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Forecasting electronic waste flows for effective circular economy planning

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ABSTRACT

Rapid evolution in the consumer electronics sector has created new resource and waste challenges that are inadequately managed in the current linear product system. Circular economy (CE) strategies offer potential to close the loop on electronic products and materials, but often lack the future-oriented perspective needed to keep pace with this dynamic sector. The present study addresses this challenge by developing a logistic forecasting material flow model that can predict future resource and waste flows for products with abundant historic sales data (mature products) as well as for products that have just entered the market (emerging products). One of the key trends observed across current and legacy electronics is the steadily shrinking innovation cycle, where the time between a product's market entry and peak sales is decreasing over time. This trend, coupled with extensive historic and modern product sales data, was used to create adoption scenario forecasts for emerging products, like fitness trackers, smart thermostats, and drones. Findings show that these devices are likely to have rapid uptake in the market, but may be quickly replaced by subsequent product innovations. In contrast, waste flow forecasts for mature products like CRTs, desktops, monitors and flat panel TVs showed their declining contribution to the U.S. e-waste stream. This study contributes a modeling framework that can be used to inform CE strategies in electronics by identifying near term opportunities and risks in end-of-life management of products to extend product life and close the loop on key materials.

1. Introduction

Consumer electronics make up one of the fastest growing market segments in the United States, with annual shipments worth over $200 billion in revenue (Consumer Technology Association, 2017). Unprecedented innovation and increased consumer demand for faster, sleeker, and smaller devices have drastically changed the electronics landscape in the last decade. Large, single function products have been replaced with multifunctional portable products (Ryen et al., 2014) and electronic components are increasingly integrated into accessories, clothing, appliances, and fitness products (Perera et al., 2015). Industry groups predict that consumers will increasingly adopt smart home technology products including thermostats and security systems, while at the same time maintaining high ownership levels of traditional products like smart phones and televisions (Consumer Technology Association, 2017).

While the evolution and expansion of consumer electronics has enabled social, education, and communication advances, it has also created new sustainability challenges (Balde et al., 2017). Electronic products are characterized by environmental impacts across all life cycle stages, from raw material extraction to end-of-life product management (Kohler and Erdmann, 2004). The functionality of modern electronics is realized through a mix of complex components composed of precious, scarce and base metals (Cucchiella et al., 2015; Tansel, 2017), which are extracted through energy intense processes leading to significant upstream emissions (Dutta et al., 2016). Many of the critical materials found in electronics, such as cobalt, lithium, and rare earth elements, are also widely used in electric vehicles and clean energy technologies, leading to concerns about their long-term supply security (Gaustad et al., 2018). In addition, legacy electronic components may contain hazardous materials like mercury, lead, and cadmium, which may cause harmful health and environmental impacts if not managed properly at end-of-life (Chen et al., 2011; Kiddee et al., 2013). Given rapid innovation cycles, increasing consumer adoption, and declining product lifespans in the electronics sector (Bakker et al., 2014), material consumption and waste generation are bound to increase in the future. Therefore, consumer electronics are ripe for a transformation via the circular economy, to minimize resource consumption, extend product lifespan through reuse, repair, and remanufacturing (Bakker et al., 2014; Reike et al., 2018; Zlamparet et al., 2017; Zlamparet et al., 2018), and close the loop on material supply chains (Işıldar et al., 2017; Zeng et al., 2018).

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Circular solutions may offer sustainability benefits for electronics, but they also face obstacles to widespread adoption (Mars et al., 2016). As the electronic product "ecosystem" grows, the number, type, and diversity of devices requiring circular management also expand (Ryen et al., 2014). This complexity can confound product repair, upgrade, disassembly, and material identification and segregation, all of which are labor-intense processes further slowed by product heterogeneity and lack of standardization (Cucchiella et al., 2015). Where materials are recovered, recycling economics often hinge on a few low-volume, high-value materials, such as gold, which are increasingly diluted in the e-waste stream due to product light-weighting trends (Kasulaitis et al., 2019). The presence of hazardous materials like lead and mercury in complex components like older printed circuit boards and display units also can limit recovery efforts (Chen et al., 2011; Kiddee et al., 2013). In addition, shrinking product lifespans (Babbitt et al., 2009) are effectively narrowing the window in which circular innovation can be deployed, leaving our e-waste management system to be "backwards looking" - focusing on legacy devices that have been in the market for a long time, even while new products are emerging in the waste stream (Babbitt et al., 2017).

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

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

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

2. Literature review

E-waste estimation methods in the literature include input-output models, factor models, time series, econometric analysis, and direct waste analysis (Li et al., 2015; Wang et al., 2013). Among these, material flow analysis (MFA), which is an extension of input-output modeling, is widely used and an appropriate choice for CE planning, as it enables estimation of the product and material demand and management of secondary resources (Kalmykova et al., 2018). MFA estimates the stocks and flows of materials within a defined temporal and spatial system, commonly using data on commodity flows into the system and their discard rates (Brunner and Rechberger, 2004). In most e-waste literature, MFA applications are typically static or retrospective (Kasulaitis et al., 2019; Li et al., 2015; Miller et al., 2016; Wang et al., 2013), due to the nature of available data. However, CE planning requires a more proactive approach, thus requiring forecasts of product adoption and obsolescence. Such information is not commonly available, but potentially can be approximated according to models of product adoption cycles.

Forecasting product adoption is commonly achieved using the "S-shaped" logistic curve, or sigmoid curve, to describe a product market adoption cycle (Fisher and Pry, 1971; Kucharavy and De Guio, 2015, 2011; Marchetti and Nakicenovic, 1979; Meyer et al., 1999; Yang and Williams, 2009). The three parameter logistic curve commonly used in socio-technical systems (Kucharavy and De Guio, 2011), has its roots in ecology, where it was originally used to model population growth of biological species (Lefkovitch, 2018). While the logistic curve describes a product's growth until it reaches market saturation, it does not capture the entire market life cycle, which includes an inevitable decline due to substitution by competing technologies. The Norton-Bass model, which includes logistic distribution as a special case, captures both adoption and substitution leading to a product's decline (Norton and Bass, 1987). This approach has been applied to forecasting consumer electronics, including LCD TVs (Tsai (2013), mobile phones, computers (Islam and Meade (1997), and desktop displays (Lu et al., 2015). However, as pointed out by Tseng et al. (2009), the Norton-Bass model is mostly suited for modeling direct substitutions by successive generations of technology, which is not always observed in consumer electronics, particularly in the case of disruptive innovation. The Fisher-Pry model (1971) has also been applied in electronics forecasting, an approach that uses a two-parameter logistic model to describe technology substitution (Cho and Daim, 2016). The logistic Fisher-Pry model was extended by Marchetti and Nakicenovic (1979) to include mutliple generations of energy technologies, based on the assumption that technologies grow and decline at logistic rates. This model has been used to study adoption of music media (Meyer et al., 1999) and OLED TVs (Tseng et al., 2009). While these studies show that logistic growth-decline is an apt approximation to describe product adoption cycles, these models are again reliant on knowledge of subsequent generational replacements.

In reality, replacement cycles and product innovation in consumer electronics are challenging to predict, as decline of one technology generation is not always predicated solely on substitution by the next generation. In many cases, functional convergence leads to decline of many single function devices due to simultaneous substitution by one new multifunctional product. For example, the decline of digital cameras, camcorders, and MP3 players was driven by the advent of smartphones, which would not be otherwise predicted as a successive generation of those products. Similarly, in the case of AV (audio-visual) media, the decline of Blu-ray and DVD players was triggered by the advent of new streaming media services, rather than a new product generation (Fig. S1 in the Supplemental Information illustrates the technological shifts and substitution in AV products). Therefore, to integrate product adoption cycles in electronics forecasting, it is useful to develop modeling capability that can capture adoption trends on a product-by-product basis, even in the absence of information about subsequent generations of technology.

The methods applied in this paper build on the foundation of models described above, through use of the logistic growth and decay curves that have been applied to technology adoption broadly and e-waste forecasts specifically. One new contribution is the construction of these curves independently, without the specification of an unknown successive replacement technology required to trigger product decline. Another contribution is the focus on emerging electronic technologies that are not yet widely adopted. Literature examples have provided several demonstrations of forecasting waste flow from specific product categories that already comprise a major part of the e-waste stream, such as computers (Kahhat and Williams, 2012; Petridis et al., 2016; Rahmani et al., 2014; Yang and Williams, 2009; Yu et al., 2010), or on products with known hazards, such as cathode ray tube (CRT) TVs (Gusukuma and Kahhat, 2018). However, for CE planning, it is equally important to forecast adoption for newer technologies, requiring modeling advances in data-scarce cases.

3. Methodology

This paper's objective is to present an MFA model developed to proactively inform key leverage points that can enable CE solutions for electronics. For example, for mature products that are declining or no longer sold in the market, a critical CE challenge is how to recover and manage these products over the remainder of their life cycle, particularly if no demand exists for their reuse or for their component materials. Another challenge is to understand how e-waste policy implementation might be affected by the decline of these products in the waste stream. For emerging products, which may have unforeseen sustainability risks but that are not typically covered by e-waste policies, projections are essential to model timing and magnitude of potential resource demand or the extent to which circular material systems can provide these resources with secondary or closed-loop supply. Thus, the predictive MFA model was developed with the aforementioned CE challenges in mind. The overarching approach was to use historical sales data to construct logistic curves of product adoption and decline, and then apply these curves to project future product consumption and waste flows (Fig. 1), as explained in more detail in the following subsections.

3.1. MFA model framework

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

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

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

3.1.1. Product sales

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

$$S_{p,t} = \begin{cases} \frac{a}{1+e^{-b_1(t-c_1)}} & \forall\ t \le t_{\text{peak}} \\ \frac{a}{1+e^{+b_2(t-c_2)}} & \forall\ t > t_{\text{peak}} \end{cases} \tag{2}$$

Here, a product's sales over its entire market cycle can be described by the time it takes to reach peak adoption (t_{peak}), the maximum adoption level or peak sales units (a), growth and decay rates (b1 and b2), and growth and decay midpoints, which are the times at which the curve reaches the inflection point of a/2 (c1 and c2). For simplicity, the parameter b is replaced by the equation ln(81)/ Δt, where Δt is the time required for the logistic curve to grow from 10% to 90% of the carrying capacity (for b1) or decay from 90% to 10% (for b2), a simplification demonstrated by Meyer et al. (1999). Additional information on the estimation of parameters a, Δt, and c is provided in section 3.2.

The choice of logistic curve was verified by testing Eq. (2) against real product sales data. Ten products were selected that had high quality sales data spanning the entire period between the product's entry into the market to present (or to the point at which the product was no longer sold). These data were provided by the Consumer Technology Association as reported in Babbitt et al. (2017). The growth and decline curve for each product was tested against candidate distributions using a least squares estimation approach as implemented in MATLAB. Goodness of fit parameters, including R-squared, SSE (sum of squared errors) and BIC (Bayesian Information Criterion) were used to confirm that logistic curves were the best distribution to represent adoption cycle of electronics. The MATLAB code for the MFA model and all related data sheets are provided at Althaf (2019).

3.1.2. Product lifespan

The other key input to the forecasting MFA model according to Eq. (1) is the lifespan probability distribution for each product. A Weibull distribution is applied here, as it is the most commonly used distribution to model lifespan of electronics in literature (Bakker et al., 2014; Gu et al., 2018; Nakatani and Moriguchi, 2014; Oguchi and Kameya, 2008). The Weibull PDF (probability density function) is given below:

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

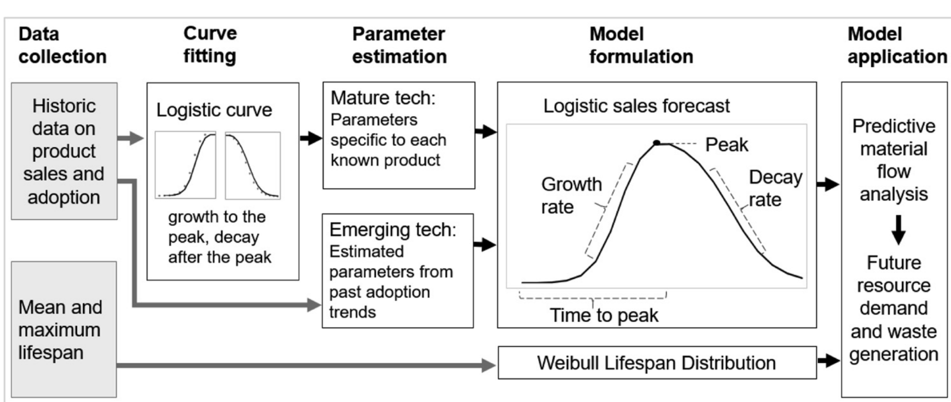

Fig. 1. Conceptual framework of the methodology adopted in this study to enable proactive CE planning in the electronics sector. Gray boxes and arrows represent data inputs collected from literature and electronics industry sources. All other boxes and arrows represent model calculations and outputs.

where γ is the shape parameter, α is the scale parameter and t is the time. The shape and scale parameters describing the distribution are computed from mean and maximum product lifespan estimates from literature (see the Supplementary Information (SI) file, Table S1). In this study, lifespan is defined as the total time that a product resides within a household during its first life, after which it becomes available for end-of-life management, which may include reuse, recycling for material recovery, or discarding.

3.2. MFA model parameters for mature products

Parameterizing the model described in Eqs. (1) and (2) is relatively straightforward for mature products, because past sales data are readily available. The 11 products considered in the mature product category are: CRT (Cathode Ray Tube) monitors, CRT TVs, desktop computers, printers, laptop computers, LCD (liquid crystal display) monitors, LCD TVs, Plasma TVs, LED (light emitting diode) monitors, LED TVs, and tablets. For these products, parameter estimation was carried out by fitting the three-parameter logistic curve to each product's unit sales over time. Depending on the product, different degrees of the market life cycle are covered by the available sales data, ranging from only a few years (for LED displays) to a full life cycle (for CRT TVs). In all cases, parameters were extracted from the product-specific logistic curve based on least squares estimation. (see SI Table S2 for logistic parameters extracted for each product in the mature category).

The application of the MFA model to mature products is particularly important from the standpoint of assessing e-waste policy in relation to CE planning. The mature products analyzed here are those that are most commonly covered by e-waste legislation in U.S. states. The MFA results describe waste flows in units of products, which were then translated to overall waste stream magnitude based on each product's average mass. Mass results help relate the waste projections to mass-based collection or recycling targets used by most states in the U.S. Product mass estimations were determined using literature and disassembly as described in Babbitt et al. (2017) and Kasulaitis et al. (2019), as summarized in SI Table S3.

3.3. MFA model parameters for emerging products

In the case of emerging products, for which historic adoption data are scarce, the guiding approach in estimating parameters for logistic forecasting was to analyze how past products behaved in the market, identify trends in the underlying logistic curve size and shape, and then extend these trends to products recently introduced. The historic sales data of over 15 products (Table 1) that entered the market between 1962 and 2009 were compiled, and the key parameters that describe their logistic market trajectory (time to peak, sigmoid midpoint and Δt) were extracted. One of the clear relationships revealed was that these parameters were inversely related to year of market entry. In other words, innovation cycles, or the time between a product entering the market and reaching saturation at peak sales, are shrinking in a steady and predictable way. Curve fitting to this temporal trend was tested to determine if year of market entry could effectively predict time to peak and growth rate, resulting in an exponential curve ($R^2 = 0.82$) as shown in Fig. 2, where t_{peak} is the time until a product reaches its peak sales and Y_m is the year the product enters the market. To validate this trend, the predicted exponential curve was compared against a different set of 10 products (also shown in Table 1) that were not part of the original curve formulation. This strong agreement was consistent for exponential curves relating year of market entry to other necessary logistic parameters, including growth rate and sigmoid midpoint (See SI Table S4 and Fig. S2 and S3). Thus, most of the parameters required to construct the logistic sales curve (Eq. (2)) for emerging products can be predicted by specifying only the year in which that product is first sold in the market.

The other parameter required to apply the logistic model (Eq. (2)) is

Table 1
Products used to identify temporal trends in parameters describing logistic product adoption curves. Products shaded in gray were used to construct predictive trends while remaining products were used to validate the resulting curves.

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

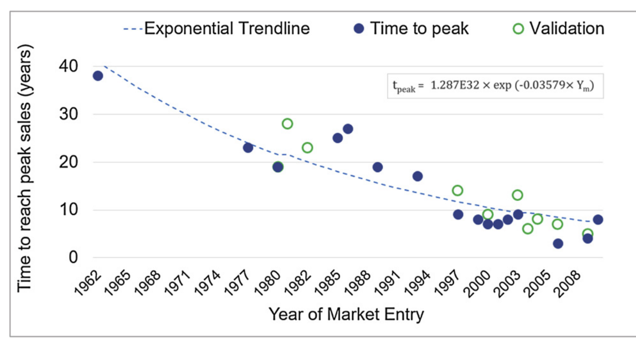

Fig. 2. The time between a product entering the market and reaching its peak sales volume is shown here to steadily decrease over time. A predictive relationship is built using products represented by filled circles and then validated by comparison against additional products (open circles).

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

The historical peak sales per household were tabulated for all products listed in Table 1, and grouped under categories that describe a product's form or function: Computing (including computers, monitors,

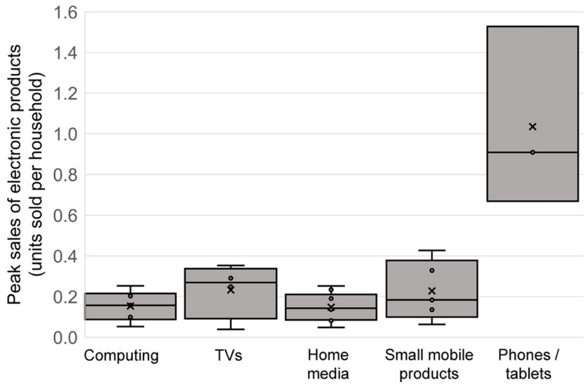

Fig. 3. Ranges of peak sales (in units sold per U.S. Household) for products according to functional categories. Median values are shown as a line across each box.

and printers); TVs (including multiple technologies of CRT, LCD, LED, and plasma); Home media (VCR, gaming consoles, etc.); Small mobile devices (MP3 players, digital cameras, portable navigation systems, etc.); and Phones (including basic and smartphones and tablets). A full list of products assigned to each category and their peak sales is provided in the SI Table S5. These data are summarized in Fig. 3, which visually illustrates the ranges in peak sales observed. Most product categories demonstrated consistent ranges of adoption peaks. One exception was for those products that were ultimately only adopted to a limited degree (maximum sales of only about 0.05 – 0.1 products per household even in the highest sales year). These products, which represent a scenario of "limited adoption," included devices like Plasma TVs and e-readers, both of which were quickly outcompeted by products seeing "mainstream adoption," such as LCD TVs and tablets, respectively. The limited and main stream adoption ranges assigned to each product category is presented in SI Table S6.

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

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

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

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

4. Results

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

4.1. Model validation

The use of a three-parameter logistic curve in modeling adoption cycles (growth and decline) of products was tested against real sales curves of existing electronics products. Logistic was the best distribution of those compared, based on goodness of fit parameters such as SSE, R square and BIC. The full list of curve fitting statistics is reported in SI Table S7. The forecasting capability of the MFA model is validated by comparing model generated e-waste flows of CRT monitors, Desktops, Printers, LED monitors, LCD TVs and Laptops with waste flows estimated using actual annual sales data from 2000 to 2018.

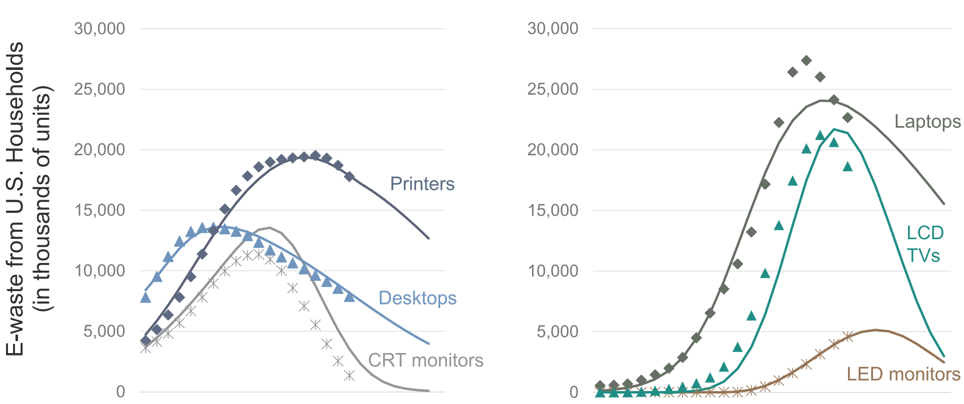

Fig. 4. Comparison of e-waste flows estimated using the three-parameter model of logistic sales to e-waste flows calculated directly from real sales data of the products. E-waste flows reflect annual outflows from U.S. households in thousands of units. Line plots indicate forecasting model results while scatter plots indicate waste flows estimated from real sales data.

Results (Fig. 4) show that forecast results are in strong agreement with those generated from real data, with less than 5% error in cumulative flows across products. Waste flows forecasted five years forward show how the model captures the effect of product market decline on e-waste estimations.

Waste flow forecasts in Fig. 4 predict that CRT monitor units in the residential e-waste stream will soon be insignificant, which should help alleviate concerns about lead exposure during their downstream management. However, in the short term, few opportunities exist for closing the loop on these materials, as no demand exists for product reuse or CRT glass recovery. Waste flow forecasts for computing and display technologies like laptops and LCD TVs and monitors show that these products have likely reached their peak and will start slowly declining in the waste stream. In five years, laptops and printers are forecasted to decrease 20% from their current waste flow while waste LCD TVs are predicted to decline more than 50% from present. Desktop computers are expected to sharply decline (40%) in the waste stream in the next five years, which is expected to have interactive effects on monitors, which are typically purchased to use with desktop computing. A comparison with waste flow forecasts by past studies (Mars et al., 2016) show that while our model results deviate for some products such as laptops and printers (MFA results are -38%), results are close to past estimations for desktops (-14%), flat panel monitors (+7%), and TVs (-7%). While desktop waste flows estimated by the MFA model for year 2010 differed by less than 1% (-0.03% from low adoption scenario) from those reported by Miller et al (2016), monitor waste flows deviated by more than 20% from the study which applied the same sales-lifespan MFA method. Here the difference is likely due to our underlying assumption that monitor adoption follows a 1:1 ratio with desktop sales, based on input from consumer technology industry experts (Babbitt et al., 2017) rather than using real monitor sales data, which is available to a limited degree but does not account for monitors sold with desktops as a package.

Other differences from past studies could be attributed to uncertainties in lifespan assumptions, as definition of product lifespans vary widely (Babbitt et al., 2009). While model forecasts are impacted by lifespan uncertainties, the trends shown in this and other studies are consistent, and the projected decrease in forecast e-waste flows is unlikely to change, as it is primarily driven by inflows to households in the way of new sales, which have begun to decline for all mature products studied. These results have significant implications to e-waste policy planning, as the products analyzed here are the commonly covered devices in U.S. state e-waste policies.

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

Under extended producer responsibility (EPR) policies adopted for end-of-life management of electronics in many US states, collection targets are set based on manufacturers' shares of covered products in the waste stream, as determined by sales-adjusted mass estimates (Electronics TakeBack Coalition, 2015). The process of setting collection targets often relies on observed trends in past years' product collection rates as the main factor in determining the next year's recovery goals (Oregon E-Cycles Program, 2018). Neither states nor manufacturers typically have the modeling capability to predict future waste flows, limiting their ability to set appropriate targets or plan for end-of-life management. Therefore, the predictive MFA model offers significant utility for these stakeholders in its ability to project e-waste flows over a near-term time horizon. To assess how this model might be used by policy stakeholders, it is applied to commonly covered devices in U.S. state policies, which include mature products such as TVs, monitors, computers, and printers, to estimate their cumulative waste flows in the U.S. (Fig. 5). These estimates were generated using the logistic forecasting model for a 15-year period, which includes recent past and six years beyond the present. Note that the model predicts the total mass of products coming out of households, which may then go into reuse, recycling, or discard pathways.

E-waste flow forecasts in Fig. 5 suggest that the mature products that are currently the focus of state e-waste policies are beginning to decline in the waste stream, a trend expected to continue in the next several years. This trend is largely attributable to the changing mix of display technologies, where heavy CRT TVs and monitors are no longer sold and slowly empty from consumers' households, while being replaced with lighter products such as flat panel displays and tablets. These results point to potential sustainability benefits of reducing the overall amount of e-waste requiring management, particularly devices which contain hazardous materials such as CRT (lead) and LCD displays (mercury). On the other hand, the shift introduces new uncertainties for the recycling industry, which has long been established around processing large products with high potential for disassembly and component and material recovery. Further, the decline of mature products will be offset to a degree by other products that are now emerging or growing, but that are not covered under such policies. For example, smartphones, which are a small contribution to e-waste by mass, contain a high concentration of valuable materials including gold, cobalt, and lithium (Cucchiella et al., 2015). In addition, TVs, which show significant dynamism within this policy case, contain indium, a scarce material for which very limited recycling is currently possible (Buchert et al., 2012).

As policy is a key enabler of the circular economy, e-waste regulations are expected to increase the ability to repair and reuse products or recover materials that can be returned to functional use in new devices. However, the forecasted decreasing trends in cumulative waste flow suggest that states will need to fundamentally shift from product collection and recovery targets based on mass alone. Already, states have informally reported declining collection rates, and at least one state, Illinois, is moving away from mass targets to convenience-based systems, which emphasize consumer access to e-waste collection points. It is challenging to benchmark these forecasts to other studies, as most literature applies a retrospective rather than prospective approach. Comparison of e-waste flow estimates with past studies (Powell and Chertow, 2018; U. S. Environmental Protection Agency, 2016b) show comparable trends in the lead-up to peak waste flows (estimated in Fig. 5 to be 2016–2017). However, it should be noted that results presented here are for the U.S. residential/consumer sector only, and so the magnitude of flows will naturally be smaller than the above-mentioned studies, which include residential and commercial sectors together. A direct comparison of results to a U.S. Environmental Protection Agency (2011) study, which applied the same sales-lifespan method for e-waste estimations from 1990 to 2010, is provided in SI Fig. S4, confirming consistency in trends for the overlapping period.

4.3. Forecasting implications of emerging technologies

The predictive MFA model was applied to four case study products that represent a wide array of emerging technologies for which data are scarce and near-term forecasting is necessary to identify potential opportunities and risks for CE planning. For each of the emerging technologies (fitness trackers, smart thermostats, drones, and OLED TVs) both mainstream and limited adoption trajectories were projected based on the peak sales ranges for the product categories to which these technologies most closely align. The forecasts, shown in Fig. 6, were generated using only the year of market entry (as predictor of logistic parameters associated with growth rate and time to peak sales) and the product category (as predictor of the maximum sales).

Forecast results, compared against the limited real sales data that are available (See SI Table S13), show that among the products studied, drones and fitness trackers have reached or may soon approach their peak. As per the adoption forecasts, fitness trackers have entered mainstream adoption in a manner consistent with other small mobile products and have reached the maximum carrying capacity or peak sales to households. On the other hand, drones appear to be unlikely to

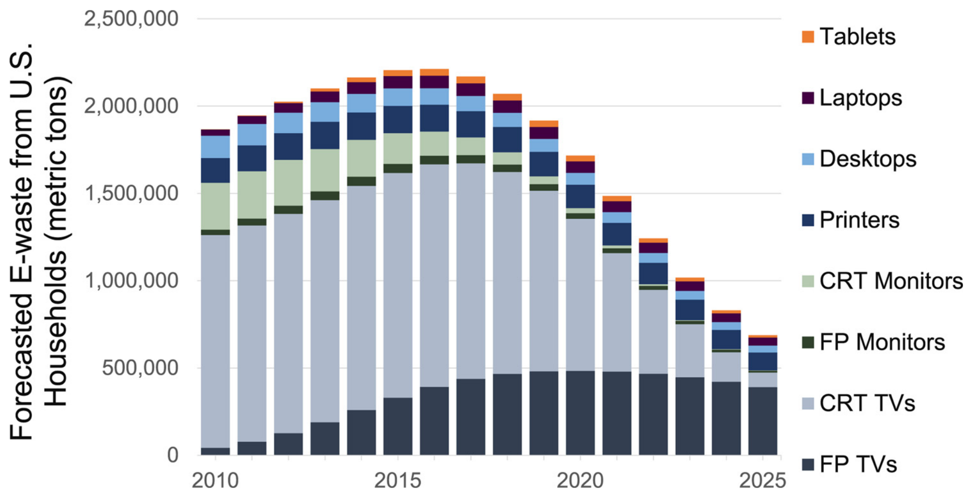

Fig. 5. Application of the predictive model to inform e-waste policies, demonstrated through estimation of cumulative waste flows (in metric tons) of devices commonly covered for recovery under U.S. state e-waste legislations. (FP: Flat Panel, which includes LCD and LED displays; CRT: Cathode Ray Tube).

enter mainstream adoption as a household product. Annual sales of fitness trackers, which are currently around 22 million units, are unlikely to go above 35 million units, while maximum annual sales of drones are unlikely to go above 10 million units, if these products follow the trends of past products in their respective categories. The smart thermostat results suggest that they are still in the growth phase, but as a home product, the annual sales will likely peak at less than 25 million units, even if they enter mainstream adoption. Even though it is too early to confirm which adoption scenario OLED TVs will follow, the mainstream ranges are more likely, given past TV turnover and a recent peak of LED TV sales, which is usually a harbinger that a substitute product is beginning to invade the market niche.

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

4.4. Forecasting interactions between mature and emerging products

TV technology evolution is a unique case because it allows for a

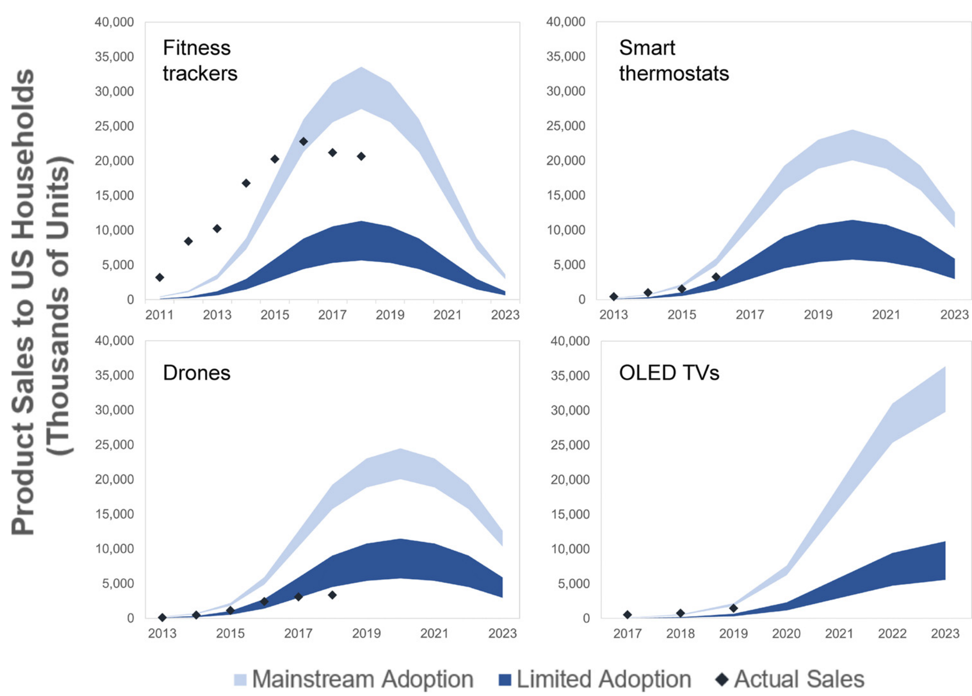

Fig. 6. Forecast sales of emerging products: fitness trackers, smart thermostats, drones and OLED TVs. Comparison of possible mainstream and limited adoption scenarios (which include a range of peak sales) with the actual available sales data suggests which of the two adoption trajectories each product may follow.

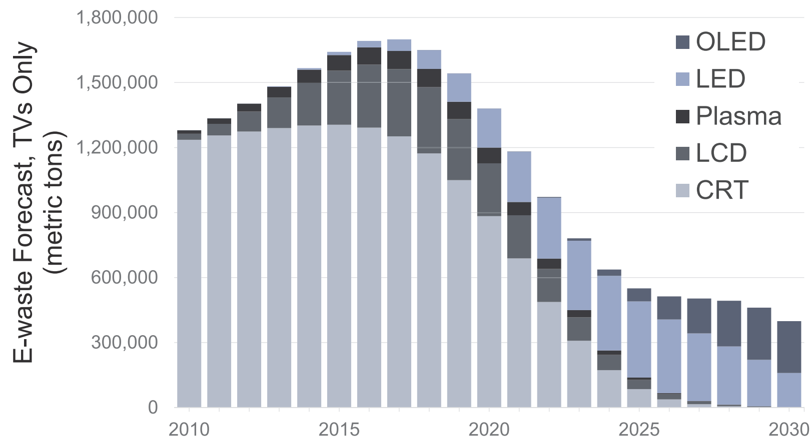

Fig. 7. The evolving U.S. TV waste flow, reflecting multiple generations of technology substitution, and its implication on reducing the e-waste stream due to lightweighting over time.

direct assessment of how product interactions, technological shifts, and substitution cycles ultimately influence e-waste flows and resource demand. From a circular economy standpoint, this information is critical to understand the capacity for closed-loop systems, in which materials are recovered from one type of product and returned to another of the same type. Such an approach may be most useful in products containing unique materials, such as the cobalt contained in mobile products' batteries, or the rare earth phosphors used in LED-lit flat panel TVs. As technology shifts, gaps open between increasing secondary material supply from products that have peaked and the demand for secondary materials by the product starting to emerge (Kasulaitis et al., 2019). This dynamic is illustrated in Fig. 7 by coupling the waste flow forecasts of OLED TV with those of mature TV technologies presented in section 4.1.

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

5. Implications to CE planning

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

Similar potential for circularity is observed in critical metals like cobalt and lithium, found in lithium-ion batteries that are key components of mobile electronics. For example, adoption and waste flow estimates of laptops show that cobalt contained in laptop batteries in the U.S. e-waste stream outweighs its demand in batteries for new laptop computers, a product where sales are slowing while batteries are also becoming lighter and more material efficient. In fact, the projected cobalt waste flow from laptops ($>$ 1000 metric tons in year 2021) is likely to soon exceed the combined cobalt demand for batteries in laptops and drones ($<$ 900 metric tons in 2021). (See SI Tables S8-S12 for the data and calculations used in these informal estimates). While these trends in material flows, where material content in e-waste exceeds its demand, indicate theoretical potential to close the material loop in electronics, implementation is limited at present by lack of effective recycling technologies and infrastructure. This highlights the need to enable other circular economy strategies that extend product and component lifespan, such as product reuse, repair, refurbishment and remanufacturing. The methods developed in the present study can support these CE strategies through estimations of product waste flows that represent the products available after primary use, for life span extension or material recovery measures. However, consumer education and implementation of effective e-waste policies and collection systems are key in ensuring circular end-of-life pathways to recover used products from consumers, and for enabling all aspects of CE including reuse, repair, remanufacturing and recycling (Gaustad et al., 2018).

The study findings also imply the need to shift the focus of end-of-life management of electronics away from mass-based diversion mechanisms and towards a broader perspective on sustainable materials management. The projected trends in e-waste generation emphasize the need to move away from the use of policy where all materials are treated equally, to explore alternate methods for setting collection targets, such as those based on environmental or economic savings associated with the circular economy. A holistic waste management approach was proposed by Anshassi et al. (2018) in which they demonstrated use of life cycle inventory-normalized collection targets for solid waste management in Florida. Similar waste management mechanisms are worth exploring in the electronics sector, as it will shift the focus to materials and products with the greatest benefit for recovery via circular economy initiatives. In electronics, a similar approach was proposed by Wang and Gaustad (2012), to prioritize economic value, energy saving potentials, and eco-toxicity in prioritizing material recovery from printed circuit boards. However, planning for such policy targets requires product level sustainability analysis, the key barrier being the lack of comprehensive knowledge on environmental and economics tradeoffs associated with material use and material recovery, topics that should be prioritized in future study.

6. Conclusions

For CE strategies to keep pace with the rapid pace of innovation in the electronics sector, proactive tools are needed to generate near term forecasts of resource demand and e-waste flows. This study contributes a novel method for informing circular economy planning in the electronics sector. The key contribution of this model is the use of historic sales data for over 25 products to create future-oriented sales curves that can then be used to forecast demand and waste flow of products irrespective of their historic data availability. Application of the model to mature and emerging electronic products helped identify near-term challenges and opportunities for CE planning. This model is flexible, and with appropriate validation, can be used to study other product categories and a broader range of consumer electronics. The model also provides a scaffold on which other circular economy metrics can be built, coupling product flows with material profile data and sustainability impacts associated with specific materials. While material flow forecasts for emerging products based on generalized trends can be burdened with uncertainty, this study takes the view that we cannot wait until data are perfected, or otherwise, proactive opportunities to implement circular economy strategies will be lost.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.resconrec.2019.05.038.

References

Althaf, S., 2019. Predictive Material Flow Model, V1.0.0. https://doi.org/10.5281/zenodo.3244095.

Anshassi, M., Laux, S., Townsend, T.G., 2018. Replacing Recycling Rates with Life-Cycle Metrics as Government Materials Management Targets. Environ. Sci. Technol. 52, 6544–6554. https://doi.org/10.1021/acs.est.7b06007.

Babbitt, C., Kahhat, R., Williams, E., Babbitt, G., 2009. Evolution of Product Lifespan and Implications for Environmental Assessment and Management : A Case Study of Personal Computers in Higher Education. Environ. Sci. Technol. 43, 5106–5112.

Babbitt, C.W., Althaf, S., Chen, R., 2017. Sustainable Materials Management for the Evolving Consumer Technology Ecosystem. Summary Report of Phase 1 Research.

Bagher, A.M., 2017. Quantum dot display technology and comparison with OLED display technology. Int. J. Adv. Res. Phys. Sci. 4, 48–53.

Bakker, C., Wang, F., Huisman, J., Den Hollander, M., 2014. Products that go round : exploring product life extension through design. J. Clean. Prod. 69, 10–16. https://doi.org/10.1016/j.jclepro.2014.01.028.

Balde, C.P., Forti, V., Gray, V., Kuehr, R., Stegmann, P., 2017. The Global E-waste Monitor 2017: Quantities. Flows and Resources.

Bocken, N.M.P., De Pauw, I., Bakker, C., Van Der Grinten, B., 2016. Product design and business model strategies for a circular economy. J. Ind. Prod. Eng. 1015, 1–12. https://doi.org/10.1080/21681015.2016.1172124.

Boks, C., Stevels, A., 2014. Essential perspectives for Design for Environment : Experiences from the electronics industry. Int. J. Prod. Res. 45, 4021–4039. https://doi.org/10.1080/00207540701439909.

Brunner, P.H., Rechberger, H., 2004. Practical Handbook of Material Flow Analysis. Taylor & F. ed. Lewis Publishers.

Buchert, M., Manhart, A., Bleher, D., Pingel, D., 2012. Recycling Critical Raw Materials From Waste Electronic Equipment.

Chen, A., Dietrich, K.N., Huo, X., Ho, S., 2011. Developmental neurotoxicants in E-Waste: an emerging health concern. Environ. Health Perspect. 119, 431–438. https://doi.org/10.1289/ehp.1002452.

Cho, Y., Daim, T., 2016. OLED TV technology forecasting using technology mining and the Fisher-Pry diffusion model. Foresight 18, 117–137. https://doi.org/10.1108/FS-08-2015-0043.

Chopra, S.S., Theis, T.L., 2017. Comparative cradle-to-gate energy assessment of indium phosphide and cadmium selenide quantum dot displays. Environ. Sci. Nano Nano 4, 244–254. https://doi.org/10.1039/C6EN00326E.

Consumer Technology Association, 2017. 19th Annual Consumer Technology Ownership and Market Potential Study_April 2017.

Cucchiella, F., Adamo, I.D., Koh, S.C.L., Rosa, P., 2015. Recycling of WEEEs : An economic assessment of present and future e-waste streams. Renew. Sust. Energy Rev. 51, 263–272. https://doi.org/10.1016/j.rser.2015.06.010.

Dutta, T., Kim, K., Uchimiya, M., Kwon, E.E., Jeon, B., Deep, A., Yun, S., 2016. Global demand for rare earth resources and strategies for green mining. Environ. Res. 150, 182–190. https://doi.org/10.1016/j.envres.2016.05.052.

Electronics TakeBack Coalition, 2015. Scope of Products in E-Waste Laws. Retrieved from. http://www.electronicstakeback.com/wp-content/uploads/Scope_of_Product_in_Ewaste_Laws.pdf.

Fisher, J.C., Pry, R.H., 1971. A simple substitution model of technological change. Technol. Forecast. Soc. Chang. 3, 75–88.

Gaustad, G., Krystofik, M., Bustamante, M., Badami, K., 2018. Circular economy strategies for mitigating critical material supply issues. Resour. Conserv. Recycl. 135, 24–33. https://doi.org/10.1016/j.resconrec.2017.08.002.

Gu, Y., Wu, Y., Xu, M., Mu, X., Zuo, T., 2018. Waste electrical and electronic equipment (WEEE) recycling for a sustainable resource supply in the electronics industry in China. J. Clean. Prod. 127, 331–338. https://doi.org/10.1016/j.jclepro.2016.04.041.

Gusukuma, M., Kahhat, R., 2018. Electronic waste after a digital TV transition : Material flows and stocks. Resour. Conserv. Recycl. 138, 142–150. https://doi.org/10.1016/j.resconrec.2018.07.014.

Işıldar, A., Rene, E.R., van Hullebusch, E.D., Lens, P.N.L., 2017. Electronic waste as a secondary source of critical metals: management and recovery technologies. Resour. Conserv. Recycl. 135, 296–312. https://doi.org/10.1016/j.resconrec.2017.07.031.

Islam, T., Meade, N., 1997. The Diffusion of Successive Generations of a Technology : A More General Model. Technol. Forecast. Soc. Change 56, 49–60.

Kahhat, R., Williams, E., 2012. Materials flow analysis of e-waste : Domestic flows and exports of used computers from the United States. Resources, Conserv. Recycl. 67, 67–74. https://doi.org/10.1016/j.resconrec.2012.07.008.

Kalmykova, Y., Sadagopan, M., Rosado, L., 2018. Circular economy – from review of theories and practices to development of implementation tools. Resour. Conserv. Recycl. 135, 190–201. https://doi.org/10.1016/j.resconrec.2017.10.034.

Kasulaitis, B.V., Babbitt, C.W., Krock, A.K., 2019. Dematerialization and the circular economy dematerialization and the circular economy comparing strategies to reduce material impacts of theConsumer electronic product ecosystem. J. Ind. Ecol. 00, 1–14. https://doi.org/10.1111/jiec.12756.

Kiddee, P., Naidu, R., Wong, M.H., 2013. Electronic waste management approaches : An overview. Waste Manag. 33, 1237–1250. https://doi.org/10.1016/j.wasman.2013.01.006.

Kohler, A., Erdmann, L., 2004. Expected environmental impacts of pervasive computing. Hum. Ecol. Risk Assess. 10, 831–852. https://doi.org/10.1080/10807030490513856.

Kucharavy, D., De Guio, R., 2015. Application of logistic growth curve. Procedia Eng. 131, 280–290. https://doi.org/10.1016/j.proeng.2015.12.390.

Kucharavy, D., De Guio, R., 2011. Logistic substitution model and technological forecasting. Procedia Eng. 9, 402–416. https://doi.org/10.1016/j.proeng.2011.03.129.

Lefkovitch, L.P., 2018. The study of population growth in organisms grouped by stages. Biometrics 21, 1–18.

Li, B., Yang, J., Lu, B., Song, X., 2015. Estimation of retired mobile phones generation in China : A comparative study on methodology. Waste Manag. 35, 247–254. https://doi.org/10.1016/j.wasman.2014.09.008.

Lu, B., Liu, J., Yang, J., Li, B., 2015. The environmental impact of technology innovation on WEEE management by Multi-Life Cycle Assessment. J. Clean. Prod. 89, 148–158.

https://doi.org/10.1016/j.jclepro.2014.11.004.
Marchetti, C., Nakicenovic, N., 1979. The Dynamics of Energy Systems and the Logistic Substitution Model.
Mars, C., Nafe, C., Linnell, J., 2016. The Electronics Recycling Landscape. Retrieved from. . https://www.sustainabilityconsortium.org/wp-content/uploads/2017/03/TSC_Electronics_Recycling_Landscape_Report-1.pdf.
Meyer, P.S., Yung, J.W., Ausubel, J.H., 1999. A Primer on Logistic Growth and Substitution : The Mathematics of the Loglet Lab Software. Technol. Forecast. Soc. Chang. 61, 1–23.
Miller, T.R., Duan, H., Gregory, J., Kahhat, R., Kirchain, R., 2016. Quantifying domestic used electronics flows using a combination of material flow methodologies: a US case study. Environ. Sci. Technol. https://doi.org/10.1021/acs.est.6b00079.
Nakatani, J., Moriguchi, Y., 2014. Time-series product and substance flow analyses of end-of-life electrical and electronic equipment in China. Waste Manag. 34, 489–497. https://doi.org/10.1016/j.wasman.2013.11.004.
Norton, J.A., Bass, F.M., 1987. A diffusion theory model of adoption and substitution for successive generations of HIGH-TECHNOLOGY Products. Manage. Sci. 33.
O'Connor, M.P., Zimmerman, J.B., Anastas, P.T., Plata, D.L., 2016. A strategy for material supply chain sustainability: enabling a circular economy in the electronics industry through green engineering. ACS Sustain. Chem. Eng. 4, 5879–5888. https://doi.org/10.1021/acssuschemeng.6b01954.
Oguchi, M., Kameya, T., 2008. Product flow analysis of various consumer durables in Japan. Resour. Conserv. Recycl. 52, 463–480. https://doi.org/10.1016/j.resconrec.2007.06.001.
Oregon E-Cycles Program, 2018. Oregon E-Cycles Collections Determination for 2018.
Perera, C., Liu, C.H., Jayawardena, S., 2015. The Emerging Internet of Things Marketplace From an Industrial Perspective : A Survey. IEEE Trans. Emerg. Top. Comput. 3, 585–598. https://doi.org/10.1109/TETC.2015.2390034.
Petridis, N.E., Stiakakis, E., Petridis, K., Dey, P., 2016. Estimation of computer waste quantities using forecasting techniques. J. Clean. Prod. 112, 3072–3085. https://doi.org/10.1016/j.jclepro.2015.09.119.
Powell, J.T., Chertow, M.R., 2018. Quantity, Components, and Value of Waste Materials Landfilled in the United States. J. of Industrial Ecol. 0, 1–14. https://doi.org/10.1111/jiec.12752.
Rahmani, M., Nabizadeh, R., Yaghmaeian, K., Hossien, M.A., Yunesian, M., 2014. Estimation of waste from computers and mobile phones in Iran. Resour. Conserv. Recycl. 87, 21–29. https://doi.org/10.1016/j.resconrec.2014.03.009.
Reike, D., Vermeulen, W.J.V., Witjes, S., 2018. The circular economy : New or Refurbished as CE 3. 0? — Exploring Controversies in the Conceptualization of the Circular Economy through a Focus on History and Resource Value Retention Options. Resour. Conserv. Recycl. 135, 246–264. https://doi.org/10.1016/j.resconrec.2017.08.027.
Ryen, E.G., Babbitt, C.W., Tyler, A.C., Babbitt, G.A., 2014. Community ecology perspectives on the structural and functional evolution of consumer electronics. J. Ind. Ecol. 18, 708–721. https://doi.org/10.1111/jiec.12130.
Scalbi, S., Fantin, V., Antolini, F., 2017. Environmental assessment of new technologies : Production of a Quantum Dots-Light Emitting Diode. J. Clean. Prod. 142, 3702–3718. https://doi.org/10.1016/j.jclepro.2016.10.098.
Tansel, B., 2017. From electronic consumer products to e-wastes : Global outlook, waste quantities, recycling challenges. Environ. Int. 98, 35–45. https://doi.org/10.1016/j.envint.2016.10.002.
Tsai, B., 2013. Modeling diffusion of multi-generational LCD TVs while considering generation-speci fi c price effects and consumer behaviors. Technovation 33, 345–354. https://doi.org/10.1016/j.technovation.2013.05.002.
Tseng, F., Cheng, A., Peng, Y., 2009. Assessing market penetration combining scenario analysis, Delphi, and the technological substitution model : The case of the OLED TV market. Technol. Forecast. Soc. Chang. 76, 897–909. https://doi.org/10.1016/j.techfore.2009.02.003.
U. S. Environmental Protection Agency, 2016. Electronic Products Generation and Recycling in the United States, 2013 and 2014.
U S Environmental Protection Agency, 2011. Electronics Waste Management in the United States Through 2009.
Vanegas, P., Peeters, J.R., Cattrysse, D., Tecchio, P., Ardente, F., Mathieux, F., Dewulf, W., Duflou, J.R., 2018. Ease of disassembly of products to support circular economy strategies. Resour. Conserv. Recycl. 135, 323–334. https://doi.org/10.1016/j.resconrec.2017.06.022.
Wang, X., Gaustad, G., 2012. Prioritizing material recovery for end-of-life printed circuit boards. Waste Manag. 32, 1903–1913. https://doi.org/10.1016/j.wasman.2012.05.005.
Wang, F., Huisman, J., Stevels, A., Peter, C., 2013. Enhancing e-waste estimates : Improving data quality by multivariate Input – Output Analysis. Waste Manag. 33, 2397–2407. https://doi.org/10.1016/j.wasman.2013.07.005.
Yang, Y., Williams, E., 2009. Logistic model-based forecast of sales and generation of obsolete computers in the U.S. Technol. Forecast. Soc. Chang. 76, 1105–1114. https://doi.org/10.1016/j.techfore.2009.03.004.
Yu, J., Williams, E., Ju, M., Yang, Y., 2010. Forecasting Global Generation of Obsolete Personal Computers. Environ. Sci. Technol. 44, 3232–3237.
Zeng, X., Mathews, J.A., Li, J., 2018. Urban Mining of E-Waste is Becoming More Cost-Effective Than Virgin Mining. Environ. Sci. Technol. 52, 4835–4841. https://doi.org/10.1021/acs.est.7b04909.
Zlamparet, G.I., Ijomah, W., Miao, Y., Awasthi, A.K., Zeng, X., Li, J., 2017. Remanufacturing strategies : A solution for WEEE problem. J. Clean. Prod. 149, 126–136. https://doi.org/10.1016/j.jclepro.2017.02.004.
Zlamparet, G.I., Tan, Q., Stevels, A.B., Li, J., 2018. Resource conservation approached with an appropriate collection and upgrade-remanufacturing for used electronic products. Waste Manag. 73, 78–86. https://doi.org/10.1016/j.wasman.2017.11.053.