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Ecological foraging models as inspiration for optimized recycling systems in the circular economy

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ABSTRACT

Converting the consumer electronic product system from a linear system to a circular one has a number of key challenges. A mismatch is observed between the rapidly changing devices entering the market and the slowly evolving voluntary design policies, regulations, and e-waste processing business strategies. Conventional electronic waste (e-waste) management systems were historically optimized to extract high-value components from large products that were relatively easy to disassemble, but the products now entering the waste stream are more often light-weight mobile devices that are typically not covered by regulations or do not contain as high a concentration of valuable metals. This article proposes that transformations in the e-waste processing system aimed at closing the material loop should look to the circular processes found in natural ecosystems, which have evolved to optimize closed loop nutrient cycling. Like species in nature, e-waste processors make decisions about where and what to "eat," balancing a food's quality and abundance with the energy expended in obtaining it. Adapting the concept of optimal foraging theory, we demonstrate here a conceptual framework that draws parallels between foraging behavior in the ecological and industrial world, evaluates four potential mathematical models that case be applied to the e-waste case, and demonstrate how optimal foraging decisions can guide business, design, and end of life management toward circular economy goals in the consumer electronic system.

1. Introduction

The consumer electronic product system (smart phones, televisions, computers, etc.) has permeated modern society across individual, household, industry, and national scales. Over the last 25 years, the average U.S. household went from owning fewer than eight to more than 20 different electronic devices, with rapid replacements spurred by shortened product lifespans, technological advances, lower costs, changing consumer preferences, and decreased emotional or personal attachment to the devices themselves (Ryen et al., 2014, 2015; Chapman, 2015; Lauridsen and Jørgensen, 2010). Compounding the rapid growth in consumption and adoption patterns, significant resources are invested in product manufacturing (Williams et al., 2002; Williams 2004; Kasulaitis et al., 2015), but never fully recovered after the product's useful life. Consumer electronic products typically have short lifespans, are difficult to upgrade or recycle, and as a result, only a fraction of materials embedded in electronics are recycled back into new technology products (Lauridsen and Jørgensen, 2010). The linear management of consumer electronics also results in an unprecedented expansion of the global electronic waste stream (Widmer et al., 2005; Huisman et al., 2008; Zoeteman et al., 2010; Herat and Agamuthu, 2012; Taghipour et al., 2011).

Converting this linear system to a circular one is a widely held goal, but faces a number of key challenges that must be addressed. For example, electronic products contain both valuable and potentially hazardous materials and components, which on one hand can be recycled as substitutes for more expensive or scarce primary materials, but on the other have the potential to create negative impacts to human health and the environment if managed improperly (Widmer et al., 2005; Williams, 2011; Williams et al., 2008; Pérez-Belis et al., 2015; Kiddee et al., 2013). Conflicting circumstances that currently pose challenges to recycling efforts can be attributed to material content including: 1) toxic substances (e.g., mercury, lead), 2) abundant, low value materials (e.g. plastic from computer casings), 3) low volume, high value materials (e.g. precious metals found in printed circuit boards), and 4) low volumes of scarce and critical materials (e.g. dysprosium in hard drives) (Kang et al., 2012; Williams et al., 2008; Widmer et al., 2005; Robinson, 2009; Park and Fray, 2009; Wang and Gaustad, 2012; Chancerel et al., 2013).

In addition, the complex and quickly evolving nature of the electronic product system sharply contrasts with the slow pace at which

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conventional waste management approaches are being developed to safely recover and return components and materials back into the value chain. These conventional approaches include voluntary design and purchasing standards, regulations based on the concept of extended producer responsibility, and formal collection and processing of electronic devices. For example, voluntary standards such as the Electronic Product Environmental Assessment Tool (EPEAT) attempt to encourage product repair and more efficient recovery of high value materials through design features such as easy access to internal components, material labeling, radio frequency identification (RFID) tags, and bill of material databases (GEC, 2009). While these design standards were first created to improve the environmental performance of large, legacy products like desktop computers and monitors, standards aimed at smaller products, like mobile phones (EPEAT, 2017), have only recently emerged. Moreover, a trend towards using automatic shredding processes in electronics recycling (GEC, 2009) suggests that disassembly may not be the most effective strategy to process the smaller, mobile electronic devices anticipated in future waste streams.

Regulations have also been developed to formally manage devices in a circular system. Extended producer responsibility (EPR) laws like the European Union (EU) Waste Electric and Electronic Equipment (WEEE) Directive 2012/19/EU were originally designed to encourage the recovery of products and materials for a range of electronic devices entering the waste stream (Pérez-Belis et al., 2015), and drive innovation to enable product disassembly, repair, and recyclability (Lauridsen and Jørgensen, 2010). However, the WEEE Directive has lost some of this original intent, as third parties involved with the collection and recovery of materials are often not collaborating with manufacturers or designers and there is limited ability to reintegrate recovered products, components, and materials back into the same industry (Singh and Ordoñez, 2016; Ghisellini et al., 2016).

In comparison to the EU's unified approach, a bottom-up "patchwork" of state and local e-waste policies in the U.S. has resulted in varied recycling strategies based on the concept of EPR (Nnorom and Osibanjo, 2008; Kahhat et al., 2008; Hickle, 2014). For example, New York State (NYS) laws (e.g., NYS Electronic Equipment Recycling and Reuse Act and New York State Wireless Telephone Recycling Act) focus on larger products (computers, monitors, VCRs, and gaming consoles), some newer devices (DVD, TV set top boxes) and mobile phones (NYS, 2016). Producers are required to pay for collection, transportation and recycling of these devices and their costs are allocated based on market share (Electronic Take Back Coalition, 2013). While manufacturers are required in many states to take back and recycle their electronic devices, some states provide limited reimbursement or center reimbursement on mass-base standards (a combination of allocating costs by return and market shares) (Gui et al., 2013). As a result, third party collection parties may target larger or heavier devices, which are being phased out and are of limited use for direct recovery of material or components into new, lightweight products.

These challenges are likely to be magnified by ongoing trends in the consumer technology industry, estimated to be worth $287 billion in retail revenues in 2016 (CTA, 2016). For example, rapid expansion of connected, mobile and wireless devices like wearables, audio, video, and smart home devices has led to widespread expansion of the Internet of Things. As a result, products that were never before considered to be "electronics" – like clothing, shoes, watches, toys, and household products – are embedded with sensors, circuitry, and batteries, all of which consume significant materials and energy while also creating new waste management challenges. At the same time, "traditional" consumer electronics are themselves undergoing rapid evolution in design and functionality and a diversification of sizes and material compositions.

Some of these trends may lead to net resource improvement. For example, the elimination of cathode ray tube (CRT) televisions and replacement with lightweight flat panel devices has created a net material reduction, although tradeoffs in terms of energy use, scarce material demand, and waste management are not yet quantified (Babbitt et al., 2017). To a large extent, though, trends toward light-weighting and diversification in physical attributes of electronic products has served to confound efforts aimed at converting this linear materials system into a circular, closed-loop system. For example, from 2014 to 2015, the volume of "covered" (or regulated) electronics collected in Oregon declined by 11% (Evans, 2016) because the majority of products entering the waste stream during that period were small, mobile devices not covered under existing state legislation. It is clear that new resource management strategies, like the circular economy, must take into account the dynamic nature of electronic products and their attendant material consumption and waste generation.

2. Ecological inspirations to optimize e-waste recycling systems

To create a closed-loop system for material recovery, one of the clearest design inspirations comes from biological systems themselves. Natural ecosystems have evolved over hundreds of millions of years to provide the qualities we now aim to emulate in industrial systems: circularity in closed systems, trophic level energy cascading, efficient material cycling, robust network topology, stable interdependence among species, and diverse material flows (Jorgensen, 1992/1997; Jorgensen, 1992; Korhonen, 2001; Nielson, 2007). Nutrient cycling is a primary feature of most ecological systems, where it is commonly seen that the waste from one type of organism becomes an input for others in the system (Stahel, 2016), as illustrated in Fig. 1a.

In ecosystems comprised of complex organisms, ecological nutrient and energy flows are often mediated by the evolution of behaviorally-based foraging decisions, which in turn are influenced by both interactions among the species present at any given time, as well as individual responses to exogenous factors, such as food limitations or temperature fluctuations (Pyke et al., 1977; Ricklefs and Miller, 2000). Foraging decisions influence the behaviors employed by animals to search for and handle food (e.g., physical efforts associated with capturing and debilitating prey, maintaining territory against intrusion, and/or systematically searching the landscape for opportunity).

Foraging has been widely studied by ecologists and resulted in many quantitative models because the "…stomach sways the world" (Fabre, 1913 as noted in O'Brien et al., 1990 p.152), through its influences on ecosystem level services and processes (O'Brien et al., 1990). Animals engage in foraging activities and make decisions critical to health: where to search for prey, what prey to eat, whether or not to pursue the prey, and when to leave the patch or area once the prey is found (Perry and Pianka 1997; Stephens and Krebs 1986). Invoking a combination of both instinctive and learned behaviors in animal systems, ecologists have explained and predicted foraging behaviors first with simple cost-benefit ratios and then later with more complex empirical models (Pyke et al., 1977). These foraging decisions play an important role in the ecosystem as a whole; breaking down and recovering resources and energy to be reused, minimizing waste, and competing and cooperating together to enhance the system capacity to withstand perturbations.

Like its ecological counterparts, the consumer electronics ecosystem (Fig. 1b) consists of several species or stakeholders (e.g., manufacturers, households, e-waste processing business) that interact with one another. For example, households provide a source of food or prey (i.e., obsolete devices) to e-waste processing businesses. Because in the U.S. most devices are still stored in homes or disposed landfills (U.S. EPA, 2014), e-waste processing businesses make important foraging decisions that enable a circular flow of nutrients (materials) and embodied energy in the ecosystem while minimizing waste. Decisions include where and how to find the obsolete devices and then what type of techniques or handling strategy (e.g., testing, repair, disassembly, or shredding) to employ to break down the devices and recover technical nutrients (components and materials) for resale or resource recovery. Like a natural ecosystem, the consumer electronics ecosystem is vulnerable to external perturbations such as government regulations, technological advances, material scarcity, market price changes, and

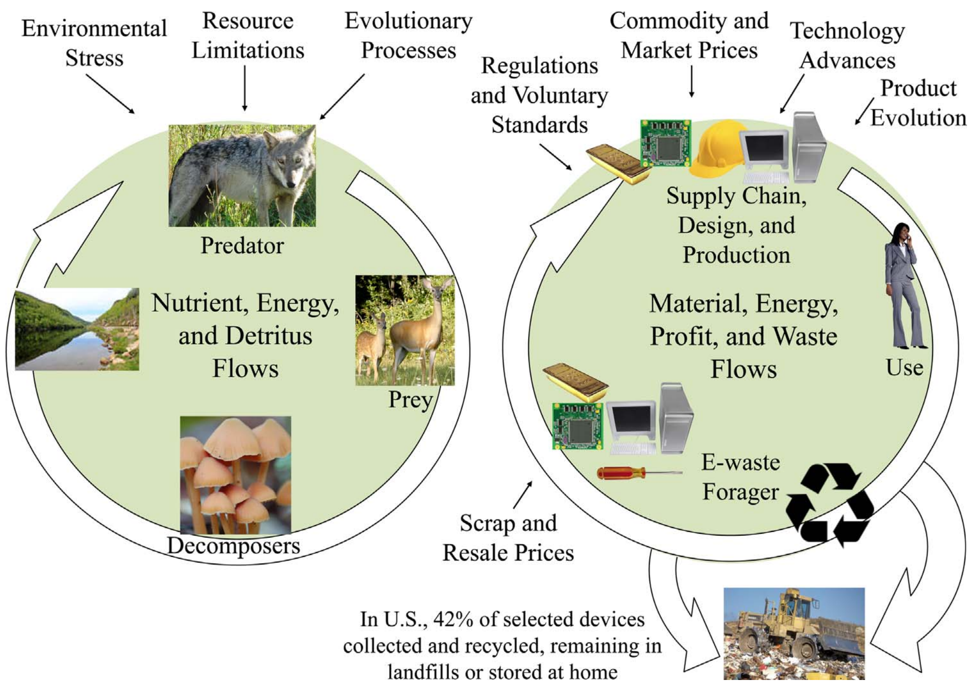

Fig. 1. Comparison of Ecological and Consumer Electronic Ecosystem Flows: a) illustrates the efficient cycling of nutrient, energy and detritus matter in an example ecosystem in the Adirondack Park, NY with a predator (e.g., grey wolf) and its prey (white tail deer), and b) less efficient flow of devices, energy, materials, and waste in the consumer electronic 'ecosystem,' which consists of interacting species like the supply chain, designers, manufacturers, consumers, and e-waste processing businesses). Each system is impacted by exogenous factors. Images are from the Wikimedia Commons (2017), Microsoft clipart, and Flickr.com (2017). E-waste collection data is from the U.S. EPA (2014).

adoption pattern trends, which could alter ecosystem levels flows of nutrients and waste materials.

The concept of optimized foraging borrowed from behavioral ecology is a novel source of models and methodologies that can be used to systematically understand the criteria driving material and component processing and recovery decisions. This research builds upon previous research that has demonstrated the utility of ecological analogs to assess the evolving structure, function, and environmental impact of the consumer electronic product system (Ryen et al., 2014, 2015). To date, optimal foraging theory has not been applied to the management of e-waste, although foraging models have been used in research on optimal facility siting based on honeybee behavior (Vera et al., 2010), optimizing power distribution and predicting stock market prices using bacteria foraging behavior (Tabatabei and Vahidi 2011; Majhi et al., 2009), adapting the prey model by Stephens and Krebs (1986) to optimize the speed and task processing choices for an autonomous vehicle (Pavlic and Passino 2009), and product disassembly analyses based on ecological genetic algorithms (Hula et al., 2005) and self-guiding ant behavior (Tripathi et al., 2009). However, these examples do not fully address the important generalities and potential differences when applying ecological foraging concepts and models to industrial systems. It stands to reason that principles and methods underlying the study of foraging in an ecological context could inform the decision making by which industrial systems collect, handle, and process resource and waste streams to keep valuable technical nutrients in the value chain.

3. Methods

We hypothesize that the concept of *Optimal Foraging Theory*, which reveals how organisms in nature have evolved to maximize nutrient consumption while minimizing the energy expended to obtain these resources, can be adapted to guide optimized decision making processes in material recycling systems, thereby better enabling return on investment within a circular economy. Here, we develop a conceptual framework for this approach by drawing parallels between foraging behaviors in nature and analogous behaviors typically observed during e-waste recycling.

First we describe optimal foraging concepts in ecological systems and identify general search and handling strategies. Next, we review four candidate mathematical models (optimal diet, patch use, central place foraging, and grazing) commonly used to study optimal foraging theory in ecology and discuss their applicability to our case of e-waste management. In our conceptual framework, the e-waste "forager" is a business that searches for and collects obsolete consumer electronic devices providing information, communication and entertainment services (smartphones or laptops). The e-waste forager participates in a wide variety of component and material recovery practices (e.g., disassembly and shredding). Finally, we demonstrate, for the case of e-waste, how optimal foraging decisions can directly map onto business, design, and management decisions of critical importance to enabling the circular economy for consumer electronics. Terminology is translated from the ecological optimal diet model into the industrial case of the e-waste forager. The E-waste Optimal Diet model results are illustrated for our case study of two consumer electronics, smartphones and laptops, which have seen rapid changes in functionality and consumption patterns (Ryen et al., 2014).

3.1. Overview of optimal foraging in ecological systems

In biological systems, organisms generally use three different types of foraging strategies, which have evolved to affect both morphological (physical appearance) and behavioral characteristics: 1) passive acquisition (e.g. filter feeding or ambush predators that sit and wait for the prey), 2) active foraging, where animals can either exploit a defendable home-range with territorial behavior, or else move nomadically across landscape in response to external factors or disturbances that favor the foraging strategy employed (e.g. fire, hydrology, disease), or lastly 3) some combination of both passive and active strategies, which is also called 'saltatory' (Schoener, 1971; O'Brien et al., 1990). Active foraging requires a larger fraction of the overall energy budget, and therefore optimal foraging theory postulates that there must be a payoff in food quality whenever more activity is required to obtain and process the food (Pianka, 1973; O'Brien et al., 1990; Evans and O'Brien, 1988; Pough et al., 2009). Active predatory behavior reflects this principal in that a carnivorous diet can deliver more calories per unit mass than an herbivorous diet.

Organisms are generally observed to handle (i.e., process and consume) prey differently due to evolution (towards partitioning in niches to reduce competition), as well as the ever-present need to continually adapt to their changing surroundings. For example, the octopus (*O.*

minus) was observed to conduct extensive handling activities (e.g., drilling) in order to access and consume prey protected by shells (e.g., gastropods or bivalves) (McQuaid, 1994; Cortez et al., 1998). Most grazers will regulate biting and stepping rates in response to food patch quality (Spalinger and Hobbs, 1992). Two closely related lizard species (Iguanian and Autarchoglossan) have each evolved to use different chewing or processing activities to handle prey (McBrayer and Reilly, 2002). Semi-sessile or stationary species, like bivalves (mussels, oysters, and scallops), optimize filtering rates to efficiently consume phytoplankton and other suspended particulate matter in balance with waste discharge (Zhou et al., 2006).

3.2. Mathematical models of optimal foraging theory in ecological systems

To better understand how we can apply the foraging modes and search strategies to our industrial e-waste foragers, we look to the models developed by behavioral ecologists. Beginning with Emlen (1966) and MacArthur and Pianka (1966), a variety of foraging models have been developed to understand the feeding decisions of ecological species and to quantify and predict foraging decisions. Since 1966, the number of empirical and field studies related to optimal foraging theory has surged (Schoener, 1971; Perry and Pianka, 1997). The four models described below are those that are mostly widely applied in the literature and that were found to have the highest applicability to industrial foragers, particularly for the e-waste case.

3.2.1. Optimal diet model

The simple 'Optimal Diet Model' (e.g. Charnov, 1976a; McArthur, 1972; Schoener, 1971) evaluates the types of prey that a predator can choose from, given variable "profitability" (Krebs, 1980; Hirvonen and Ranka, 1996; Holling, 1959), as shown in Eq. (1). Here, profitability or prey value is the net amount of food consumed per unit of handling time (Krebs, 1980). Early development of this model assumed that the predator's goal is to maximize the net rate of energy intake during a feeding period to maintain fitness (Pyke et al., 1977; Schoener, 1971; McQuaid, 1994; Charnov, 1976a) and feeding decisions are made without considering other factors such as the risk of predation (Krebs 1980; Charnov, 1976a; Pyke et al., 1977). Early ecological studies also assume that prey with the highest profitability or energy content per unit of searching and handling time would be selected (Emlen, 1966; MacArthur and Pianka, 1966; Charnov, 1976a) and less profitable prey will be eliminated from the predator's diet (Krebs, 1980). The amount of time allocated to foraging is generally assumed to be fixed and optimal fitness occurs when the maximum amount of energy is gained (Pyke et al., 1977; Stephens and Krebs, 1986).

$$\frac{E_n}{T} = \frac{E}{T_S + T_H} \tag{1}$$

The classic ecological optimal diet model maximizes the net rate of energy intake (E_n) per unit of feeding time (T), which includes both the time required to search for (T_S) and then handle the prey (T_H) (Schoener, 1971; Charnov, 1976a; Stephens and Krebs, 1986). Many studies have explored the relationship with diet choices and other factors like prey size or density. Schoener notes that certain types of birds and mollusk will include a larger range of food items in the diet in conditions of lower food abundance (1971). Another study successfully predicts that as the time between encounters of prey (*daphnia*) increases, the diet of bluegill sunfish expands to include smaller class sizes of the prey (Werner and Hall, 1974; Pyke et al., 1977). Handling time generally increases as the size of prey increases in relation to predator size, so the profitability of larger prey declines if more energy must be spent capturing it (Hirvonen and Ranta, 1996).

3.2.2. Patch use model

The 'Patch Use Model' (Charnov, 1976b) is based on scenarios where food is found in groupings or clumps, and certain types of predators may move from patch to patch (Charnov, 1976b). The predator has two primary decisions: which patch to visit and when to leave (Krebs, 1980; Charnov, 1976b; Pyke et al., 1977). This model has been used to predict how much time a predator should spend in a patch while it is gradually being depleted of food and assumes that the predator's food intake rate (net energy per unit of time spent traveling) rises and then decreases as time is spent in the patch (Krebs, 1980) as the intake rate function rises to an asymptote (Charnov, 1976b). A predator should leave a patch when the intake rate in the patch falls below the average rate for all the patches in the habitat (a line stemming from the zero axis) (Charnov, 1976b; Pyke et al., 1977). The mathematical formulation of the model is similar to the optimal diet model equation shown previously.

The decision to select a patch is affected by travel time, food density and quality, and other patch characteristics. For example, the Patch Use Model successfully predicted the travel time for birds (Great Tits) searching for prey (mealworms) hidden in different patches (pots) increases as time spent in each patch increases (Cowie, 1977; Krebs, 1980). Another study finds that birds would change the patches if the quality of food is changed and that time spent in a patch mirror the abundance of food (Smith and Sweatman, 1974; Pyke et al., 1977). Lewis (1980) observes gray squirrels prefer higher over lower value acorns, but a patch with a net high rate of energy intake is selected even if it contains lower amounts of the preferred type of acorn.

MacArthur and Pianka (1966) rank patch types by prey calories caught per unit of time, similar to the optimal diet model and ranking of prey value. The authors predict that specialization of prey will occur in patches with greater food density, particularly for species that pursue rather than search for prey, because less search time is needed in patches with higher food density (MacArthur and Pianka, 1966). Larger patches are to be used in a specialized way than smaller ones because less travel time between patches is needed (MacArthur and Pianka, 1966). If food becomes scarce in a patch due to competition or other issues then including these types of patches is less likely due to the need to increase hunting time (MacArthur and Pianka, 1966).

Patch selection studies have also focused on how information is used to help make foraging decisions. For example, Klaassen et al. (2006) models decisions on how far between patches a predator will travel based on how well a predator is informed about the food density within a patch: a predator that is not completely informed or ignorant about the contents or quality of the patch will minimize costs by traveling to the nearest unexploited patch, while a predator with complete information will only feed in full patches, thereby increasing its net energy gain by sampling the environment in larger special units (Klassen et al., 2006).

3.2.3. Central (place) foraging theory

Some social species like birds or ants live in a centralized place (e.g., nest or colony), so resources are collected and brought back to feed others in addition to the forager (Ydenberg and Schmid-Hempel, 1994). This type of behavior is called 'Central Foraging Theory' or 'Central Place Foraging Theory,' which is a special case of the 'Patch Use Model' by Charnov (1976b) (Ydenberg and Schmid-Hembel, 1994; Olsson et al., 2008). Some fish and mammal species also behave like central place foragers by using a burrow to hide from predators (Kramer and Nowell, 1980; Olsson et al., 2008). Central place foraging models consist of two activities; feeding oneself and provisioning or finding and delivering food for the offspring or colony. Traditional models for social insects (ants) do not separate the costs and benefits of feeding from provisioning, even though different parties are responsible for finding and eating the food and assume that the net energy intake rate to the central place is maximized (Ydenberg and Schmid-Hempel, 1994).

As shown in Eq. (2), the central place foraging model assumes that a forager (bird or insect) will maximize its average long term rate of energy gain (Γ), which is a function of the average number of prey (or amount of food) ($\bar{n}$) taken per patch, average search time ($\bar{t}$) in a patch, and the one way average travel time ($\bar{\Gamma}$) (Olsson et al., 2008):

Table 1
Comparison of Ecological and E-waste Foraging Modes and Species Traits.

	Ecological			Industrial
Species example				
	Octopus	**Sheep**	**Bird**	**E-waste Processing Facility**
Mode	Sit and wait (passive)	Widely Ranging (active)	Saltatory (combination of passive and active modes)	All possible:1) sit and wait for products to come to facility, 2) individuals active search for scrap at curbsides or actively searching for valuable components within a product, 3) at a facility, both actively searching and sometimes stopping to decide whether or not a product should be disassembled to the component level or shredded
Range size	Small	Large	Intermediate	Small (within the facility) or large if collection region is outside the facility
Search strategy and movements	Ambush Generally sedentary Search during pauses	Highly active Search while moving	Active, stop & go Feed self vs. young at central place Search during pauses	All possible: 1) wait at facility or location in the community for products to be dropped off and then pounce to collect or 2) facility serves as central place and personnel leave to collect products at other locations and bring them back
Handling activities	Beak & suckers	Chew all	Beak	Testing, resale, disassembly & shredding
Prey Type	Large, active, mobile	Sedentary, and often smaller, clumped	Intermediate to small, little movement	Small and large, Size/type of product to disassemble to be determined

Notes: Table adapted Perry and Pianka (1997), O'Brien et al. (1990), Pough et al. (2009), and images from Flickr.com (2017).

$$\Gamma = \frac{\bar{n}}{\bar{t} + 2\bar{\tau}} \qquad (2)$$

The classic central place foraging model predicts that time spent in a patch and load size (number of prey) will increase with increasing distance from a forager's central place because the average long term rate of energy gain decreases as average travel time increases (Olsson et al., 2008; Charnov, 1976b). There are direct costs of increasing load size (energy and predation costs associated with transporting food back to the nest) and indirect costs (predation cost within the patch) with increases in distance from one's central place (Olsson et al., 2008). For birds, the rate of self feeding influences delivery rate, but less so for other social species like ants that need to find a range of food and other resources (mud, water, and wood scraps) for the colony (Ydenberg and Schmid-Hempel, 1994). For ants, the delivery of food/resources is function of number of workers finding and gathering food and the rate at which it is being delivered (Ydenberg and Schmid-Hempel, 1994).

3.2.4. *Grazing models*

While processing and searching for food are separate activities for some species, mammalian herbivores like horses, sheep, cows, or other grazing species conduct both activities simultaneously; searching for the next bite as the animal chews and swallows an existing bite (Fortin, 2006). The classic grazing model developed by Spalinger and Hobbs (1992) is used to understand the relationship between plant abundance and short term diet of grazing organisms, the relationship between bite size and site selection (Milne, 1991), and the regulation of nutrients (e.g., Simpson et al., 2004). The Bite Mass model, as shown in equation 3, examines how certain characteristics of prey (in this case plants) affect the energy intake rate (I) of the herbivores (Spalinger and Hobbs, 1992).

$$I = \frac{R_{\max} {*} S}{R_{\max} {*} h + S} \qquad (3)$$

The net energy intake rate (I) is a function of bite mass (S) in grams, time to crop or harvest a bite (h) in minutes, and the rate of processing of food in the mouth ($R_{\max}$) in grams per minute. This model finds that herbivores face a trade-off between the food abundance and quality: tall grass patches are eaten faster (higher intake rate), but are digested less fully due to fiber content while shorter grass patches are highly digestible, but have lower intake rate (food abundance) (Edouard et al., 2010). While for many species, it is assumed that the organisms will maximize energy intake, grazing species, like bison, are often referred to as 'Time Minimizers' due to having a fixed energy requirement (Belovsky, 1987; Bergman et al., 2001). Feeding time, digestive capacity, and nutritional requirements affect an herbivore's ability to optimally forage (select, chew, and process) plant material and field observations find that as plant quality increases and plant abundance decreases, the herbivore body size also decrease (Belovsky, 1987).

Grazing models are often used to show hierarchical nested decision-making processes (Senft et al., 1987 and Kotliar and Wiens, 1990 as noted in Spalinger and Hobbs, 1992). Spalinger and Hobbs (1992) use the grazing model to show how patches of different plant densities (dispersed vs. concentrated) and visibility (hidden or apparent) traits influence instantaneous intake rate (net energy per unit of foraging time). Their model predicted shifts in the energy intake rate as a result of food availability (spatially concentrated or dispersed) and visibility in patches; when food is located in small clumps and dispersed, bite density regulates encounter rates (asymptotic relationship between intake and bite density), but when food is concentrated, bite size has more influence on energy intake rate causing a competition between cropping and chewing (Spalinger and Hobbs, 1992).

3.3. Application of optimal foraging to industrial systems

3.3.1. Adapting models to e-waste forager case

In Table 1, we compare and contrast ecological foraging strategies mentioned in section 3.1 to the industrial case, although direct translation between systems is imperfect. An e-waste "forager" might actively search for obsolete products by traveling from the 'nest' or facility to decentralized collection programs and/or to specific company and institution locations, and then bringing the devices back to the facility. Individuals may also act as a grazing species by driving around neighborhoods each week and actively seeking out scrap metal and other products with secondary value in recycling bins and piles at the curb. On the other hand, the e-waste forager could apply a passive strategy by 'sitting and waiting' for customers to drop off obsolete products at the facility and then 'pounce' on the collected products. The e-waste forager handles or processes products with a variety of techniques (disassembly or shredding) to access valuable components and materials within the products. Finally, like the ecological counterparts, the e-waste forager engages in a type of detritus feeding that is critical to supporting eco-system flows of scrap materials, especially with growing concerns of material scarcity. The e-waste processing facility breaks down the obsolete electronics so components and materials can be recovered for use in electronics and other products. An e-waste forager may be considered 'facultative' or opportunistic in deciding which material and component recovery strategy to select for each product. In a rapidly evolving consumer electronic ecosystem, the inability of an e-waste processor to adapt their handling or processing activities has significant consequences on system-level material and waste flows.

To adapt optimal foraging modeling for use in industrial systems and in our case, the EOL processing of e-waste, we mirrored a process used by ecologists to model an animal's foraging behavior (Schoener, 1971; Pyke et al., 1977): 1) identifying a currency to be optimized, 2) selecting an appropriate cost benefit function and constraints, and 3) solving for the optimal solution (minimizing or maximizing the currency). Foraging models are typically based on the "currency" of energy intake rate, which relates to the calorific value of food obtained. In the industrial case, the most likely analog is economic value of the material processed and subsequently recovered. However, considering the environmental goals of e-waste recycling, these models could also be based on metrics like embodied energy of recovered materials as compared to energy input to the recycling process (labor and electricity to operate equipment). Next, we demonstrate (Table 2) how one might adapt the foraging models described previously to our e-waste forager.

In Table 2, we lay out the parallels between optimal foraging models and modeling approaches that may inform sustainable e-waste recovery. For example, the optimal diet or profitability of prey model could be applied to a simple two-prey model of devices like smartphones and laptops. These devices are part of functional groups that have undergone rapid changes in performance and consumption (Ryen et al., 2014). In this model, we can better understand what components should be designed for disassembly, or if the product itself should be shredded. On the other hand, the patch use model could test two decisions faced by ecological and e-waste foragers: which patch to visit and when to leave. Data from small e-waste material and component recovery businesses can characterize the search for new and existing markets of obsolete products, as influenced by the changing product waste stream and governmental policies.

A grazing model may also be applicable because the e-waste forager often has to process or ingest every product it encounters. As described earlier, manufacturers are required in New York State to provide free recycling for products covered by the state e-waste EPR policy. Thus, like mammalian herbivores (e.g., sheep), an e-waste facility may need to recover both high volume (plastics) and high value (components with precious metals) materials, requiring flexible handling tools (labor/equipment) and ability to supplement the diet through complementary activities, such as data destruction contracts. Finally, a central place foraging model could be used to optimize facility siting and logistics planning by examining the economic and environmental impacts of collection and transport an evolving and diverse group of products and materials within the e-waste forager's range.

3.3.2. Translating optimal diet model terms to industrially relevant parameters

Just as early ecologists assumed animals conducted foraging activities efficiently to maximize fitness (Charnov 1976a), it is assumed that the e-waste forager would strive to maximize its profitability and ultimate ability to survive in the market. Using the terms from the Optimal Diet model as an example, Table 3 provides a translation of terms from the ecological to industrial case, the e-waste forager, considering here either the currency of profit (US$) or embodied energy (MJ).

The e-waste forager's objective function is to maximize energy (E_i) per unit of feeding time (T_i), which is translated as net profit ($) per second of time spent on processing each component (i) by shredding and disassembly. For all products (j) and components (i), the net profit (E_n) per unit of EOL processing time (T) maximized the sum of revenues (E) for each strategy (i.e., shredding (s) or disassembling (d)), handling costs (C_d or C_s), and search costs (C_S) divided by the time needed to search for (T_S) and complete each EOL processing strategy (T_d or T_s). Profit ($) could also be substituted with embodied energy (MJ)

Table 2
Potential Adaption of Foraging Models to the E-waste Forager.

Foraging Model	Potential Application
Optimal diet	Decision tool to help determine the profitability of prey (obsolete electronic devices) and the optimal balance of obsolete products and the appropriate material recovery strategies (shred vs. disassemble consumer electronics). Use information to help design products for these optimal strategies.
Patch Use	Selecting clientele or centralized collection locations with the optimal density of obsolete products. Could integrate with Geographic Information System (GIS) tool and bill of material data to estimate the impact of the degree information on device component and material values.
Central Place	Site identification and collection logistics planning for e-waste or battery recycling facilities. Could integrate with GIS tool.
Grazing	All incoming products processed (eaten) due to state law. Bite size (product mass to be shredded or disassembled) is a function of the material and component values found in the product. Nutritional needs (profit) of a recycler met by balancing the variety of high and low-quality materials and components.

Table 3
Translation of ecological model parameters into e-waste equivalents.

Parameter	Ecological	E-waste
E_n/T	Net calories (or biomass) per foraging time unit (joules (or mass) per second)	Net profit (or embodied energy) gained per time unit spent processing ($ or MJ per second)
E_n	Net energy gained (joules or mass) while foraging	Net profit (or embodied energy) ($ or MJ) in 2008 USD
T	Total time (seconds, minutes, or hours) spent foraging (searching and handling prey)	Total time (seconds) spent foraging (searching and handling) component (i) and product (j)
E_i	Energy gained (joules or mass) per unit of prey (i)	Total scrap or component revenue or value ($) or embodied energy (MJ) from gained from disassembling or shredding each component (i)
$C_{S,i,}$	'Costs' or energy expended (joules or mass) while searching and locating prey (i)	Total costs ($) of searching, collecting, and managing each component (i)
$C_{H,i}$	'Cost' or energy expended (joules or mass) while subduing and handing prey (i)	Total costs ($) expended while processing each component (i) via shredding or disassembling
$T_{S,i}$	Time expended (seconds, minutes, or hours) while searching for prey (i)	Time (seconds) expended to search for products; assumed to be zero because products were dropped off
$T_{H,i}$	Time expended (seconds, minutes, or hours) while handling prey	Time (seconds) to shred products or disassemble each product to the component level

associated with the different type of materials recovered. Further assumptions would be necessary to carry out this approach. For example, the model would likely assume that all products are processed, since it is unlikely that an e-waste firm would dispose of electronics already collected, particularly in states with relevant recycling policy. In the cases where products are dropped off at a facility, then the time to search (T_S) for products would be zero. To apply this approach in e-waste or other industrial cases, careful consideration of appropriate parameters or modifications would be needed.

4. Results

4.1. Potential utility of optimal foraging theory to create circular e-waste systems

To illustrate the benefits of optimal foraging models in informing recycling decisions, we describe here how the conceptual framework would be applied to a specific material recovery challenge. An e-waste processing business makes many decisions that influence the "food" (waste materials) that they can process, such as where to site the facility, how to locate and collect obsolete products, and what type of processing strategies to employ with each product at the facility. Within the facility, another important decision is matching the appropriate processing strategy with the incoming stream of obsolete products, particularly given the continued evolution of physical attributes and material composition of consumer technology. A spectrum of different types and sometimes, conflicting processing activities is often leveraged to earn profits, including: 1) triage (sorting and testing), 2) data destruction, 3) refurbishment, reuse, and resale, 4) disassembling into subassemblies and components (including resale of these items), 5) depollution, material separation, and mechanical processing of similar and mixed materials, and 6) refining/smelting of metals (GEC, 2009; Johnson and McCarthy 2014). Most facilities engage in some form of manual disassembly to isolate and sell components for a higher commodity scrap value (GEC, 2009). For many businesses, there is a tradeoff between the decision to disassemble for high value material recovery or repair and remanufacture resale (Johnson and McCarthy 2014), which is often based on simple heuristics, like product age, color, or model (Sunnking site visit, 2010, 2013).

Among the e-waste activities described above, two competing

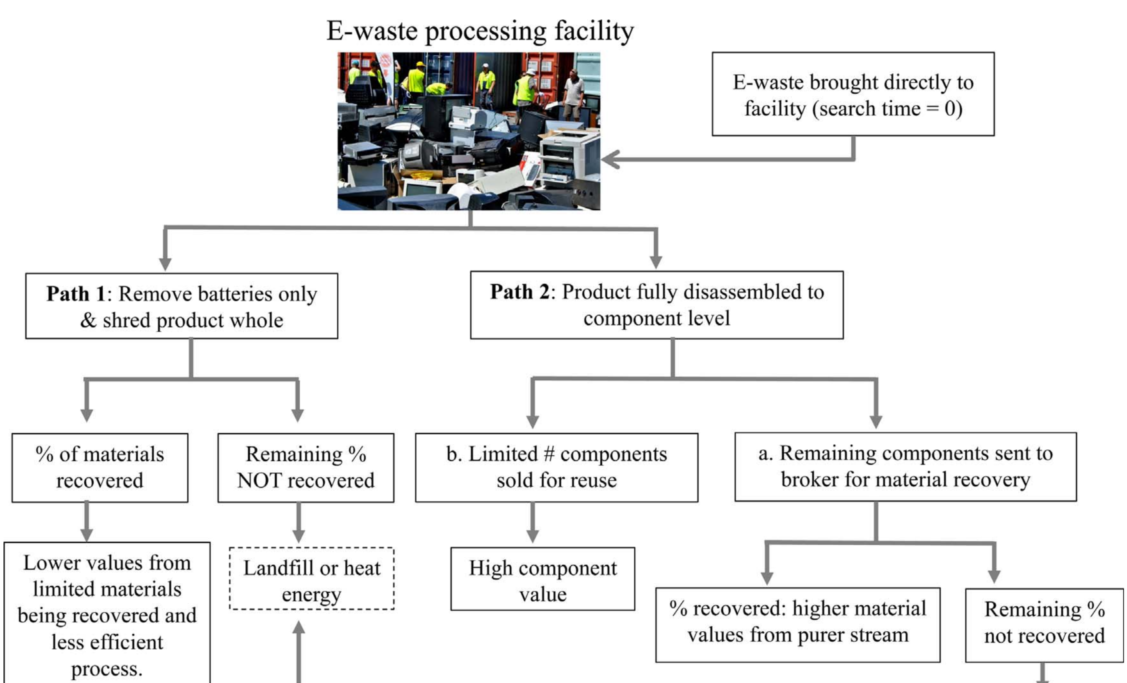

Fig. 2. E-waste Forager Decision Pathway.

decisions are shown in Fig. 2: should an e-waste business invest in expensive equipment to shred an intact product for lower value material recovery (Path 1) or invest in costly labor to disassemble a product to the component level and then sell components to a broker for higher value material recovery (Path 2). In Path 1, a company has purchased a large shredder, and while there is some basic material separation, the bulk of the shredded residue goes to a smelter where a specific set of materials is recovered. The downside of this path is that mechanical separation results in losses, particularly in the very fine fraction, and the resulting presence of other non-recoverable materials can possibly reduce the overall processing efficiency. In Path 2, a company disassembles to major components and then sells these components to a broker who sells them to reuse markets or on to a smelter. Disassembly (Path 2) is a labor-intensive approach that focuses on the materials within a component/product and ends up with a relatively pure stream of materials that can be processed together to provide high yields and efficient material recovery. Given that each path has its own economic implications, which are further conflated by the evolving nature of the consumer electronic ecosystem, should we prioritize design for disassembly, to enable recyclers to dismantle products and resell, *or* to disassemble and shred components to recycle high value components like the hard drive or printed circuit board?

Translating this problem to the Optimal Diet model, we can evaluate the two paths for a diet comprised of two or more food sources. For simplicity, we consider here the possible prey to be either a smartphone, which is extremely prevalent in the waste stream, but small with low material content, or a laptop computer, which is larger and more easily disassembled. To demonstrate the model and explain the results, we focus only on the financial (US$) rather than environmental impacts of the different processing strategies.

Plotting the solutions space for the Optimal Diet model (Fig. 3), which is adapted from ecologists like Charnov (1976b) and Krebs (1980), we would expect based on today's devices and recycling infrastructure that the model would result in either Strategy #1 or #2 (Fig. 3), depending on the type of device and the exogenous factors (policy, economics, consumer demand) governing the system. For example, if consumer demand or business innovations continue to encourage the development of smaller but easily disassembled products like the Fairphone 2®, then the model would suggest to invest more in disassembly labor and switch towards Strategy #2 (disassembly). Without knowing the location of the valuable components, then these businesses may tend to instead invest in large shredding machines rather than disassembly labor. Another condition that may drive the decision towards Strategy #1 (shredding) would be the substitution of low for high valued materials (e.g., plastics for metals), as e-waste processors are vulnerable to secondary market fluctuations. Implementing policies to raise the minimum wage towards $15 per hour will increase labor costs and may also inadvertently tip the model to select Strategy #1.

For larger products, a variety of conditions would change the selection from Strategy #1 (shredding) to Strategy #2 (disassembly) such as designing products to easily access high value parts with snaps or fasteners and increasing the interaction between designers/manufacturers e-waste processors. Recently Dell® modified their design of the Latitude series laptops to have a single service access door, a change motivated by feedback from e-waste recyclers (Siegel, 2016). Other changes that could facilitate Strategy #2 are designing products to include materials with high reuse or recycling potential or including product bills of material data and easy to understand disassembly directions. External conditions favoring Strategy #2 may include policies that encourage formal e-waste processing businesses to remain in the U.S. (e.g., with subsidies or tax breaks to reduce costs), or a sudden material scarcity or fluctuation in the secondary market that results in higher demand and higher material values. However, even with these conditions, e-waste processors may invest in expensive robotic technology rather than human labor to efficiently retrieve valuable components and materials, which would result in the selection of Strategy #1.

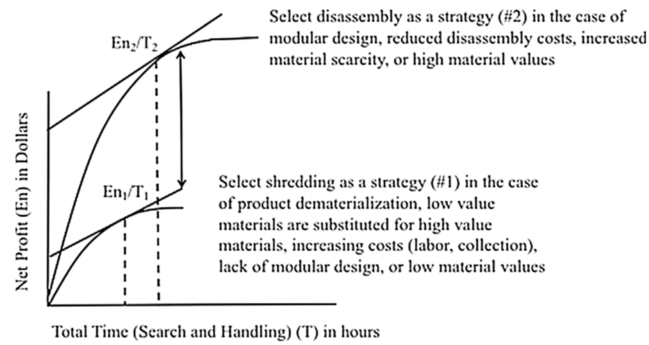

Fig. 3. Conceptual Results for the E-waste Optimal Diet Model. Optimal energy intake per unit of search and handling time (En/T) per product would change depending on market and policy conditions. Strategy #1 is investing in shredding equipment that provides faster, but less efficient material recovery, and strategy #2 is investing in labor to disassemble products to enable more valuable components and more efficient material recovery.

As optimal foraging theory predicts foraging decisions are behaviorally or evolutionary responsive to external disruptions in the environment and changes in population, the e-waste processors can use data about their 'habitat' (e.g., size of range or customers and existence of other competitors) along with data about the evolving product waste stream to inform future investments in labor and capital, ultimately helping them to maximize return on investment for these business decisions. For example, just as grazing species have evolved to more efficiently process larger amounts of lower quality plant material, while browser species are able to be selective and target younger plants rich in nutrients, e-waste processors will need to modify their equipment to adapt the changing waste stream and be selective about what they dissemble and how they obtain materials. Optimal E-waste foraging models can guide decisions such as selecting between active vs. passive foraging (invest in trucks, collection routes, and decentralized hubs versus centralized collection points), optimizing operation size, and providing some flexibility to adapt strategies (shredding or disassembly) in response to the changing waste stream.

While the e-waste optimal diet foraging model was adapted for the recovery of components and materials from consumer electronic devices and illustrated with a simple two-prey case of smartphones and laptops, it could also be applied to other waste streams such as the recovery of organics from food waste. For example, the patch use model could evaluate the time, environmental (greenhouse gas reduction), and economic impacts of diverting of food waste from landfills to other preferred waste management strategies of feeding people, feeding animals, composting, or conversion to biogas (U.S. EPA, 2017). For example, feeding people may take less time and result in positive environmental (reduced greenhouse gas) and social impacts (human health), but product quality may remain the same (or lower) or not be entirely consumed and become waste. On the other hand, recycling organics from food waste into energy, creates a high quality product (biogas), positive environmental impacts (energy security and reduced greenhouse emissions), but takes longer and is more costly. Integrating central place foraging with GIS tools, logistic planning, and facility siting tools can explore how to optimize the collection, transportation, and siting businesses in other sectors like the apparel industry that consumes and upcycles waste material into a new product (converting tires into shoe soles and plastic bottles into fabrics) (Hower, 2016).

As no single ecological species aligns perfectly with characteristics of the e-waste forager, future work must consider specific cases of e-waste systems and perhaps integrate multiple models such as the grazing model (Spalinger and Hobbs, 1992) and central foraging theory (Ydenberg and Schmid-Hembel, 1994). Since the composition of the material and product e-waste stream will continue to change with future consumption patterns, a comprehensive model that include stochastic patterns of product and material compositions may help e-waste foragers quantify decisions to identify how to adapt EOL processes to maximize net profit. This conceptual framework can be used to provide quantified results to strengthen existing extended producer responsibility policies to better understand the impacts of policies and the changing consumer electronic ecosystem. It may also encourage collaborations between e-waste foragers and product designers by linking design changes with EOL material and component recovery decisions' impacts on profit, as well as environmental impacts like maximizing embodied energy, maximizing critical material recovery, or minimizing use of toxic materials.

5. Conclusion

Nature is a vast source of inspiration we can use to guide the decisions of policy makers, manufacturers, designers, and waste management businesses to design and implement more sustainable material recovery and EOL management systems for consumer electronics. Here we show how optimal foraging theory and its models could be adapted for our case study, the consumer electronic ecosystem. Optimal foraging theory has already revealed how natural systems have achieved behavioral adaption by balancing efficient cycling of nutrients and energy with minimal waste. With more light-weight mobile devices entering the market, optimal foraging theory provides a novel source of tools to guide EOL decisions. By mimicking natural systems, we can develop the partnerships, infrastructure, tools, and policies needed to ensure a long lasting, adaptable, and profitable e-waste ecosystem that can endure material scarcity, price fluctuations, or innovation changes. Ultimately, more products will be collected, components and materials will be recovered for reuse in other products, and waste will be minimized, thus achieving the important goal of a circular economy. If e-waste processors are not equipped or supported to address these changes, less efficient material recovery and flow will occur in the industrial ecosystem.

To transition the concept of a circular economy from a hypothetical ideal into a potent reality, we must need to expand our toolbox by borrowing well established methodology from other sciences that have already examined the very natural systems that we would hope to emulate within industrial settings. We have shown here that the concept of applying ever more advanced and appropriately analogous ecological models to our evolving industrial systems will ultimately guide us toward reaching our circular economy goals. The application of optimal foraging theory to e-waste recycling, is an initial step in this necessary direction.

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