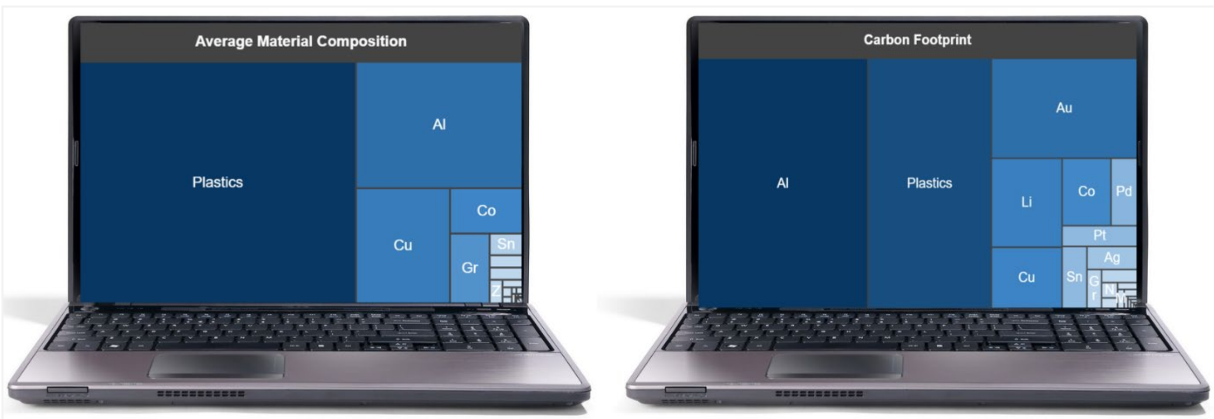

Figure 1. Comparing the average material composition of a typical 14-inch laptop to the relative contribution to total material carbon footprint (supply chain greenhouse gas impact of producing all materials contained in the average laptop bill of materials)**.** It is to be noted that reported carbon footprint is material specific and do not include production manufacturing and use phase impacts. Analysis is performed by applying global warming potential metric to laptop material profile compiled for MFA in chapter 2.

Table 9. Battery materials recycling yields, defined as the ratio of material recovered to total material input to a recycling process (does not account for collection, etc.)

Battery Materials	Current Recycling Yield	Lab Scale Yields (Mid)	Lab Scale Yields (High)
Co	68%	80%	99%
Li	0%	55%	10%
Al	42%	55%	98%
Ni	57%	99%	99%
Mn	0%	92%	98%