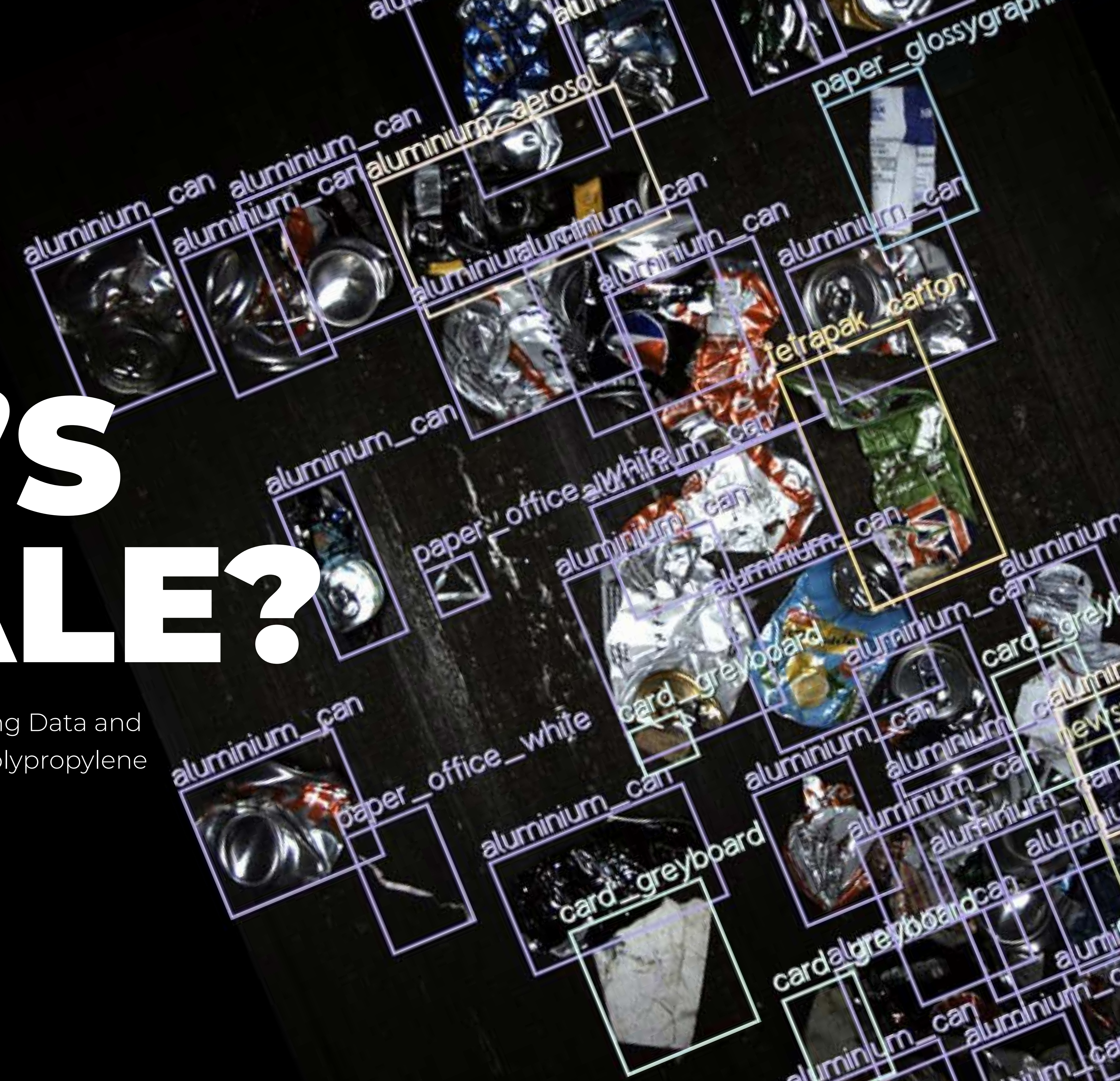
WHAT'S IN A BALE?

Leveraging AI to Unlock Unprecedented Recycling Data and Identify Opportunities to Recover Food-Grade Polypropylene



CLOSED LOOP partners | THE CENTER FOR THE CIRCULAR ECONOMY

TABLE OF CONTENTS

CLOSED LOOP partners | THE CENTER FOR THE CIRCULAR ECONOMY

About the Closed Loop Foundation and the Center for the Circular Economy

Based in New York City, the Closed Loop Foundation (CLF) aims to further the research and development needed to build a more circular economy. Since its founding, the Foundation has supported numerous organizations, companies and communities working to reduce food, packaging and plastic waste.

The Center for the Circular Economy is the innovation arm of Closed Loop Partners, a firm focused on building the circular economy. The Center executes research and analytics, unites organizations to tackle complex material challenges and implements systemic change that advances the circular economy.

NEXTGEN CONSORTIUM

About the NextGen Consortium

The NextGen Consortium, managed by Closed Loop Partners' Center for the Circular Economy, is a multi-year consortium that addresses single-use foodservice packaging waste by advancing the design, commercialization and recovery of sustainable foodservice packaging alternatives.

The Consortium brings leading brands, industry experts and innovators together to reimagine foodservice packaging, increase access to recycling and accelerate sustainable and circular solutions to reduce waste. Starbucks and McDonald's are the founding partners of the Consortium, with The Coca-Cola Company and PepsiCo as sector lead partners. Wendy's, Yum! Brands, Delta Air Lines, Toast and Keurig Dr Pepper are supporting partners. World Wildlife Fund (WWF) is the environmental advisory partner.

Together with its managing partner, Closed Loop Partners' Center for the Circular Economy, the NextGen Consortium led this body of work, as part of its goals to advance the recovery of foodservice packaging.

The report may not reflect the views or positions of every funding partner and stakeholder in all respects.

Acknowledgements

We would like to thank all partners and stakeholders that have contributed to this work, including the Center for the Circular Economy; the NextGen Consortium; four participating MRFs: Balcones Recycling, a Circular Services company*, Cougles Recycling, Rumpke Waste & Recycling and Eureka Recycling*, including their leaders and staff who supported the project; Curt Cozart at Common Sense Solutions; and Jon Powell at Apex Catalytic.

In particular, we would like to extend our gratitude to the NextGen Consortium for co-funding this work, helping to fill a current knowledge gap around food-grade polypropylene recovery and circularity within the U.S., and conducting extensive research to keep more valuable materials within supply chains and out of landfills.

*Circular Services is a Closed Loop Partners company.

*Eureka Recycling is a portfolio company of Closed Loop Partners.

EXECUTIVE SUMMARY

Demand for recycled food-grade polypropylene is on the rise, but supply is limited.

Polypropylene (PP) is one of the most commonly used resins for foodservice packaging today—used for yogurt containers, iced coffee cups, fountain beverage cups and more.

Driven by policy shifts and commitments from foodservice brands to use recycled PP in their packaging, market demand for recycled food-grade PP is rapidly increasing—but supply remains limited.

What is limiting supply?

Infrastructure limitations, and the sheer volume of materials flowing through materials recovery facilities (MRFs), have made it difficult for MRFs to track objects in their recycling streams with accuracy and granularity. Different materials become anonymized, losing identity and trackability.

With no easy way to identify and quantify objects, such as food-grade and non-food-grade PP, these materials typically blend together at MRFs. This limits the ability to direct food-grade materials to end markets and converters that can incorporate these items back into food-grade packaging. **As a result, it has been challenging to amass the appropriate quantities of food-grade PP** with the right purity requirements to meet end market specifications.

Why must we address this now?

In North America, millions of tons of valuable materials with strong market demand and mature recycling supply chains are **lost to landfills.**[1]

Furthermore, without available supply, **brands with large-scale demand for food-grade recycled materials will not meet recycled content needs** driven by sustainability goals and external mandates, among other factors. This is a significant lost opportunity to pull valuable material back into supply chains.

To increase material supply, we must first find out: **what exactly is in the PP recycling stream today, and how much of it is food-grade or clear food-grade PP?**

The first step to meet demand? We must uncover what's inside a polypropylene bale.

Led by Closed Loop Partners' Center for the Circular Economy and the Closed Loop Foundation, in collaboration with Greyparrot,[a] this study aims to fill historical data gaps on the characterization of PP bales—those large, compacted blocks of recyclable materials that are reprocessed into new materials—and address key bottlenecks in recycled PP supply chains. Using advanced artificial intelligence (AI)-enabled technology deployed at four operating MRFs across the U.S., the research aims to:

1. **Quantify and rigorously characterize PP**—including overall amount, color, format and food-grade status.[b]
2. **Assess the accuracy and reliability of automated AI classification technology** against manual methods of classifying materials at scale.
3. **Examine results to identify potential new or enhanced recovery opportunities for PP in the U.S. and beyond,** and highlight key data gaps that could be addressed in future work to further strengthen circular supply chains for PP.

a. Greyparrot is a portfolio company of Closed Loop Partners.
b. Recycled plastics that are "food-grade" represent a special class of recyclable materials with purity and characteristics making the material suitable for use in food-contact packaging. Food-grade plastics represent a critical class of materials that are in demand from consumer product and retail companies to satisfy circularity goals and commitments, and may be included in emerging Extended Producer Responsibility (EPR) regulations for products and packaging.

Food-grade polypropylene is abundant in recycling streams, and AI can provide data that may enhance future recovery.

In one of the most extensive and granular recyclable material characterization campaigns ever completed, this study characterized more than 45 million individual PP and non-PP items at four MRFs for approximately three-months. What did we find?

1

Clear and white food-grade PP is abundant in recycling streams

Clear and white material collectively comprised 75-85% of all PP characterized in this study, with most of these formats found to be likely food-grade material. These results were consistent across the four MRFs. The results demonstrate the substantial amount of clear and white food-grade PP flowing through the study MRFs, which has important implications for meeting food-grade PP demand in the U.S.

2

AI-enabled technologies can reliably quantify and classify recyclables with granularity, at scale

Automated AI technology provided accuracy that closely mirrored that of manual counts, suggesting these systems are capable of providing effective material characterization data at previously unavailable scales. This is dependent, however, on the systems (and the facilities at which the AI classification systems are deployed) operating according to best practices and incorporating sufficiently granular and validated material detection algorithms.

3

AI can help measure and track facility and equipment performance

Contemporary optical sortation technology provides dramatically better separation performance for recyclables. During this study, one MRF replaced an optical sorter that had reached the end of its service life. The AI classification system effectively quantified a 13 percentage-point performance improvement in PP purity after the new optical sorter's installation.

Our PP Characterization Study by the Numbers

4 MRF
participants

1 AI
technology provider

45M
individual items characterized

>50%
of PP items analyzed were clear, likely food-grade containers

>30%
of clear PP items analyzed were beverage cups

650+ tons
of materials characterized

We are at a critical juncture for U.S. recycling, requiring new insights on recycling data collection and material recovery.

This study provides essential data and transparency about AI technology's performance and potential capabilities within MRFs. It also provides new, critical data on the presence and quantity of food-grade materials within the PP stream. Together, this can help to accelerate circular outcomes for various types of PP packaging and add to the growing body of best practices. However, gaps remain.

Continued deployment of AI technology—and the transparent presentation of findings—can help uncover key data that had been unavailable prior to the implementation of AI-enabled characterization systems.

Additional studies may focus on ways to further leverage large-scale, granular data from AI technology that is strategically deployed at various points in MRFs, plastics reclaimers and elsewhere across circular supply chains. This can help to identify the effect of different communication and education protocols on the quantity and characteristics of materials captured. It can also inform novel operating practices that can result in better financial outcomes in recycling systems.

Although the methods and analyses in this study are focused on PP, **similar work for other commodities may yield similarly valuable insights** to support decision making and actions that strengthen circular supply chains for recyclable materials in the U.S. and beyond.

WHY NOW?

The tailwinds behind increased demand for recycled food-grade polypropylene

The growing need for strong, domestic recycling calls for upgrades in U.S. recycling infastructure and data.

Today, the demand for local recycling is accelerated by a renewed call for local supply chains in the U.S., spurred by increased global trade pressures, as well as supply chain bottlenecks, intensifying climate impacts and increasingly volatile trade routes.

Yet, demand for recycling had already been rising over the last decade, with geopolitical and economic shifts driving an urgent need for domestic recycling infrastructure. .

Global Recycling Shifts

Historically, in the U.S. recycling system, domestic collection and sortation efforts for plastics focused on polyethylene terephthalate (PET) and high-density polyethylene (HDPE) bottles and containers.

Remaining plastics—such as polypropylene (PP), polystyrene (PS) and others—which were customarily characterized as "mixed plastics"—were commonly shipped to international markets in Asia.

The management of these mixed plastics was significantly altered in 2018 when China—then a key end market for mixed plastics collected and sorted in the U.S.—implemented its National Sword policy, prohibiting the import of plastic and related recyclables into China.[2]

Following the implementation of this policy, U.S. stakeholders were left to reassess how to manage the domestic mixed plastics stream.

At the time, PP was increasingly being used for various consumer products and packaging applications, such as yogurt containers and beverage cups.

Commitments from brands and retailers followed, including using more recycled content and having their PP be more recyclable. This led to a spike in demand to recover more recycled PP in U.S. markets.[3]

Lost Value in Landfills

Amidst growing demand to recycle valuable materials locally, studies identified the quantity and location of large volumes of mismanaged materials, including plastics.[4]

Research showed that in North America, millions of tons of potentially valuable materials with strong recycling markets and supply chains are lost to landfills,[5] representing a loss of critical resources, a net increase in lifecycle greenhouse gas emissions in many cases and a missed economic opportunity.

The reasons for these material losses are wide-ranging, including a lack of adequate collection infrastructure, insufficient recycling sortation systems, commingling of the materials with problematic or otherwise non-recyclable materials along the supply chain, contractual or related economic conditions, geographic limitations or restrictions, and others.

Material Recovery Initiatives

Solving the challenge of recyclable materials lost to landfills (or worse, the natural environment) requires, in part, a targeted and coordinated set of technological innovations and interventions, investments and communications.

Following this, substantial efforts in North America and elsewhere have worked to improve material supply chains to foster better outcomes, including increasing materials reuse, reducing material disposal into the environment and strengthening recycling supply chains to keep valuable materials in circulation. PP is among these materials with increased efforts for recovery.

Initiaves to enhance polypropylene recycling are on the rise.

Growing market demand led to a series of coordinated efforts to understand how much PP might be available for recovery, where the end markets are, and how the various points in U.S. recycling supply chains could be strengthened to ensure the collection, effective sortation and preparation of high-quality PP as a raw material for burgeoning end markets.

The focus on strengthening various parts of recycled PP supply chains accelerated in the early 2020s, including:

- **The Polypropylene Recycling Coalition**,[6] a collaboration launched by The Recycling Partnership, which provides funding to enhance consumer education, capture and sortation for PP recovery in the U.S.
- **The launch of the Closed Loop Circular Plastics Strategy** managed by Closed Loop Partners, which invests catalytic capital in solutions that advance PP and PE collection and recovery in the U.S. and Canada.
- **Ongoing efforts to increase PP cup recovery by the NextGen Consortium**, an industry collaboration advancing circularity for foodservice packaging, managed by Closed Loop Partners' Center for the Circular Economy.

Broadly, the goal of these and other initiatives involved capturing more recycled PP to support end market demand.

As of 2024, these initiatives alone have helped to increase access to PP recycling infrastructure for tens of millions of people and catalyzed the recovery of millions of pounds of PP.[7]

While these types of initiatives have made an impact, there is a continued need to support the recovery of PP with the goal of capturing much more of the estimated 22 pounds of PP produced each year from a single-family household in the U.S.[8]

End markets for PP—and other recyclables, for that matter—are varied and can be fairly rigid in their material specification requirements. Different end market needs span a range of material characteristics (e.g., density, how readily the material melts, color, size and purity).

As the market for recycled PP continues to grow and develop in North America, opportunities for improvement remain largely in the continued deployment of enabling technologies that help improve the quality and quantity of recycled PP supply.

Policy and market demand are underscoring the need for recycled food-grade polypropylene recovery, but supply is limited.

One promising opportunity within recycled PP supply chains involves meeting the demand for so-called "food-grade" recycled plastic materials, a sub-category within the broader category of recycled PP.

The demand for food-grade PP stems from various factors, including:

- **Publicly stated sustainability commitments** from dozens of brands and retailers to incorporate recycled plastics, including PP, in their products and packaging;
- **New and emerging regulations** such as California's Plastic Pollution Prevention and Packaging Producer Responsibility Act (SB54), Extended Producer Responsibility (EPR) laws passed in various states requiring greater recycling of products and packaging, and others;
- **Post-consumer recycled content mandates** launched in several states.[9]

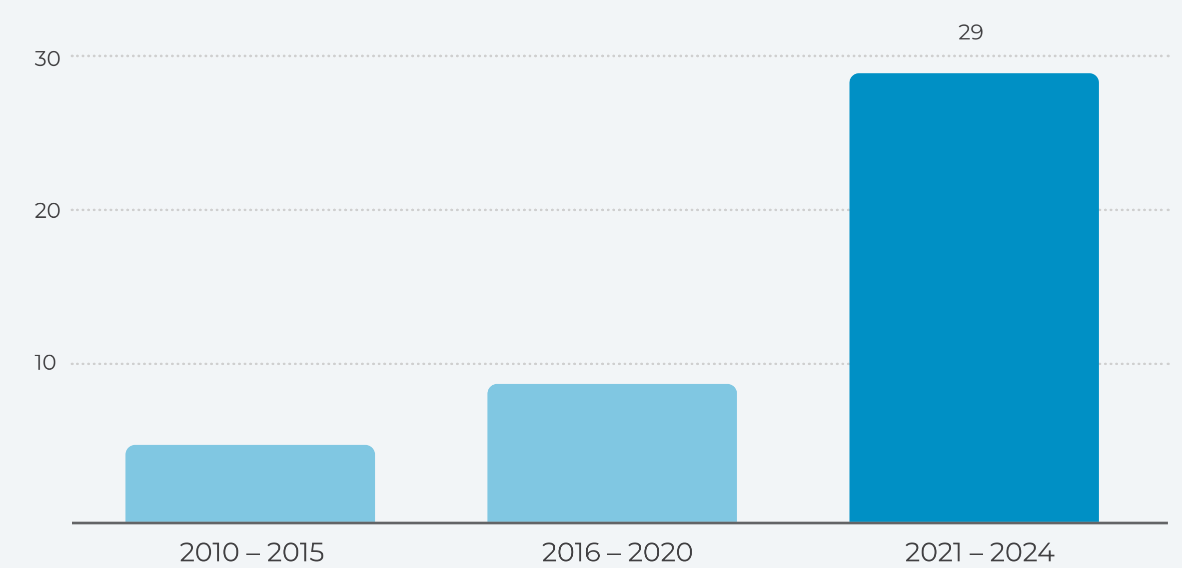
Food and Drug Administration Requirements and Letter of Non-Objection

In the U.S., the Food and Drug Administration (FDA) has a rigorous process for issuing a formal "Letter of Non-Objection" (LNO). This signals that a plastics recycler sufficiently demonstrated to the FDA that its proposed process for sourcing and converting recycled material meets the FDA's standard for allowance in food-contact packaging. In the last 15 years, there has been a notable uptick in the number of PP-specific LNOs issued by the U.S. FDA—see **Figure 1.**[10]

To obtain an LNO, a plastics recycler must demonstrate that their material sourcing and recycling process achieves product purity so that the material will not result in human exposure to harmful substances when the recycled plastic is used in food-contact applications. The LNO process occurs on a case-by-case basis, and the process differs depending on the material type and the source of the recycled material. Plastic recyclers must demonstrate that (i) source materials used in the proposed recycling application are suitable for the proposed end use, and (ii) the recycled material undergoes processes that render contaminants (or the migration of contaminants) below a threshold defined by the FDA.[11]

The FDA's guidance on recycling plastics into food-grade applications explicitly mentions "source control." This is critical to effectively aligning with the FDA's requirements to allow recycled plastics into food-grade applications.[12] However, the current challenge in demonstrating source control (i.e., ensuring that material sources were those previously containing food)—but even more importantly in collecting, separating and sending large-scale quantities of food-grade recycled materials to recycling markets—is linked to the longstanding challenge of effectively, efficiently and accurately characterizing recycled materials in supply chains at sufficient granularity to align to source control requirements to FDA-approved processes for food-contact recycled plastics, including PP.

Figure 1. PP-specific Letters of Non-Objection (NOLs) issued by the U.S. FDA since 2010.[13,14]



Innovative technologies are creating new possibilities for recycling and data.

In recent years, various equipment and technology firms have developed and deployed object detection systems that use cameras and AI-enabled classification systems to characterize individual recyclable materials at MRFs, supplementing manual methods that had been the norm.

Historically, materials recovery facilities (MRFs) that sort recyclables collected from households and businesses represented the earliest point in recycling supply chains where materials could be credibly characterized at scale.

The material streams are sorted, compressed and consolidated into brick-like forms called "bales." The bales are then loaded into a truck that can normally accommodate around 40,000 pounds of recyclables per truckload, and are shipped to a reclaimer or processor that further sorts, cleans and reprocesses the recyclable materials.

Characterizing the quality or purity of a bale of any type of recyclable material has been a longtime challenge due to the sheer volume of individual materials in a bale and the time, effort and cost required to count each material and quantify its purity. To put this challenge in numbers for PP, a typical bale of PP produced by a MRF is approximately 1,000 pounds. A truckload of PP bales may contain 40 bales of material (1,000 pounds per bale x 40 bales = 40,000 pounds). Assuming a single PP object (e.g., a cup or a tub) weighs 15 grams, the bale may contain around 30,000 individual packaging items (or around 1.2 million pieces in a truckload).

Just one bale may take a team of two or three people up to a full day to fully characterize, which limits the quantitative information available on bale quality at MRFs.

AI classification systems hold promise in that they could characterize substantially more materials than manual "bale break" methods. Yet while AI-enabled object classification units have been in commercial operation for some time, a transparent and systematic review of their performance, including detecting category-level materials (e.g., PP) and sub-category-level materials (e.g., food-grade materials), is lacking.

Performance data systematically comparing measurements by AI systems to manual methods is needed to inform the former's role in recycling supply chains.

WHAT WAS OUR APPROACH?

The methods and partnerships to unlock new data from artificial intelligence-powered vision technology

We aimed to characterize captured polypropylene with unprecedented detail, and assess the potential of AI-powered technology in the recycling system.

We deployed AI-enabled object classification technologies at multiple MRFs across the U.S. to quantify recovery opportunities for PP, including food-grade materials such as clear cups.

This work addresses several critical gaps, helping bring new transparency, quantification and rigor to data collection in the U.S. recycling system and in support of broader investments and initiatives to increase the quantity and quality of PP supply.

This study was led by the Closed Loop Foundation and the Center for the Circular Economy, the innovation arm of Closed Loop Partners, and co-funded by the NextGen Consortium.

Our research aimed to understand:

1. The quantity of PP in a given material stream

2. The amount of food-grade PP in a bale, including details such as color and format (i.e., clear cups or white tubs)

3. The split between PP and non-PP materials at the locations where the analyzers were placed

4. The ability of the results of items 1 through 3 to improve U.S.-based PP supply chains, and what actions or future work could further accelerate the supply and recovery of PP, including food-grade materials

5. The accuracy of an AI-enabled object detection system in classifying materials, compared to manual methods

We worked with partners with a shared vision for better recycling data and openness to experimentation.

Choosing the Materials Recovery Facilities

The study team solicited requests for participation from multiple U.S. MRFs to select locations for experimentation.

The team identified four U.S. MRFs who volunteered to be host sites for the PP characterization project, each sharing the following characteristics:

- **The MRFs served communities that accept and collect PP**;
- **The MRFs used optical sortation technology** that positively identifies and sorts PP;
- **The MRFs had the basic infrastructure needed to allow the installation and operation of the analyzer** (i.e., sufficient room for installation, sufficient lighting and line of sight for the camera to have an unobstructed view of the conveyor belt and access to internet connectivity);
- **The MRF owners and operators were willing to participate in the project** for the targeted duration of approximately three months;
- **The MRFs were located in geographically dispersed locations in the U.S.**, thus representing different communities.

Table 1 summarizes basic information regarding each host MRF used in this study. Note that the study team agreed to keep each MRF's identity anonymous. A "MRF ID" is used to display results throughout this report.

Although each MRF aligned with the previously stated characteristics for study participation, the type, manufacturer and placement of sorting equipment for each MRF differed.

Notably, all four MRFs had an optical sorter that positively sorted PET before the next optical sorter that positively sorted PP.

Still, not all MRFs positively sorted HDPE from the stream before the PP optical sorter (and, therefore, the analyzer). Thus, the composition of material observed by the analyzer differed across MRFs, and the overall composition of each does not necessarily reflect what ultimately finds its way to the PP bale that goes to market.

Table 1. Summary of identifying information, study period and amount of materials characterized at each MRF in this study.

Anonymized MRF ID	U.S. Region	Study Characterization Period	Calculated Tons of Material Characterized in the Study (US Ton)
1	South	11/13/23 - 1/25/24	104
2	Mid-Atlantic	7/21/23 - 11/18/23	183
3	Midwest	11/1/23 - 2/2/24	147
4	Midwest	11/1/23 - 2/2/24	245

Choosing the AI Technology Provider

The project team selected an AI classification technology through a competitive process. The requested scope included the following requirements of technology providers:

- **The technology must have the ability to characterize recyclable materials in a MRF setting.**
- **The provider must undertake any site-specific calibration as needed to achieve acceptable accuracy.**
- **The technology must have demonstrated the capability to add new materials to its existing material classification technology to include different colors, formats and indications of likely food-grade material.**

The project team evaluated and scored each technology provider's proposals using a rubric that included the provider's ability to meet the project's schedule requirements, technology capabilities, data transparency, pricing and ability to furnish details of reference projects.

Based on the robust criteria outlined, Greyparrot was the selected technology provider for this study.

Although the results presented here reflect the capability and performance of Greyparrot's system, we acknowledge there are other providers in commercial operation.

Implications and suggestions for the creation of standards for AI classification systems in the recycling industry are discussed in the concluding remarks of this report.

We designed and orchestrated placement of AI classifiers to characterize PP materials at an unprecedented scale.

The AI classification technology used for this study comprised a Greyparrot Analyzer unit installed above the moving belt of a MRF. The AI-enabled camera captured images of objects in real time as they passed beneath it. Each image was processed by the analyzer unit, where AI characterized the material.

The system directly measures and records an image of each distinct object and produces a series of data points (established through prior measurements and calibration during setup at the MRF).

This data includes, but is not limited to:

- **Classification** based on Greyparrot's taxonomy of 89 material classes;
- **Unit area** of an object;
- **Mass of the object**, which is a computed value derived in one of two ways: (i) the classification of the object, or (ii) by unit area. In each case, Greyparrot uses a database across material classes to compute the mass of each material class over a desired period;[c]
- **Likelihood of being food grade**, determined by shape, cap style, labels, color and other visual markers.

Figures 2 and 3 depict a simple schematic of the analyzer object detection system, and **Figure 4** shows a photo of one of the units installed at one of the MRFs in this study.

Greyparrot's material taxonomy includes 20 unique objects considered to be PP. **Table 2** summarizes the PP-specific taxonomy.

c. Note that the mass calculation is subject to conditions that could result in an error, so mass values are considered approximate. The presence of moisture or dirt attached to an item, or adjacent objects on the MRF's belt might skew the estimated area and therefore overestimate mass.

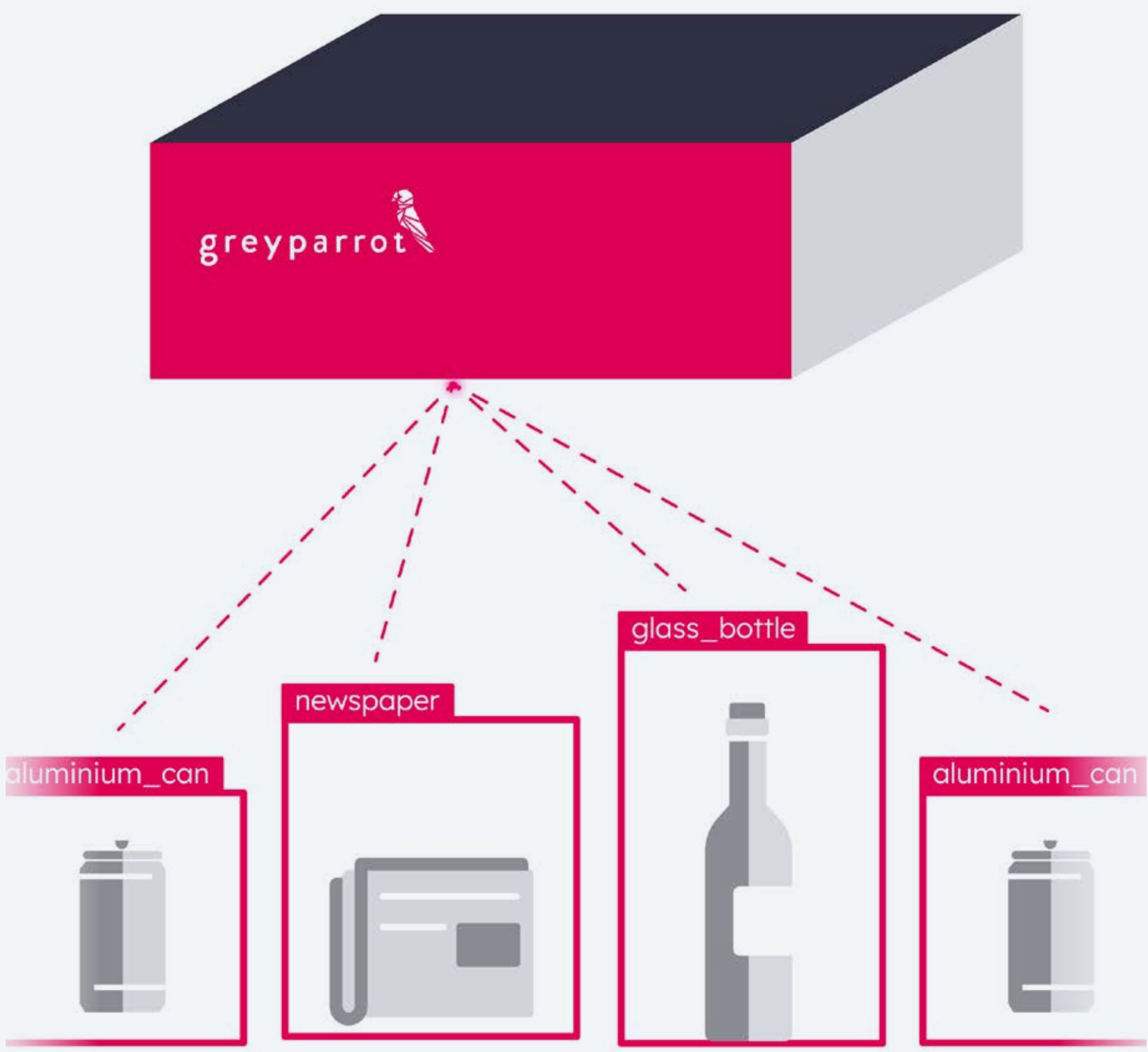


Figure 2. Simplified diagram (cross-sectional view) of the Greyparrot Analyzer and materials passing beneath the system. The dashed lines denote line-of-sight by the system's RGB camera that identifies individual items on moving conveyor belts.

Diagram courtesy of Greyparrot.

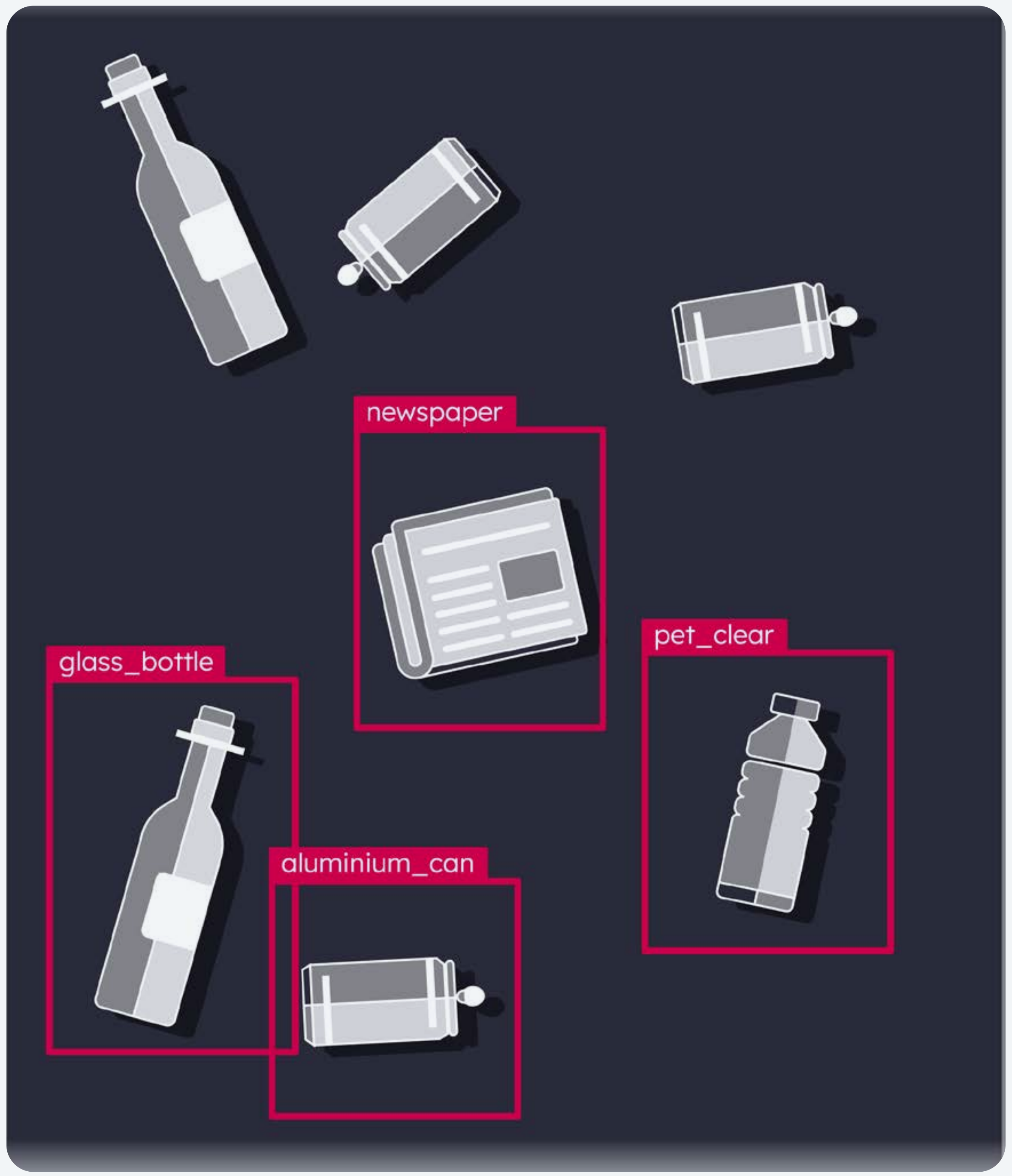


Figure 3. Simplified portrayal of the plan-view classification system used by the Greyparrot Analyzer. The rectangles denote identified recyclable and non-recyclable items, and the accompanying label denotes the item's classification within Greyparrot's material taxonomy of 89 items.[15]

Diagram courtesy of Greyparrot.

Figure 4. Image of the operational analyzer units retrofitted on a conveyor belt at a participating MRF in this study.

Image courtesy of one of the anonymized MRFs.

Table 2. Greyparrot's taxonomy of 20 different PP materials, including those considered likely food grade.

Color	Shape	Likely Food Grade	Category (Class)
Clear	All*	Yes	Clear Container
Black	Fragment	No	Black Container - Fragment
Black	Lid	No	Black Container - Lid
Black	Pot	No	Black Container - Pot
Black	Tray	No	Black Container - Tray
Black	Tub	No	Black Container - Tub
Colored	Fragment	No	Colored Container - Fragment
Colored	Lid	No	Colored Container - Lid
Colored	Pot	Yes	Colored Container - Pot (Food)
Colored	Pot	No	Colored Container - Pot (Non Food)
Colored	Tray	Yes	Colored Container - Tray (Matte)
Colored	Tray	Yes	Colored Container - Tray (Shiny)
Colored	Tub	No	Colored Container - Tub
White	Fragment	No	White Container - Fragment
White	Lid	Yes	White Container - Lid
White	Pot (Rectangle)	Yes	White Container - Pot (Rectangle)
White	Pot (Circle)	Yes	White Container - Pot (Circle)
White	Tray	Yes	White Container - Tray
White	Tub	Yes	White Container - Tub (Dairy Spread)
White	Tub	No	White Container - Tub (All Other)

*Further manual breakdown was done to identify the ratio of lids, cups, tray, pots and tubs.

We assessed the accuracy of the AI system compared to manual methods.

A sub-study conducted at one MRF in this project assessed the accuracy of the automated characterization performed by the Greyparrot Analyzer against a battery of human-led, manual tests.

The assessment evaluated (i) the accuracy of the automated Greyparrot Analyzer against manual counts of objects by a team of annotators trained on the same set of images as the AI, and (ii) the accuracy of the analyzer compared to hand counts of objects in a bunker immediately located downstream of the analyzer.

The purpose of this part of the study was to quantify the internal consistency of the automated analyzer (i.e., how effectively does the analyzer's object characterization compare to visual analysis done by the trained waste annotators), to compare physical material counts to the automated system counts and to understand the factor(s) that influence the accuracy of the analyzer and by how much.

The results support the assertion that the analyzer provides reasonably accurate estimates of the target objects and good agreement between methods. The median relative percent difference between manual methods and the analyzer was just 12%.

These results, taken together, support the assertion that the automated analyzer provides reasonably accurate estimates of the target objects.

For more details on the validation study and results, please see the **Appendix**.

WHAT DID WE FIND?

The volumes and characteristics of polypropylene, and the role AI can play in transforming recycling data collection

AI systems unlock accurate material classification at an unprecedented scale.

The study represents one of the most extensive published material characterization campaigns completed to date.

The analyzers collected data at the four MRFs across an average 94.5-day operational period, characterizing more than 45 million individual PP and non-PP items, representing approximately 678 tons of material.

The data in **Figure 5** reflects the sheer volume and granularity of characterization with the automated AI system. The results show that nearly 100,000 individual objects traveling on the MRF belt at the analyzer's location were characterized in a typical day. This figure contrasts with the number of insights available through manual methods.

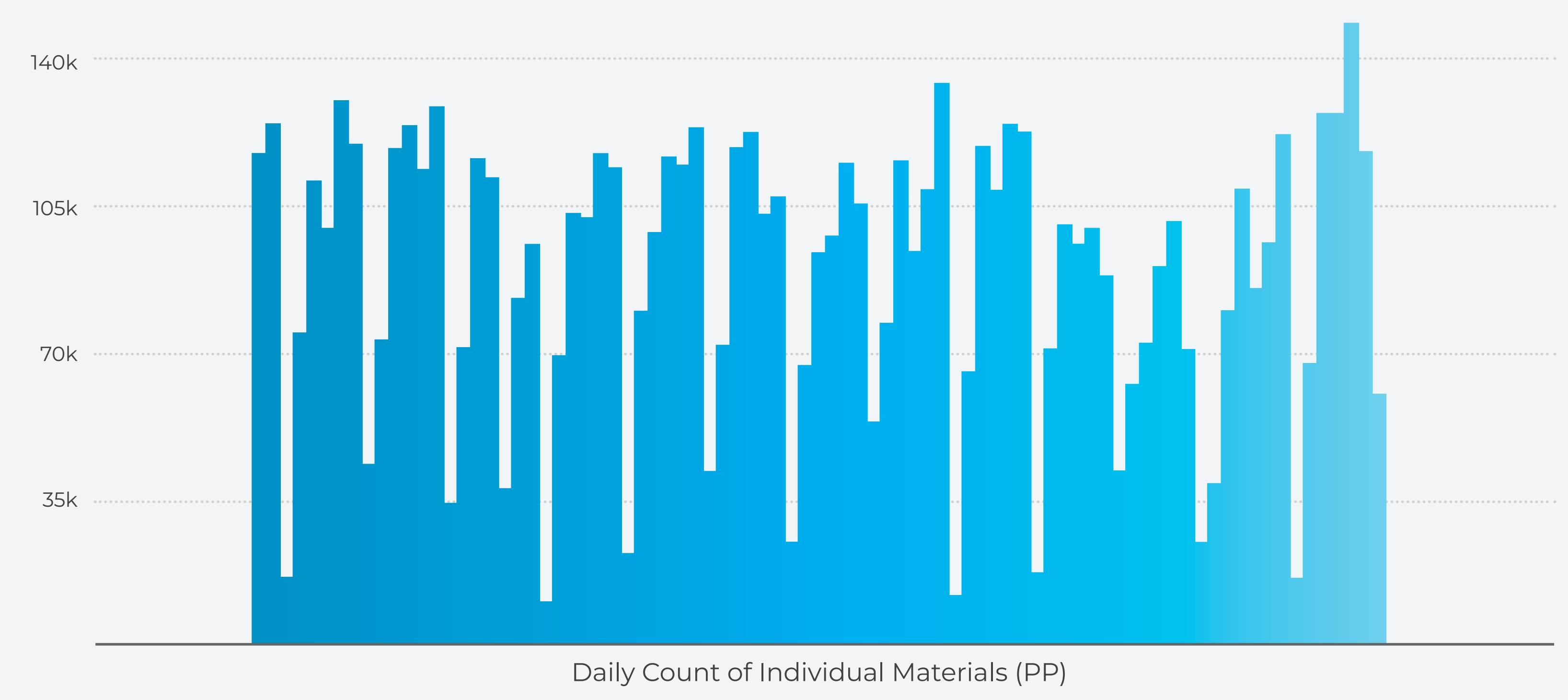
Based on the previously discussed estimate that manually characterizing a 1,000-pound bale could take up to a day, manually characterizing the objects captured in this study could take up to four years. AI proved an effective addition to the MRFs—offering just as much accuracy, while also ensuring statistically relevant and consistent data.

Furthermore, point-in-space intelligence also reveals the non-static nature of PP material flows. This reveals a novel and unique capability that analyzers could provide to help MRF operators understand how material flows and quality may change based on various factors.

Figure 5. Daily count of individual PP materials characterized by the Greyparrot Analyzer at one of the MRFs in this study.

Representative Count of PP Materials Measured by the Analyzer at One of the Study's MRFs: Nov 1, 2023 to Feb 2, 2024

The figure highlights the non-static nature of PP material flows through the MRF and captures key events like partial-day operations.



Most PP captured is clear and white, and predominantly food-grade, highlighting an opportunity to meet growing market demand.

In each of the MRFs, clear material comprises the most considerable fraction, followed by white materials, which comprise about a third of the PP stream.

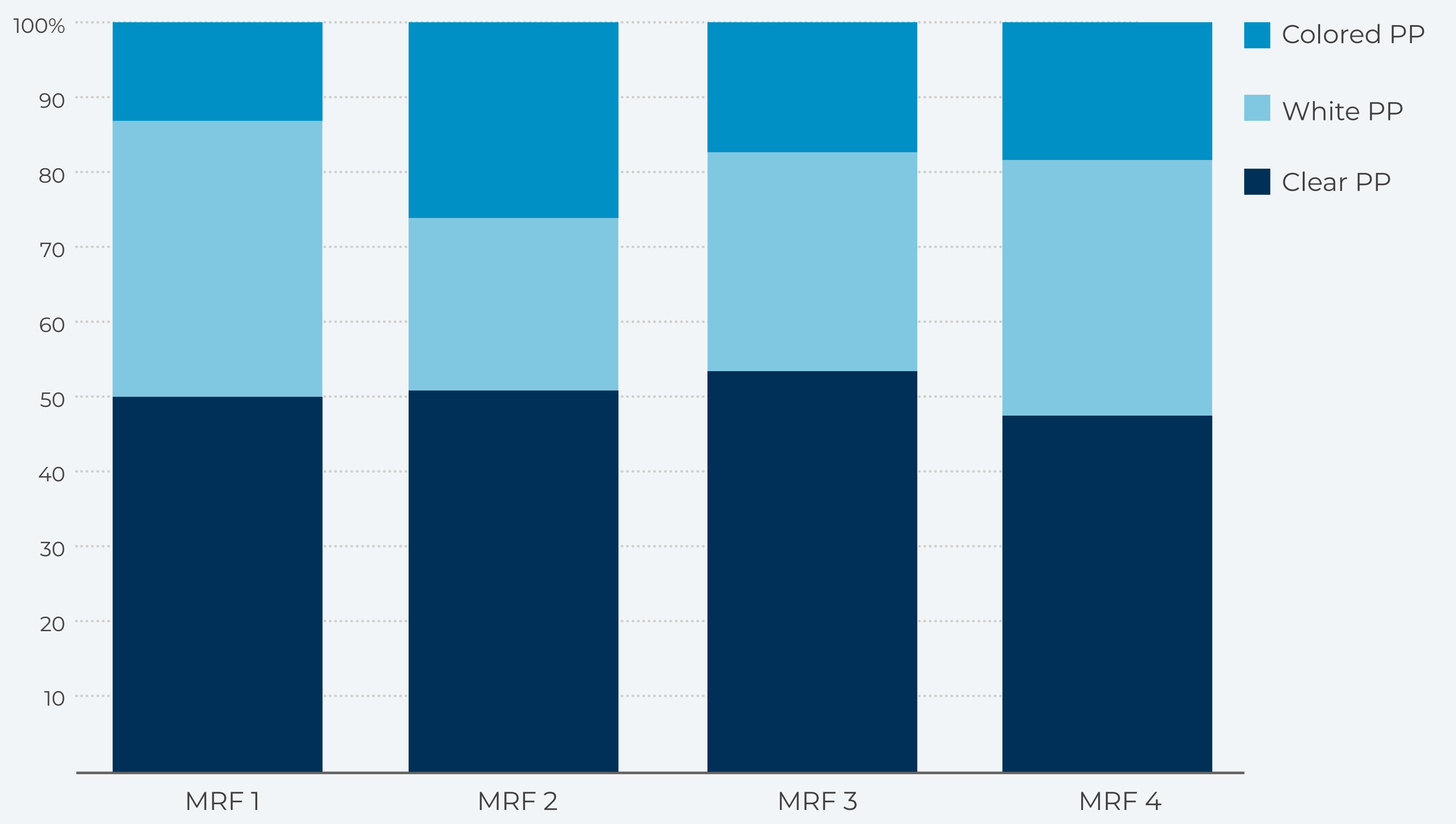
Figure 6 displays the distribution of clear, white and colored materials within the PP stream at each of the four MRFs. The balance is comprised of colored PP (including black). Despite having different operating infrastructure and being located in geographically disparate areas, the aggregated results in **Figure 6** show remarkable consistency across the MRFs.

The Greyparrot Analyzer further characterized the data from **Figure 6** to quantify the portion of each color category that reflected likely food-grade materials. **Table 3** presents the results of this characterization.

Figure 6. Relative proportion (mass basis) of clear, white and colored PP materials characterized at the four MRFs during the study period.

Clear Containers Comprised More Than Half of All PP Analyzed During Testing

White containers comprised about one-third across the four MRFs with the balance comprising colored PP



Data reflect computed mass percentages during the testing period.

Table 3. Range of estimated proportion of clear, white and colored PP that is likely food grade across the four MRFs (Mass %).

PP Color Category	Proportional Range of PP Type Identified by the Analyzer as Likely Food Grade (Mass %)[d]	Proportional Range of PP Type Identified by the Analyzer as Likely Non-Food Grade (Mass %)[d]
Clear	88-94%	6-12%
White	94-95%	5-6%
Colored	7-16%	84-93%

d. Values rounded to the nearest whole number.

The results in **Table 3** show that nearly all clear and white PP is made of food-grade objects, while around 90% of colored PP is likely made of non-food-grade objects.[e] **Figure 6** and **Table 3** also show that a large proportion of PP stream at the four MRFs are made of food-grade objects, with clear food-grade PP comprising the largest fraction and about 10 percentage points more proportional to white food-grade PP.

e. This includes objects where food-grade is visually hard to confirm; non food-grade was assumed due to guidelines.

Takeaway cups (also referred to as take-out cups) comprised the largest fraction of the formats analyzed at around 31% (mass basis), followed by lids, then by pots and tubs.

Figure 7 presents data further characterizing clear PP materials into specific formats, pooled across results from all four MRFs.

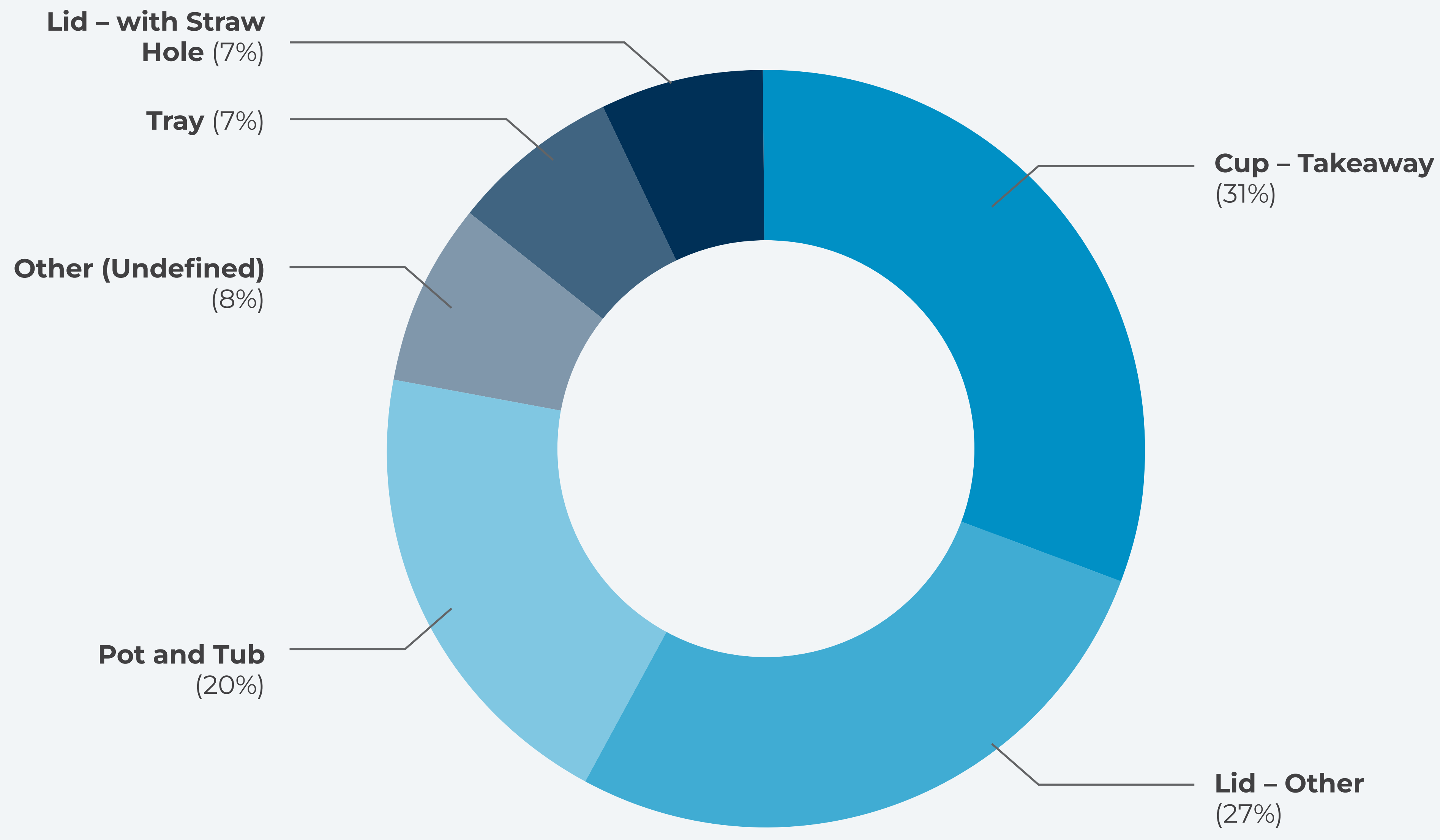
By definition, these results align with the previously presented results, showing nearly all clear PP as food grade. The magnitude of specific drivers behind the relative proportions of formats observed at the four MRFs is hard to assess, as insufficient information about influencing factors (e.g., how acceptable recyclable materials, including format, is communicated to each community sending the MRF recyclable materials, characteristics of those inbound materials at a community-specific level, etc.), but this highlights an important opportunity for future work.

Regardless, the results underscore the quantity and characteristics of food-grade materials that communities recycle and put back into circulation.

Figure 7.
Format-specific characterization of clear PP materials at the four MRFs in this study (pooled, mass-basis).

Greyparrot Analyzer Reveals Granular Details of Clear PP Format Proportions

Takeaway cups and lids represented the majority category analyzed at the four MRFs. Data represents pooled average mass percentage basis.



CASE STUDY

How an Optical Sorter Upgrade Affected Material Quality, and How AI Systems Helped Quantify the Benefit

During the study period, one MRF removed two optical sorters from service (those targeting PET and PP), and replaced them with new optical sorters. This created a unique opportunity to compare the composition of PP with the AI classification technology before and after the new optical sorter installation.[f]

The PP optical sorters in this MRF were positioned downstream of the PET optical. Below, we present results in an approximately split sample, with analysis starting on November 13, 2023, and concluding on April 1, 2024. The new optical sorters went online and were operational as of January 27, 2024, leaving approximately 75 days of composition data before and 65 days after the optical sorter installation.

Figure 8 displays a cumulative summary of PP and non-PP materials on the MRF's belt, downstream of the optical sorter before and after the replacement. The AI classification system effectively quantified a 13 percentage-point performance improvement in PP purity after the new optical sorter's installation, reflecting the important effects of the new equipment. A few important discoveries:

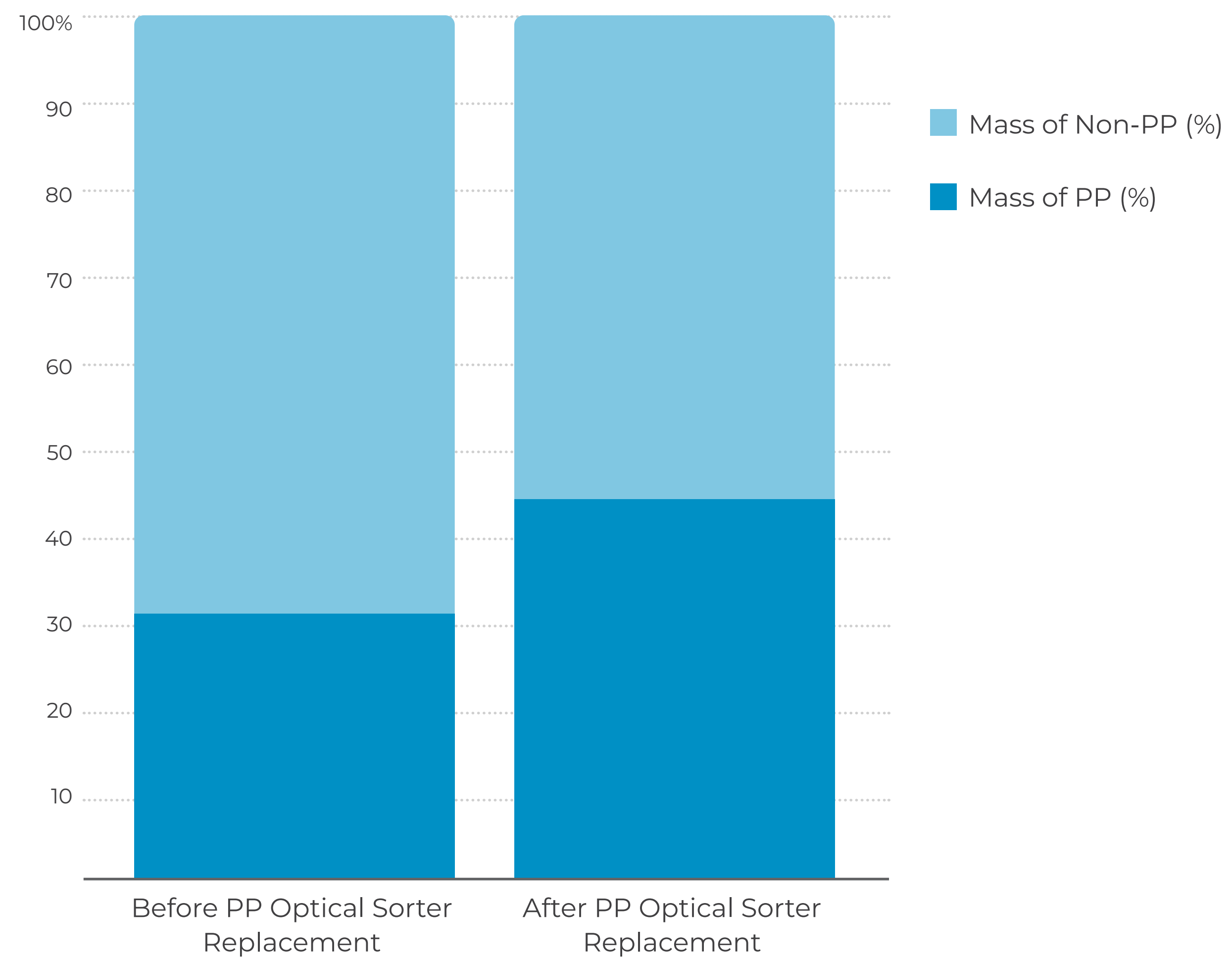
- The new PET optical more effectively sorted PET, so a far smaller amount of PET (and other non-PP materials) reached the PP optical sorter.
- The new PP optical sorter more effectively identified and sorted PP, helping to increase the overall quantity of PP seen by the analyzer.

Note that at this MRF, additional sorting of recyclables occurs downstream from the PP optical (notably, manual sorting of HDPE), which largely explains the high occurrence of non-PP materials as shown in Figure 8.

These results show the dramatic effect that modernized sortation equipment can have on material separation performance and purity. They also show the role that automated AI analysis and classification can play in confirming and quantifying specific improvements in operating infrastructure. The results additionally imply that AI can signal the need for equipment maintenance, upgrades or replacement, when effectively calibrated and the data analyzed in this manner.

Figure 8. Summary of PP fraction measured by the analyzer at one of the MRFs in this study before and after a new optical sorter installation.

Replacing End-of-Life PP Optical Sorter Substantially Increased PP Purity



f. The optical sorters reached 12 years of service life and were already due for replacement before this study was initiated. This service life aligns to that typical for well-maintained optical sorters operated at MRFs, see for example: https://www.recyclingtoday.com/article/best-practices-optical-sorter-maintenance/ .

This unprecedented work reveals the power of data in driving circular outcomes for packaging, and new potential opportunities for polypropylene.

Our key findings are summarized as follows:

1

Automated AI classification systems can characterize massive amounts of material with granularity, at a scale that is orders of magnitude larger than could be accomplished with manual methods;

2

A substantial proportion of characterized PP (75-85% at the four MRFs) was clear and white material; nearly all of these materials were food grade;

3

Tests comparing manual and AI-enabled material counts closely agreed, demonstrating that properly calibrated automated AI systems can produce accurate material characterizations when operated according to best practices. Most notably, materials are individuated on the MRF belt before passing beneath the Greyparrot Analyzer. See more details in the Appendix;

4

The MRF with newly installed optical sorters for PET and PP showed a large uplift in quality, underscoring the positive impact that modern sortation equipment has on material purity and, therefore, recycling outcomes at MRFs.

WHAT'S NEXT?

The possible future for material recovery and recycling analytics, powered by artificial intelligence-enabled technologies

This work will advance efforts focused on accelerating circular outcomes for various PP packaging formats, and add to the growing body of best practices, but gaps remain.

Notably, this study focused on uncovering better data at one node of the PP recycling value chain. Leveraging this data to generate new, valuable recovery opportunities for food-grade PP further downstream is a critical next step that will require additional investigation.

Some areas for further research may include secondary sortation, decontamination processes, format compatibility (i.e., injection molding vs. thermoforms) and clear vs. non-clear bales.

With greater data and transparency around the performance of AI technology and its capabilities within MRFs, along with new, critical data on the presence and quantity of food-grade objects within the PP stream, more MRFs can be equipped to recover valuable materials.

What is now possible for the recovery of PP and other valuable recyclable materials?

Greater Transparency and Reliability

Deploying automated AI classification technology, coupled with transparently reporting results by MRFs and reclaimers, can help illuminate material quality dynamics, inform valid use cases where the technology can be helpful and pinpoint areas where its limitations require improvement.

New Bales and Quality Improvements

MRFs equipped with the appropriate sortation and characterization infrastructure could experiment with creating bespoke bales reflecting food grade-only PP, for example. Transparently providing bale purity details can signal available supply to meet demand for food-grade materials and may help to foster more favorable off-take terms for MRFs.

Data Sharing and Advanced Value Chains

Accelerated work and deeper collaboration among value chain partners to more openly share operating data (including material characteristics) and address bottlenecks preventing high-quality materials (including food-grade materials) from reaching their highest and best end-use markets.

Replicability

Additional work at other points in MRFs or value chains that similarly dive deeply into PP and other material types and sub-types can help identify additional opportunities to inform community education and engagement techniques, MRF recovery opportunities, opportunities to supply more and higher quality materials to reclaimers, and opportunities to meet end-market demand for food-grade materials.

Standardization

With the emergence and variety of AI-enabled material characterization technology at MRFs and material reclaimers, there is a need (as in other manufacturing sectors) to develop and administer agreed-upon operational and/or performance standards. This helps ensure that, as the growth and penetration of AI technology in MRFs increases, various supply chain participants leveraging AI align on agreed-upon standards to engender trust as materials transfer from one node in circular supply chains to the next.

APPENDIX

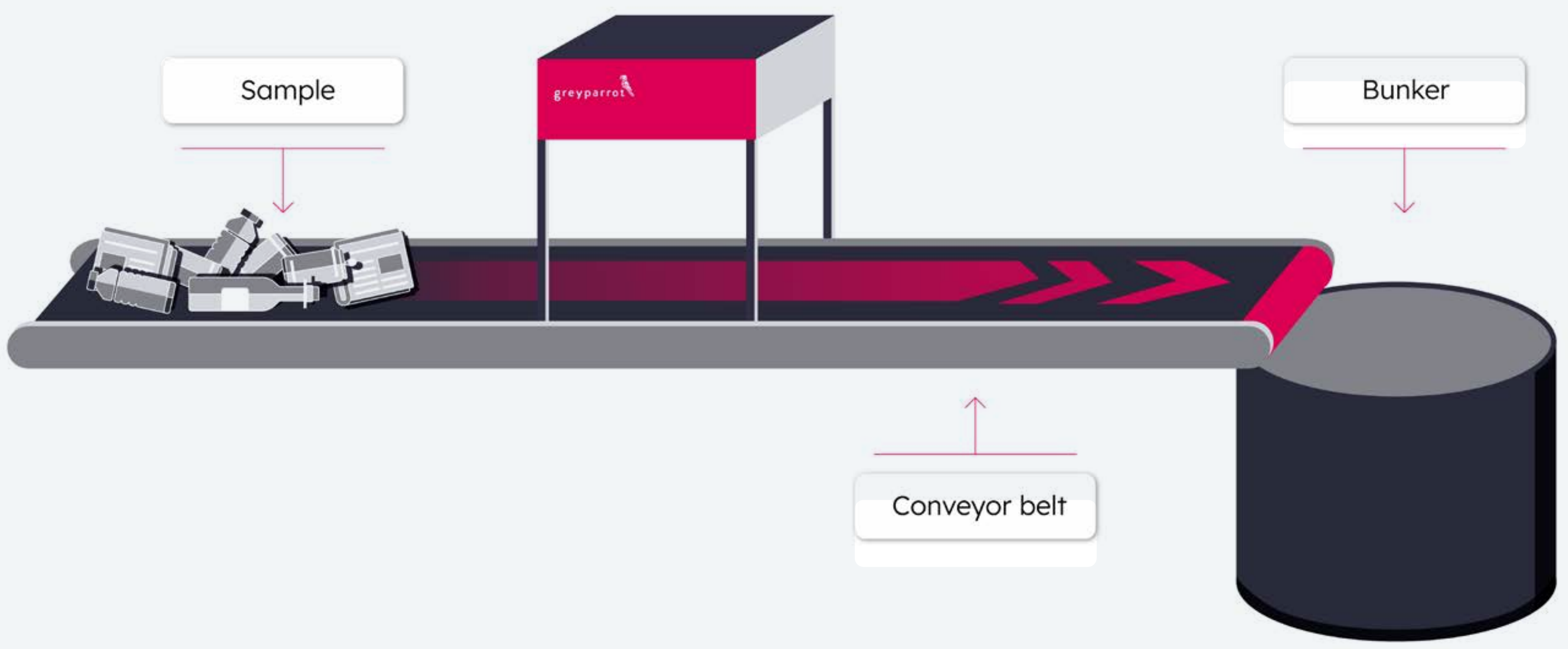
Assessing How Accurate the Greyparrot Analyzer Is in Automatic Classification

A sub-study conducted at one MRF in this project assessed the accuracy of the automated characterization performed by the Greyparrot Analyzer against a battery of human-centered, manual tests. The accuracy assessment evaluated (i) the accuracy of the automated analyzer against manual counts of objects by a team of annotators trained on the same set of images as the AI, and (ii) the accuracy of the automated analyzer compared to hand counts of objects in a bunker immediately located downstream of the analyzer.

For the internal consistency testing, the Greyparrot Analyzer (placed just downstream of the PP-focused optical sorter unit) classified materials on the belt from images collected and randomly selected across an approximately seven-day operational period. Randomly selected photos (2,909 in total) were classified by the analyzer and by a person (trained in material annotation by Greyparrot according to Greyparrot's taxonomy) separately and without the annotator's knowledge of the analyzer's results.

Manual counts of containers (the most relevant format for PP) conducted by facility personnel trained in material classification according to Greyparrot's taxonomy were compared with the Greyparrot Analyzer's container classification results over an approximately two-week testing period. Eight separate classification tests are summarized here after an initial system calibration and optimization period. Before each test, the conveyor belt and bunker immediately downstream of the analyzer were emptied by facility personnel to create a "zero" condition. The MRF was then started up, and the testing period began, with each test comprising approximately 20-60 minutes of system run-time. A site worker recorded the start and end times to align results from the Greyparrot Analyzer to the manual counts of items in the bunker. The analyzer operated normally, while the objects reaching the bunker were hand-sorted into predetermined material categories by the on-the-ground sorting team and subsequently counted and results recorded.

Figure 5. Daily count of individual PP materials characterized by the analyzer at one of the MRFs in this study.



Greyparrot Analyzer Accuracy Assessment Results

The material counts measured by the analyzer were compared with two manual methods in samples totaling approximately 30,000 individual objects. **Table 4** compares containers that the automated AI system counted to manual counts of the materials in the bunker just downstream of the AI unit.

The results in **Table 4** show good agreement between each method, with a relative percent difference ranging from 1% to 21% (median relative percent difference = 12%). Manual and analyzer counts of likely food-grade and non-food-grade materials were also performed, and these results are reflected in Test 8, shown in **Table 4**. The results showed an approximately 2 percentage-point difference between the two methods (AI counts showed a 79%/21% food/non-food split, while the manual method showed an 81%/19% food/non-food split).

The accuracy comparison between the Greyparrot Analyzer and the trained annotator showed good agreement. Of the 2,909 images analyzed, the analyzer computed a count of 5,567 unique containers, while the human annotator identified 5,553 containers, a difference of 0.25%.

These results, taken together, support the assertion that the automated analyzer provides reasonably accurate estimates of the target objects. It's important to note the following information and method limitations:

1. Visual characterization (whether by a human or an analyzer linked with a camera) requires separated materials (not overlapping) for accurate identification and quantification.

2. Mass estimates—whether via an AI-linked estimate or direct manual measurement—are subject to some error, although the sources and magnitude of error differ. Material misclassification and other substances on recyclable material (e.g., dirt, moisture, etc.) could influence the difference between the actual mass and the estimated or measured mass.

3. Manual characterization and AI characterization are both subject to misclassification. Even though the team conducting the manual sorts during this study was trained on the item taxonomy also used by the AI system, there could still be differences in how the human team characterized objects in the field compared with how the analyzer characterized the object. This could skew (high or low) the characterization results for different materials.

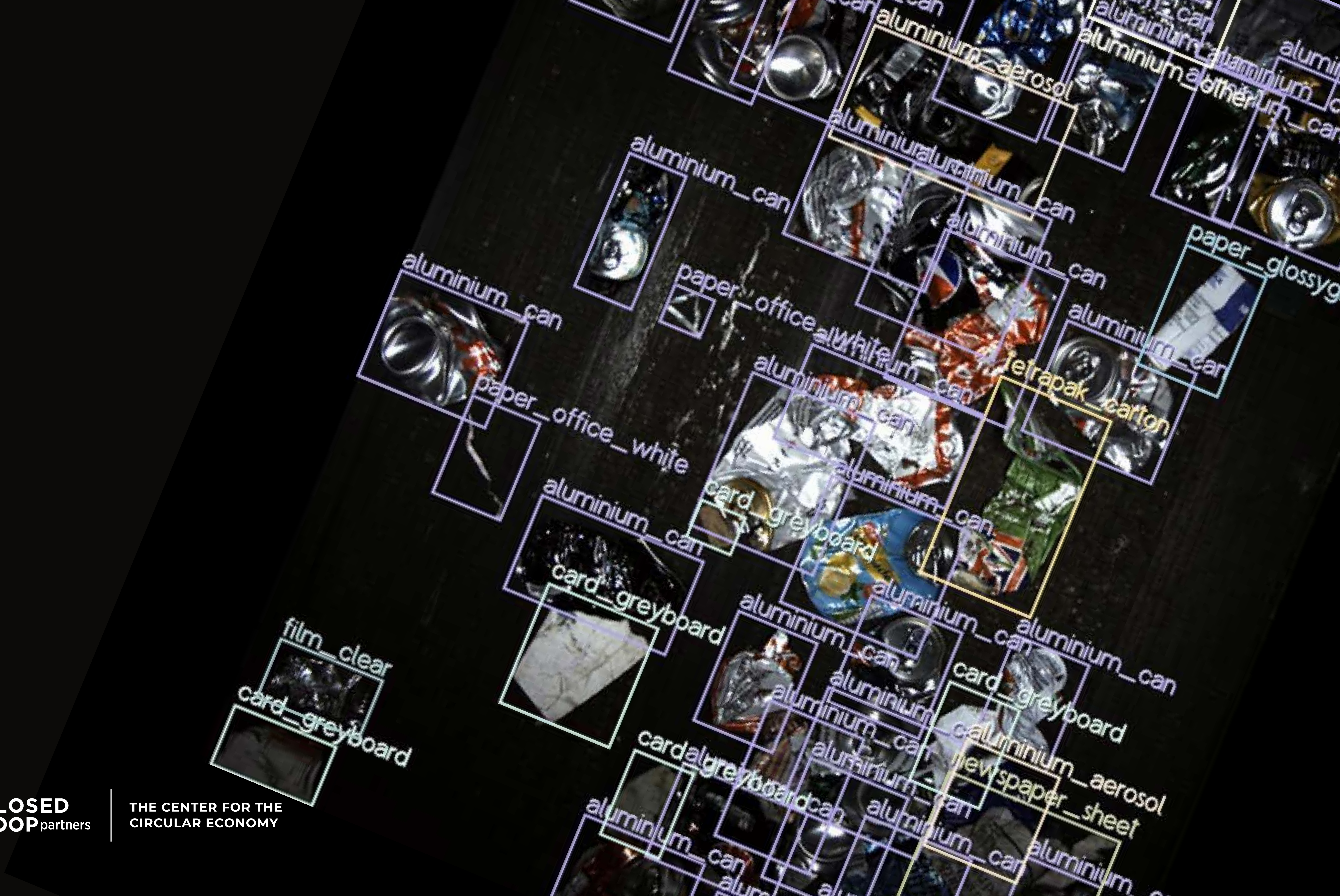
Table 4. Summary of material count comparison between the Greyparrot Analyzer and manual count.

Test ID	Count of Containers: AI Analyzer	Count of Containers: Manual Count	Relative Percent Difference[g]
1	4,598	5,266	14
2	4,004	4,406	10
3	2,763	2,887	4
4	2,166	2,440	12
5	4,864	5,987	21
6	3,276	3,678	12
7	3,514	3,556	1
8	2,162	2,682	21

g. Relative Percent Difference is calculated as the absolute difference between the AI count and the manual count divided by the sum of the counts from both methods divided by 2, all then multiplied by 100.

Endnotes

1. Powell and Chertow 2018 - Quantity, components, and value of waste materials landfilled in the United States. Journal of Industrial Ecology, doi: 10.1111/jiec.12752
2. Vedantam, Aditya, Nallan C. Suresh, Khadija Ajmal, and Michael Shelly. 2022. "Impact of China's National Sword Policy on the U.S. Landfill and Plastics Recycling Industry" Sustainability 14, no. 4: 2456. https://doi.org/10.3390/su14042456
3. Victory and Tudball. 2021. "Current recycled polymer price competitiveness fuelling switch away from virgin material" Sustainable Plastics, https://www.sustainableplastics.com/news/current-recycled-polymer-price-competitiveness-fuelling-switch-away-virgin-material
4. Jambeck et al 2015 - Plastic inputs from land into the ocean. Science, doi: 10.1126/science.1260352
5. Powell and Chertow 2018 - Quantity, components, and value of waste materials landfilled in the United States. Journal of Industrial Ecology, doi: 10.1111/jiec.12752
6. The Recycling Partnership 2024 - Polypropylene Recycling Coalition Homepage
7. The Recycling Partnership 2024 - Polypropylene Recycling Coalition Annual Report, https://recyclingpartnership.org/Polypropylene-Recycling-Coalition-Annual-Report/
8. The Recycling Partnership 2024 - State of Curbside Recycling Report, https://recyclingpartnership.org/wp-content/uploads/dlm_uploads/2024/05/SORR_Methodology-1-1.pdf
9. Association of Plastics Recyclers – 2024, https://plasticsrecycling.org/tools-and-resources/policy-hub/policy-priorities/recycled-plastic-content-requirements/
10. Food and Drug Administration 2025, Submissions on Post-Consumer Recycled (PCR) Plastics for Food-Contact Articles, https://www.hfpappexternal.fda.gov/scripts/fdcc/index.cfm?set=RecycledPlastics
11. Food and Drug Administration 2020, "Recycled Plastics in Food Packaging", https://www.fda.gov/food/packaging-food-contact-substances-fcs/recycled-plastics-food-packaging#:~:text=If%20appropriate%2C%20additional%20migration%20testing,recycled%20plastics%20for%20food%20packaging.
12. Ibid
13. This and other figures throughout the report were developed using Datawrapper (http://www.datawrapper.de).
14. Adapted from US Food and Drug Administration (2024) - Submissions on Post-Consumer Recycled (PCR) Plastics for Food-Contact Articles. https://www.hfpappexternal.fda.gov/scripts/fdcc/index.cfm?set=RecycledPlastics. Accessed 2 December 2024.
15. Greyparrot Taxonomy. https://www.greyparrot.ai/how-it-works#:~:text=What%20our%20AI%20can%20recognise



CLOSED LOOP partners

THE CENTER FOR THE CIRCULAR ECONOMY