HOUSEHOLD MANAGEMENT OF CONSUMER ELECTRONICS IN THE UNITED STATES

by

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To my Family and Rae

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LIST OF ABBREVIATIONS

U.S. United States
ISEE Integrated Systems Engineering Development
EOL End of Life
MICE Multiple Imputation by Chained Equations
PCB Printed Circuit Board
USGS US Geological Survey
CPS Current Population Survey
LCA Life Cycle Assessment
REM Rare Earth Metals
PM Precious Metals
HHS Household Size
TC Transfer Coefficient

ABSTRACT

Electronic waste is one of the fastest growing waste streams, spurred by their rising market and demand. However, these devices contain an array of metals that is recyclable for economic and environmental benefit through secondary manufacturing. As the turnaround rate for newer models quickens, consumers are motivated to purchase novel devices, leaving their current ones behind. Focusing on how United States (U.S.) households manage their electronics, a top-down approach stock and flow STELLA model was created to model the lifecycle of eight common electronics. Input data for the model came from a public online survey directed to U.S. household owning adults. From the model, a metallic stock and flow analysis was conducted to quantify the trends, environmental footprint, and economic value of stored devices in U.S. households and how it compares to devices being used, disposed, and recycled. The number of stored devices in the U.S. was found to be increasing annually with a stored amount of over 757 million stored individual electronic devices, nearly half of which originate from cell phones, carrying an economic value of 32.6 billion US dollars (USD) and carbon emissions of 7.6 billion kilograms (kg) from their metallic components alone for the year 2020. Most of the pollution and economic value stems from precious metals (PMs) and in a circular economy, these stored metals can have a significant impact to the environment and economy through recycled. Also, with advancing capabilities of smartphones, the metallic composition for device components of Samsung galaxy smartphones was quantified to assess their evolving metallic content. With the growing market of electronic devices, knowing the value and importance of devices currently in U.S. households is critical. This underlies the influence of sustainable design through a circular economy to push initiatives to manufacture recyclable friendly devices, expand the metal recycling industry, and motivate citizens to properly handle their stored devices.

1. U.S. HOUSEHOLD STORAGE OF ELECTRONIC DEVICES

1.1 Introduction and Problem Statement

Electronic devices in U.S. households have been a staple to a growing capacity within the 21st century, revolutionizing the consumer electronics sector[1]. As the number and type of electronics expands, feeding into a growing number of devices placed into consumers' hands, less is known about how these electronics behave in U.S. households in terms of what consumers do with both old and new electronic devices. Furthermore, current and past research on consumer behavior of electronic devices is fragmented and sparse, focusing on smaller timescales, limited range of devices, and countries outside of the United States. Limited to China, the United Kingdom, and Switzerland dominating most research from the past 15 years[2]. From these studies, only 2 included a spatial component with empirical data to see how consumer behavior for devices changes over time, restrained within the past decade[3,4]. Natively, only 3 surveys have been conducted in the U.S. covering consumer behavior for devices, with the latest occurring over a decade ago in in the year 2011. Two of the three studies considered only college students, a small subset of the general household population, and none factored in a time dependence[5,6,7]. They also did not account for the economic benefit and environmental impact of devices from a circular economy. Limited in scope due to their sample population, different economic markets, and governmental bodies, it is difficult to draw any conclusions about the quantities and trends in behavior of device usage for the U.S.'s specific consumer market and geographic location over an extended length of time.

This research aims to fill these gaps of knowledge by first answering how many devices are in-use, stored, and disposed of from U.S. households for a range of common household electronic devices, and their annual fluctuating trends during entirety of the 21st century. Second, determine if the quantity of metals from stored devices in U.S. households can meet the U.S. demand for valuable metals. Lastly, estimate the environmental impact and economic value of these devices at a metallic level, and which elements and devices are significant contributors to both.

Exploring how many devices are given to another user, stored, and disposed provides important insights into how effective a circular economy could be in the U.S., and which metals from these devices are useful from an economic and environmental perspective. Shorter lifecycles for devices like cell phones has resulted in an increase in electronic waste (e-waste) disposal, estimated at 2.3 million tons of e-waste landfilled or incinerated in the United States annually and is expected to grow three times faster than municipal waste generation[8,9]. However, this increase in e-waste disposal has not led to increases in device recycling with an estimated 9% of electronics sold between the years 1980 and 2004 put to storage after use within the United States[10]. Due to the expanding complexity of these devices and changing consumer behavior, measures to implement a circular economy by diverting stored devices away from disposal and into secondary manufacturing is important to reduce the growing metal scarcity of rare earth and critical metals[11,12,13]. Understanding the behavioral dynamics of devices in U.S. households and quantifying their trends, allows identification of which devices and metals will be of most use to secondary manufacturing, and whether a circular economy provides substantial benefits to both the U.S.'s economy and environment.

To collect information about how U.S. households manage their electronic devices an online public survey was distributed within the U.S. to household owning adults. The survey asked responders how they used both current and past electronic devices in terms of use and storage duration, and handling after they were finished with them. An online survey was deemed as the most effective tool to collect information at this geographic scale due to its ability to reach out to a broader population with ease of access[14]. Utilizing the internet allows multiple methods of distribution through social media, email communication, and scannable barcodes making the survey reachable to 85% of all U.S. households, who reported having a broadband internet subscription in their home for the year 2018[15,16].

To quantify the effects of a circular economy on electronics from U.S. households, a top-down approach stock and flow STELLA model was developed to determine where metals from devices are moving and their trends within U.S. households, especially metals in storage, from the past two decades. The metal categories of interest are Rare Earth Metals (REMs), Precious Metals (PMs), and critical metals, as defined by the U.S. Geological Survey (USGS), in order to cover a wide range of metals found in electronic devices[17]. A full list of metals organized by metal category is shown in Appendix E.

The environmental impact and economic value were also assessed on metals used, stored, and disposed or recycled in U.S. households to determine the potential savings in emissions and monetary value from secondary manufacturing. The processes for mining and refining these metals are energy extensive, contributing to global warming, and release large quantities of toxic waste that can harm the environment if not handled properly[18,19]. Additionally, due to the large number of stored devices, metals from each category present high value propositions for recycling them. Hence, understanding the trends and extent of what can be reclaimed, and impact avoided is key under a circular economy standpoint[20,21]. Additionally, REMs and PMs, due to their scarcity as a natural resource and limited mining globally, presents a fragile supply chain[22]. Therefore, integrating the U.S.'s current demand of these metals provides a realistic application of the effectiveness of re-introducing stored metals back into the U.S.'s economy.

Through the STELLA model, the quantity of devices in storage in U.S. households was found to be increasing annually, with smaller devices like cell phones and headphones comprising most of the stored devices in U.S. households. This underscores a shift in behavior as users begin to commonly store devices rather than discard them. PMs within these devices contained the most monetary value from all three metal categories along with a majority of the environmental impact emissions pertaining to human toxicity. This presents a focus to recycling PMs for both economic and environmental benefit. Lastly, when compared to gold demand in the U.S and combined with current recycling amounts, enough gold is present in stored devices to exceed U.S. demand proving the effectiveness of reclaiming gold from unused devices.

1.2 Materials and Method

1.2.1 Stock and Flow Model

STELLA (Systems Thinking, Experimental Learning Laboratory with Animation) is a visual programming language to model dynamic systems[23]. It is developed by the Integrated Systems Engineering Environment (ISEE) and a simulation program to model systems. The 8 devices modeled here are cell phones, laptops, tablets, smart watches, headphones, desktop PCs, televisions, and printers. These devices were chosen based on their popularity and abundance within US households[24]. This approach separates the device lifecycle into multiple subcomponents, defined as stocks. Devices can be in one of four different stocks: in-use, storage, disposal, and recycled. Devices in-use mean they are currently in the household and being used. Devices in storage mean the device is currently in the household but not being used. Recycled devices mean the device was recycled at a recycling facility, recycling collection event, or company take-back program. Devices that have been disposed of mean the device is no longer in possession and was not recycled. The number designations 1, 2, and 3 for each stock signify which user currently possesses the device or last user to possess the device before disposal. A device in the Use 1 stock means the device is currently being used by the 1st user, while a device in the Use 2 stock means the device is currently being used by the 2nd user. The same is true for storage meaning a device in the Storage 1 stock means the device is currently stored by the 1st user and Storage 2 means device is currently stored by the 2nd user. A device in the Disposal 1 stock means it was disposed by the 1st user of the device, and Disposal 2 means the device was disposed of by the 2nd user.

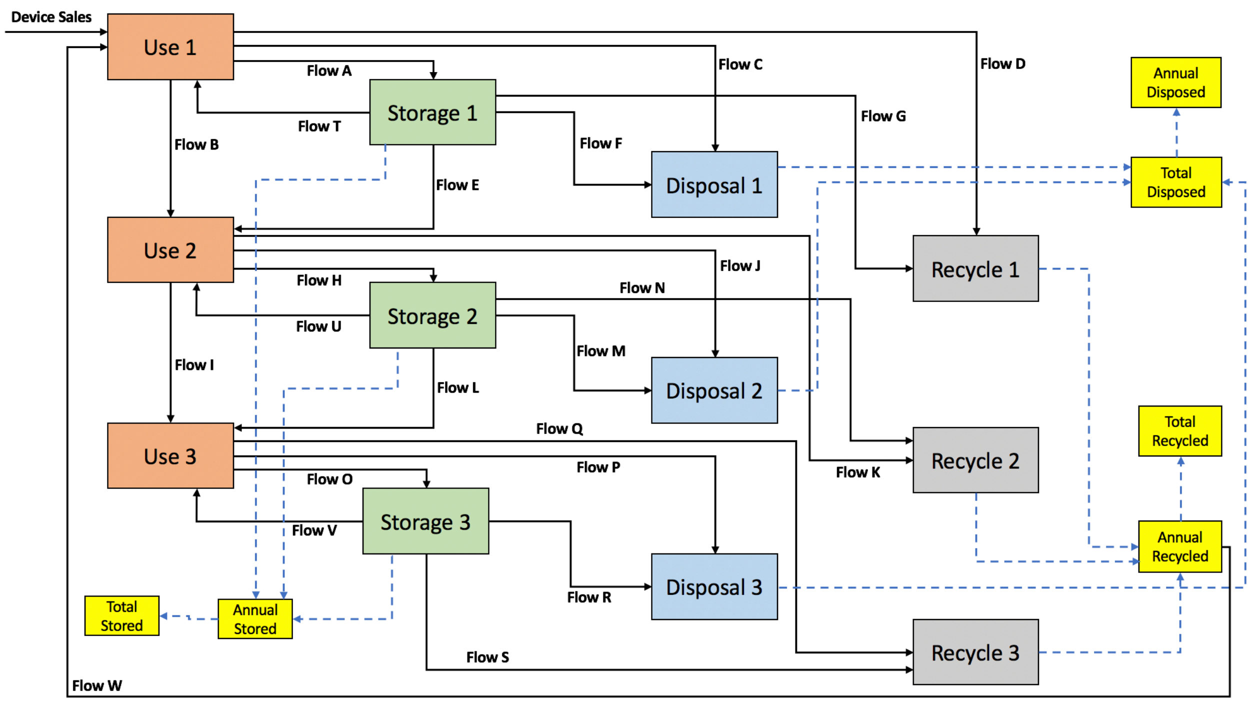


Figure 1: Stock and Flow Model of electronic devices depicting their life cycle as they move from the first user to end of life. Stocks are represented by boxes and flows are represented by arrows and labeled alphabetically.

Flows transfer devices between stocks and are controlled by transfer coefficients, which act as valves that open or close to allow more or fewer devices to move between stocks. A transfer coefficient of zero corresponds to zero devices flow between stocks, while a transfer coefficient of 1 corresponds to all devices in a stock flow to another stock. The ratio of the total amount of flow leaving a stock is called the Stock Exit Ratio and determines the total amount of flow leaving a stock per year. Brand new devices enter the model through annual sales data into a User 1 Stock, then flow to different stocks, for example Storage 1, until they reach a Disposal or Recycle Stock which represents the end of life (EOL) for that device. Devices will continuously flow in the model from the initial year of 2000 up to the year 2021 until they reach their EOL. A representation of the model is shown in Figure 1.

Each stock is defined by differential mass balance equations calculated from flows entering and exiting through the stock exit ratio and transfer coefficients, and the initial stock amount from the previous year (Eq. 1) (see section 1.2.4). The STELLA model simultaneously solves these equations to determine the stock amounts and flows. This process is repeated for each year from the year 2000 to 2021. Refer to Appendix A.6 for the mass balance equations for each stock.

$$\frac{dM_{stock}}{dt} = \text{Flow}_{\text{in}} - \text{Flow}_{\text{out}} + M_{\text{stock,t}-1} \qquad \text{(Eq. 1)}$$

Where:
M_{stock} = model stock amount [# of devices]
t = time [year]
$Flow_{in}$ = sum of flows entering stock [# of devices]
$Flow_{out}$ = sum of flows leaving stock [# of devices]
$M_{stock, t-1}$ = stock amount from previous year [# of devices]

The model inputs for these stock equations were collected via a survey that was distributed to adult participants (18 years of age or older) who reside in U.S. households. The goal of the survey was to determine how U.S. households use, store, and dispose of devices they are currently using and have previously owned (see section 1.2.2).

1.2.2 Survey – Generation

The survey consists of 5 sections: Introduction, Devices Currently Used, Devices Currently Stored, Devices that have been disposed of or Recycled, and Demographic Info. Survey questions were based on a prior study conducted in Switzerland[4]. Refer to Appendix E for a table with the survey questions mapped to the STELLA Model parameters and Appendix A.1 for screen shots of the complete survey, as viewed from Qualtrics.

Each section of the survey collects time-specific data translatable into input for the STELLA Model (see section 1.2.4). The 1st section of the survey is the introduction and gives survey respondents a brief overview of the questions, International Review Board protocol statements, and terminology along with the survey purpose. A screenshot of the terminology portion of the Introduction Section is shown in Figure 2.

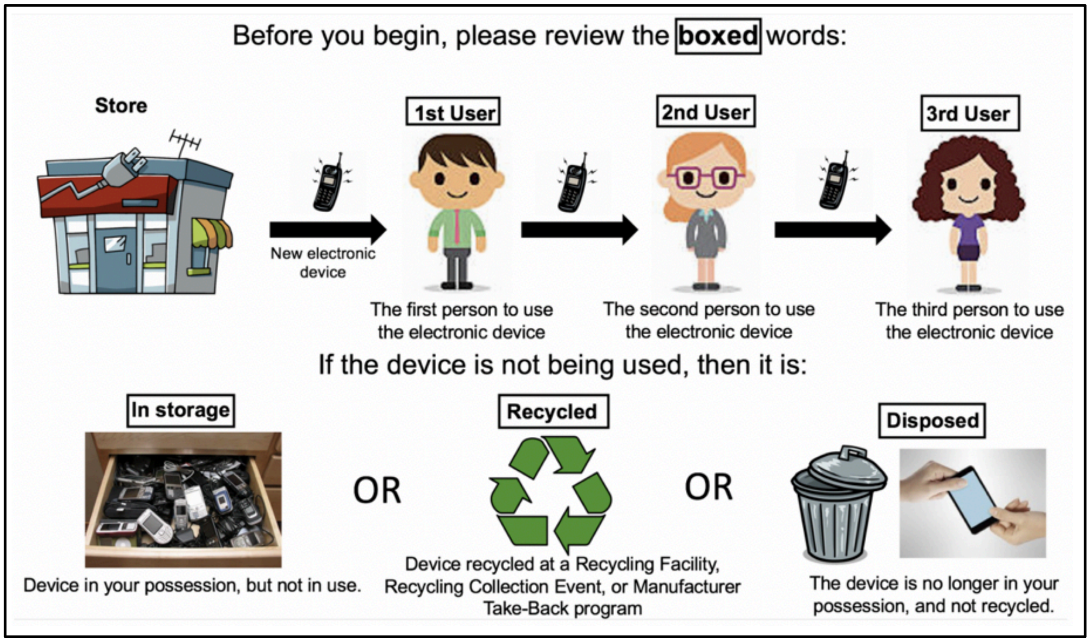


Figure 2: Introduction Section of Survey containing a breakdown of device users with definitions for each of the 4 stocks.

The following 3 survey sections asks respondents information about the 8 electronic devices. The 2nd section of the survey asks information about devices in the in-use stock, the 3rd section about devices in the storage stock, and the 4th section about devices that are in the disposal or recycle stock. These survey questions are time-sensitive asking year the device was acquired, given to a new owner or stored, and disposed of or recycled. The last section asks about demographic information including the current number of residents in their household and zip code. This section aids in demographic weighting of the results (see section 1.2.4) and survey distribution (see section 1.2.3). A figure summarizing the outline of the survey is represented in Figure 3.

Devices of Interest Cell Phone, Laptops, Tablet Computer, Smart Watch, Headphones, Desktop Computer, Printer, Television	Shared Questions	Unique Questions	Outcomes
1. **Start of Survey** In-Use	• Year Acquired • Current user/last user • Previous usage duration • Previous storage duration		Pathways of devices currently in-use
2. In-Storage		• Year last used	Pathways of currently stored devices
3. EoL (recycling, disposal)		• Year last used • Year disposed/recycled • Method of disposal/recycle	Pathways of devices not currently owned
4. Demographic **End of Survey**	• Household Members • Gender • Age • Education • Zip Code		Pathway trends based on US demographics

Figure 3: Summary outline of survey distributed to household owning adults in the US, highlighting the continuity of the survey and questions asked for each device

By knowing the entirety of the user lifecycle from device purchase to end of life through either disposal or recycle for each device the survey collects information for, the survey data provided the stock location and year of transfer from one stock to another for each year from each device the survey responder provided information for. With this data, the number of devices in each stock and flow from the survey were summed for each year to calculate the required inputs into the STELLA model (see section 1.2.4).

1.2.3 Survey – Distribution and Response Screening

The survey was distributed digitally through a variety of channels, including social media and Amazon MTurk. Responses were collected between February 2021 until January 2022.
Responses were screened to filter and remove incomplete and poor-quality responses from the sample size[25,26,27]. The screening process consisted of evaluating: 1. Response Quality, 2. Response Completeness, 3. Attention-Checks, 4. Response Time. The first two screening steps eliminated illogical user input and incomplete responses. Step 3 of the screening process applied attention-check questions imbedded throughout the survey, and if participants failed a majority of these questions their responses were removed from the sample size. Step 4 of the screening process removed responses that had a total survey-taking time below 6 minutes. These last 2 steps of the screening process ensured responders were not rushing through the survey just to receive compensation.

Data was collected from 903 households with representation from every state in the US except for Alaska. This was determined as a sufficient sample size based on a coefficient of variation of .51 based on average household size (HHS) (Eq. 2), similar to how the US Census Bureau survey acquires a sample size for their Current Population Survey (CPS)[28].

$$\mathrm{CV} = \frac{\sigma}{\mu} \times 100 \qquad \text{(Eq. 2)}$$

Where:
CV = coefficient of variation [%]
σ = standard deviation
μ = mean

1.2.4 STELLA Model – Preparation and Operation

Survey results, annual stock and flow quantities for each device, were weighted by their HHS based on information from the CPS to ensure the ratio of HHS from survey respondents was aligned with distributions in the U.S.[29] (Eq. 3). A table describing current HHS from the CPS and survey along with calculated weights is shown in Appendix E.

$$\mathrm{Weight_{hhs}} = \frac{\mathrm{N_{CPS,hhs}}}{\mathrm{N_{CPS,total}}} \div \frac{\mathrm{N_{survey,hhs}}}{\mathrm{N_{survey,total}}} \qquad \text{(Eq. 3)}$$

Where:
$\mathrm{Weight_{hhs}}$ = weight for hhs
$\mathrm{N_{CPS,\,hhs}}$ = population for hhs from CPS
$\mathrm{N_{CPS,\,total}}$ = total household population from CPS
$\mathrm{N_{survey,\,hhs}}$= population for hhs from survey
$\mathrm{N_{survey,\,total}}$ = total household population from survey

Each stock and flow were summed per year to calculate the stock exit ratios, transfer coefficients, and initial stock amounts. Stock exit ratios were calculated by dividing the total number of devices leaving a stock by the total amount in that stock (Eq. 4). Total stock amounts and number devices leaving each stock were summed for each year for each device from the survey. Transfer coefficients were calculated by dividing the total number of devices in a specific flow by the total number leaving that stock (Eq. 5). The number of devices flowing from one stock to another specific stock was quantified and summed for each year for each device from the survey. These calculations were done per year for each device.

$$\mathrm{SR_{stock}} = \frac{\mathrm{Flow_{out}}}{\mathrm{M_{stock,t-1}}} \qquad \text{(Eq. 4)}$$

$$\mathrm{TC_{Flow\ i}} = \frac{\mathrm{Flow_i}}{\mathrm{Flow_{out}}} \qquad \text{(Eq. 5)}$$

Where:
$\mathrm{SR_{stock}}$ = stock exit ratio
$\mathrm{M_{stock,\,t-1}}$ = stock amount from previous year
$\mathrm{TC_{Flow\ i}}$ = transfer coefficient for Flow i
$\mathrm{Flow_i}$ = number of devices in Flow i
$\mathrm{Flow_{out}}$ = sum of flows leaving stock

Initial stock amounts are the number of devices in each stock for the first year the model is run. The survey stock amounts from the initial year are scaled up using a ratio of the total U.S.

household sales to the survey sales (Eq. 6). First, the total quantity of devices from the survey in each stock was summed up for the initial year. This total initial quantity for each stock was then multiplied by a ratio of the total household sales (Eq. 8) divided by the total household sales from the survey for that initial year. The household sales from the survey were also calculated by summing up the total sales of each device for that initial year as reported from the survey. This scale-up process allows each device in each stock to represent a scaled amount of the total household sales from the survey to the total household sales from the U.S.

$$\mathrm{MI_{stock}} = \frac{\mathrm{THS_{device}}}{\mathrm{HS_{survey}}} \text{ x } \mathrm{M_{stock,survey}} \qquad \text{(Eq. 6)}$$

Where:
MI_{stock} = initial stock amount for model [# of devices]
THS_{device} = total household sales for device [# of devices]
HS_{survey} = household sales for device from survey [# of devices]
$M_{stock, survey}$ = stock amount of device from survey [# of devices]

The initial stock year for cell phones, laptops, headphones, desktop computers, televisions, and printers were the year 2000. However, since newer devices like tablets and smart watches were also considered in this study, sales and survey data for them was limited. The initial stock year for them reflected the year they were introduced into the market through the company Apple. The initial stock year for tablets is 2010 and for smart watches is 2015[30].

The last input is the annual number of devices entering the model through total U.S household sales. Sales data in the U.S. was acquired from Digital America through the Consumer Technology Association (CTA), provided as sales to U.S. distributors[31]. Sales to U.S. households was extracted from this by first calculating the household sales ratio. This ratio reflects the ratio between devices sold to households and devices sold to all distributors. It is calculated by first taking the household sales from the survey and multiplying it by a ratio between the total U.S. household population and total survey population to calculate the scaled U.S household sales. Then, the scaled household sales are divided by the sales to distributors to calculate the ratio of household sales to sales to distributors (Eq. 7). In order to calculate the total household sales for a specific device and year, the sales to distributors for that respective device and year was multiplied by the household sales ratio for that device to determine what quantity of sales to distributors went to U.S. households specifically (Eq. 8).

$$\mathrm{HSR_{device}} = \frac{HS_{survey} \text{ x } \frac{\mathrm{N_{CPS,total}}}{N_{survey,total}}}{\mathrm{Sales_{dist}}} \qquad \text{(Eq. 7)}$$

$$\mathrm{THS_{device,y}} = \mathrm{HSR_{device}} \text{ x } \mathrm{Sales_{dist,y}} \qquad \text{(Eq. 8)}$$

Where:
HSR_{device} = household sales ratio
HS_{survey} = household sales for device from survey [# of devices]
$N_{survey, total}$ = total household population from survey [# of households]
$N_{CPS, total}$ = total household population from CPS [# of households]
THS_{device} = total household sales for device at year y [# of devices]
$Sales_{dist, y}$ = total sales to distributors for device at year y [# of devices]

Due to the limited availability of source data, sales data was unavailable from the years 2016 to 2021 for each device, except for cell phones and smart watches. Also, due to the limited sample size, transfer coefficients and stock exit ratios from the survey were unobtainable for every year and each device. Missing data from these model inputs were replaced through Multiple Imputation by Chained Equations (MICE) imputation to create a full dataset for each device and year. MICE imputation applies a chained polynomial regression process that calculates missing values from similar behaving data for each absent data point[32]. Allowing similar behaving devices to replace missing values of each other based on known trends. A summary of the model inputs is shown in Appendix A.3 through Appendix A.5.

1.2.5 Data Analysis – Metallic Stock and Flow

A metallic stock and flow analysis were conducted to determine the flow of metals within U.S. households. Metal composition data for cell phones, printers, desktop computers, headphones, and laptops were acquired from previous studies characterizing their metal composition[11,33-36]. Due to a lack of metal composition data for tablets and smartwatches, the printer circuit board (PCB) composition for cell phones was used as the composition for these devices due to their similar functionalities, but with weights that reflected the PCB weights of tablets and smartwatches. Metal amounts in devices were calculated by multiplying metal concentrations by average device weights[37,38] (Eq. 9). A concentration table by metal category, along with device weights is shown in Appendix C.1.

$$M_{element,device} = M_{device} C_{element} \qquad (Eq. 9)$$

Where:
$M_{element, device}$ = Mass of element in device [kg]
M_{device} = Mass of device [kg]
$C_{element, device}$ = Concentration of element [kg/kg]

With known device metal amounts, a stock and flow of devices was translated to a stock and flow of metals by multiplying stock and flow amounts by the metal amount contained within them (Eq. 10).

$$M_{element,total} = \sum_{i}^{j=12} \sum_{i}^{k=8} M_{element} \ x \ M_{stock} \qquad (Eq. 10)$$

Where:
$M_{element, total}$ = total mass of element [kg]
j = number of stocks
k = number of unique devices
$M_{element}$ = mass of element in device [kg]
M_{stock} = model stock amount [# of devices]

1.2.6 Data Analysis – Environmental Impact

The environmental impact was evaluated to quantify the potential savings in impact to the environment if U.S. household devices were to be recycled under a circular economy. The environmental impact was calculated for each device along with stock impacts based on the mass quantities of metals in each stock. Environmental Impact Categories considered were Climate Change, Human Toxicity, and Water Depletion. The Impact Factors was collected using SimaPro8.03 Life Cycle Assessment (LCA) and ReCiPe 1.10 (World) method (10) with impacts based on kilogram of metal from cradle-to-gate[39]. A table with Environmental Impact Factors for each Environmental Impact Category is shown in Appendix C.2. The environmental impact for each device was calculated by multiplying the amount of metal in device (see section 2.1.5) by its corresponding impact factor, and then summating for each metal (Eq. 11). A table with the Environmental Impact for each Impact Category and device can be found in Appendix B.2.

The Stock Environmental Impact was calculated for each stock to determine which stocks contained the most significant impacts in relation to each other. Calculated by multiplying the number of devices in each stock by the environmental impact for each device and summing for all devices (Eq. 11). Afterwards, this was aggregated into a Total Environmental Impact for each Environmental Impact Category by summing up the impacts for each stock in a given year (Eq.

11). A table with the Stock Environmental Impact for each stock and Total Environmental Impact from the year 2020 can be found in Appendix B.3.

$$EI_{total} = \sum_{i}^{j=12} \sum_{i}^{k=8} \sum_{i}^{l=51} M_{element} \times IF_{element} \times M_{stock} \qquad (Eq. 11)$$

Where:
EI_{total} = total environmental impact [kg]
j = number of stocks
k = number of unique devices
l = number of elements
$M_{element}$ = mass of element in device [kg]
$IF_{element}$ = impact factor for element [kg/kg]
M_{stock} = model stock amount [# of devices]

1.2.7 Data Analysis – Economic Impact

An economic analysis was also performed to determine the potential monetary value of metals present in U.S. household devices if the metals within them were to be recycled as well. Market data for each metal was acquired through USGS and the Institute for Rare Earth and Metals[40,41]. A table showing the market value for each metal is shown in Appendix C.3. The value for each device was calculated by multiplying known metal device amounts (see section 1.2.5) by the market value for each metal (Eq. 12). A table of the market value price per device and metal category is shown in Appendix B.4. Stock Values were calculated by multiplying the number of devices in each stock by the monetary value for each device and summating for all devices. Similar to the Total Environmental impact, each Stock Value was then aggregated to a Total Value in U.S. Households for a given year. A table of Stock Values for each stock and Total Value for the year 2020 can be found in Appendix B.5.

$$EV_{total} = \sum_{i}^{j=12} \sum_{i}^{k=8} \sum_{i}^{l=51} M_{element} \times Cost_{element} \times M_{stock} \qquad (Eq. 12)$$

Where:
EV_{total} = total environmental value [USD]
j = number of stocks
k = number of unique devices
l = number of elements
$M_{element}$ = mass of element in device [kg]
$Cost_{element}$ = price for element [USD/kg]
M_{stock} = model stock amount [# of devices]

1.3 Results and Discussion

1.3.1 Transfer Coefficients – Devices Flowing from User to Storage

Annual device flows and stock amounts were controlled by their transfer coefficients, determining how many devices leaving each stock would transfer into a specific stock. Device transfer coefficients varied for each year and device, exhibiting unique device stock and flow trends. Data for a majority of the transfer coefficients lies with flows pertaining to Use 1. As a majority of devices from the survey are retained by the first user and did not reach a subsequent user before disposal or recycle. Complete annual transfer coefficients for each device are shown in Appendix A.5. The largest transfer coefficients are associated with devices moving from user to storage and is represented in Figure 4 for handheld devices and Figure 5 for non-handheld devices, separated by device size for comparison and clarity.

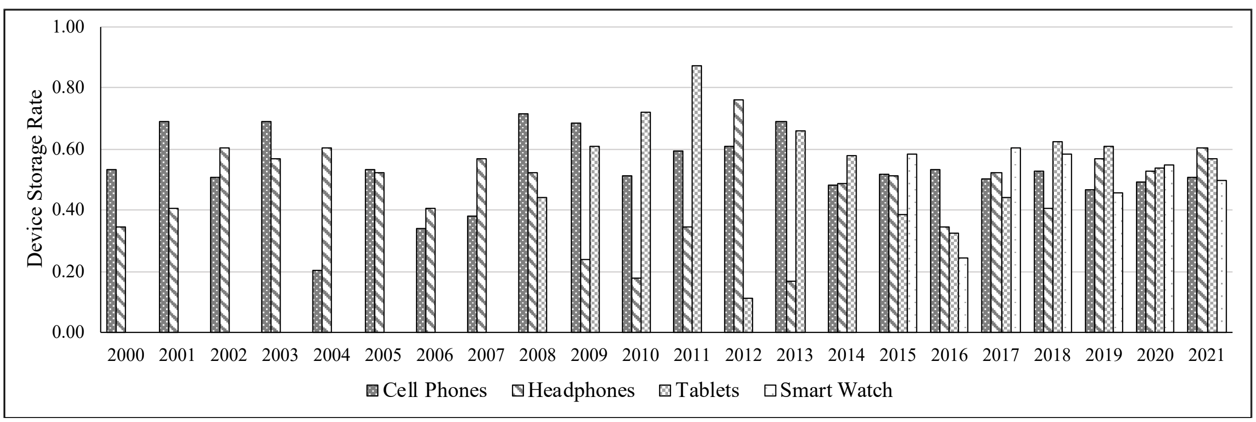


Figure 4: Transfer Coefficients for storage rate of handheld devices in U.S. Households flowing from use 1 to storage for the year 2000 to 2021. Transfer coefficient remains relatively constant for handheld devices with cell phones on average being most likely to be transferred to storage.

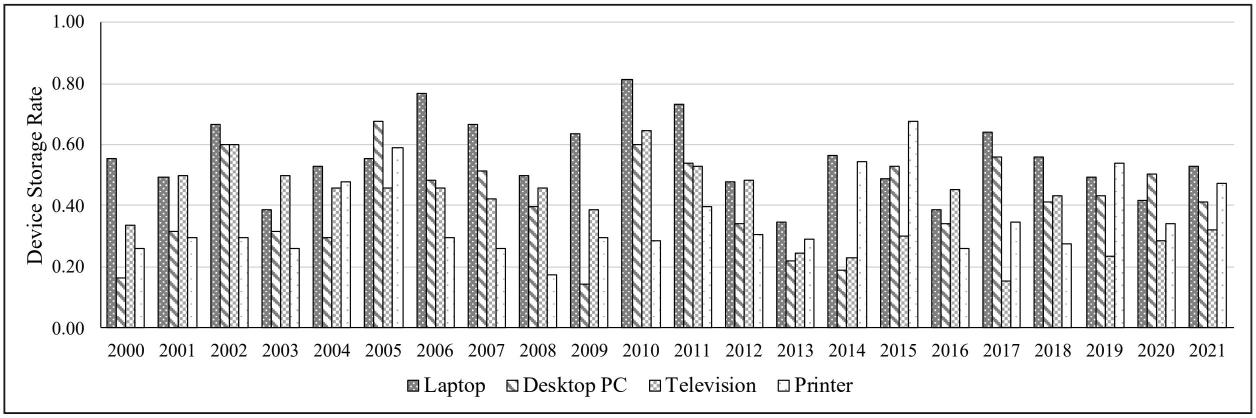


Figure 5: Transfer Coefficients for storage rate of non-handheld devices in U.S. Households flowing from use 1 to storage for the years 2000 to 2021. Transfer coefficient remains relatively constant for non-handheld devices with laptops being most likely to be transferred to storage.

Transfer coefficients for devices flowing from user to storage fluctuated annually for all devices and stayed relatively constant within the past 2 decades, showing a slight peak in storage rate between the years 2009 and 2012 before gradually decreasing back to initial storage rates. On average, smaller devices like smart phones, tablets, smart watches, laptops, and headphones exhibited greater storage rates than larger devices. Smaller devices contained a yearly average storage rate of about 51%, while the remaining larger devices displayed a yearly average storage rate of 39%. Transfer coefficients from previous studies are sparse and fragmented based on year and geographic location, primarily focusing on cell phones. Within the U.S., a previous study estimated a lower storage rate of 35% for smaller devices like cell phones, likely due to their smaller sample size and limited timescale[6]. Outside the U.S., studies from Australia also estimated a lower but closer storage rate of 44% for cell phones, while countries like China and South Korea estimated a slightly higher storage rate of 47% and 40% respectively[2,3,42,43]. In Europe, the countries Switzerland, United Kingdom, and England reported higher closer storage rates to that seen in this study at 58%, 54%, and 56% respectively for cell phones, contributed to their stricter electronic waste recycling regulations that could deter users from disposing of their device[4,13,44]. In conclusion, the storage rate of devices is geographic and device dependent with European Countries reporting the highest storage rates, followed by the U.S. and Asia, with smaller devices being more likely to be stored. Consequently, the storage rate for all devices and countries is somewhat constrained, converging at about 40% to 50% of devices stored for a majority of studies.

1.3.2 Transfer Coefficients – Devices Flowing from User to User

For devices that were not transferred to storage after use, the second most likely flow was to another user for reuse. These transfer coefficients are represented in Figure 6 for handled devices and Figure 7 for non-handheld devices.

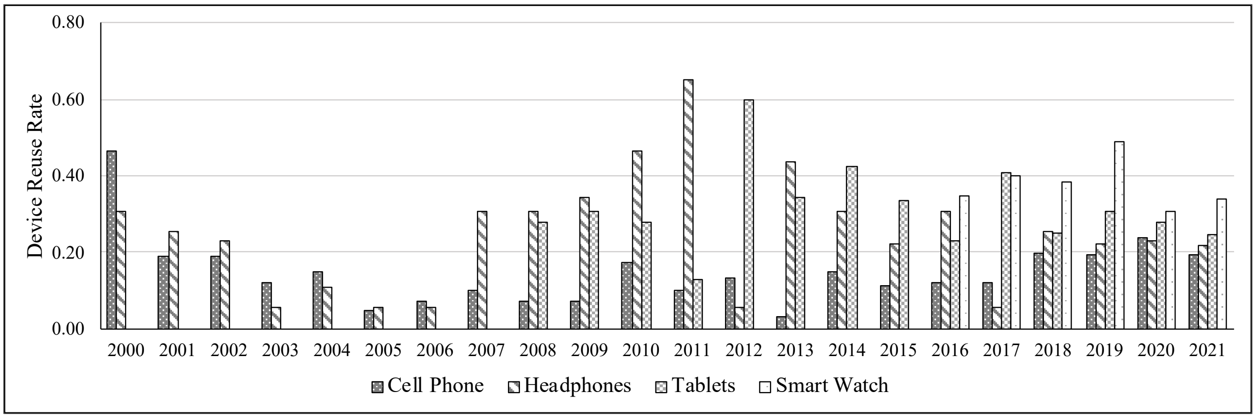


Figure 6: Transfer Coefficients for reuse rate of handheld devices in U.S. Households flowing from use 1 to use 2 for the years 2000 to 2021. Transfer coefficient remains relatively constant for handheld devices with newer devices being most likely to be reused.

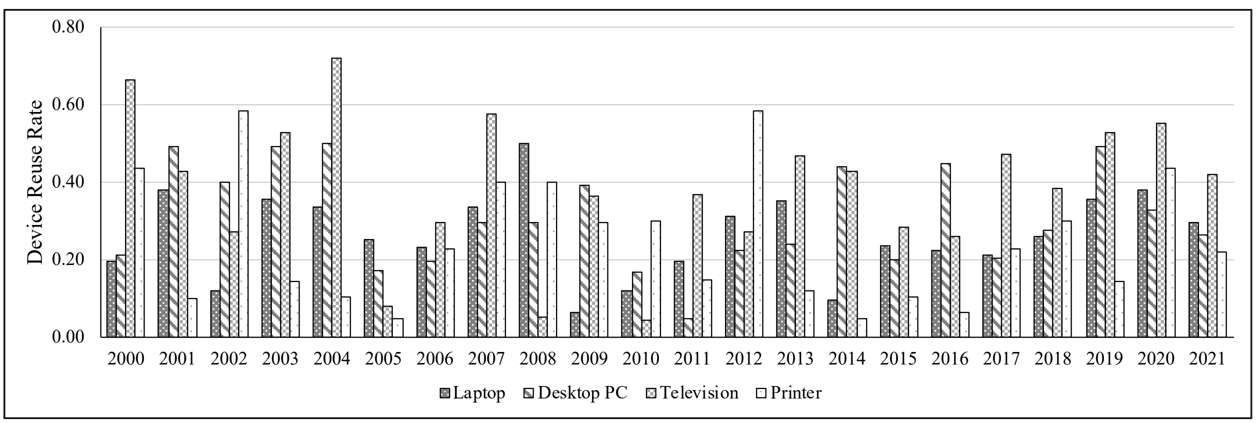


Figure 7: Transfer Coefficients for reuse rate of non-handheld devices in U.S. Households flowing from use 1 to use 2 for the years 2000 to 2021. Transfer coefficient remain relatively constant for non-handheld devices with televisions being most likely to be reused.

Device reuse also showed relatively stable trends from the past 2 decades for all devices, fluctuating annually but showing no significant changes. Televisions had on average the highest reuse rate at 38%, influenced by having a low storage rate. Coincidentally, smaller and newer devices like smartwatches and tablets also displayed high reuse rates at 37% and 31% respectively, unlike their cell phone counterpart, which had a low reuse rate at 14%, underscoring the widening gap between more cell phones being stored rather than reused when compared to other similar devices. Within the U.S., a previous study estimated a higher reuse rate at 28% for cell phones in U.S., which again, could be contributed to their smaller sample size and limited timeframe[6]. Outside the U.S., Australia reported a reuse for cell phones very similar to this study at 10%[2]. The same is true for countries in Asia, which reported reuse rates at 16% and 12% for the countries China and South Korea[2,3,42,43]. Studies in Europe projected slighter higher values for Switzerland, United Kingdom, and England at 15%, 20%, and 22% respectively for cell phones[4,13,44].

Overall, reuse rates show a lesser dependence on device size and geographic location, with both small and large devices being heavily reused, while the most popular device cell phone is the least reused as users prefer to store it after use. This trend is similar for countries outside the U.S. as well, with reuse rates more precise than storage rates, averaging about 15% to 30% reuse.

1.3.3 Transfer Coefficients – Devices Flowing from User to Disposal

Devices not transferred to storage or another user after use, then one of two EOL stocks for the device is disposal, in which the device was not recycled but trashed. These transfer coefficients are represented in Figure 8 for handled devices and Figure 9 for non-handheld devices.

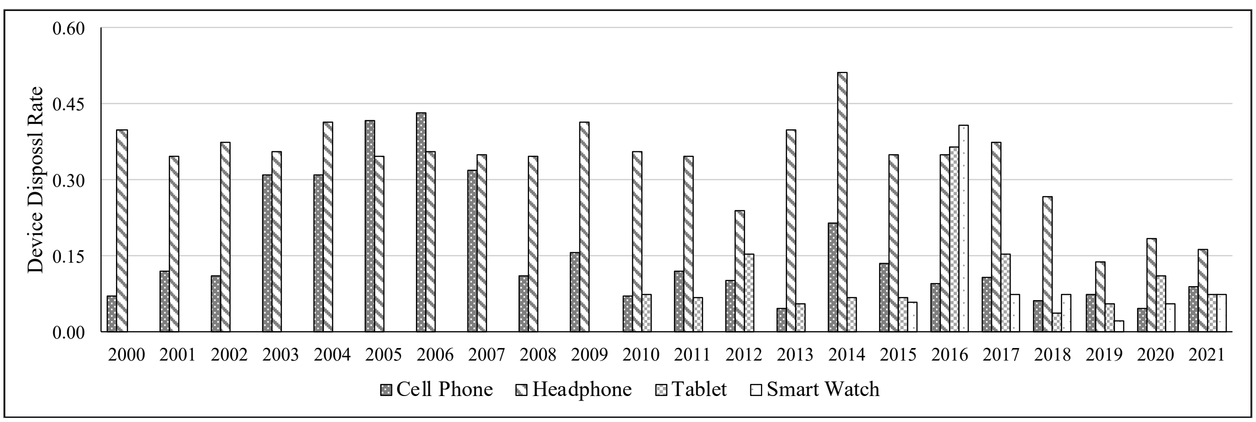


Figure 8: Transfer Coefficients for disposal rate of handheld devices in U.S. Households flowing from use 1 to disposal for the years 2000 to 2021. Transfer coefficients have decreased for handheld devices within the last couple of years with headphones being the most frequently disposed of device.

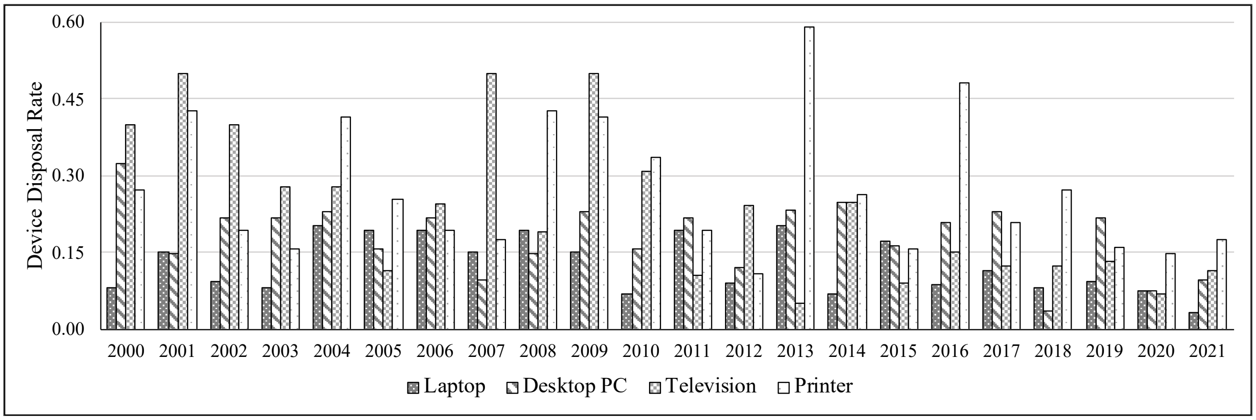


Figure 9: Transfer Coefficients for disposal rate of non-handheld devices in U.S. Households flowing from use 1 to disposal for the years 2000 to 2021. Transfer coefficients have decreased gradually for non-handheld devices within the last few years with printers being the most frequently disposed of device.

Device disposal rate gradually decreased for all devices from the past 2 decades. Headphones had on average the highest disposal rate at 33% along with the larger devices printers, televisions, and desktop PCs. These devices showed higher disposal rates than the smaller handheld devices cell phones, tablets, and smartwatches. Accounting for a difference of about 10% disposal between these two groups. This emphasizes larger devices higher tendency to be disposed than smaller devices in U.S. households, with the exception being headphones. In comparison to a previous study in the U.S., cell phones had a reported disposal rate of 15%, similar to this study's 16%[2]. However, European countries estimated a much lower disposal rate for cell phones ranging from 1% to 6%, most likely due as well to their stricter and more rigorous recycling policies preventing the disposal of electronic waste[4,13,44]. Device disposal shows an overall decline within the past few decades but is heavily influenced by geographic location and device type as different governmental and societal regulations can inhibit devices from being trashed, and select devices tend to be favorably disposed than others with larger devices more prone to disposal.

1.3.4 Transfer Coefficients – Devices Flowing from User to Recycle

Device that was disposed of and not trashed, were then recycled. These transfer coefficients are represented in Figure 10 for handled devices and Figure 11 for non-handheld devices.

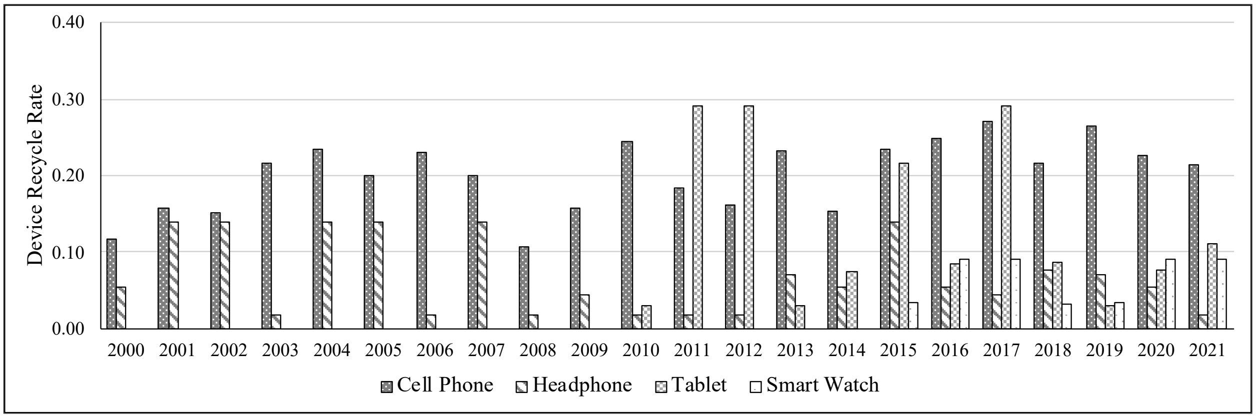


Figure 10: Transfer Coefficients for recycle rate of handheld devices in U.S. Households flowing from use 1 to recycle for the years 2000 to 2021. Transfer coefficients have remained relatively the same for handheld devices years with cell phones the most heavily recycled device.

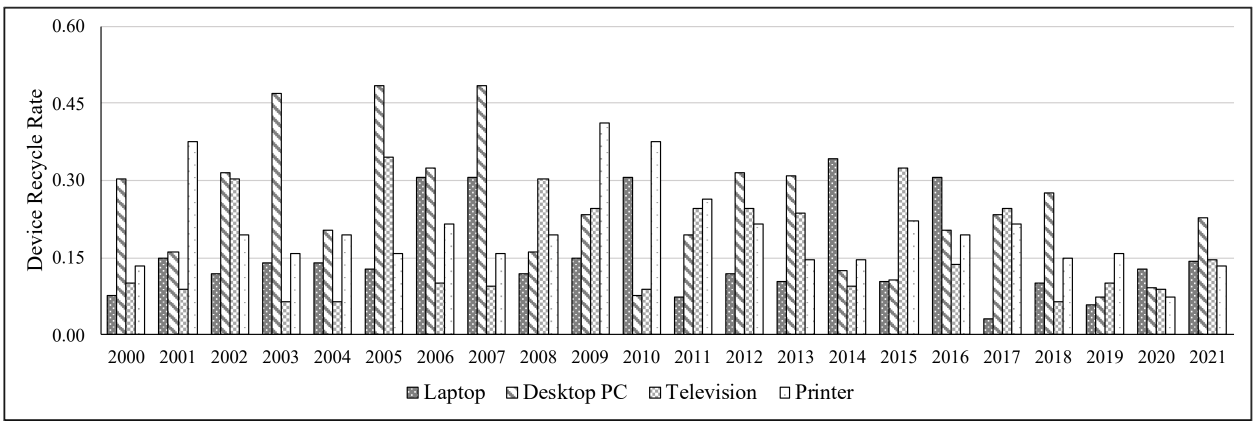


Figure 11: Transfer Coefficients for recycle rate of non-handheld devices in U.S. Households flowing from use 1 to recycle for the years 2000 to 2021. Transfer coefficients have gradually decreased for non-handheld devices with desktop PCs as the most heavily recycled device.

The device recycling rate has decreased gradually for larger devices like desktop PCs and televisions, and the smaller devices tablets and headphones, underlying a shift for both smaller and larger devices transitioning away from recycling within the past couple of years, possibly due to the cost of recycling larger devices in the United States. However, despite the decreasing recycling rate of desktop PCs, they still contain the largest recycling rate out of all devices at about 24%. Due to the large mechanical components, they contain, which house greater amounts of recyclable materials and resources, it makes them easier and more valuable to recycle. The headphones recycling rate is also decreasing, contrasted with them having one of the highest disposal rates, emphasizing their growing propensity to be placed into disposal rather than recycling after use. Cell phones, however, was the only device that had a gradually increasing recycle rate, likely due to more phone manufacturers incentivizing phone users to recycle old devices for perks like discounts on new devices. Compared to previous studies, the cell phone recycling rate have shown to be closer to recycling rates reported in Switzerland at 22%, compared to the 20% reported in the U.S.[4]. Asian countries, however, have reported recycling rates much lower than the US at about 6% to 9% demonstrating a strong shift in recycling based on geographic location[2,3,42,43]. Overall, larger devices are more frequently recycled than smaller devices in US households with the exception being cell phones. Also, geographic location can cause large discrepancies and differences in recycling rates, likely due to their recycling infrastructure and availability to the public.

1.3.5 Stock and Flow of Devices In-Use

The transfer coefficients directly determined the stock and flow of devices from the model, varying significantly for each device. The in-use stock contained the largest number of devices meaning most devices in U.S. Households were currently being used. Devices going into this stock originated from the household sales data, with each device having a unique household sales ratio adjusting the flow of devices into the use stock. The larger devices televisions, printers, desktop PCs, and laptops estimated higher percentages of sales going directly to U.S. households averaging 80% of devices in the U.S. electronics market reaching U.S. households. In contrast, smaller devices cell phones, tablets, smartwatches, and headphones experienced on average lower penetration rates of about 60%, stressing that a smaller percentage of handheld devices reach personal household use compared to larger devices.

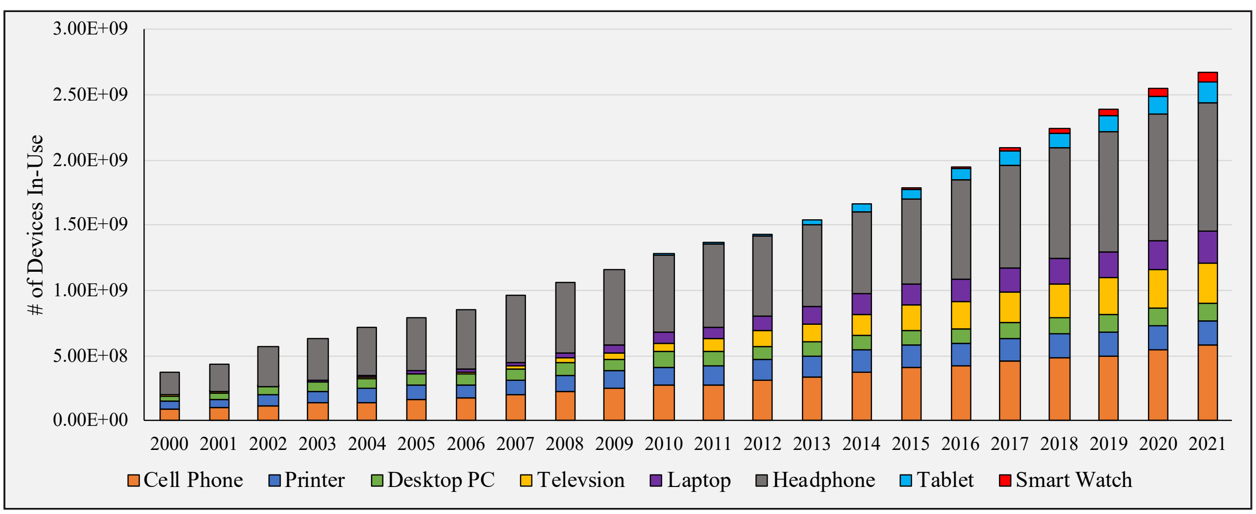


Figure 12: Annual stock amounts for devices in-use in U.S. households from the years 2020 to 2021, showing the steadily increasing number of devices being used per year in U.S. households.

All eight devices exhibited increasing trends for in-use in U.S. households from the year 2000 to 2021, shown in Figure 12. Headphones dominated devices in-use for each year displaying the largest increasing trend and amount equating to about 990 million devices by the year 2020, while cell phones showed a smaller and steadier increase totaling to about 574 million devices in-use. This accounts that over half of devices found in U.S. households stem from either a cell phone or headphone. A previous study in Australia with a household size about a tenth the size of the U.S.'s, estimated an in-use amount of cell phones at about 46 million devices for the year 2014, compared to U.S.'s cell phone use of about 376 million cell phones for the same year[2]. Europe, with a household size that doubles the U.S.'s, estimated 700 million cell phones being used for the year 2016 compared to the U.S.'s estimated 424 million[45]. These comparisons suggest varying device usage based on geographic location and countries with larger households tend to have more devices in-use and vice versa for countries with smaller households.

Non-handheld devices were used in significantly fewer amounts in U.S. households than handheld devices with laptops and televisions use increasing annually, while printer and desktop PCs have remained stagnant. Indicating laptops and televisions growing ownership in U.S. households, while more traditional devices like desktop PCs and printers stalling in users. Due to similar behaving devices becoming more portable through laptops and the internet, reducing the need for printers in households. The more novel devices smartwatches and tablets had the fewest amount of device usage, suggesting slow growing in-use amounts in U.S. households for newer devices introduced into the electronics market.

1.3.6 Stock and Flow of Devices in Storage

Devices still in households but not being used are in the storage stock and was the next largest stock amount found in U.S. households, following devices in-use. Each device increased in storage amount from the year 2000 to 2021 accounting for over 757 million stored electronic devices in US households by the year 2020, shown in Figure 13.

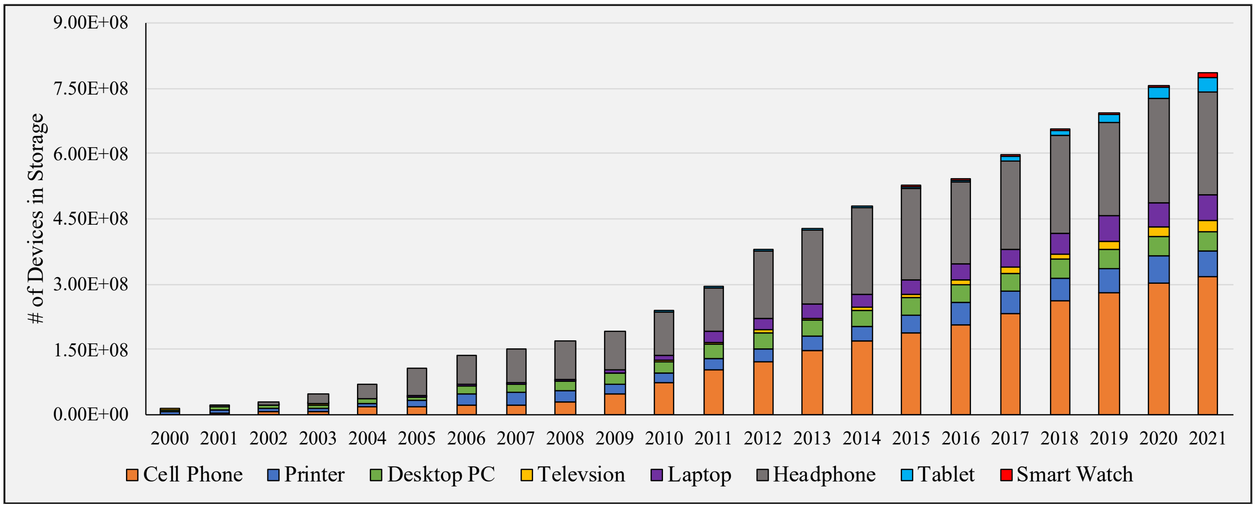


Figure 13: Annual stock amounts for devices in storage in U.S. households from the years 2020 to 2021, showing the increasing number of devices in storage each for all 8 devices.

Th most stored devices in U.S. households were cell phones and headphones. By the year 2021, the cell phones storage stock had the greatest number of devices in storage and the largest increase over time. Totaling over 317 million stored devices and accounting for almost half of all stored devices in U.S. households. Cell phones initially had a slow increasing amount in annual storage, but accelerated in storage starting in the year 2009, about two years after the introduction of the smart phone into the electronics market. For comparison, a previous study in Europe estimated 300 million cell phones in storage by the year 2016 increasing similarly to that of cell phones stored in U.S. households[45]. A similar study conducted in Denmark and Korea saw increasing storage trends annually as well for cell phones, similar to the U.S., but eventually plateauing by the year 2018 for Denmark. The study in Denmark reported a storage amount of 4 million cell phones by the year 2018, and Japan 6.4 million for the year 2007[43,46]. Both are significantly smaller than the amount stored in U.S. households, being 23 million and 208 million devices in storage for their respective years. Therefore, the storage amount for cell phones relates to geographic location and number of households, with more households increasing storage amounts. Holistically, however, the storage amount is steadily increasing annually for most countries. The same can be concluded for headphones as well, which saw similar increases in annual storage amount, plateauing by the year 2016 to about 237 million stored devices. Outside of cell phones and headphones, the other devices behaved more stagnantly and were found in significantly lower storage amounts.

The larger non-handheld devices had substantially lower storage amounts in U.S. households, along with the newer device's tablets and smartwatches. Although they did increase annually as well, the rate of increase was much lower than cell phones and headphones, reducing the amount in storage for these devices. Compared to a survey study done in Japan, with about half the household amount of the U.S., they estimated a storage amount of about 12 million desktop PCs in the year 2021 increasing at a higher rate than the U.S.'s, which estimated 44 million desktop PCs in storage[47]. Laptops were estimated to be 38 million devices in storage in US households for the year 2016, comparable to the estimated 40 million in storage for the same year in Europe[45]. For the same year, tablets were estimated to be 6 million in storage in U.S. households, similar to the estimated 10 million in Europe[45]. Therefore, storage for these devices in U.S. households behave similarly to devices stored in Europe in both annual changes and stock amount, and newer devices tend to be stored in fewer amounts behaving similarly to non-handheld devices.

1.3.7 Stock and Flow of Devices in Disposal

Devices reaching its EOL and are not stored or recycled, are placed into the disposal stock where it was either landfilled or discarded by another means. The number of total devices disposed of by U.S. households increased annually overall to an estimated 63 million disposed of devices for the year 2021, shown in Figure 14.

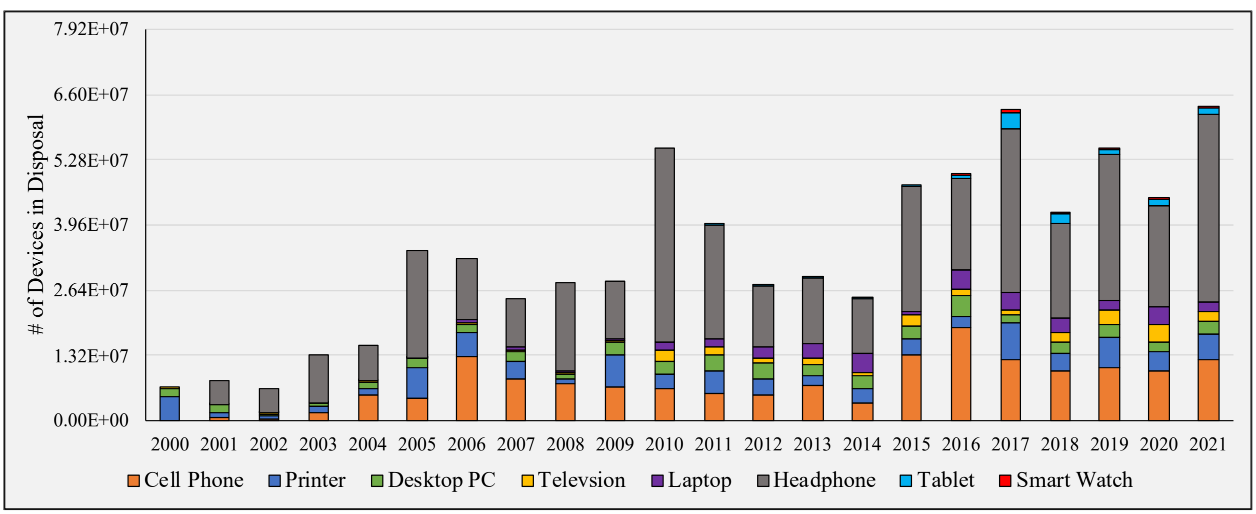


Figure 14: Annual stock amounts for devices in disposal from U.S. households for the years 2020 to 2021, showing the increasing number of devices being placed into the disposal stock per year.

The majority of devices disposed of are headphones and cell phones accounting for about 37 million and 12 million disposed devices respectively for the year 2021. They also had the largest increases in disposed of devices annually. Larger devices, however, were disposed in smaller quantities, fluctuating annually while increasing slightly. Newer devices had even fewer number of devices in disposal, with tablets disposal decreasing annually. In conclusion, smaller older devices tend to be disposed more often than larger non-handheld devices by a wide margin in U.S. households, with newer devices behaving similarly but in smaller disposal quantities. Annual changes in disposal amounts are strongly dependent on the device, with newer handheld devices like tablets showing decreases in annual disposal, as opposed to headphones which increased considerably every year.

1.3.8 Stock and Flow of Devices in Recycle

Devices reaching their EOL and are not disposed, are placed into the recycle stock. The number of total devices recycled by U.S. households is similar to the number of devices disposed equating to about 65 million devices recycled for the year 2021, shown in Figure 15.

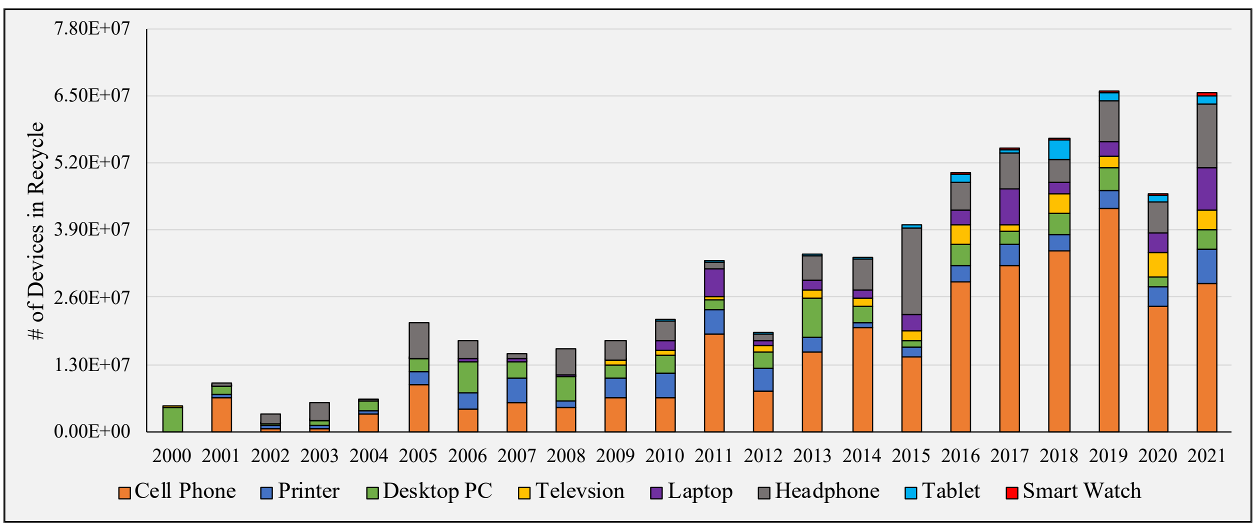


Figure 15: Annual stock amounts for devices in recycle from U.S. households for the years 2020 to 2021, showing the increasing number of devices being placed into the recycle stock per year.

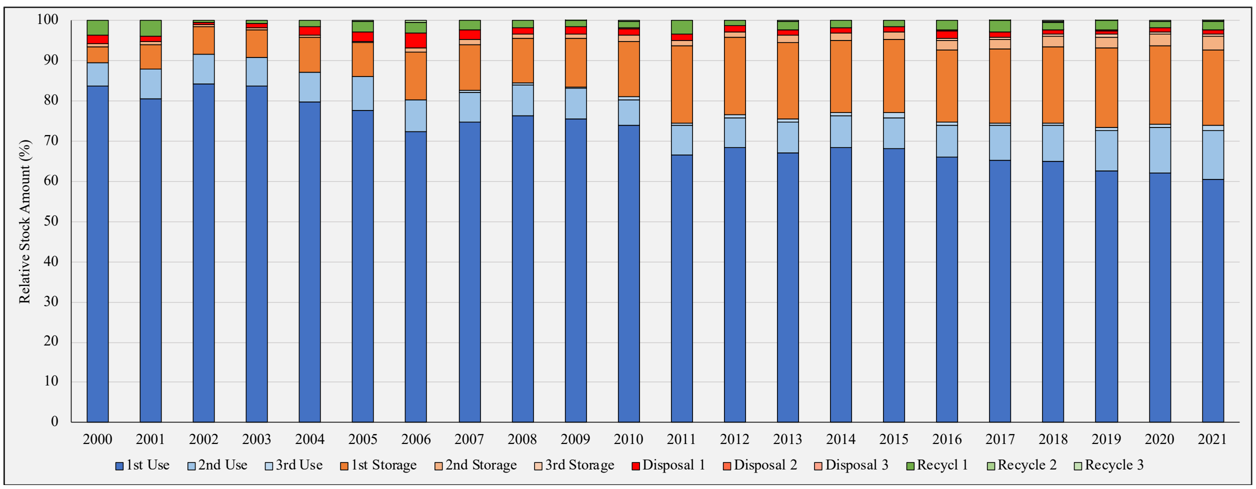
Cell phones dominate a majority of the devices recycled annually showing the largest overall increase and recycle amount of about 28 million recycled devices for the year 2021.This accounts for about half of all devices placed into recycle. Headphones and larger devices were recycled in smaller amounts fluctuating annually and increasing marginally. Similar to devices placed in the disposal stock, the newer devices tablets and smartwatches were also the least recycled devices at about 1.5 million and 475 thousand recycled devices respectively for the year 2021 with a slightly decreasing trend similar to their disposal counterparts. In conclusion, cell phones overwhelmingly are the most recycled device per year from U.S. households and is increasing annually, plateauing within the last few years, while larger devices tend to be recycled in fewer amounts increasing marginally. Newer devices, however, behave similarly to their disposal counterparts, being the least recycled devices as well and decreasing slightly. Suggesting newer devices tend to remain longer in households with annually decreasing disposal and recycling amounts.

Stock and transfer coefficient data for all devices have shown to be unique and varied depending on the device at hand. Storage and second use rates have remained relatively consistent despite annual fluctuations, while disposal rates have seen a gradual decrease. In terms of stock amounts both devices in-use and storage have been increasing steadily, spurred predominantly by cell phones and headphones. These transfer coefficient and stock amounts is comparable to previous studies to a fault. Due to the wide variability and sparseness of the previous studies' limited time frame of interest and geographic location, allows this study to fill a gap in knowledge to provide a comprehensive and holistic understanding in household management of electronic devices. By presenting consistent quantitative stock and flow data over an extended time span for eight common electronic devices in the US, this data provides broad applications to compare and interpret how electronics will and won't behave both within and outside the US, and how novel devices with similar functionalities might behave in households. Refer to Appendix A.7 for device stock amounts and Appendix A.8 for device flow amounts.

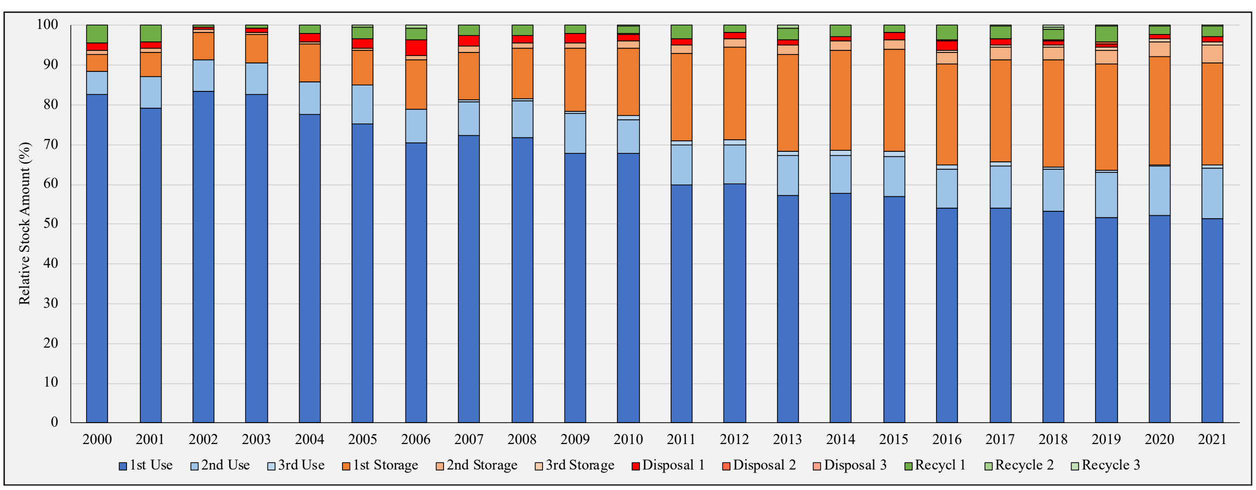
1.3.9 Stock and Flow of REMs and PMs

The stock and flow of REMs and PMs was estimated from the stock and flow of devices. The metals of interest are primarily REMs and PMs due to their increased value, extensive environmental footprint, and growing scarcity as a natural resource[18]. Figure 16 represents the relative temporal stock amounts for gold, platinum, and palladium. These elements were chosen due to their large potential value and environmental impact from stored devices in U.S. households (see section 1.3.10 and 1.3.11). The in-use stock dominates for all 3 metals as expected since most devices people own, they use. However, it is clear that the storage stock is gradually increasing over time, while the in-use stock decreases plateauing around the year 2018 for all 3 metals. By the year 2021, about 20% to 30% of the total amount of each metal in U.S.

households is stored. This represents a shift of where metals from electronic devices are present in U.S. households, with more devices moving gradually from the in-use to storage stock over the past 2 decades. Also, a lower relative amount of gold is stored than platinum and palladium accounting for a 10% difference in storage stock amounts for the year 2021, meaning more platinum and palladium is found in the storage stock than in-use stock compared to gold. Overall, the significant shift and growth of the storage stock for all 3 metals over time underlies the growing potential to recover these metals.



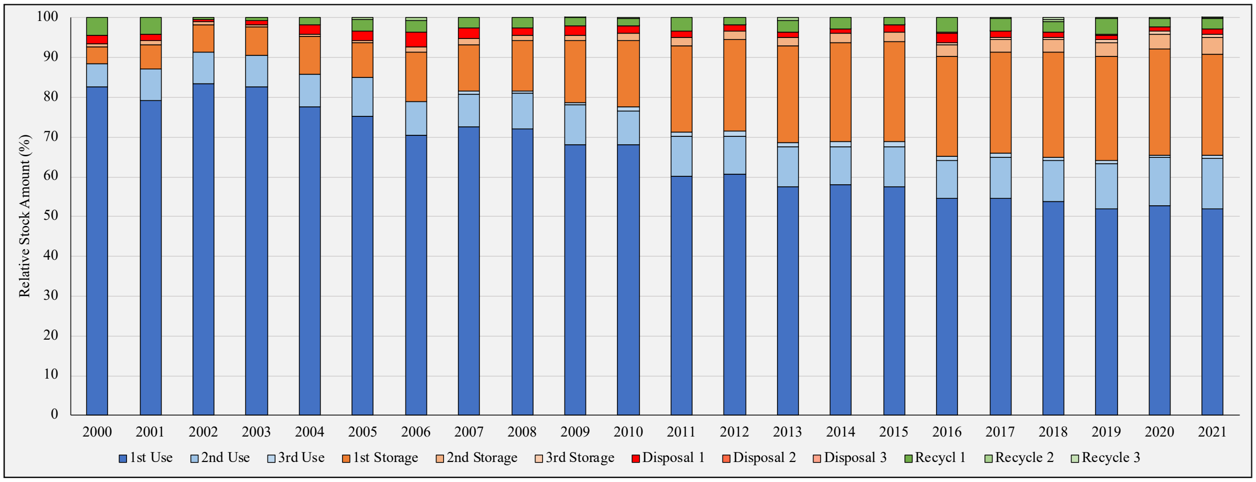
(a) Gold Stock Amounts



(b) Platinum Stock Amounts

Figure 16: Relative stock amounts of select metals from Electronic Devices in U.S. households for the years 2000 to 2021 showcasing the annual growing storage stock amount and decreasing in-use stock amount for each metal.

Figure 16 Continued



(c) Palladium Stock Amounts

To view a complete picture of the changing dynamic of metallic stocks in U.S. household devices, a Sankey diagram depicting the stock and flow amounts of select metals was created to visualize the flow and changing stocks amounts over time. Represented in Figure 17, the stocks and flow of gold in tons is shown for the year 2020. This presents a comprehensive picture of the metallic landscape for gold in U.S. households, showing the quantity that travels between each stock and the amount of gold present in smaller stocks like 2nd and 3rd users of gold. Most gold that is moving between stocks flows from the 1st User to Storage 1 stock with 8.02 tons of gold being newly stored for the year 2020. The same is true for platinum, shown in Figure 18, and palladium with about 38 and 33 tons respectively moving from 1st User to Storage 1 for the same year. Collectively this equates to 3.28 billion USD and 719 million kg of potential carbon dioxide emission savings being transferred to storage. The 2nd largest flow amount of gold and palladium for the year 2020 was 1st User to 2nd User at 5.91 and 18.8 tons respectively. Platinum, however, had a 2nd largest flow amount of 1st User to Recycling at 18.9 tons of platinum going into recycle from the 1st User. This suggests that as users purchase brand new devices, they tend to keep and store the device they are currently using rather than sell or give away to another user.

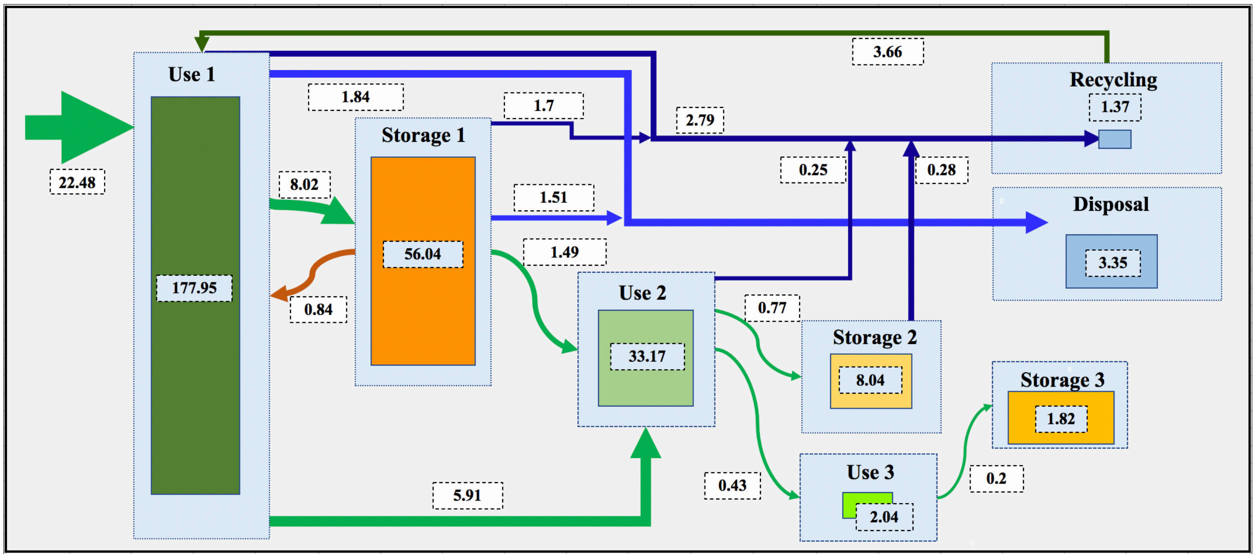


Figure 17: Sankey diagram depicting the relative stock and flow of gold in tons inside U.S. Households for the year 2020 with a majority of gold in U.S. Households residing in the Use 1 stock and flowing from Use 1 to Storage 1.

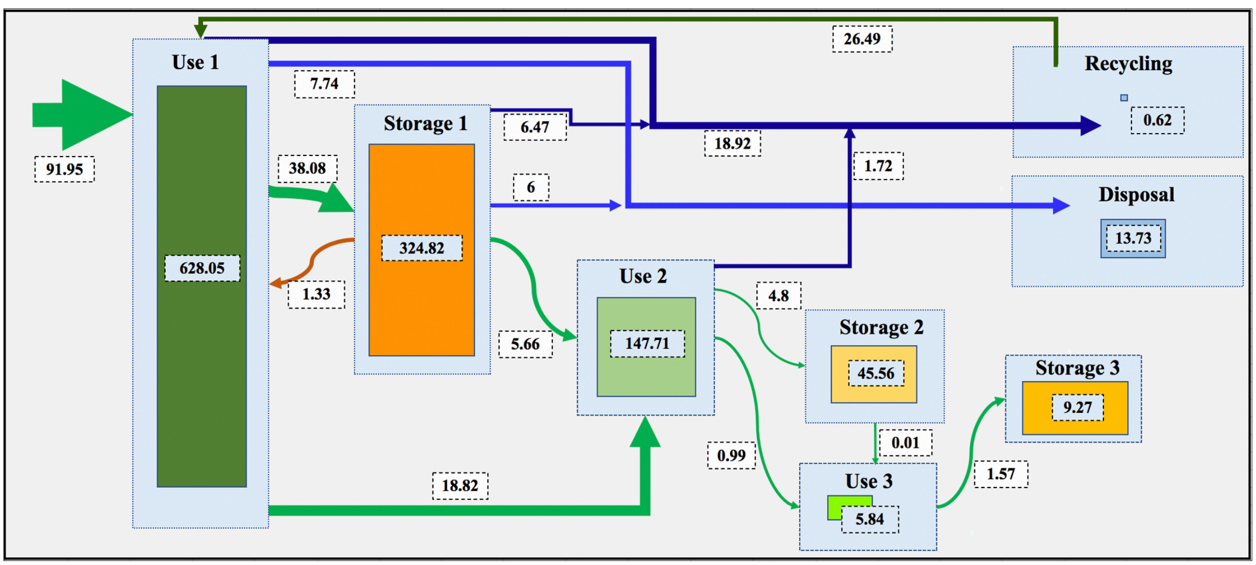


Figure 18: Sankey diagram depicting the relative stock and flow of platinum in tons inside U.S. Households for the year 2020 with a majority of platinum in U.S. Households residing in the Use 1 stock and flowing from Use 1 to Storage 1.

The same conclusion is applicable to REMs as well, represented in Figure 19 through the REM neodymium. A majority is in the Use 1 and Storage 1 stock with most neodymium moving from Use 1 to Storage 1 for the year 2020. Due to its higher concentrations in heavily used and stored devices like headphones and headphones, there is a large presence of neodymium in these stocks, totaling to an estimated 896 and 241 tons respectively. Interesting to note, however, that in 2020 more neodymium from devices was recycled back to another user than devices recycled that year, resulting in a deficit of about 16 tons in the Recycling stock. This means that although recycling rates of neodymium are high, there are still large quantities of stored neodymium in US households available for recycling. A complete stock and flow analysis for REMs and PMs is shown in Appendix B.1 along with Sankey diagram videos depicting the annually changing stock and flow for gold, platinum, and palladium in Appendix B.7.

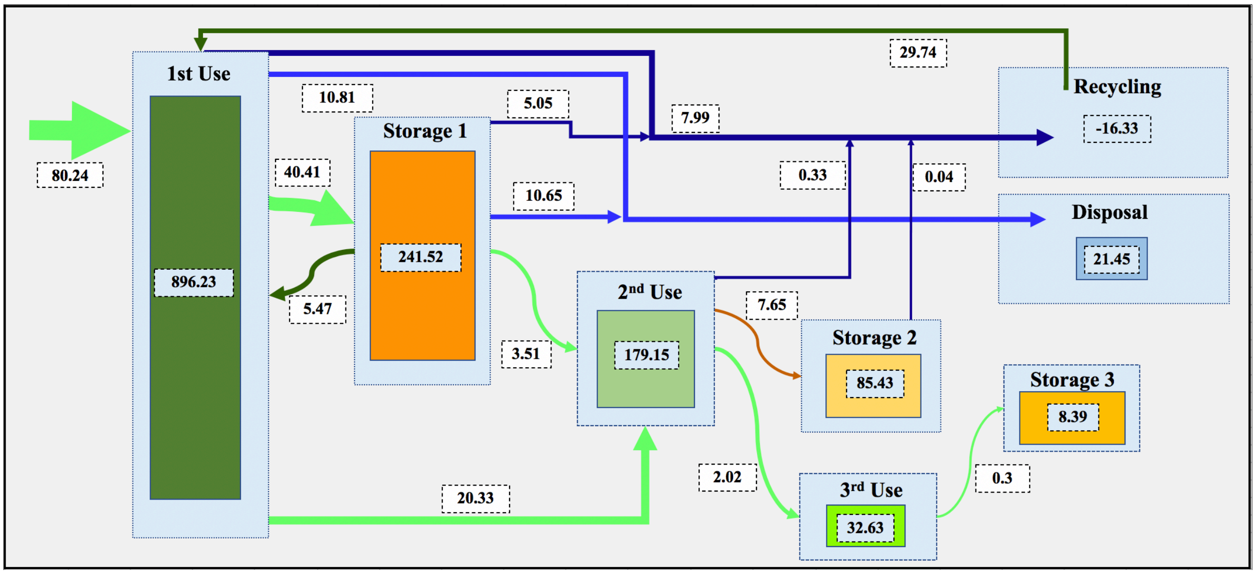


Figure 19: Sankey diagram depicting the relative stock and flow of neodymium in tons inside U.S. Households for the year 2020 with a majority of neodymium in U.S. Households residing in the Use 1 stock and flowing from Use 1 to Storage 1.

To understand the impact of stored metals on the U.S.'s economy, data for the U.S.'s demand for metals was acquired through the USGS's mineral commodity datasets to determine if stored metals in U.S. households would meet or exceed their demand in the U.S.[48]. Figure 20 represents the demand and recycling of gold with added stored gold amounts from devices in U.S. households for the same year. Although the demand for gold in the US remains steady spiking sharply only within the last 3 years, the recycling of gold fluctuates heavily steadily decreasing within the past decade. However, with the introduction of stored gold in U.S. household devices, combined with current recycling amounts, gold recycling is able to meet and exceed gold demand in the U.S. from the past decade save for the year 2021 due to the large spike in demand. This highlights the significant impact of stored gold in meeting U.S. demand and incentivizes secondary manufacturing to avoid imports and mining of new ore.

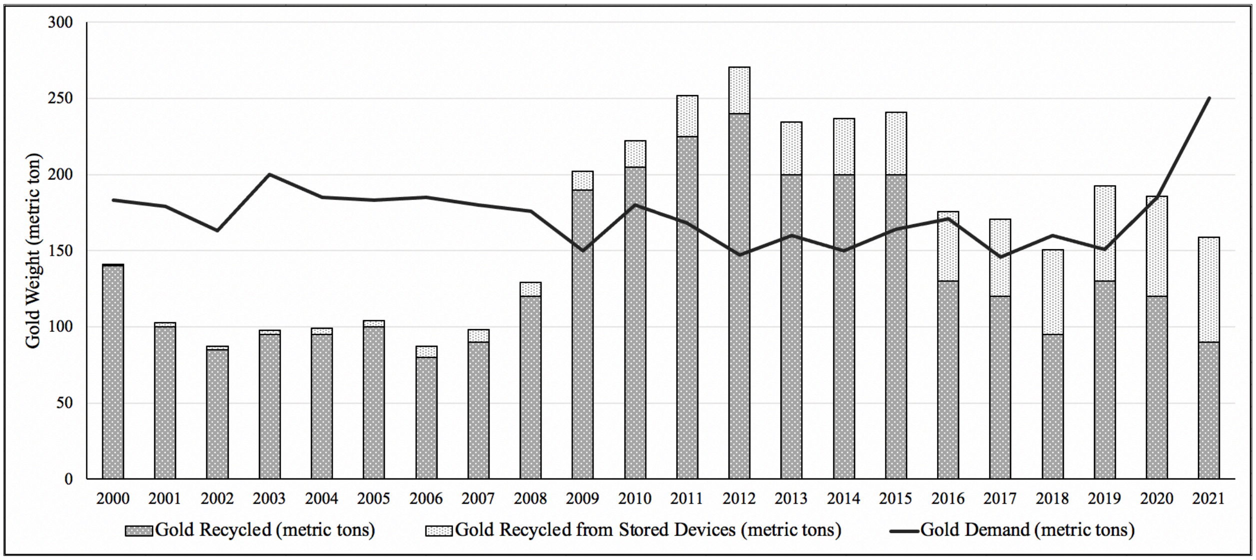


Figure 20: Gold demand in U.S. with current amount of gold being recycled and stored gold in U.S. Household Devices for the years 2000 to 2021, highlighting the capability of stored gold in U.S. household devices to exceed the demand of gold in the U.S. from the previous half decade.

Since demand data is scarce for platinum and palladium along with no recorded recycling, exports and imports were used to compare the economic impact of stored amounts in US household devices. Stored platinum and palladium both exceed the amount imported and exported combined from the U.S. by the year 2011. Platinum exceeds over three times the amount imported and exported by the year 2020 equating to 379 tons of recyclable stored platinum compared to the 93.7 tons of platinum imported and exported, shown in Figure 21.

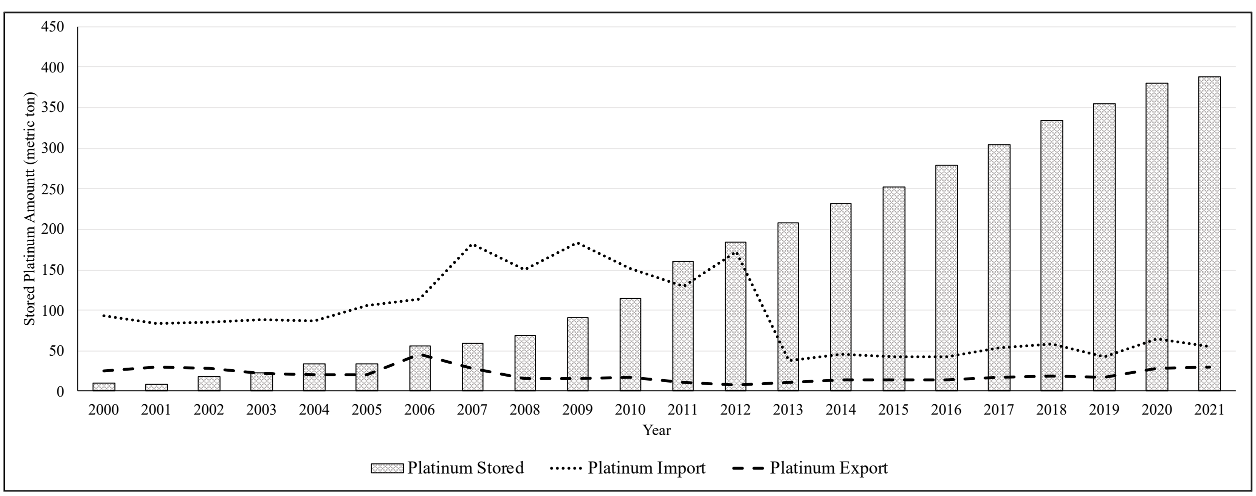


Figure 21: Platinum imports and exports from the U.S. in metric tons with current amount of platinum stored in U.S. Household Devices for the years 2000 to 2021, highlighting the capability of stored platinum to exceed both current exports and imports combined in the U.S.

The same is true for palladium with recyclable storage amounts totaling to 329 tons compared to the 125 tons that was exported and imported, shown in Figure 22. Representing even larger economic impacts than gold, the U.S. can rely solely on just a third of the recyclable platinum and palladium from stored household devices to meet current export and import rates. Refer to Appendix B.6 for the demand economic analysis for stored REMs and PMs.

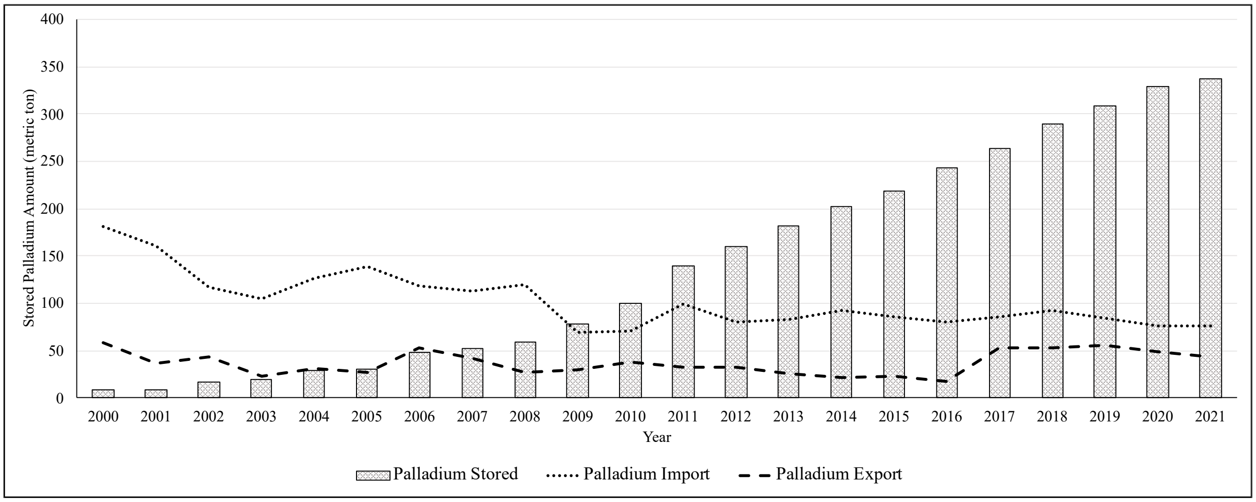


Figure 22: Palladium imports and exports from the U.S in metric tons with current amount of palladium stored in U.S. Household Devices for the years 2000 to 2021, highlighting the capability of stored palladium to exceed both current exports and imports combined in the U.S.

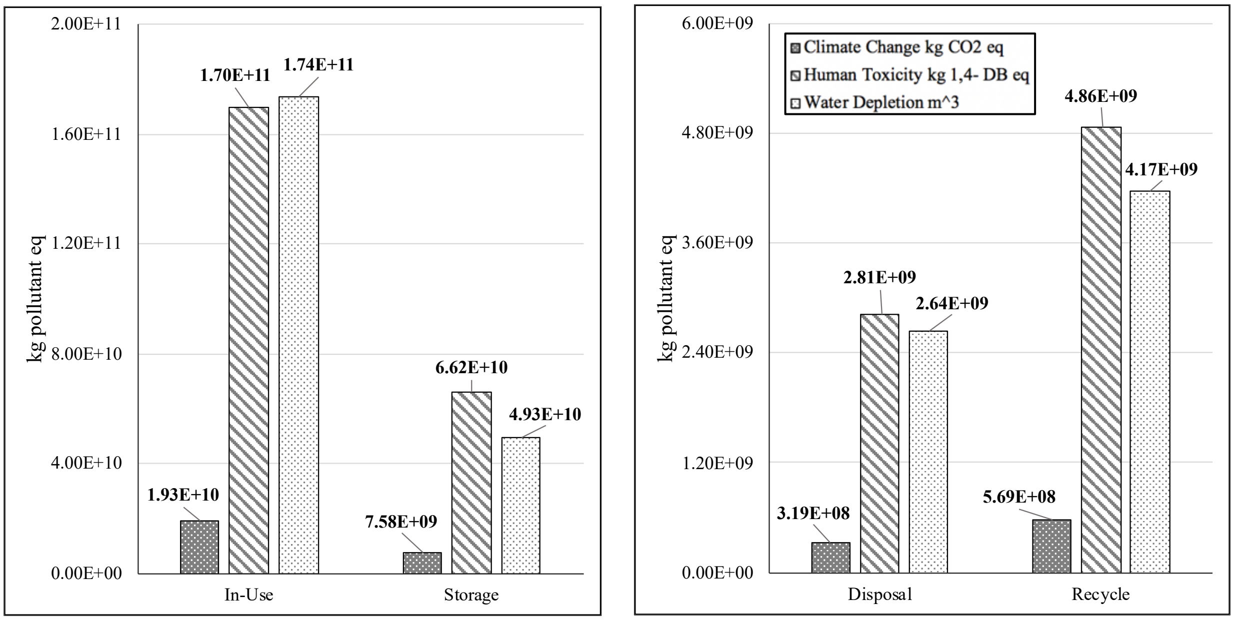
Over time, more devices are being put into storage within the past 2 decades. Collectively, the most expensive and impactful metals in U.S. household devices equate to 32.1 billion USD worth of gold, platinum, and palladium stored in U.S. household devices, carrying a potential environmental impact savings of 7 billion kg of carbon dioxide emissions. From an economic standpoint, these stored metals can help meet the current demand and international trading of these metals in the U.S. to avoid their primary manufacturing, reducing costs and environmental impact. Due to the changing landscape of metals in U.S. households moving to storage in greater quantities over time, implementing a circular economy to recycle and re-insert these metals into the economy in a sustainable manner becomes ever more evident and compelling.

1.3.10 Environmental Impact of U.S. Household Devices

The cradle-to-gate environmental impact of the metals in U.S. Household devices for each stock was evaluated and compared to quantitatively determine the extent of impact savings under a circular economy. The impact categories evaluated were climate change potential, human toxicity, and water depletion. These impacts reflect only the mining and refining of metals used in manufacturing each device.

Represented in Figure 23, stock impacts for household devices aggregated during the year 2020 breakdown the impact potential based on the device stock and impact category. In-use and storage hold a majority of the impact for all three impact categories, while disposed and recycled devices have a more minor role. Within the in-use and storage stocks, there is a significantly greater impact for human toxicity and water depletion when compared to climate change potential, accounting eight times greater impact on a per mass basis. Although the in-use stocks contain the most impact potential for all impact categories, the storage stocks still hold a substantial amount of impact potential, underlying the significance of properly disposing stored devices since they currently serve no active purpose.

The largest metallic contributors to each impact category consist of precious metals including gold, platinum, and palladium, accounting on average over 90% of the total impact per each device and impact category. Gold is regularly used in electronics due to its high conductive efficiency along with its stronger resistance to corrosion making it an idea element for connective wiring[49]. However, gold mining and refining is damaging to the environment due to its high energy and resource demand, including sulfuric concentrate, resulting in high on-site emissions to the surrounding environment[50]. Platinum is used in hard disks drive to increase storage and palladium is used in manufacturing of the printed circuit board (PCB) through capacitors for energy storage. However, mining and refining these metals also carry a large environmental footprint due to the high energy intensive processes needed to extract low grade ore of its platinum and palladium[51]. The same can be said for REMs, which do exhibit a lower environmental impact when compared to precious metals yet are still present in quantifiable amounts in stored devices and consequently noticeable contributions to the environmental footprint. Given their global increasing demand and decreasing supply, a shift of focus to recycling REMs will not only be beneficial from a demand standpoint, but environmental aspect as well[52]. This emphasizes the importance of recycling and reusing these metal groups to reduce environmental impact in carbon emissions, human toxicity, and water depletion throughout the United States.



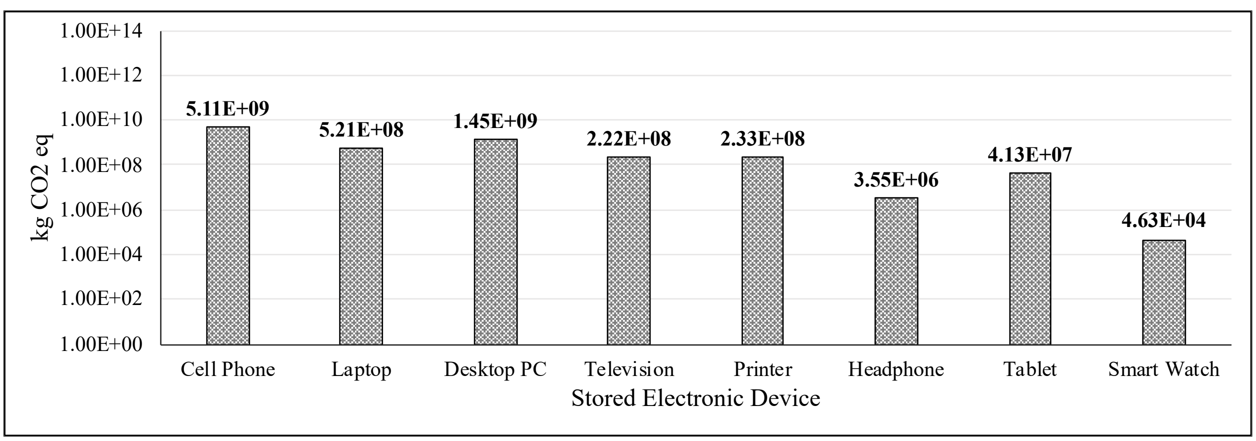
(a) In-Use and Storage Stock (b) Disposal and Recycle Stock

Figure 23: Environmental Impact Potential for Devices in U.S. Households in kilograms (kg) of pollutant equivalent (eq) based on the device stock for the year 2020, emphasizing the larger impact potential for devices in the in-use and storage stocks.

Total stock impacts for each environmental category were also quantified to determine the extent of impact for devices in US households. The total climate change potential for devices during the year 2020 was about 27.8 billion kg of equivalent carbon released. This is comparable to the CO2 emitted from a high polluting coal-fired power plant in operation for 59 days[53]. About 16 days' worth of these CO2 emissions is equivalent to the number of devices stored in US households. The total human toxicity potential for devices in U.S. households for the year 2020 was about 244 billion kg of 1,4-DB equivalent emitted, comprising the largest per mass of pollutant released from the three impact categories. The total water depletion potential for devices in U.S. households for the year 2020 was about 230 billion meters cubed of water consumed. This is comparable to 92 million Olympic sized swimming pools with 20 million of these pools equivalent to the water demand of stored devices in US households alone[54].

By recycling devices in-use in U.S households, the environmental impact compared to their primary manufacturing is significantly reduced. A previous study quantifying the end-of-life environmental impact for recycling computers and televisions estimated that the climate change, human toxicity, and water depletion potential to be 68.53 kg CO2 equiv., 84.37 kg 1,4-DB equiv., and $7.17\text{x}10^{-3}$ m^3 water consumed respectively from recycling 1 ton of computers and televisions[55]. Scaling to the quantity of computers and televisions currently used in U.S. households for the year 2020, this equates to a climate change potential of 537 million kg CO2 equiv., 660 million kg 1,4-DB equiv., and 108 million m^3 water consumed respectively by recycling these devices. By recycling these in-use devices to avoid primary manufacturing of new devices, computers and televisions can save an estimated 6.5 billion in CO2 and 49.8 billion kg 1,4-DB emissions and reduce water consumption by 69.9 billion m^3 water for the year 2020. Applied to the quantity of stored devices in U.S. households for the year 2020, stored devices can save an estimated 1.6 billion in CO2 and 12.7 billion kg 1,4-DB emissions and reduce water consumption by 12.8 billion m^3 water through recycling rather than manufacture new devices.

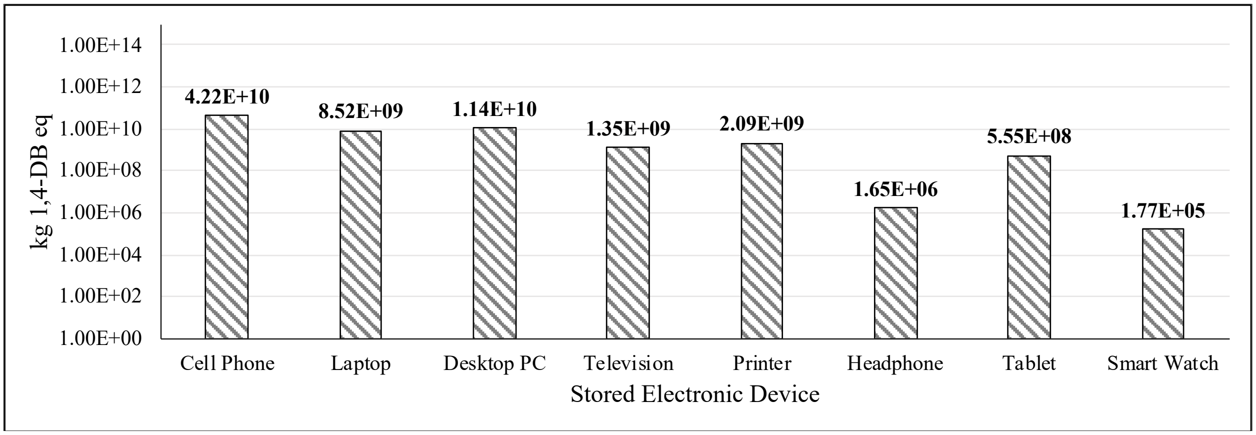
It is evident that stored devices in U.S. households hold significant environmental impact potential. Examining closer, the environmental impact for each impact category by the number of each device stored in U.S. households from the year 2020 is shown in Figure 24. Due to the large environmental footprint and volume of cell phones stored compared to other devices, they carry the most amount of environmental impact for each impact category by a wide margin. With Laptops and Desktop PCs trailing afterwards at about four to five times less impact than Cell Phones for each category. Smaller relatively newer devices like tablets, smart watches, and headphones have significantly less impact compared to larger devices due to their smaller mass of metals within them. Larger devices tend to have greater impact for each impact category with the exception being cell phones due to their high storage count and environmental footprint.



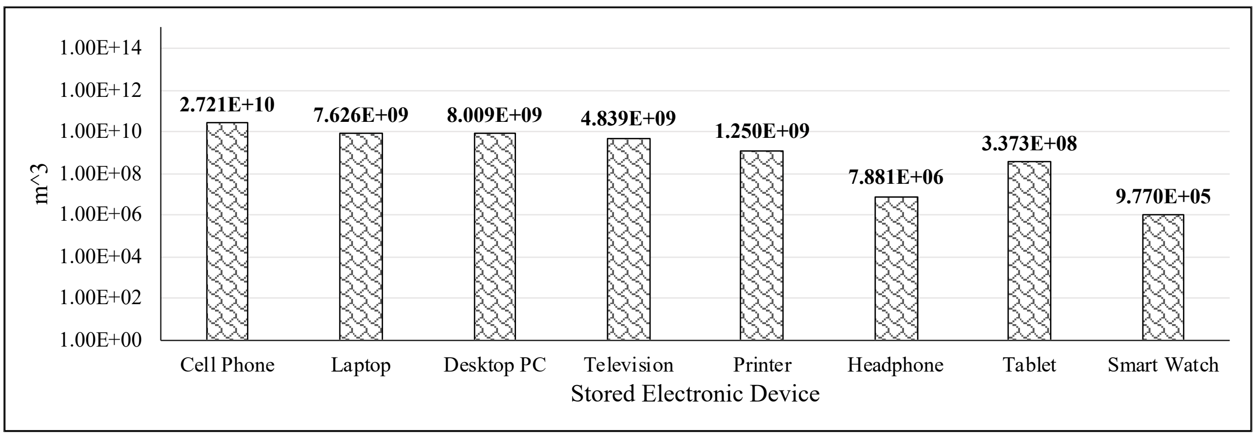
(a) Climate Change Potential

Figure 24: Environmental Impact for Stored Devices in U.S. households for the year 2020 based on device type and environmental impact category. Largest amount of impact residing with cell phones and larger devices for each impact category. Note: y-axis is in logarithmic scale.

Figure 24 Continued



(b) Human Toxicity Potential



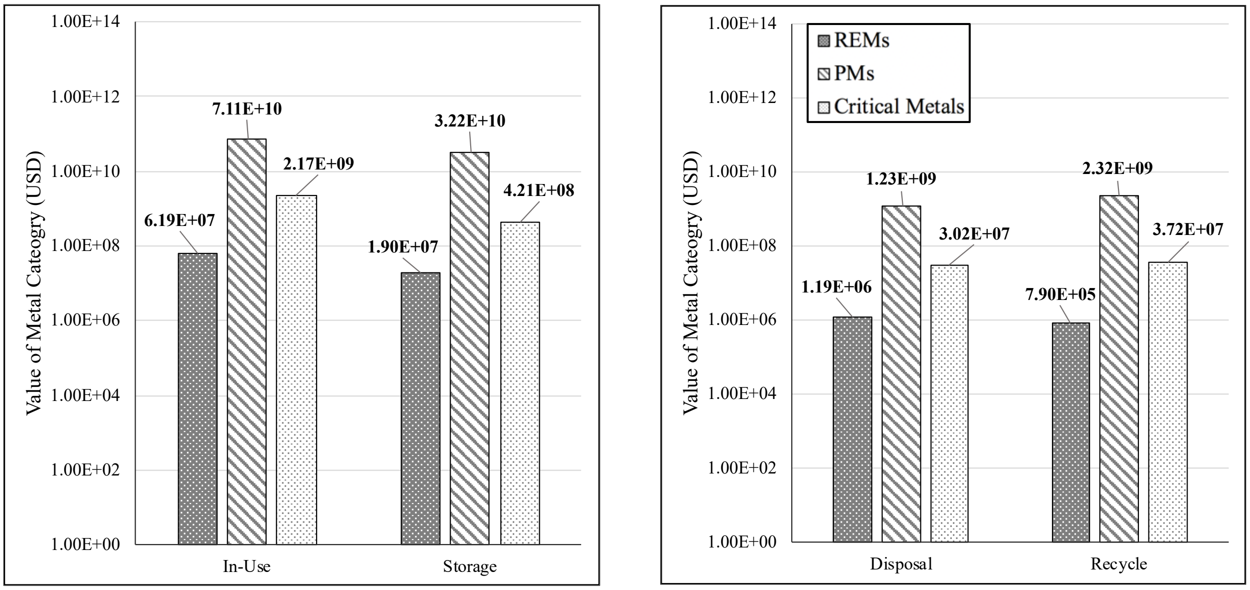
(c) Water Depletion Potential

In conclusion, in-use and storage stocks contain the largest environmental footprint for all three impact categories with precious metals contributing the most to their respective pollution emissions. From the storage stock, cell phones have the most environmental impact potential for all three impact categories as well. With larger devices also having a meaningful comparable impact due to their higher mass amounts of metals contained within them.

1.3.11 Economic Value of U.S. Household Devices

The economic monetary value of household devices in the U.S. was quantified to determine the monetary value contained in household consumer electronics. Represented in Figure 25, a breakdown of monetary value for all household devices is shown, separated by the device stock and metal group. Devices in the in-use and storage stocks have a considerably greater amount of value compared to devices disposed and recycled. This is expected due to the larger number of devices actively used and stored in U.S. households than disposed or recycled. Although the in-use stock contains a majority of the value from household devices, the storage stock is still significant equaling roughly half of the total value from devices in-use.

By metal category, PMs comprise of a majority of the value for all stocks, accounting on average 97% of the total monetary value for all household devices. This is due to the high market price and larger quantities of PMs present in devices including gold, platinum, and palladium. As discussed in section 1.3.9 these metals are present in high quantities in electronic devices due to their favorable capabilities that improve device performance. Since mining and refining PMs is a very energy and resource intensive process, along with high demand for device functionalities, they carry a higher market price. The next leading metal group based on value are critical metals. Though these metals do not contain a high market price per unit mass, since they are in abundance in many devices, especially larger devices like desktop computers and televisions, they have a significant amount of value based solely on the sheer amount of these metals present in devices. The major contributors of value for these group of metals include aluminum, tin, nickel, and barium. They are used for a variety of purposes in electronic devices mainly for PCB and hard disk drive functionality, batteries, and projection screen monitors[56]. REMs contain the smallest amount of value present in household devices. Though they have a higher value than critical metals on a per mass basis, since they are in smaller quantities in devices than critical metals and PMs, the total value of REMs in devices is relatively small. These metals have a wide array of functionality in devices, mainly through neodymium and dysprosium for strong magnets within hard disk drives and speaker systems[57]. Due to their natural scarcity and growing demand for electronics manufacturing, implementing recycling techniques to reuse these metals under a circular economy is equally as important from a sustainability standpoint even though their value is relatively smaller.

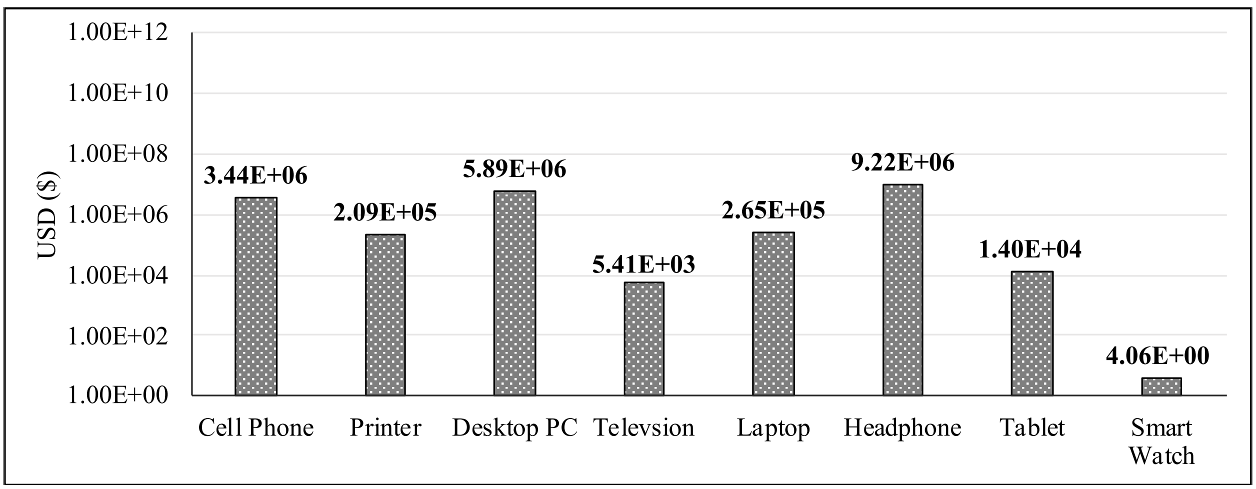


(a) In-Use and Storage Stock (b) Disposal and Recycle Stock

Figure 25: Economic value of household devices in U.S. dollars (USD) based on the stock of the device and metal group for the year 2020, showing the greatest amount of value lies with critical and precious metals in the in-use and storage stocks. Note: y-axis is in logarithmic scale

The total value of metals in U.S. households by metal category was calculated to determine the potential economic benefit from recycling household electronics. The total value of REMs in U.S. household devices for the year 2020 was about 83 million USD with 19 million USD of that amount from stored devices. The total value of PMs in U.S. household devices for the year 2020 was about 107 billion USD with 32 billion USD of that amount solely from stored devices. Lastly, the total value of critical metals from U.S. household devices for the year 2020 was 2.65 billion USD with 420 million USD of that amount from stored devices. This totals a value of an estimated 110 billion USD from U.S. household devices for the year 2020 with 32.6 billion USD of that from stored devices. For perspective, the technology company Apple made roughly double this amount profiting 64 billion USD in gross sales from its app store for the same year[58]. It is clear that the storage stocks contain a huge amount of value from devices that serve no active purpose to the user, and therefore these devices hold the most accountability to be recycled for its resources and economic benefit.

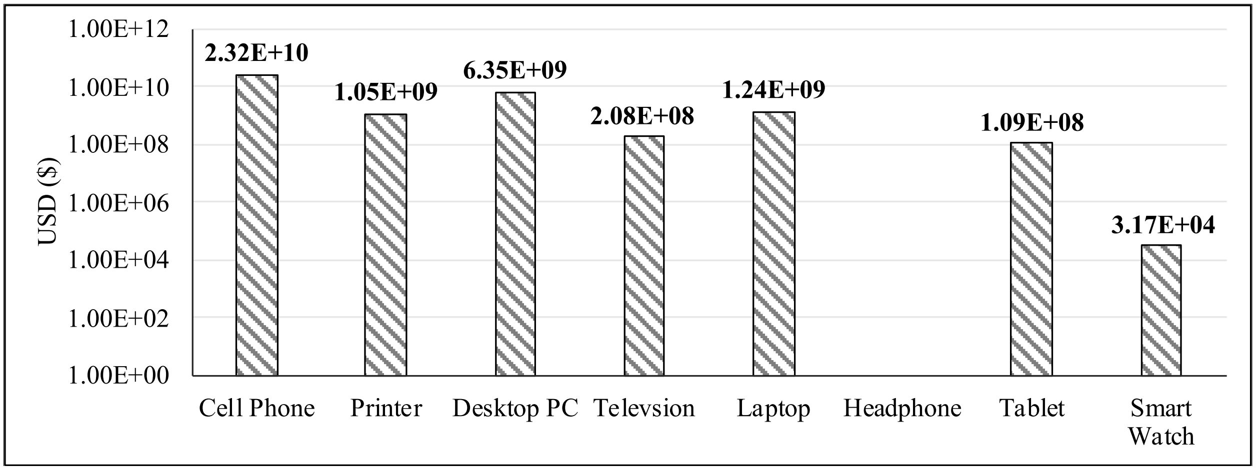
To better understand which stored devices and metal groups comprise the most value, Figure 26 depicts the total value of each device based on metal category for devices in storage in U.S. households. Headphones, desktop PCs, and cell phones contain the most value for REMs due to their higher presence of neodymium and dysprosium magnets. Cell phones, however, significantly contain the most value for the most expensive metal group, PMs, due to the high market prices of gold, platinum, and palladium and larger amount of cell phones in storage compared to the other devices. Most of the value for critical elements is stored with larger devices like desktop PCs, televisions, and printers due to their larger mass presence of aluminum, tin, and copper per device. Though these larger devices are relatively in smaller storage quantities than smaller devices like cell phones and headphones, their larger framework and device weights requires greater amounts of critical metals generating more value per device from these metals. Collectively, cell phones hold the most amount of metallic value equating to about 23 billion USD from stored devices in U.S. households, with stored desktop PCs containing the second most amount of value at about 6.5 billion USD.



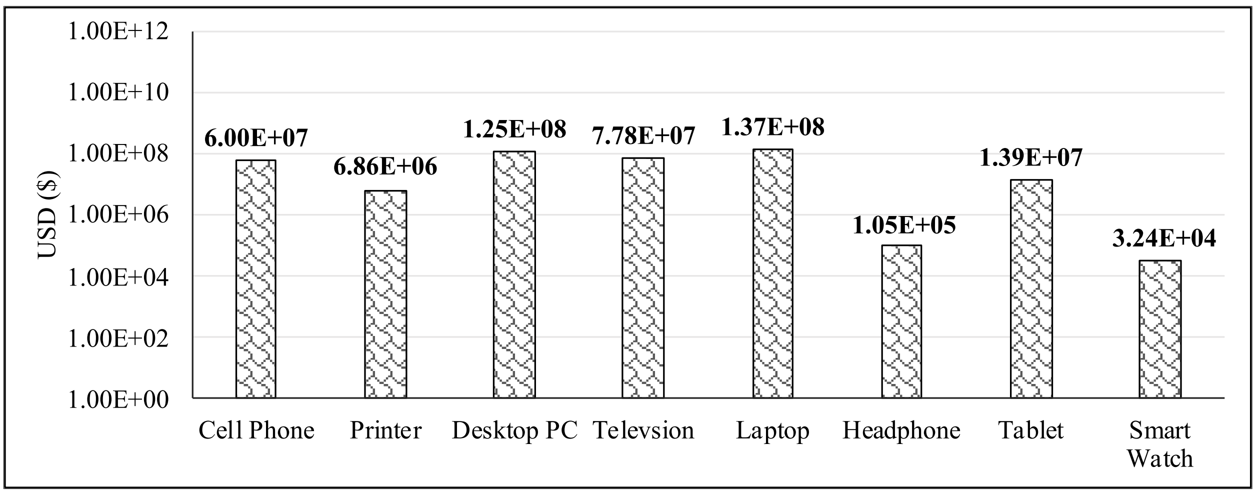
(a) REM Value

Figure 26: Value of Stored Devices in U.S. Households for the year 2020 based on device type and metal group. Value for each metal category is device dependent with cell phones having the most overall value due to their precious metal content. Note: y-axis is in logarithmic scale.

Figure 26 continued



(b) PM Value



(c) Critical Metal Value

It is evident that the in-use and storage stocks contain the most amount of economic potential with PMs comprising a substantial portion of this value. From the storage stock, larger devices have a greater value for critical metals, while cell phones and headphones have more value for the more expensive PMs and REMs respectively. Due to the large amount of cell phones in storage within US households, and presence of costly PMs in their hardware, they generate the most monetary value potential by a wide margin for devices in storage.

Limitations of this study comprise of an incomplete representation of transfer coefficients pertaining to the stocks Use 2 and Use 3. Due to unavailable data from the survey sample size for a significant portion of years, transfer coefficients for these stocks and flows can be underrepresented with no available data corresponding to a value of 0, while some transfer coefficients can be overrepresented with a value of 1. This can lead to an underestimation in which no devices are present or an over estimation in these stocks and flows. Also, the metal concentration for devices was indicative of only a single model from previous research and do not reflect the metal concentration of devices from different manufacturers and changing models. Lastly, the only demographic consideration factored into the scale-up from the survey sample size to the U.S. household sample size is the household size due to it being deemed as the most influential variable when it comes to the quantity of devices found in households.

1.4 Conclusions and Future Work

A top-down stock and flow STELLA model was developed to determine how U.S. households manage common consumer electronic devices. The most radically changing stock within the past 2 decades is storage, increasing in size six times greater than the initial storage amount on a per mass basis. This increase is seen in other countries as well suggesting similar behavior at a global scale. Smaller handheld devices tend to be stored in greater quantities than larger non-handheld devices, with cell phones being the most abundantly stored device. Newer devices like smart watches and tablets, however, also had low storage amounts but behave similarly to non-handheld devices in terms of increasing annual storage.

By the year 2020, the monetary value of metals in storage from these household electronics is estimated to be 32.6 billion USD with about 30.6 billion USD of this stemming from precious metals. Under a circular economy, the potential savings in environmental impact from these stored metals equates to an estimated 7.6 billion kg of carbon dioxide and 66.2 billion kg of 1,4-DB equivalent avoided emissions for the environmental impact categories of global warming and human toxicity respectively by the year 2020. For the same year, the amount of avoidable water depletion from these stored metals is estimated at 49.2 cubic meters of water. About 90 percent of emissions for these three impact categories all come from precious metals as well. These stored metals can have a significant impact to the US economy able to meet and exceed their U.S. demand and economic trade for the most impactful and expensive metals found in electronic devices. Furthermore, the stored device with the largest amount of monetary value and environmental footprint being cell phones. This is due to the sheer volume of cell phones stored in U.S. households, equating to an estimated storage amount of 453.8 million devices, and vast array of REMs and PMs they contain, equating to a value of 76.5 USD and 16.8 kg of carbon equivalent emissions pe device. In combination with more devices and metals being moved to storage in U.S. households, a shift in focus to tap into this growing goldmine of devices collecting dust in the cabinet becomes ever more prevalent. As metals found in the natural world become scarcer due to their growing demand from consumers, the gap between the idea and implementation of a circular economy widens with possibility. The first step to a plausible solution to cross traverse this gap is presented here by showing the growing impact and relevance of stored metals within U.S. household devices.

Future work conductible on this study include a comprehensive demographic analysis to determine what forms of environmental factors pertaining to age, gender, and location effect how households store their devices. For example, if changing storage trends is region specific within the U.S. and different between rural and urban communities. Also, the inclusion of more devices into the model both old and new like MP3 players, speakers, and smart home devices would provide more information about how these other devices behave in U.S. households. These updates would provide a greater understanding and more realistic look at the storage trends and accompanying economic and environmental impact of electronic devices in U.S. households.

2. EVOLUTION OF SMARTPHONES METALLIC CONTENT

2.1 Introduction and Problem Statement

Change in the behavior of how U.S. households manage devices is not the only important evolving trait to modeling a circular economy on electronic waste. Evolution within the device themselves is critical to understanding which metals are present and predicting changes with future more advanced devices. These changes in metal concentration can directly affect the environmental and economic ramifications of electronic waste.

Previous studies have focused on a limited range of metals involving only critical metals, and some PMs, excluding rare earth metals due to their lower concentration in devices[59,60]. However, due to the large number of devices increasing annually in storage inside U.S. households (see section 1.3.6), encompassing more metals would provide the most realistic and accurate representation of a circular economy. Also, previous research has not conducted generational comparisons to subsequent device models from the same manufacturer, instead studying devices of multiple different backgrounds making it hard to decipher direct comparisons of similar devices[61].

This research aims to fill these gaps of knowledge by first answering what REMs, PMs, and critical metals are present and in what concentration for three cell phone device components: Wi-Fi antennas, vibration motors, and front cameras. Second, visualize the trends in metal concentration for these device components from succeeding generational devices with the same manufacturer and model type, the Samsung Galaxy phone. Incorporating more metals and device components from the same model type provides a clearer and holistic view at cell phone's development over time in terms of their metallic contents, having direct implications into quantifying the metallic stock and flow amounts in U.S. households.

2.2 Materials and Methods

The Samsung Galaxy phone components that were analyzed for their metallic content were the Wi-Fi antenna, vibration motor, and front camera. The Samsung Galaxy Phone models analyzed were the Galaxy S1 to S6, S6E, and S6E+. Experimental methodology involved first digestion of phone components through a Microwave Digester with hydrochloric acid, nitric acid, and hydrofluoric acid if necessary. Afterwards, the digested components were subjected to ICP-OES to characterize the concentration of 58 different metallic components in these phone components. The experimental procedure was performed following the procedure from Tantawi's article in which they also characterized the evolving metallic concentration of back cameras, PCB, and NFC antenna/wireless charger for the same Samsung Galaxy phone models[11].

2.3 Results and Discussions

2.3.1 Metal Content of Wi-Fi Antennas

The three components analyzed from the Samsung Galaxy phone models showed a wide variety of metals present at varying concentrations for subsequent phone models. The highest concentrations present for Wi-Fi antennas stems from nickel, copper, zinc, and platinum comprising of concentrations in the range of 10^6 ug/g of Wi-Fi antenna, shown in Figure 27. This is due to the wiring being comprised of mostly copper. As models progressed from the Galaxy S1 to Galaxy S6E+, the amount of these metals in Wi-Fi antennas increased. Shown in Figure 28, Zinc and magnesium increased the most in newer models, while copper increased slightly. Small amounts of rare earth metals in the form of lanthanum, neodymium, gadolinium, and dysprosium were present in Wi-Fi antennas as well, with a majority of the remaining metals originating from critical metals like titanium and manganese. The amount of titanium peaked in the Galaxy S5 but then decreased in future models, while the amount of manganese increased gradually, showing a sharp peak in concentration for the Galaxy S6E before decreasing to concentrations levels exhibited in previous models for the Galaxy S6E+.

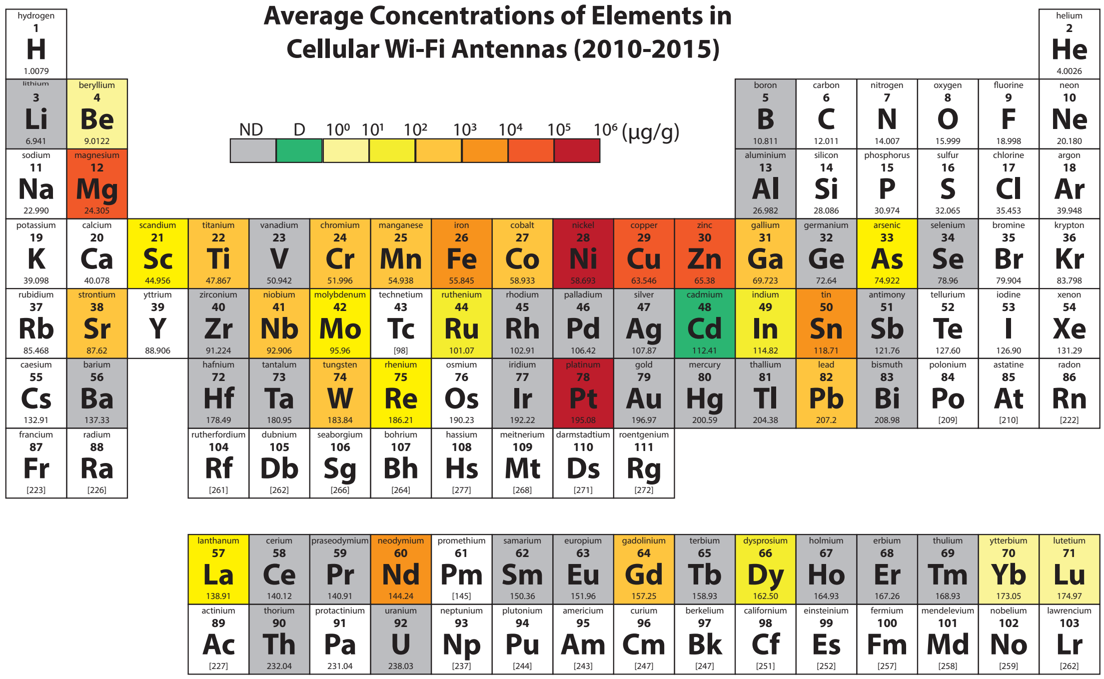


Figure 27: Average Concentrations of Metals in Wi-Fi Antennas from the year 2010 – 2015 (ug/g), showing the high concentration of platinum and other critical metals present in Wi-Fi Antennas.

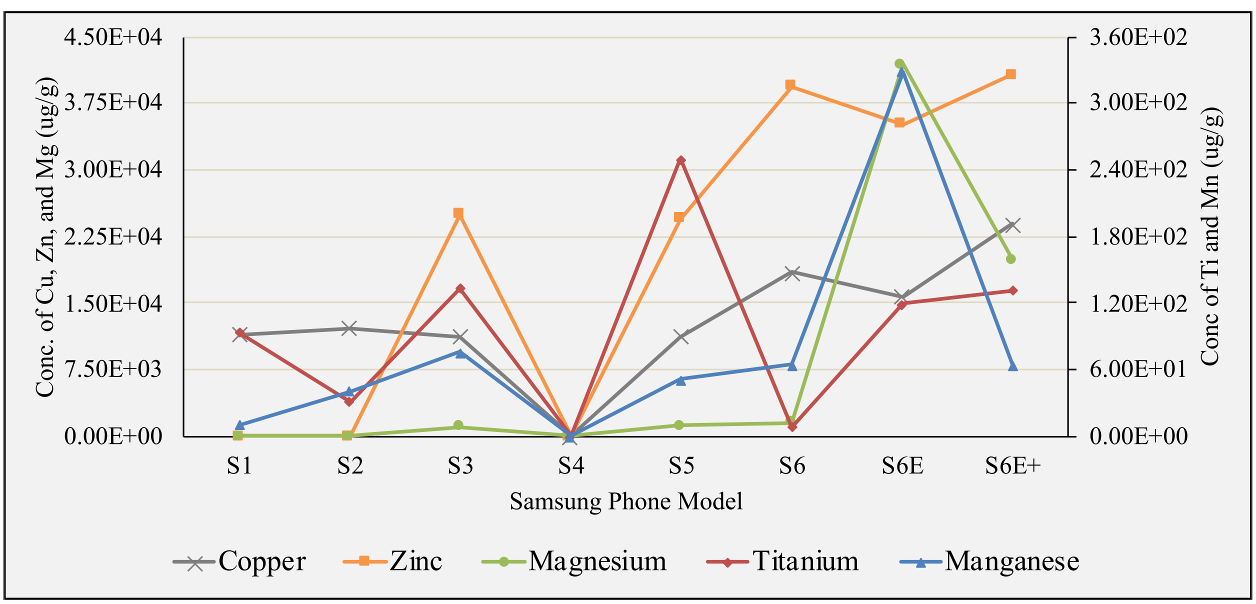


Figure 28: Concentrations in ug/g for most abundant metals present in the Wi-Fi antennas for the Samsung Galaxy Models S1 to S6E+. Concentrations of metals are increasing and being to plateau in more recent models.

2.3.2 Metal Content of Vibration Motors

The highest concentrations of metals present in vibration motors were neodymium, copper, chromium, and platinum in the range of 10^1 and 10^2 ug/g of vibration motor, shown in Figure 29. This is due to the presence of a neodymium magnet in the vibration motor to produce the vibration and sound. Shown in Figure 30, the amount of these metals in vibration motors stayed relatively constant across all Samsung models. Chromium, copper, and platinum decreased in concentration, and neodymium increased in concentration for newer Galaxy models. Small quantities of REMs were present in vibration motors as well, mostly in the form of lanthanum and dysprosium, present in only a few Galaxy models, with a majority of metals stemming from critical metals and PMs like iridium and nickel. Both of which displayed slight decreases in metal concentration for vibration motors in newer Samsung models.

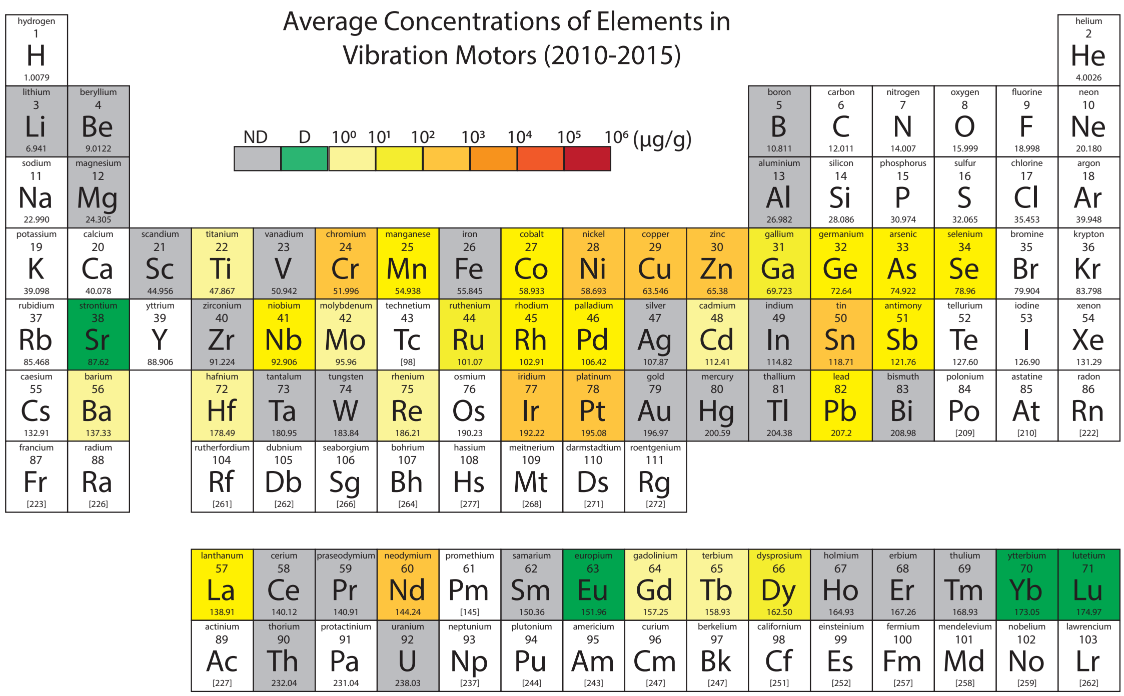


Figure 29: Average Concentrations of Metals in Vibration motors from the year 2010 - 2015 (ug/g), showing higher concentrations of neodymium, platinum and other critical metals present in vibration motors.

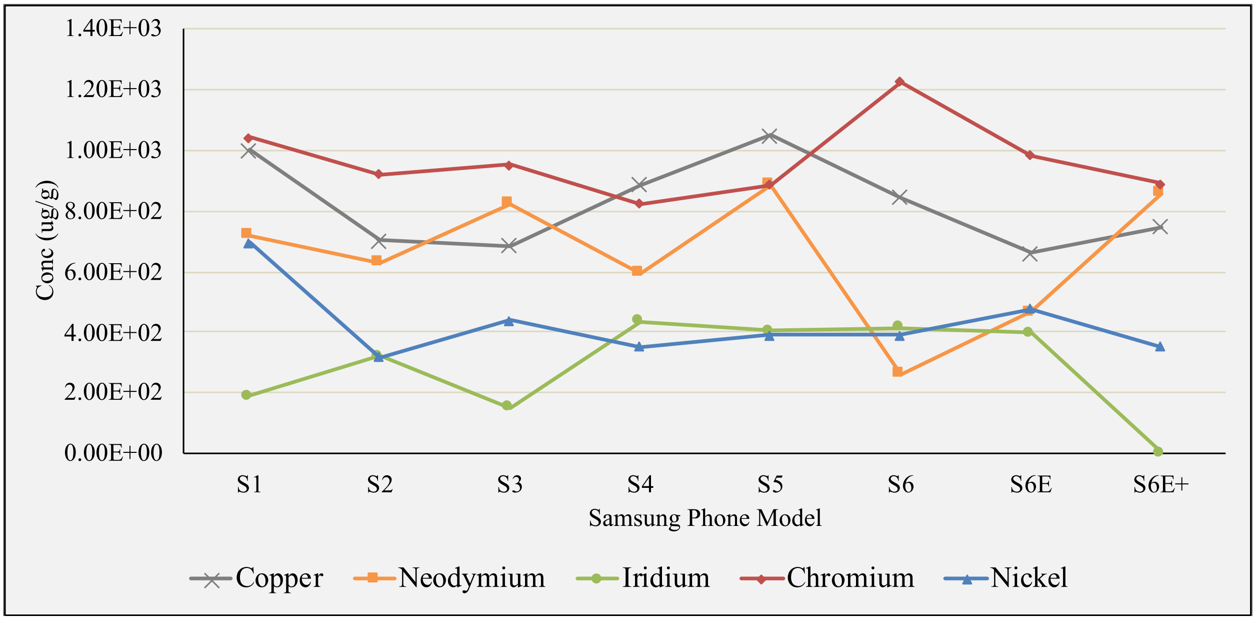


Figure 30: Concentrations in ug/g for most abundant metals present in the vibration motor for the Samsung Galaxy Models S1 to S6E+. Concentrations for all metals slightly decreasing in newer models except for neodymium, which displayed overall increases in concentration.

2.3.3 Metal Content of Front Cameras

Front cameras contained the highest concentrations of metals out of all three phone components producing high amounts of platinum, copper, and aluminum in the range of 10^6 ug/g and REMs as well, shown in Figure 31. The amount of copper in front cameras gradually increased, with aluminum and copper both peaking in concentration at the Galaxy S5 before decreasing back to similar concentrations from previous models for the Galaxy S6, S6E, and S6E+, shown in Figure 32. Front cameras also contained lower concentrations of critical metals, similar to that seen in Wi-Fi antennas, including iron, chromium, and nickel. With nickel increasing in metal concentration as well, peaking at the Galaxy S5 before returning to initial concentrations for the Galaxy S6 and beyond. Also, front cameras contained the lowest variety of REMs, having only 3 present through lanthanum, samarium, and gadolinium. However, they were in the highest concentrations out of all three phone components, reaching concentrations of 10^3 ug/g. Although, lanthanum and gadolinium were only present in a select few models, Samarium was present in each model slightly peaking in concentration for the Galaxy S5, before decreasing to lower concentration levels than previous models. The presence of higher concentrations of metals including REMs, compared to the vibration motor and cellular antenna, is likely attributed to the more complex and sophisticated functionalities front cameras have. While vibration motors and cellular antennas are relatively simple and straightforward in their designed purpose in smart phones.

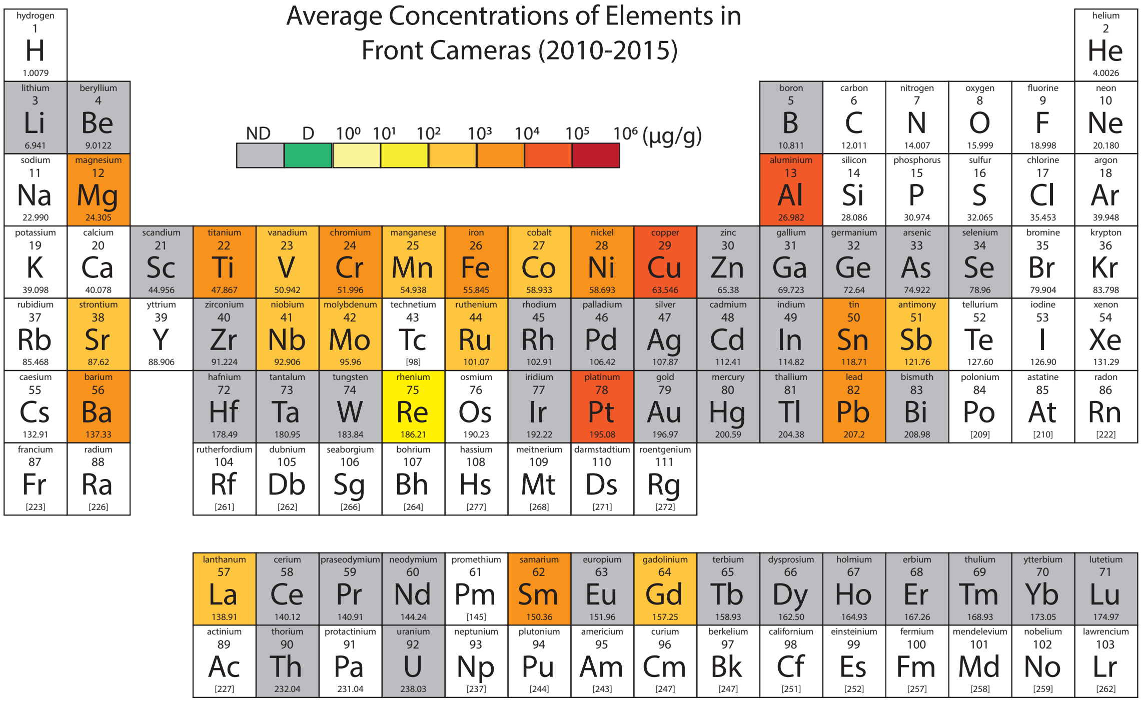


Figure 31: Average Concentrations of Metals in Front Cameras from the year 2010 – 2015 (ug/g), showing higher concentrations of platinum, copper, aluminum, and rare earth element samarium in front cameras.

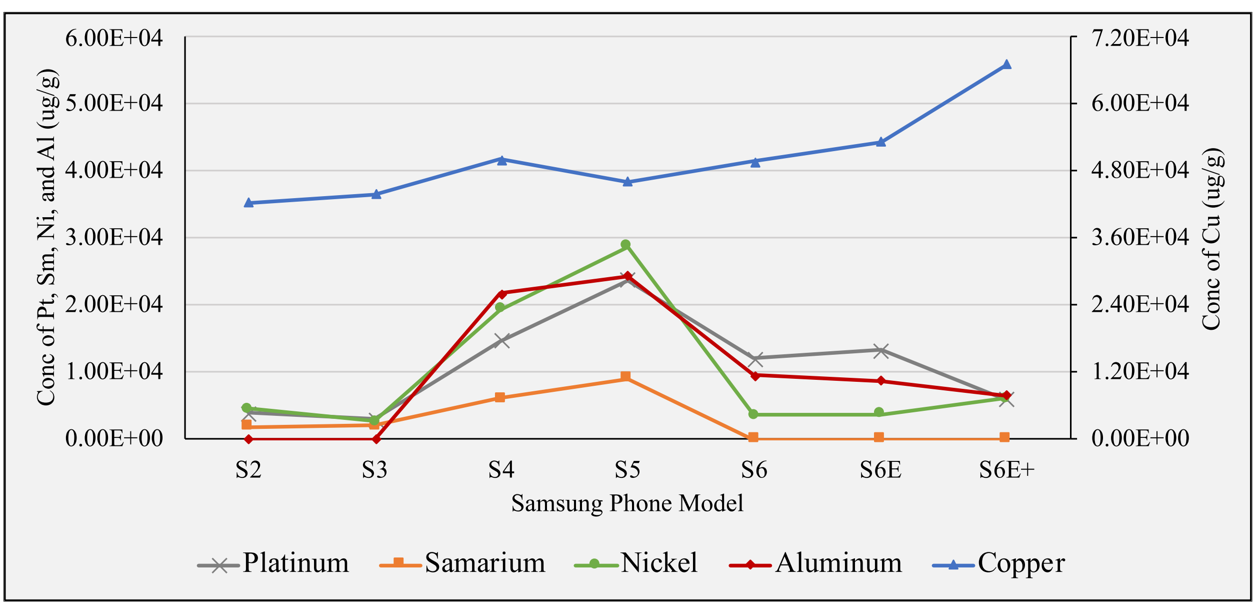


Figure 32: Concentrations in ug/g for most abundant metals present in the front camera for the Samsung Galaxy Models S1 to S6E+. Concentrations for copper gradually increase, while the remaining metals peaked in concentration in the Galaxy S5.

2.4 Conclusions and Future Work

In conclusion, each component showed varying amounts of different metals from each generational phone model. Front cameras contained the highest concentration of metals, although the lowest variety of metals as well, attributed to their higher functioning capabilities. The lesser complex components, Wi-Fi antennas and vibration motors, showed lower concentrations of metals. With Wi-Fi antennas and vibration motors comprising mostly of critical metals and some precious metals like palladium for vibration motors. In total, the metals contained in these components increased the mass amount of metals estimated from Tantawi's previous analysis on cell phone PCBs, front cameras, and NFC antenna and wireless charger by about 1%. This is heavily influenced by the mass differences in components analyzed in Tantawi's components, accounting for about a 95% smaller mass weight for components in this study.

Comparing metal concentrations to different Galaxy Models, Wi-Fi antennas showed significantly increasing concentrations of multiple metals, especially zinc and copper. While vibration motors had metal concentrations slightly decreasing for most metals. Lastly, front cameras had most metal concentrations increasing initially, with max concentrations in the Galaxy S5, but then gradually decreasing in new models afterwards. In conclusion, different components behave differently when it comes to evolving metal concentrations for brand new devices from the same manufacturer. Less complex components like Wi-Fi antennas exhibited steadier increases in metal concentrations, while more complex components like front cameras have more fluctuating concentrations for each new model. Complete concentrations of each component and phone model along with the calculated error for each concentration quantified are shown in Appendix D.1.

Future work to progress this research would involve characterizing the metallic concentrations for more phone components from the same Samsung phone models including the multi-layered screen and frame of the phone. This would give a better overall picture of what kinds of metals and in what quantity are present in the cell phone device as a whole. Also, conducting a similar analysis to other subsequent phone models from other cell phone manufacturers like Apple or Google would provide relevant comparisons across companies' diverse phone models.

3. CLOSING STATEMENT

The quantity of stored devices entering U.S. households has increased drastically in the 21st century, changing the dynamic of how devices are used within them. Overall, all eight devices modeled in this study increased in both in-use and storage amount in households annually, with cell phones and headphones being the most used and stored device. Focusing on cell phones, specifically, the metallic concentrations of the Wi-Fi antenna, vibration motor, and front cameras for eight generational Samsung Galaxy phone models displayed high amounts of select precious and critical metals, and smaller concentrations for a few REMs. Although their concentrations varied from each subsequent model, exhibiting varying trends in concentration unique to each phone component, the presence of these metals has promising secondary manufacturing value to recover them. The benefits, especially for PMs and REMs due to their scarcity as a natural resource and high-polluting processes to retrieve, provide an economic and environmental benefit to the U.S. and currently a majority of the monetary value and environmental impacts reside in devices that are currently in-use and stored inside U.S. households.

To reduce the most impact potential to the environment and acquire the most economic value, this study concludes a stronger focus and proactive approach on recycling and reusing devices in-use and stored in U.S. households is necessary. This means further incentives to move stored electronics to new users and recyclers to extend the device lifetime and reuse valuable metals they contain, minimizing the quantity of devices kept in storage while acquiring the most value possible out of them. Also, a more well-informed public about where to recycle stored electronics and why it's important through findings for example made in this study provide an urgency and relevancy to the public on the importance of collective action and participation in reusing and recycling currently stored electronics and users thinking about storing electronics. Through these actions, the idea of a circular economy becomes less idea and more reality, pioneering the way towards a sustainable planet for generations to come.

APPENDIX A. MODEL INPUTS AND OUTPUTS

For Appendix A please see attached excel sheet titled “Appendix A”

APPENDIX B. DATA ANALYSIS RESULTS

For Appendix B please see attached excel sheet titled "Appendix B"

APPENDIX C. DATA ANALYSIS INPUT

For Appendix C please see attached excel sheet titled “Appendix C”

APPENDIX D. EVOLUTION OF SMARTPHONES METALLIC CONTENT RESULTS

For Appendix D please see attached excel sheet titled “Appendix D”

APPENDIX E. SUPPLEMENTARY TABLES

Table 1: Mapping of Survey Questions to Model Parameters that each question addresses.

		Transfer Coeficient ("X" relates question asked in survey to transfer coefficient it addresses)																			
	From	Sales	1st Use				Storage 1			2nd Use				Storage 2			3rd Use			Storage 3	
	To	1st Use	Storage 1	2nd Use	Disposal 1	Recycle 1	2nd Use	Disposal 1	Recycle 1	Storage 2	3rd Use	Disposal 2	Recycle 2	3rd Use	Disposal 2	Recyce 2	Storage 3	Disposal	Recycling	Disposal 3	Recycle 3
Survey Table	Question	Z	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
Table 1.	How many of these devices do you currently use?	X		X			X				X			X							
	How many of these devices do you currently store in your household?		X							X							X				
	How many of these devices have you recycled or disposed of in the past 12 months?				X			X				X			X			X			
	How many of these Seconday devices (ipod, portable dvd player, or eReaders) do you currently use or store																				
Table 2.	Previous Condition of aquired device	X		X			X				X			X							
	If device previously owned, how long in years was the device previousely used			X							X										
	If device previously stored, how long in years was the device previously stored						X							X							
	Year obtained ownership of device	X		X			X				X			X							
Table 3.	Previous Condition of aquired device		X							X							X				
	If device previously owned, how old in years was the device when acquired		X							X							X				
	Year obtained onwnership of device		X							X							X				
	Year device was last used		X							X							X				
Table 4.	Previous Condition of aquired device				X	X		X	X			X	X		X	X		X	X	X	X
	If device previously owned, how old in years was the device when acquired				X	X		X	X			X	X		X	X		X	X	X	X
	Year obtained onwership of device				X	X		X	X			X	X		X	X		X	X	X	X
	Year device was last used				X	X		X	X			X	X		X	X		X	X	X	X
	If stored, until what year was the device stored after use							X	X						X	X				X	X
	How was device recycled or disposed of				X	X		X	X			X	X		X	X		X	X	X	X
	If recycled, through which 3rd party did you recycle with					X			X				X			X			X		X
Table 5.	Gender?																				
	Age?																				
	Highest Level of Education?																				
	Ziip Code?																				
	Current # of members in your household (including you)?																				

Table 2: Household Size Amounts in US from CPS and survey along with calculated weights.

hhs (residents)	# of Households in US by hhs (from CPS)	# of Households by hhs - Relative Ratio (from CPS)	# of Households in US by hhs (from Survey)	# of Households by hhs - Relative Ratio (from Survey)	Calculated Weights
1	36,198	0.282	161	0.187	1.505
2	44,742	0.348	261	0.303	1.148
3	19,337	0.151	161	0.187	0.804
4	16,262	0.127	188	0.219	0.579
5	7,446	0.058	57	0.066	0.875
6	2,919	0.023	19	0.022	1.029
7+	1,546	0.012	13	0.015	0.796
Total	128,450	1.000	860	1.000	

Table 3: Metals of Interest in this Study categorized by their metal group.

Metals of Interest by metal group			
REE	PGMs	Critical Metals	
Cerium (Ce)	Gold (Au)	Osmium (Os)	Rubidium (Rb)
Dysprosium (Dy)	Silver (Ag)	Aluminum (Al)	Scandium (Sc)
Erbium (Er)	Platinum (Pt)	Antimony (Sb)	Tantalum (Ta)
Europium (Eu)	Iridium (Ir)	Arsenic (As)	Tellurium (Te)
Gadolinoum (Gd)	Palladium (Pd)	Barium (Ba)	Tin (Sn)
Holmium (Ho)	Rhodium (Rh)	Beryllium (Be)	Titanium (Ti)
Lanthanum (La)	Ruthenium (Ru)	Bismuth (Bi)	Tungsten (W)
Lutetium (Lu)		Cesium (Cs)	Vanadium (V)
Neodymium (Nd)		Chromium (Cr)	Zinc (Zn)
Praseodymium (Pr)		Cobalt (Co)	Zirconium (Zr)
Samarium (Sm)		Gallium (Ga)	Magnesium (Mg)
Terbium (Tb)		Germanium (Ge)	Manganese (Mn)
Thulium (Tm)		Hafnium (Hf)	Nickel (Ni)
Yttrium (Y)		Indium (In)	Niobium (Nb)
Ytterbium (Yb)		Lithium (Li)	

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