The circular economy meets artificial intelligence (AI): understanding the opportunities of AI for reverse logistics

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Abstract

Purpose – Technology is an important force in the entrepreneurial ecosystem as it has the potential to impact entrepreneurial opportunities and processes. This paper explores the emerging technology of artificial intelligence (AI) and its implications for reverse logistics within the circular economy (CE). It considers key reverse logistics functions and outlines how AI is known to, or has the potential to, impact these functions.

Design/methodology/approach – The paper is conceptual and utilizes the literature from entrepreneurship, the CE and reverse logistics to explore the implications of AI for reverse logistics functions.

Findings – AI provides significant benefits across all functions and tasks in the reverse logistics process; however, the various reverse logistics functions and tasks rely on different forms of AI (mechanical, analytical, intuitive).

Research limitations/implications – The paper highlights the importance of technology, and in particular AI, as a key force in the digital entrepreneurial ecosystem and discusses the specific implications of AI for entrepreneurial practice. For researchers, the paper outlines avenues for future research within the entrepreneurship and/or CE domains of the study.

Originality/value – This paper is the first to present a structured discussion of AI's implications for reverse logistics functions and tasks. It addresses a call for more research on AI and its opportunities for the CE and emphasizes the importance of emerging technologies, particularly AI, as an external force within the entrepreneurial ecosystem. The paper also outlines avenues for future research on AI in reverse logistics.

Keywords Reverse logistics, Circular economy, Digital entrepreneurial ecosystem, Artificial intelligence, Reverse supply chain

Paper type Research paper

Introduction

The circular economy (CE) reflects a system in which waste is minimized by maintaining inputs – including products, materials or other resources – for as long as possible (European Commission, 2015; Stahel, 2016). While there are many conceptualizations of the CE, researchers generally agree that it involves reduction, reuse and recycling activities (Kirchherr *et al.*, 2017). The CE can be described as a closed-loop system in which resources are continually used and waste is eliminated as much as possible. This system is designed to be restorative or regenerative (EMF, 2012), i.e. what is viewed as waste in the traditional linear economy should become an input for another industrial process or as a regenerative resource for nature.

The benefits of such a system are numerous. Reports indicate that implementing a CE could reduce carbon emissions by up to 70% while also creating millions of jobs (Wijkman and Skanberg, 2015). Organizations that implement a CE within their operations may benefit

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from a competitive advantage as the CE protects against the scarcity of resources (European Commission, 2015) and generally seeks to extract the maximum value of an input at any stage in the industrial life cycle. One component of a CE is reverse logistics, which refers to the flow of goods from consumers back to manufacturers. This process is considered to be a key driver of a closed-loop supply chain (Guide and Van Wassenhove, 2009) as without reverse logistics, a product flow typically culminates with consumers sending products to landfill. Thus, reverse logistics is a critically important element when creating a closed-loop system.

Recent years have, unsurprisingly, shown rapidly increasing academic, government and practical interest in the broad topic of CE (Kirchherr *et al.*, 2017), including reverse logistics (Govindan *et al.*, 2015; Kazemi *et al.*, 2019). As the transition toward circular material flows continues, entrepreneurs will play a central role in the success or failure of this process (Veleva and Bodkin, 2018a). Specifically, entrepreneurs will be paramount to achieving goals through addressing environmental uncertainty, providing innovation and engaging in resource allocation (York and Venkataraman, 2010). Research already identifies a number of success stories of entrepreneurs making meaningful contributions to the CE (Veleva and Bodkin, 2018a, b), with Henry *et al.* (2020) referring to new ventures with circular business models as "circular start-ups." An important consideration when understanding outcomes related to implementing a CE or building a circular start-up is that a CE operates within an "entrepreneurial ecosystem," which is the set of actors (e.g. customers, suppliers, policymakers) and forces (e.g. cultural forces, technological supports) that interact with each other and form the environment in which entrepreneurship occurs (Isenberg, 2010, 2011; Autio and Levie, 2017). With respect to the CE, one particularly important component is technology. As others have noted (Elia *et al.*, 2020), the entrepreneurial ecosystem is impacted by new technologies that change and develop rapidly, constantly presenting new opportunities and challenges.

One emerging technology that has tremendous potential to impact the CE is that of artificial intelligence (AI). This paper explores the implications of integrating AI technology into the CE. Specifically, it focuses on the role of AI in reverse logistics. In reverse logistics, goods move from their final destination, typically, the end consumer or user, to retailers, distributors or manufacturers with the goal of recapturing value (Rogers and Tibben-Lembke, 2001). This investigation is important for a number of reasons. First, AI has wide-ranging applications in reverse logistics, yet a structured analysis of how AI can support key reverse logistics tasks and the opportunities is currently lacking. Second, AI is growing in importance in broader research fields that are often seen as foundational for entrepreneurship research, yet AI has received little attention within contemporary entrepreneurship research to date (Obschonka and Audretsch, 2019). Third, AI is up-ending application field associated with entrepreneurship, including industry, business management and innovation, thus impacting the process and outcomes of entrepreneurship.

The remainder of this paper is structured as follows: first, we review the literature of current research on the CE, with a focus on reverse logistics and its key functions and tasks. Following this, we discuss the literature on the entrepreneurial ecosystem and the role of technology, particularly AI, in this ecosystem. Subsequently, we assess how different forms of AI are known to, or have potential to, impact reverse logistics functions and tasks. We conclude with a general discussion of the implications of the paper for practice and for future research.

Literature review

The circular economy

The most widely used CE definition (Schut *et al.*, 2016; Geissdoerfer *et al.*, 2017; Kirchherr *et al.*, 2017) is that of the Ellen MacArthur Foundation (2012, p. 7), which defines the CE as "an industrial system that is restorative or regenerative by intention and design. It replaces the "end-of-life" concept with restoration, shifts towards the use of renewable energy, eliminates the use of toxic chemicals, which impair reuse, and aims for the elimination of waste through the superior design of materials, products, systems, and, within this, business models." Thus, the CE consists of a series of closed-loop systems throughout an entire industrial economy that are intended to minimize harmful environmental impacts and support sustainable economic growth.

Research on the CE has explored its wide-ranging benefits, challenges and implications. In particular, there are large bodies of research on CE and its relationship to environmental sustainability (Geissdoerfer *et al.*, 2017; Korhonen *et al.*, 2018) and related policy implications (McDowall *et al.*, 2017). Other research on the CE recognizes that while the main impetus for research on the CE may be linked to environmental sustainability, the movement toward adopting CE has implications in other domains. For instance, research suggests that there are synergies between the CE and social welfare (Moreau *et al.*, 2017) such as through increased government revenue and the creation of employment opportunities (Zhao *et al.*, 2017). From the business model perspective, the CE has implications for value creation and capture, which yet another stream of research explores (e.g. Ranta *et al.*, 2018). This research stream reveals that adopting a CE approach requires strategic rethinking across many functional areas of a business, including human resources (Jabbour *et al.*, 2019), supply chain management (Genovese *et al.*, 2017; Govindan and Hasanagic, 2018; Ripanti and Tjahjono, 2019), especially related to reverse logistics (Bernon *et al.*, 2018), and marketing management (Chamberlin and Boks, 2018; Kalverkamp and Raabe, 2018; Confente *et al.*, 2020), especially related to product design (Bocken *et al.*, 2016; Den Hollander *et al.*, 2017) and end of product life management (Atlason *et al.*, 2017).

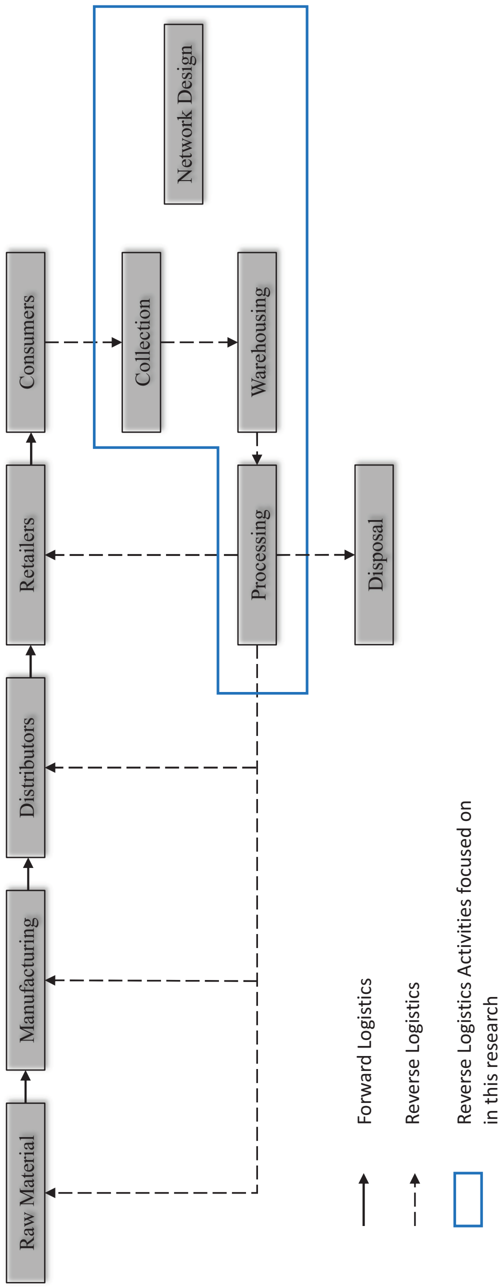
Ultimately, the macro-level impacts of a CE span economic, societal and environmental domains, while at the organizational level, a CE involves decision-making across different functional areas of a firm. Given the extraordinarily wide-ranging impacts of the CE, narrowing a research focus onto a specific element of a CE allows researchers to provide more nuanced and practical findings than would otherwise be possible. In this paper, we narrow our focus onto reverse logistics as one important element of the CE. Using "backwards" channels to reclaim goods from consumers has been investigated by scholars for many decades (Zikmund and Stanton, 1971). From a managerial perspective, reverse logistics is a particularly important element of the CE as it is the critical activities that facilitate the flow of products from consumers back to manufacturers, rather than sending them to landfill. Reverse logistics can thus be considered as the "engine" of a closed-loop supply chain (Guide and Van Wassenhove, 2009). Furthermore, as reverse logistics encompasses all of the main downstream elements of the CE, it has major implications for marketing and distribution practice. In what follows, we review reverse logistics and related research in more detail.

Reverse logistics

Reverse logistics is "the process of moving goods from their typical final destination for the purpose of recapturing value, or proper disposal" (Rogers and Tibben-Lembke, 2001, p. 2). Figure 1 illustrates the basic flow of forward and reverse logistics. We conceptualize four main activities in reverse logistics – network design, collection, warehousing and processing. These four main activities were chosen as they will generally apply across different types of organizations or different industries that implement reverse logistics. In what follows, we review each of the four reverse logistics activities in more detail.

Network design

Network design includes strategic considerations that are relevant to all functions of reverse logistics. That is, on a strategic level, managers must decide on the general configuration of



Source(s): Adapted from Agrawal *et al.* 2015

Figure 1.
Activities in forward and reverse logistics processes

the reverse logistics infrastructure. This involves determinations such as the number and location of collection points, processing facilities and disposal plants; the product flows between each and the buffer inventories needed throughout the system, among other considerations. Indeed, the question of collection points for product returns has received significant attention in logistics research (e.g. Alumur *et al.*, 2012; Diabat *et al.*, 2013; Lee and Chan, 2009; Li *et al.*, 2017). As there are numerous key differences between forward and reverse logistics, it is important that the reverse system does not simply mimic the forward channel. For example, a typical distribution channel is arranged to transport large quantities of uniform goods from one to many points, as quickly as possible. Thus, the destination and routing of items is clear, forecasting is straightforward and consistent inventory results in lower bulk rates for transportation and handling. Conversely, when items are returned to the manufacturer, they are distributed from many points to one and their quality is highly variable. This inconsistency and unpredictability results in higher unit costs for transportation and inventory management and less visibility in the overall process.

In addition to deciding on the configuration of reverse logistics infrastructure, network design involves managerial decisions about outsourcing some or all of the reverse logistics tasks to third-party logistics (3PL) providers who may take on specific functions such as collection, transportation and/or disposal.

Collection

The reverse logistics process may be initiated as a result of customer returns, product recalls, overstock or simply due to a product reaching the end of its useful life. In any of these cases, the product enters the first activity in the reverse logistics process: collection. Collection involves all tasks associated with accumulating used products from consumers and transporting them to a centralized facility. The responsibility for collection may be assumed by the original manufacturer, the consumer, a channel partner (typically a retailer) or a 3PL provider and the collection of goods may be facilitated through buy-back programs, returned shipping, curbside pick-up, drop-off centers and retail collection points. Usually, a preliminary task of the collection phase is "gatekeeping," whereby items are screened to determine if they are authorized to be returned. Effective gatekeeping helps to keep unwanted items out of the reverse flow. The design of collection points will directly influence the transportation mode and routing schedules for product pick-up and deliveries. Due to demand fluctuations, collection activities may also need to account for product storage until there are sufficient volumes to economically transport to a central facility (Bai and Sarkis, 2013).

Warehousing

Once items are collected, the next activity of reverse logistics – warehousing – commences. Warehousing is a blanket term that may encompass a number of tasks, including inspecting, sorting, consolidating and inventory management. One of the challenges of reverse logistics is that the condition and volume of returned goods may vary significantly, which makes inspection an important and labor-intense activity (Bai and Sarkis, 2013). Based on the evaluation of the product's appearance and functionality, items may be sorted into reuse, repair, remanufacture and recycling streams. Alternately, items may need to be partially disassembled to permit sorting of various subcomponents and raw materials. As the goal of most reverse logistics systems is to maximize the value of returned goods, inspection and sorting tasks are critical to route each item to its optimal channel based on its condition, value and costs. Once sorted, products can be consolidated into stocks for further processing and disposal. Traditional inventory management tasks such as counting, tracking and storing are also typically part of the warehousing activities of reverse logistics.

Processing

Processing involves either reuse, repair, remanufacturing, recycling or disposal. Products may be directly reused if they are still functional and do not require repairs or upgrades, as is the case when consumers return unwanted new products or like-new items that are no longer desirable. These products can be repackaged and sold either as new or used. In other cases, products may need to be repaired, upgraded with new components, remanufactured or recycled, each of which requires some degree of disassembly. Disassembly is the process in which valuable materials and components are systematically extracted from returned products. Unlike assembly operations, where the quantity and quality of inputs can be strictly controlled, disassembly is highly variable and thus labor intensive (Kalayci and Gupta, 2013a). Due to the unpredictable nature of returned goods, disassembly operations are best conducted in a single workstation; however, to reduce costs, automated disassembly lines are employed where possible. "Disassembly line balancing," whereby resources in a disassembly line are optimally used, has become a key problem to solve. The disassembly process reveals product cores that become the basis for remanufacture, components of products that can be reused or resold, raw materials that can be recycled, as well as contaminated material and proprietary parts that require disposal. Outbound logistics commences at this stage to facilitate transport and delivery of these material streams. Reusable items are integrated back into the forward logistics processes and waste management companies collect material scraps destined for a landfill.

The (digital) entrepreneurial ecosystem

Reverse logistics processes are impacted by the overall environment in which they occur; this environment is known as the entrepreneurial ecosystem. The entrepreneurial ecosystem is conceptualized as dynamic and self-regulating (Isenberg, 2014) and consists of a number of different actors including entrepreneurs themselves, financial institutions, academics, nongovernmental organizations (NGOs), investors, suppliers, customers, employees, among others (Cohen, 2006; Isenberg, 2010; Brown and Mason, 2017). In addition to these actors, the entrepreneurial ecosystem is determined by larger forces. The Babson Entrepreneurship Ecosystem Project (BEEP), which is among the most influential works on the entrepreneurial ecosystem, suggests that that the entrepreneurship ecosystem includes six domains that interact and are self-sustaining: policy, finance, markets, culture, human capital and supports (Isenberg, 2010, 2011).

The BEEP conceptualization has been very impactful in supporting research on entrepreneurship. However, a technological component is not explicitly included as a key domain within the BEEP framework. Rather, the role of technology across the six domains and its implications is implicit, thus taking a position in the "background" of the entrepreneurial ecosystem. However, and as others (e.g. Elia *et al.*, 2020) have pointed out, digital technologies are fundamental to virtually all organizational processes and interactions today; in other words, technology is too important to assume a role in the background of the entrepreneurial ecosystem. Technologies are heavily involved in activating and supporting entrepreneurship, as they facilitate key functions such as information sharing or communication, support actors in developing competencies (Elia *et al.*, 2020) and are at the heart of many new ventures themselves (e.g. Aspelund *et al.*, 2005; Reymen *et al.*, 2017; Symeonidou *et al.*, 2017). Indeed, recent research highlights the critical role of technology within the entrepreneurial ecosystem and suggests that research on the separate (but related) concept of a *digital* entrepreneurial ecosystem is overdue (Du *et al.*, 2018; Elia *et al.*, 2020).

Artificial intelligence

Digital technologies are a critically important consideration for understanding the processes undertaken within a CE; in this research, our focus is on the role of AI. AI is the research and practice of developing machines that can emulate human intelligence and the processes described above (Russell and Norvig, 2016). AI has several key components, including machine learning and the ability to process unstructured data. The former encompasses computational procedures that enable AI to learn by itself; for instance, machine learning allows AI to improve its performance without being explicitly programmed to do so (Russell and Norvig, 2016). The second key component of AI is its ability to process unstructured data, such as natural language or images. Processing images – also known as computer vision – enables computers to recognize patterns in and extract meaning from pixels (Paschen *et al.*, 2019).

Given the plethora of AI applications in existence today and their fast-evolving nature, practitioners need guidance on the capabilities of different types of AI. One conceptualization distinguishes AI into four types (mechanical, analytical, intuitive and empathetic) based on its ability to perform different types of tasks (Davenport and Kirby, 2016; Huang and Rust, 2018). *Mechanical AI* has the ability to automatically perform simple, repetitive and consistent tasks that are well defined and require minimal ability to adapt and learn. Using sensor perception, mechanical AI perceives and reacts to changes in the environment using predefined rules. An example of mechanical AI in reverse logistics includes disassembly robots that "perceive" and disassemble products based on predefined criteria for their parts.

Analytical AI has the ability to problem-solve for complex, yet systematic and predictable tasks using logic and to learn from experience (Davenport and Kirby, 2016; Huang and Rust, 2018). Analytical AI uses algorithms that learn iteratively from new data and previous processing experience, without being explicitly programmed where to look for a particular piece of data or how to interpret a particular piece of new information (Paschen *et al.*, 2019; Paschen *et al.*, 2020). As an illustration, optimizing the number and location of collection points in reverse logistics using AI algorithms may fall within analytical AI capabilities.

Intuitive AI is the ability to "think" creatively and adjust effectively to new situations (Davenport and Kirby, 2016; Huang and Rust, 2018). Intuitive AI entails a large degree of adaption and learning and is well suited to handle tasks that are complex and idiosyncratic and require context awareness and learning. For example, determining the best 3PL providers as part of designing the reverse logistics network using fuzzy logic AI algorithms is an illustration of intuitive AI.

A fourth AI type – *Empathetic AI* – involves machines that can act as though they can feel (Davenport and Kirby, 2016; Huang and Rust, 2018). Although empathetic AI can play an important role in many social sciences, such as consumer behavior or service sciences, it is not well suited to addressing the needs of quantitative problems such as those faced in reverse logistics. Thus, this form of AI is not further discussed in this paper.

The use of AI within the CE has gained substantial attention among scholars, policymakers and practitioners globally (Ghoreishi and Happonen, 2020). As AI matures, its impact on the digital entrepreneurial ecosystem – and reverse logistics in particular – grows. In what follows, we analyze how AI impacts reverse logistics networks.

Analysis: the impact of artificial intelligence on reverse logistics

Here we analyze the contributions that AI can (or already does) make to each of the four functions of reverse logistics (network design, collection, warehousing and processing). Research on the key tasks or decisions relevant to each function, and the role that analytical, initiative or mechanical AI plays throughout the reverse logistics process, is summarized in Table 1.

Artificial intelligence in reverse logistics network design

The design of a reverse logistics network, including the configuration of infrastructure and the determination of outsourcing requirements, can have important implications for efficiency and cost-effectiveness. Decisions related to how a reverse logistics network is designed can be aided by the use of AI. For example, intuitive AI applications have been used to assess the most appropriate 3PL provider to select (e.g. Diabat *et al.*, 2013; Efendigil *et al.*, 2008; Senthil *et al.*, 2014). This selection problem may involve considering numerous criteria when evaluating potential providers, including level of specialization, price, quality, customer service, environmental considerations and flexibility. To complicate matters, each of these criteria is subject to varying forms of uncertainty. In an imprecise environment, where human assessment is subjective and often biased, AI can provide more robust and quantitative solutions to these multi-criteria group decision-making methods. In addition, intuitive AI applications can assess whether specific tasks should be outsourced to begin with and can rank potential vendors for these tasks (Senthil *et al.*, 2014).

Another key network design consideration is the number and location of collection points, processing facilities and disposal centers, commonly referred to as the facility or location allocation problem. Often, the economic feasibility of product recovery efforts rest on the effective arrangement of this infrastructure. Uncertain supply levels, the need for centralized inspection and sorting and the interrelation with forward logistics activities have been identified as unique considerations when planning a reverse logistics network (Fleischmann, 2000).

Reverse logistics function	Reverse logistics tasks	AI type	Illustrative literature
Network design	Selection of 3PL providers	Intuitive	Efendigil *et al.* (2008), Kannan *et al.* (2009), Senthil *et al.* (2014)
	The number and location of collection points, centralized depots and processing facilities	Analytical	Che *et al.* (2012), Diabat *et al.* (2013), Guo and Zhang (2017), Jafarzadeh *et al.* (2017), Lee and Chan (2009), Li *et al.* (2017), Min *et al.* (2006)
Collection	Transportation/vehicle routing	Analytical	Guo and Zhang (2017), Mingyong and Erbao (2010)
	Container design	Analytical	Cheng and Yang (2005)
	Customer return incentives	Analytical	Agarwal *et al.* (2012)
	Autonomous trucking	Mechanical	Further research needed
	Determination of rules for product disposal vs entry into RL flow	Analytical	Further research needed
Warehousing	Product return forecasting	Analytical	Kahraman *et al.* (2014), Marx-Gómez *et al.* (2002), Trappey *et al.* (2010)
	Sorting and inspection of (mixed) materials via robotic technologies, e.g. cobots (collaborative robots)	Mechanical	Sarc *et al.* (2019)
	Product part assessment	Analytical	Mazhar *et al.* (2007)
Processing	Selection of alternates to recycling	Intuitive	Dhouib (2014)
	Reassembly	Intuitive	Wang and Allada (2000), Zha and Lim (2000)
	Remanufacturing	Analytical	Kumar *et al.* (2015)
	Disassembly line design/ sequencing	Analytical	Huang *et al.* (2000), Liu *et al.* (2012), McGovern and Gupta (2006), Tripathi *et al.* (2009), Veerakamolmal and Gupta (2002), Wang and Allada (2000), Yeh (2012), 2011, Zeid *et al.* (1997), Zha and Lim (2000)
	Disassembly line balancing	Analytical	Ding *et al.* (2010), Kalayci and Gupta (2013a, b)

Table 1.
Analysis of the use of AI in reverse logistics

Researchers have applied various AI approaches to devise solutions to this aspect of network design. For example, AI techniques have been used to solve for the ideal structure of reverse logistics infrastructure in both small- and large-scale settings (e.g. Che *et al.*, 2012; Diabat *et al.*, 2013; Guo and Zhang, 2017; Jafarzadeh *et al.*, 2017; Li *et al.*, 2017; Min *et al.*, 2006). This area of research has aided practitioners in designing reverse logistics networks from the ground up and within the boundaries of existing infrastructure. Lee and Chan (2009) propose using analytical AI techniques in coordination with radio frequency identification (RFID) to coordinate the supply of returned products between collection points and return centers. Researchers have also used analytical AI to determine the optimal holding time for small volumes of returned products at collection points before being aggregated into large shipments (Diabat *et al.*, 2013).

Artificial intelligence in reverse logistics collection

Artificial intelligence adds value during the collection activity in a number of ways. For instance, AI can help solve complex location and routing problems in reverse logistics (Mingyong and Erbao, 2010; Guo and Zhang, 2017). In order to effectively and efficiently use existing resources, one strategy in reverse logistics extends the function of forward sales centers to also include collection tasks in addition to establishing *new* collection centers. However, it is necessary to distinguish the different roles played by the extended centers and the newly established ones since the normal processes of the forward logistics process should be unaffected. Moreover, decision makers need to consider transportation and the associated costs; while resalable products in extended centers can be sold at the same location and do not require additional transportation, resalable products in new centers first need to be transported to a sales center before being resold. Here, analytical AI can help ascertain the number of extended (versus new) collection centers and the specific location of the collection centers (Guo and Zhang, 2017).

Analytical AI applications can also help estimate the number of items returned during collection. For instance, Agarwal *et al.* (2012) describe an AI application that can identify the optimal monetary incentive for consumers to return products or product parts, thus helping to quantify the demand for collection activities while maximizing the producer's profit.

In recent years, policymakers have encouraged reusable packaging, such as reusable containers. However, there are many strategic questions to be answered before switching to reusable containers (Cheng and Yang, 2005), including the cleaning, storage, maintenance, repair and/or replacement of reusable containers. In addition, transportation and routing decisions need to be planned carefully, specifically how to get the containers back to the company. Here, analytical AI can help solve these complex problems, for example, by applying AI algorithms with the objective to minimize the cost for the producer (Cheng and Yang, 2005).

Analytical AI may also be beneficial in the gatekeeping function of collection, which is often labor intensive. That is, determining whether a returned product meets the appropriate criteria to be collected or whether it should be disposed. Lastly, intuitive AI could support collection activities with autonomous trucking vehicles. Using a network of sensors, cameras and radar devices connected to an AI supercomputer, some trucks are already transporting cargo without a driver (Wertheim, 2020). With widespread adoption of autonomous vehicles on the threshold, recent advances in AI-enabled vehicles for private transportation tasks could be broadened to industrial applications and specifically reverse logistics processes (Klumpp, 2018).

Artificial intelligence in reverse logistics warehousing

In reverse logistics, return quantities are typically more difficult to estimate than in forward logistics. Return quantities are influenced by many factors, including the reason for return (damaged goods, end-of-life returns or excess stock), population density, environmental awareness, educational status and incentives (e.g. buy-back programs). Analytical AI can help in reducing the uncertainty faced in warehousing by forecasting return quantities and improving decision support related to inventory management (Marx-Gómez *et al.*, 2002; Trappey *et al.*, 2010; Kahraman *et al.*, 2014).

In warehousing, inspection and sorting of returned items is necessary due to the differences in the condition of the products. Robotic systems, in conjunction with mechanical AI applications, are capable of carrying out multiple sorting and inspection tasks and can even be trained to deal with new waste streams (Sarc *et al.*, 2019). Collaborative robots or "cobots" embedded with machine learning capabilities are already in use in many warehousing settings. From a reverse logistics perspective, cobots can assist humans with various tasks including identifying patterns in product conditions, diagnosing failures, recognizing the presence of specific parts, interpreting results from testing equipment and communicating with other machines and systems (Lawton, 2019). Analytical AI can also be used to more accurately assess the remaining life of used components, which can then be redirected as inputs to new products (Mazhar *et al.*, 2007).

Artificial intelligence in reverse logistics processing

Product returns are subject to varying degrees of processing, depending on the industry, the component materials and the condition of the item. As such, decisions need to be made as to the most appealing processing option based on numerous quantitative and qualitative factors. For example, used vehicle tires (which have traditionally been incinerated) are now finding a second life in an array of uses, including as wave breaking material, protective bumpers for ships, roadway paving material and secondary fuel for cement kilns. As the push to extend the useful life of products intensifies, reverse logistics managers are faced with increasing options. Analytical AI can help decision makers evaluate these alternates and provide quantifiable recommendations (Dhouib, 2014). Another way in which AI can assist in extending the life of products is through disassembly planning. Specifically, intuitive AI can improve the "serviceability" of a product by identifying and ranking designs in which the sequence of disassembly tasks for the product is efficient (Wang and Allada, 2000; Zha and Lim, 2000).

Analytical AI can also support decision-making in remanufacturing (Kumar *et al.*, 2015). For instance, AI can help decision makers to quantitatively evaluate the economic viability of implementing tracking technology, which is a complex and far-reaching decision, given the substantial implementation cost of such a technology. Moreover, analytical AI has been demonstrated to help solve the complex problem of disassembly line design and sequence planning (Zeid *et al.*, 1997; Huang *et al.*, 2000; Wang and Allada, 2000; Zha and Lim, 2000; Veerakamolmal and Gupta, 2002; McGovern and Gupta, 2006; Tripathi *et al.*, 2009; Yeh, 2011, 2012; Liu *et al.*, 2012) which involves the generation of a feasible sequence to successfully disassemble a product. Here, minimizing the number of workstations and each workstation's idle time are important considerations, in addition to other disassembly-specific concerns, such as the number of components to be recovered in the product or a component's position in the sequence. Finding the optimal sequence is computationally intensive and complex, and methods based on AI are often used to find the optimal solution with high efficiency (Liu *et al.*, 2012). For instance, Yeh (2011, 2012) demonstrates enhanced efficiency and improved accuracy of disassembly line design tasks using an AI application based on machine learning. Through machine learning, the processing times of components in disassembly processing can be shortened due to the learning effect during processing. Another way that AI applications demonstrate value is in the task of disassembly line balancing – that is, minimizing resources while accounting for the divergence in the disassembly flow process

(Kalayci and Gupta, 2013b). For example, Kalayci and Gupta (2013b) propose an AI application that considers a number of disassembly goals, such as minimizing the number and total idle time of all disassembly stations, prioritizing the removal of hazardous components and the disassembly of high demand components early in the disassembly sequence.

Discussion, limitations and future research

This paper assesses the opportunities of using AI in the reverse logistics process. Our analysis outlines the different functions and tasks within a reverse logistics process and discusses how AI adds value to these tasks. The analysis suggests that mechanical, analytical and intuitive AI applications provide significant benefits across all functions in the reverse logistics process. From this analysis, we are able to extract a number of key findings. First, our analysis suggests that analytical AI (that is, AI applications that can problem-solve for complex, yet systematic and predictable tasks) is most prevalent during collection and processing activities in reverse logistics. Given that the collection and processing activities encompass tasks that are complex, yet well-defined and structured, such as transportation and routing problems, container design, disassembly or remanufacturing, among others, analytical AI is particularly well suited to add value during these tasks.

Our analysis also reveals that intuitive AI adds value to the reverse logistics process, but that AI applications of this nature are primarily focused on network design and, to a smaller extent, processing activities. Intuitive AI entails a large degree of adaption and learning based on previous experience and is particularly effective to handle tasks that are complex and unique. Network design involves decisions about the number and location of collection points, processing facilities and disposal plants; the product flows between each and considerations about 3PL providers. These decisions are often idiosyncratic and not well structured and hence intuitive AI is particularly effective in adding value to these tasks. In addition, selection of alternates to recycling and reassembly (both part of processing) are complex undertakings that involve a high degree of learning and adaption to the context, which makes them particularly well suited for intuitive AI.

Third, our analysis indicates that mechanical AI currently has few applications across different reverse logistics functions and tasks. Mechanical AI applications perform simple, well-defined and repetitive tasks using predefined rules and often rely on sensors to visually perceive an object of interest. The comparatively few applications of mechanical AI are perhaps surprising, given that a number of reverse logistics tasks (e.g. sorting and inspection of goods, product part assessments, disassembly and reassembly tasks) entail consistent and well-structured tasks where mechanical AI could provide value. As such, we suggest that exploring the use of mechanical AI in reverse logistics is an opportunity for both scholars and practitioners.

With respect to the entrepreneurial ecosystem, the large body of research on AI applications within reverse logistics signals the importance of this technological force within the digital entrepreneurial ecosystem. Our analysis confirms that AI can and does play an important role within the digital ecosystem in which reverse logistics occurs and continues to be improved by entrepreneurs. Given the incentives for and trends toward developing closed-loop processes, entrepreneurs and entrepreneurship literature would benefit from further exploration of the role of AI.

The paper is not without limitations. First, the illustrative research presented in Table 1 and discussed in our analysis is not intended to provide an exhaustive literature review of AI in reverse logistics. Rather, it is intended to demonstrate examples of studies that have investigated the use of AI in reverse logistics functions and tasks. Future research could review and catalog prior research in AI-related reverse logistics topics more comprehensively, for instance, by using data visualizing tools like VOSViewer (Feng *et al.*, 2020) to uncover research trends, themes, author relationships and others. Moreover, while our analysis discusses the value that AI can bring to reverse logistics, there are undoubtedly challenges when utilizing AI for reverse logistics (Manyika and Bughin, 2018). For example, both analytical and intuitive AI rely on machine learning that requires sufficiently large data sets to be effective, which may be difficult or impossible to obtain, particularly in the early phases of the entrepreneurial process. Moreover, the complexity of machine learning makes it difficult to show how and why a certain decision or prediction was made, a phenomenon referred to as the "challenge of explainability" (Manyika and Bughin, 2018). Future research could investigate these and other limitations of AI and thus complement our analysis with an analysis of the "dark side" of AI in reverse logistics.

Concluding remarks

Technological advancements have propelled AI into a critical force both within the digital entrepreneurial ecosystem and the CE. In this paper, we discuss the contributions that AI can bring to reverse logistics, which is a critically important aspect of the CE. Our analysis illustrates the value that different forms of AI can bring to the various functions and tasks of the reverse logistics process. We hope that our research helps practitioners develop improved understanding of these contributions and inspires scholars to conduct further research on the opportunities and challenges of using AI in the CE.

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