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Optical sensors and machine learning algorithms in sensor-based material flow characterization for mechanical recycling processes: A systematic literature review

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A B S T R A C T

Digital technologies hold enormous potential for improving the performance of future-generation sorting and processing plants; however, this potential remains largely untapped. Improved sensor-based material flow characterization (SBMC) methods could enable new sensor applications such as adaptive plant control, improved sensor-based sorting (SBS), and more far-reaching data utilizations along the value chain. This review aims to expedite research on SBMC by (i) providing a comprehensive overview of existing SBMC publications, (ii) summarizing existing SBMC methods, and (iii) identifying future research potentials in SBMC. By conducting a systematic literature search covering the period 2000 – 2021, we identified 198 peer-reviewed journal articles on SBMC applications based on optical sensors and machine learning algorithms for dry-mechanical recycling of non-hazardous waste. The review shows that SBMC has received increasing attention in recent years, with more than half of the reviewed publications published between 2019 and 2021. While applications were initially focused solely on SBS, the last decade has seen a trend toward new applications, including sensor-based material flow monitoring, quality control, and process monitoring/control. However, SBMC at the material flow and process level remains largely unexplored, and significant potential exists in upscaling investigations from laboratory to plant scale. Future research will benefit from a broader application of deep learning methods, increased use of low-cost sensors and new sensor technologies, and the use of data streams from existing SBS equipment. These advancements could significantly improve the performance of future-generation sorting and processing plants, keep more materials in closed loops, and help paving the way towards circular economy.

Abbreviations: 1D, One-dimensional; 3DLT, 3D laser triangulation; ABS, Acrylonitrile butadiene styrene; Al, Aluminum; ANN, Artificial neural network; ASR, Automotive shredder residue; Au, Gold; BC, Beverage carton; BN, Bayesian network; CBR, Case based reasoning; CDW, Construction and demolition waste; CNN, Convolutional neural network; CRF, Conditional random field; CT, Complementary troubleshooting; Cu, Copper; CuZn, Brass; CVA, Canonical variate analysis; DBC, Dissimilarity-based classifier; DT, Decision tree; ELV, End-of-life vehicles; eMFC, Extensive MFC; F, False; Fe, Iron; Fuzzy, Fuzzy based algorithm; GA, Genetic algorithm; GMM, Gaussian mixture models; GPC, Gaussian process classifier; HD, High-density; HIPS, High Impact PS; HSI, Hyperspectral imaging; ICA, Independent component analysis; iMFC, Intensive MFC; IR, Infrared; kNN, k nearest neighbors; LD, Low-density; LDA, Linear discriminant analysis; LEMAP, Laplacian Eigenmaps; LIBS, Laser-induced breakdown spectroscopy; LIDAR, Light detection and ranging; LIF, Laser-induced fluorescence; Linear, Linear regression; LWP, Lightweight packaging waste; MAE, Mean absolute error; MAP, Maximum a posteriori estimation; MCW, Mixed commercial waste; MFC, Material flow characteristic; MIR, Mid-infrared; ML, Machine learning; MLR, Multinomial logistic regression; MSW, Mixed solid waste; N, Negative; NC, Nearest centroid; Ni, Nickel; NIR, Near-infrared; P, Positive; PA, Polyamide; PBT, Polybutylene terephthalate; PC, Polycarbonate; PCA, Principal component analysis; PE, Polyethylene; PET, Polyethylene terephthalate; PLS, Partial least squares; PMMA, Polymethylmethacrylate; POM, Polyoxymethylene; PP, Polypropylene; PPC, Paper, paperboard, and cardboard; PPS, Polyphenylene sulfide; PS, Polystyrene; PSD, Particle size distribution; PVC, Polyvinylchloride; PVDF, Polyvinyliden fluoride; QA, Quality assessment; QDA, Quadratic discriminant analysis; RAMAN, Raman spectroscopy; RDA, Resemblance discriminate analysis; RF, Random forest; RGB, Red green blue; RMSE, Root mean square error; RQ, Research question; SAM, Spectral angle mapper; SBMC, sensor-based material flow characterization; SBMM, sensor-based material flow monitoring; SBPC, Sensor-based process control; SBPM, Sensor-based process monitoring; SBPM/C, SBPM or SBPC; SBQC, Sensor-based quality control; SBR, Styrene-butadiene rubber; SBS, sensor-based sorting; SCC, Spectral cross-correlation; SIMCA, Soft independent modelling by class analogy; SOM, Self-organized map; SVD, Singular value decomposition; SVM, Support vector machine; T, True; TEEE, Thermoplastic elastomer-ether-ester; THz, Terahertz; TPE, Thermoplastic elastomers; TPU, Thermoplastic polyurethane; TRL, Technological readiness level; UV, Ultraviolet; VIS, Visible; ViT, Vision transformer; VNIR, VIS-NIR; WEEE, Waste from electrical and electronic equipment.

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1. Introduction

Global material extraction has more than tripled from approximately 27 billion tons in 1970 to approximately 92 billion tons in 2017 (IRP, 2019), and may more than double by 2050 (IRP, 2017). The extraction and processing of natural resources make up approximately 50% of total greenhouse gas emissions and account for more than 90% of water stress and biodiversity loss (IRP, 2019). Accelerating climate change (IPCC, 2021) and biodiversity loss (Dirzo et al., 2014; WWF, 2020) indicate the urgency and critical importance of transitioning the world to sustainable development within current planetary boundaries (O'Neill et al., 2018; Rockström et al., 2009).

In the interests of sustainable development, the circular economy concept aims to reduce, alternatively reuse, recycle, and recover materials in production, distribution, and consumption processes (Kirchherr et al., 2017). Moving towards a circular economy requires streamlined efforts of all stakeholders along the value chain. For example, products have to be designed with a focus on durability, reusability, upgradability, and reparability; packaging materials have to be designed for reuse and recyclability. For products and packaging whose lifespan cannot be further extended ("end-of-life"), high-quality recycling should keep valuable materials in closed material loops as long as possible (European Commission, 2020).

In 2018, about 808.9 million tons of waste were generated in the EU-27 (excluding major mineral wastes) (Eurostat, 2021a), of which 38.1 wt % was fed into recycling processes (Eurostat, 2020). After recycling, secondary raw materials can—if their quality is sufficient—substitute primary raw materials, and achieve significant environmental benefits because primary raw material extraction is avoided, and secondary raw materials often have significantly lower environmental footprints (Astrup et al., 2009; Bajpai, 2014; Grimes et al., 2008; Shen et al., 2010; Simion et al., 2013).

Nevertheless, the current material supply in the EU is still largely dependent on primary resources, and as of 2018, only 12.2 wt% of used materials have come from secondary resources (Eurostat, 2021b). Therefore, significant improvements along the value chain are needed to increase the substitution of primary raw materials (IRP, 2019).

Increasing the performance of the future-generation of mechanical recycling processes would largely contribute to this goal through (i) recovering a higher amount of secondary raw materials from existing waste flows and (ii) producing secondary raw materials in higher quality to enable a high-value substitution of primary raw materials.

1.1. Concepts for increased performance of future-generation mechanical recycling processes

Mechanical recycling of valuable materials from wastes into secondary raw materials comprises two stages: First, in the pre-enrichment stage, *sorting plants* sort mixed wastes into preconcentrates (e.g., polypropylene [PP] plastic bales). Second, in the refinement stage, *processing plants* refine preconcentrates into secondary raw materials (e.g., PP recyclates). Whereby material flows from mono-collection (e.g., PET bottles from deposit return systems) can be directly passed on to the refinement stage.

Recently, several publications have argued that integrating *digital technologies* in mechanical recycling processes will increase their performance (Khodier et al., 2019; Sarc et al., 2019; Vrancken et al., 2017) and enhance circular economy in general (Antikainen et al., 2018; Berg et al., 2020; Hannan et al., 2015; Hedberg and Šipka, 2020; Hedberg et al., 2019; European Commission, 2020). More specifically, great potential is seen in increased exploitation of sensor technology in future-generation sorting and processing plants (Curtis et al., 2021; Feil et al., 2019; Khodier et al., 2019; Sarc et al., 2019; Serranti et al., 2011; Vrancken et al., 2017).

First, advanced sensors and characterization algorithms could increase sorting performance and enable new sorting possibilities in sensor-based sorting (SBS), thus improving the quality and quantity of recovered secondary raw materials. Second, an automated and adaptive process control could significantly improve the overall performance of future-generation sorting and processing plants. A key prerequisite for this is the availability of real-time material flow characteristics (MFCs) as a decision-making basis for an intelligent process control algorithm. The process control algorithm could then adapt remotely controllable actuators to maximize a given goal function (Khodier et al., 2019), e.g., to optimize the ecological or economic performance of the plant. Third, sensor-based material flow data could be used further along the value chain to improve material circulation in general; for example, by using sensor data from sorting plants for improved waste collection or sensor data from processing plants for optimized secondary raw material use in production.

Despite these promising advantages and applications, past reviews have concluded that digitization in waste management is "still in [its] infancy" (Sarc et al., 2019, p. 479) or "in an early phase" (Berg et al., 2020, p. 2). In particular, more far-reaching applications of sensor technology beyond SBS remain largely unexploited.

1.2. Key technology: Sensor-based material flow characterization

A fundamental prerequisite to improve or enable the applications mentioned above is a precise characterization of anthropogenic material flows: While SBS processes separate material flows mainly based on accurate classification decisions at the particle level, adaptive process control and further applications require precise MFCs at the material flow level. The present paper focuses on predicting characteristics of anthropogenic material flows with sensor technology and machine learning (ML) algorithms—a process we refer to as *sensor-based material flow characterization* (SBMC).

Scientific literature has so far reviewed applications of sensor technology in waste management for waste segregation (Hannan et al., 2015), recovery and production of solid recovered fuels (Vrancken et al., 2017), identification and sorting of plastics (Araujo-Andrade et al., 2021), SBS (Gundupalli et al., 2017a), digitalization in general (Sarc et al., 2019), and applications of ML algorithms for waste management (Abdallah et al., 2020; Ni et al., 2021; Xia et al., 2021b). However, a systematic review of SBMC has yet to be conducted in the context of high-value material recycling.

1.3. Aim and scope

This paper aims to expedite future research on SBMC by (i) providing a comprehensive overview of existing publications on SBMC, (ii) summarizing existing methods for SBMC, and (iii) indicating future research potentials in SBMC.

The first emphasis of this review is on *non-destructive optical sensors*, as previous reviews have highlighted their suitability for SBMC (Vrancken et al., 2017). Compared to other sensors, optical sensors are advantageous for large-scale integration in sorting and processing plants because of their lower investment and operating costs and lower health risks compared with other sensors such as X-ray detection or laser-induced breakdown spectroscopy (LIBS)[1] (Sarc et al., 2019; Vrancken et al., 2017).

The second emphasis is on *ML algorithms,* which enable automatic extraction of MFCs from the acquired sensor data (Sarc et al., 2019; Vrancken et al., 2017). Compared to traditional algorithms, ML algorithms are not required to be explicitly programmed but can instead learn prediction patterns from given training data (Marsland, 2014).

During conducting the review at hand, we noticed that there is no consistent terminology used in SBMC and that research in SBMC is

[1] Readers interested in LIBS applications may find interest in the reviews of Noll et al. (2018) and Legnaioli et al. (2020).

dispersed widely and is often not perceived as a homogeneous research field. Based on our review findings, we will thus firstly propose a unified SBMC terminology in Section 2 before we elaborate on our review method (Section 3), present and discuss obtained results (Section 4), indicate possible future research directions (Section 5), and draw final conclusions (Section 6).

2. Background and terminology

SBMC describes digitally capturing material flows with sensors and applying algorithms to extract MFCs from the acquired sensor data. As SBS (based on particle characteristics) has been applied and investigated for decades and is focused on pixel- or particle-based material classes, we focus here on process-relevant MFCs defined in Section 2.1. Section 2.2 then determines how optical sensors can digitally capture material flows, and Section 2.3 elaborates on applying algorithms to extract process-relevant MFCs from sensor data.

2.1. Process-relevant MFCs

This paper defines a material flow as a material, or a mix of materials, which is regularly transported from position *A* to position *B*. Material transportation can be achieved either with continuous conveyors (e.g., belt conveyors) or non-continuous conveyors (e.g., wheel loaders) (Griemert and Römisch, 2020). In modern sorting and processing plants, material flows are almost exclusively transported on continuous conveyors because of their higher efficiency and lower costs (Griemert and Römisch, 2020). Thus, material flows on continuous conveyors are especially relevant for SBMC applications (Sarc et al., 2019).

In the context of SBMC, we propose to divide MFCs into *extensive* and *intensive* MFCs. The magnitude of extensive characteristics (e.g., mass or volume) depends on the size of a system; however, the magnitude of intensive characteristics (e.g., material composition or bulk density) is independent of a system's size (Cohen and Mills, 2007; Tolman, 1917).

2.1.1. Extensive MFCs

Two extensive MFCs (eMFCs) of high practical relevance exist: the mass flow rate $\dot{m}$ (Eq. (1)), which is the flow of mass m per unit of time t through a process line; and the volume flow $\dot{V}$ (Eq. (2)), which is the flow of volume V per unit of time t through a process line (Ghasem and Henda, 2012).

$$\dot{m} = \frac{dm}{dt} \tag{1}$$

$$\dot{V} = \frac{dV}{dt} \tag{2}$$

While the mass flow of any closed system is constant over time (law of conservation of mass) (Whitaker, 1975), volume flows might change over time, e.g., because of changing bulk densities (Curtis and Sarc, 2021; Feil et al., 2019). Volume flows are therefore only of limited suitability for process evaluation; mass flows, on the other hand, cannot be measured directly with optical sensors.

2.1.2. Intensive MFCs

While process-relevant eMFCs are usually limited to mass and volume flows, several intensive MFCs (iMFCs) have been proposed. For example, Christensen (2011) identifies (i) *physical iMFCs* (material composition, particle size distribution [PSD], moisture content, densities), (ii) *chemical iMFCs* (pH and alkalinity, organic matter, inorganics, calorific value, heating value), and (iii) *performance iMFCs* (compressibility, aqueous leachability of substances, biological degradability [respiration tests], biochemical methane potential).

In addition, Vrancken et al. (2017) list nine so-called *critical quality attributes* in the context of material recovery and solid recovered fuel production: problematic objects, PSDs, calorific value, ash content, moisture, composition, biogenic carbon, biochemical methane potential, and contaminants.

Another group of iMFCs describes the *material flow presentation*. These presentation iMFCs include, e.g., the fluctuations of volume flows (Curtis et al., 2021; Feil et al., 2019) and occupation densities (Küppers et al., 2021; Küppers et al., 2020), as both strongly influence the (sensor-based) sorting performance (Kroell et al., 2022).

Based on the available literature, we propose to structure MFCs into two groups, namely eMFCs and iMFCs, as well as four subgroups of iMFCs, as shown in Table 1. This listing is not exhaustive, as additional iMFCs are likely to be proposed for future applications.

2.1.3. MFCs of high practical relevance for mechanical recycling processes

As the scope of this review does not extend to reviewing research on all MFCs, we focus on MFCs of high practical relevance for mechanical recycling processes and the research vision described in Section 1.1. We have already identified two relevant eMFCs in Section 2.1.1: mass and volume flows. To identify iMFCs with high practical relevance, we will investigate iMFCs used in two major applications of (currently manual) material flow characterization: (i) technical process assessment and (ii) quality control of generated pre-concentrates.

2.1.3.1. iMFCs in technical process assessment.

Sorting and processing plants comprise a sequence of mechanical unit operations. For each mechanical unit operation (sorting, sieving, or comminution), one or more *indicators* are used to assess the process performance. Each indicator is calculated on the basis of one or multiple MFCs. MFCs used in these indicators are thus likely to be of high importance for future SBMC applications.

Sorting processes are assessed on the basis of the two indicators *purity* (c_w) and *yield* (R_w) (Feil et al., 2016). Purity (Eq. (3)) describes the mass fraction of valuable material ($\dot{m}_{w,i}$) in a material flow ($\dot{m}_i$). Yield (Eq. (4)) describes how much valuable material of the input material flow of a process ($\dot{m}_{w,\text{input}}$) is transferred to the desired output material flow ($\dot{m}_{w,\text{output}}$).

$$c_{w,i} = \frac{\dot{m}_{w,i}}{\dot{m}_i} \tag{3}$$

$$R_w = \frac{\dot{m}_{w,\text{output}}}{\dot{m}_{w,\text{input}}} = \frac{\dot{m}_{\text{output}} {}^* c_{w,\text{output}}}{\dot{m}_{\text{input}} {}^* c_{w,\text{input}}} \tag{4}$$

Sieving processes are assessed on the basis of the screening efficiency η_s, which is the ratio of fines (index f) in the input material flow ($\dot{m}_{\text{input}}$) that is transferred into the fine fraction ($\dot{m}_{FF}$) (Eq. (5)) (Schmidt et al., 2006).

Table 1
Grouping of MFCs in eMFCs and iMFCs.

Group	Subgroup	Examples
eMFCs	–	Mass flow
		Volume flow
iMFCs	Physical iMFCs	Material composition
		PSD
		Moisture content
		Densities
	Chemical iMFCs	pH and alkalinity
		Organic matter
		Inorganics
		Calorific value
	Performance iMFCs	Heating value
		Compressibility
		Aqueous leachability of substances
		Biological degradability
		Biochemical methane potential
	Presentation iMFCs	Occupation density
		Particle singling
		Particle distances
		Fluctuations of iMFCs

$$\eta_s = \frac{\dot{m}_{f,\,FF}}{\dot{m}_{f,\,input}} = \frac{\dot{m}_{FF} * c_{f,\,FF}}{\dot{m}_{input} * c_{f,\,input}} \tag{5}$$

Comminution processes are assessed by comparing the PSD of the output material flow with those of the input material flow, e.g., through the *reduction ratio* (Eq. (6)), where *d* is a measure for the PSD (Wills and Finch, 2016).

$$n_c = \frac{d_{output}}{d_{input}} \tag{6}$$

Notably, all presented indicators (Eq. (3) – Eq. (6)) are based on the iMFCs *material flow composition* and *PSD*, therefore being relevant iMFCs for technical process assessment.

2.1.3.2. iMFCs in quality control. For quality control, slightly varying standards and guidelines exist across different countries. Table 2 shows that, for example, in Germany, quality control standards for secondary raw materials most frequently focus on *material flow composition* (100.0%), *PSDs* (66.7%), and *moisture content* (44.4%).

Based on these findings, subsequent sections will primarily focus on the material (flow) composition and PSD. A comprehensive overview of existing publications on sensor-based moisture content determination is given by Vrancken et al. (2017).

2.2. Optical sensors for material flow characterization

Optical sensors cover the wavelength range between 100 nm and 1 mm, which includes the ultraviolet (UV; 100 nm – 380 nm), visible (VIS; 380 nm – 780 nm), and infrared (IR; 780 nm – 1 mm) region (DIN 5031-7, 1984). For SBMC applications, various sensors are available that can be integrated into sorting and processing plants.

Table 2
Considered MFC in quality control standards and guidelines in Germany.

Material flow	Addressed MFC			
	Material composition	PSD	Moisture	Other MFCs
Plastics[1]	✓	–	–	–
Glass[2]	✓	✓	✓	–
Non-ferrous metal scrap[3]	✓	✓	✓[(a)]	Origin, condition (corrosion)[(a)]
Steel scrap[4]	✓	✓	–	Bulk density
Aggregates[5]	✓	✓	–	pH content, electrical conductivity
Paper[6]	✓	–	✓	Age[(b)]
WEEE[(c), 7]	✓	–	–	–
Textiles[8]	✓	✓[(b)]	–	Water retention, hydrophobic/ hydrophilic
Compost[9]	✓	✓	✓	rotting degree
Percentage covered	**100.0%**	**66.7%**	**44.4%**	**≤ 11.1%**

[(a)] for some fractions;
[(b)] fiber length and morphology;
[(c)] waste of electrical and electronic equipment.
[1] (Der Grüne Punkt, 2021),
[2] (Bundesverband Glasindustrie e. V., 2014),
[3] (Verein Deutscher Metallhändler e. V., 1988),
[4] (Bundesvereinigung Deutscher Stahlrecycling- und Entsorgungsunternehmen e. V., 1995),
[5] (TL Gestein-StB 04, 2007),
[6] (DIN EN 643, 2014),
[7] (ElektroG, 2015),
[8] (Bartl et al., 2011),
[9] (Bundesgütegemeinschaft Kompost e. V., 2021a, 2021b, 2021c).

2.2.1. Available optical sensors for SBMC

Optical sensors have been developed and applied to characterize materials across the UV, VIS, and IR regions (Beel, 2017; Flamme and Krämer, 2015; Küppers and Pomberger, 2017). Depending on the selected wavelength range and sensor arrangement (reflective or transmissive measurements), different material characteristics can be derived from the acquired sensor data. Despite the different wavelengths addressed, almost all currently applied sensors follow the same measuring principle: (i) an emitter emits electromagnetic radiation that interacts with the material to be characterized; (ii) a detector detects the reflected or transmitted radiation; (iii) an algorithm analyzes the captured sensor data to characterize the material (Chen et al., 2021a).

Table 3 presents optical sensors suitable for measuring material characteristics for each spatial measuring point (*pixel*). In the VIS range, two types of sensors are commonly used: RGB-sensors (VIS-RGB), which capture the intensity at three different color channels (red [R], green [G], and blue [B]) and hyperspectral imaging (HSI) sensors, which measure the intensity at more than 100 different wavelength bins (VIS-HSI). In addition, sensors that cover (parts of) the VIS and near-infrared (NIR) range (VNIR) are available. Aside from measuring these pixel-based characteristics, most optical sensors can generate a spatial representation (image) of the recorded area (Jähne, 2005), which can be further analyzed at the particle or material flow level (cf. Section 2.3.1).

2.2.2. Integration of sensors in sorting and processing plants

Sensors can be integrated at different positions in sorting and processing plants with the goal of characterizing material flows or monitoring (sub)processes. According to Kessler (2012), process-analytical methods can be classified as *offline*, *atline*, *online,* and *inline*. For all four methods, the taxonomy is defined by the process proximity of the analyzer in use (Kessler, 2012): (i) *Offline* analytics involve sampling the material flow and transporting the sample, e.g., to a laboratory, where the sample is analyzed. The obtained results are only available with a considerable time delay. (ii) *Atline* analytics are characterized by a reduced time delay, as the analysis occurs in close proximity to the process. (iii) *Online* analytics automatically analyze a part of the material flow through a bypass. (iv) *Inline* analytics measure the entire material flow, thus avoiding potential sampling errors. Real-time SBMC required for the applications outlined in Section 1.1 can only be achieved by online and inline methods, discussed in subsequent sections.

2.3. Sensor-data analysis for SBMC applications

As most material and material flow characteristics cannot be directly measured with available sensors, suitable algorithms are often necessary to extract MFCs of interest (Sun, 2009). The necessary data analysis can be performed at different *investigation levels*, depending on the application and characteristic of interest.

2.3.1. SBMC investigation levels

Sensor data analysis for SBMC can be performed at four investigation levels:

Pixel level. The information of a pixel is represented as a one-dimensional (1D) array containing a numeric value for each channel. For example, the 1D array of each pixel can represent measured heights (one channel), RGB colors (three channels), or NIR/VIS spectra (> 100 channels). In pixel-based analysis, the information of each pixel is considered independently. Characteristics extracted at pixel level include, e.g., material classes (per pixel) or heights.

Particle level. Multiple, connected pixels can represent individual particles. In particle-based analysis, the information from multiple pixels representing a particle is combined. Furthermore, new particle-based features such as particle sizes and shapes often characterize individual particles. Characteristics extracted at the particle level include, e.g., material classes (per particle) or particle sizes.

Material flow level. A material flow consists of multiple particles. In

Table 3
Available non-destructive, optical sensors for SBMC.

Sensor technology		Wavelength range [nm] from	to	Working principle	Pixel-based extractable characteristics	Surface technology	Reference
LIF	Laser-induced fluorescence	100 [(a)]	380 [(a)]	Fluorescence	Chemical composition	✓	(Küch and Gaastra, 2014)
VIS	Visual	380	780	Reflection, absorption	Color	✓ [(b)]	(Beyerer et al., 2016)
RAMAN	Raman spectroscopy	380 [(a)]	780 [(a)]	Raman effect	Chemical composition	✓	(Smith and Dent, 2019)
3DLT	3D laser triangulation	–	–	Reflection + triangulation	Height	✓	(Beyerer et al., 2016)
NIR	Near-infrared spectroscopy	780	2,500	Reflection, absorption	Chemical composition	✓ [(c)]	(Ozaki et al., 2021)
MIR	Mid-infrared spectroscopy	2,500	25,000	Reflection, absorption	Chemical composition	✓ [(c)]	(Sun, 2009)
THz	Terahertz	10^4	10^6	Transmission	Chemical composition	–	(Maul and Nagel, 2014)

[(a)] LIF uses monochromatic excitation; the numerical values indicate typical application areas;
[(b)] for transparent objects, transmissive measurements are also possible;
[(c)] limited penetration depth.

material-flow-based analysis, the characteristics of multiple particles or pixels are combined to extract MFCs. Characteristics extracted at the material flow level include, e.g., material compositions, PSDs, or volume flows.

Process level. A process involves two or more material flows. In process-based analysis, several material flows and their relationships (e.g., input and output material flow) are combined to characterize or assess a process. Characteristics extracted at the process level include, e.g., the indicators *yield*, *screening efficiency*, and *reduction ratio* (cf. Section 2.1.3.1).

Characteristics from lower investigation levels (e.g., pixel or particle level) are needed to extract characteristics at higher investigation levels (e.g., material flow or process level). Taking the determination of screening efficiency (Eq. (5)) at the process level as an example, the sensor-based assessment may involve four steps: First, pixels may be segmented into foreground and background (*pixel level*). Second, particle sizes and masses of the identified particles may be predicted (*particle level*). Third, particle sizes and masses may be combined into PSDs (*material flow level*). Fourth, PSDs and screen underflow and overflow quantities may be combined to compute the screening efficiency (*process level*). The extracted characteristics at different investigation levels can then be utilized in applications such as automatic quality control (material flow level) or adaptive process control (process level). Fig. 1 summarizes the four SBMC investigation levels and their hierarchical interplay. It is important to note that investigation levels can be skipped in specific cases; for example, characteristics from the pixel level can be directly aggregated at the material flow level (see dotted lines in Fig. 1).

2.3.2. Machine learning algorithms

Many tasks in sensor-data analysis for SBMC applications involve predicting an unknown characteristic (e.g., material class) from known sensor data (e.g., NIR spectra). In ML terminology, the unknown characteristic is called *target variable* y, and the known sensor data is called *input variable* X (Hastie et al., 2009c). In such prediction problems, the goal is to develop a mathematical *model* that predicts the target variable y from the input variable X as accurately as possible.

Supervised ML algorithms can solve such prediction tasks without being explicitly programmed by *learning* relationships between X and y from labeled training data, i.e., known input variables *and* known target variables (Marsland, 2014). Trained ML models can then predict unknown target variables from known input variables (Bishop, 2006).

Two types of supervised ML problems can be distinguished. First, in *classification* problems, the target variable is discrete. Common applications with classification problems are, e.g., the prediction of material classes (e.g., "PET", "PE", "PP") or color classes (e.g., "red", "green", "blue") from sensor data. Second, in *regression* problems, the target variable is continuous. Common applications with regression problems are, e.g., the prediction of material compositions [%], particle sizes

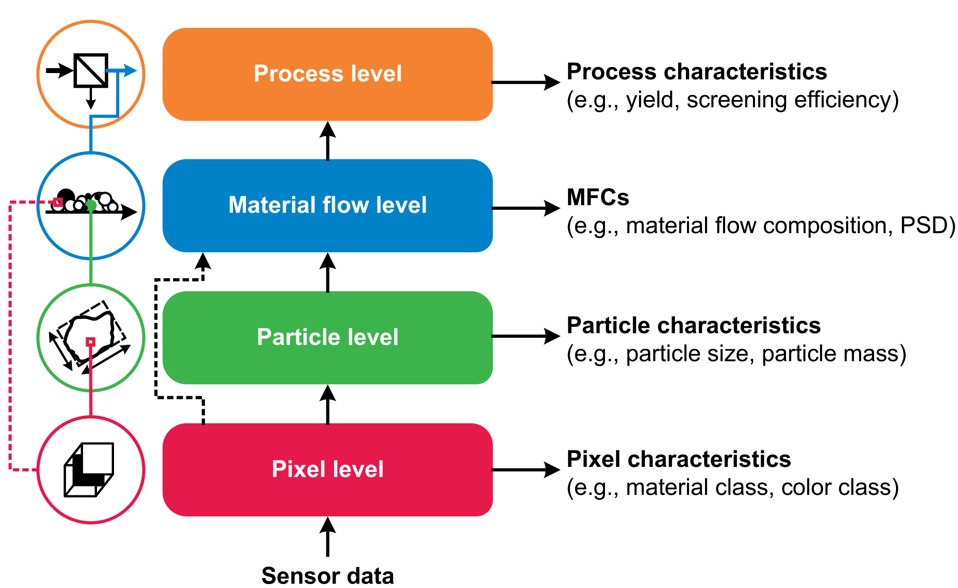

Fig. 1. SBMC investigation levels.

[mm], or moisture contents [%]. (Rebala et al., 2019).

Different metrics can be used to evaluate the performance of supervised ML algorithms. For this evaluation, a labeled dataset is divided into training and test data. ML algorithms are trained on the training dataset, and predictions of the trained algorithms based on the input variables of the test set are compared with the ground truth, i.e., the known target variables of the test dataset, to determine the prediction accuracy. (Kubat, 2017).

2.3.2.1. Classification metrics. In binary classification problems, y can have two values: "positive" (P) and "negative" (N). True (T) and false (F) predictions can then be visualized in a 2x2 *confusion matrix* (Eq. (7)) (Marsland, 2014).

$$\text{Confusion matrix}: \begin{bmatrix} TP & FP \\ FN & TN \end{bmatrix} \tag{7}$$

Based on the confusion matrix, common classification metrics can be calculated, including *accuracy* (Eq. (8)), *precision* (Eq. (9)), *recall* (Eq. (10)), and *F1-score* (Eq. (11)).

$$accuracy = \frac{\#TP + \#TN}{\#TP + \#FP + \#TN + \#FN} \tag{8}$$

$$precision = \frac{\#TP}{\#TP + \#FP} \tag{9}$$

$$recall = \frac{\#TP}{\#TP + \#FN} \tag{10}$$

$$F1 - score = 2 \bullet \frac{precision \bullet recall}{precision + recall} \tag{11}$$

Multi-class classification problems (> 2 classes) can be reformulated as a combination of binary classification problems. Calculated binary metrics can then be aggregated in terms of *macro-* or *micro-averages*. For macro-averages, all classes are weighted equally; for micro-averages, classes are weighted by the number of instances of each class. (Kubat, 2017).

2.3.2.2. Regression metrics. Regression metrics compare true target variables y_i with their corresponding predictions $\widehat{y}_i$. Common metrics for regression problems are the R^2-score (Eq. (12)), the mean absolute error (*MAE*) (Eq. (13)), and the root mean square error (*RMSE*) (Eq. (14)). Accurate predictions are indicated both by low *MAE* and *RMSE* values and R^2-scores close to 1. (Fahrmeir et al., 2009; Willmott and Matsuura, 2005).

$$R^2 = \frac{\sum_{i=1}^{n} (\widehat{y}_i - \overline{y})^2}{\sum_{i=1}^{n} (y_i - \overline{y})^2}, \text{ with } \overline{y} = \frac{\sum_{i=1}^{n} y_i}{n} \tag{12}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |\widehat{y}_i - y_i| \tag{13}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\widehat{y}_i - y_i)^2} \tag{14}$$

3. Material and methods

To achieve the research objectives outlined in Section 1.3, we conducted a systematic literature review. Systematic literature reviews are a method for identifying, evaluating and interpreting all available research relevant to a particular set of research questions (Kitchenham, 2007).

Based on the systematic literature review guidelines of Kitchenham (2007), the following steps were taken to conduct the review: formulation of research questions (Section 3.1), development of a search strategy (Section 3.2), selection of relevant publications (Section 3.3), quality assessment of selected publications (Section 3.4), and data extraction (Section 3.5).

3.1. Research questions

To achieve the research objectives outlined in Section 1.3, the following six research questions (RQs) have been formulated:

RQ 1. Which *material flows* and *material classes* have been investigated so far, and which material flows have been addressed most frequently?

RQ 2. The prediction of which *characteristics* has been investigated and which *investigation levels* have been targeted?

RQ 3. Which optical *sensors* have been applied for which tasks?

RQ 4. Which *ML algorithms* have been applied and which prediction accuracies have been achieved?

RQ 5. Which *applications* are envisioned based on SBMC methods, and at which *scales* have the investigations occurred?

RQ 6. How *interconnected* is SBMC research, and how is the research of different SBMC aspects interlinked?

3.2. Search strategy

Firstly, an initial literature set was compiled from prior known publications and initial searches. Then, based on the initial literature set, multiple search strings were developed, tested, and iteratively optimized for the full review. Furthermore, systematic forward and backward searches were applied to extend the obtained literature set.

3.2.1. Search strings

The developed search strings (Table 4) targeted different sensor applications (sorting, quality control, characterization, monitoring, process control), methods (classification/discrimination), and MFCs (material composition, PSD; cf. Section 2.1.3). Depending on the relevance for the target, the individual search words either target for the title (*TITLE*) or the title, abstract, and keywords (*TITLE-ABS-KEY*). Using Boolean operators (*AND*, *OR*) and wildcard operators (*) ensured that different spellings and synonyms were considered. All search strings were adapted to the database-specific syntax (Table 4 shows the syntax for Scopus as an example).

3.2.2. Databases

All search strings were applied to three large, multidisciplinary bibliographic databases of three different providers to minimize potential biases through database selection and identify as many relevant publications as possible. The three selected databases were Scopus (Scopus., 2021), Web of Science (Clarivate, 2021), and Google Scholar (Google LLC, 2021). All search strings were applied in October 2021.

3.2.3. Forward and backward searches

To identify relevant publications that might not be covered by the search strings (cf. Table 4), all references of the selected publications (*backward search*) as well as citations of those publications (*forward search*) were included in the review and underwent the selection process (Section 3.3). In this way, the review relies not only on the developed search strategy but also utilizes the extensive literature searches of each of the included publications and overcomes possible limitations of the developed search strings.

3.3. Selection criteria and procedures

3.3.1. Inclusion criteria

Of interest for our review are publications on in- or online applications of optical sensor technologies for material flows in dry-mechanical recycling processes of non-hazardous wastes. We considered peer-reviewed journal articles in the English language published in the time

Table 4
Developed and applied search strings for the systematic literature review; Abbr.: Abbreviation.

Abbr.	Target	Search string
Q	Quality control	*TITLE-ABS-KEY*(quality *AND* (product *OR* assess* *OR* analys* *OR* control* *OR* monitor* *OR* assurance)) *AND TITLE*((waste *OR* recyc* *OR* recover* *OR* "post-consumer" *OR* "post-industrial") *AND* (sensor* *OR* *spectr* *OR* imag*))
C	Characterization	*TITLE-ABS-KEY*(characteri*) *AND TITLE*((waste *OR* recyc* *OR* recover* *OR* "post-consumer" *OR* "post-industrial") *AND* (sensor* *OR* *spectr* *OR* imag*))
M	Monitoring	*TITLE-ABS-KEY*(monitor*) *AND TITLE*((waste *OR* recyc* *OR* recover* *OR* "post-consumer" *OR* "post-industrial") *AND* (sensor* *OR* *spectr* *OR* imag*))
P	Process control	*TITLE-ABS-KEY*("process control" *OR* real*time *OR* on*line *OR* in*line) *AND TITLE*(waste *OR* recyc* *OR* "post-consumer" *OR* "post-industrial")
S	SBS	*TITLE-ABS-KEY*((sensor*based *OR* automatic) *AND* (sort* *OR* separat*)) *AND TITLE*(waste *OR* recyc* *OR* "post-consumer" *OR* "post-industrial")
D	Classification/ discrimination	*TITLE-ABS-KEY*(classif* *OR* discrimi*) *AND TITLE*((waste *OR* recyc* *OR* recover* *OR* "post-consumer" *OR* "post-industrial") *AND* (sensor* *OR* *spectr* *OR* imag*))
CO	Composition	*TITLE-ABS-KEY*(content *OR* composition *OR* purity) *AND TITLE*((waste *OR* recyc* *OR* recover* *OR* "post-consumer" *OR* "post-industrial") *AND* (sensor* *OR* *spectr* *OR* imag*))
PS	PSD	*TITLE-ABS-KEY*((particle *OR* grain) *AND* (size *OR* distribution)) *AND TITLE*((waste *OR* recyc* *OR* recover* *OR* "post-consumer" *OR* "post-industrial") *AND* (sensor* *OR* *spectr* *OR* imag*))

range from 2000 to 2021. The scope was limited to peer-reviewed journal articles to ensure a high quality of included manuscripts (Xiao and Watson, 2019) and maximum transparency of the search and selection process (Kraus et al., 2020). The timeframe 2000 – 2021 was chosen as related reviews indicated that most publications on sensor technologies in the waste management sector had been published from 2012 onwards (Sarc et al., 2019), and far older publications are often less relevant due to advancements in sensor technologies and ML algorithms in recent years (Vrancken et al., 2017; Xia et al., 2021b).

3.3.2. Exclusion criteria

Publications on hazardous wastes, biological or chemical treatment of wastes, liquid or gaseous wastes (e.g., wastewater or sludges), and mining wastes were not considered as these applications address significantly other MFCs compared to those relevant for mechanical recycling processes (cf. Section 2.1). Similarly, (pre-)treatment of wastes for thermal processes, including solid recovered fuel production, are not considered, which have been partly reviewed by Vrancken et al. (2017). Publications using virgin materials were only considered if an intended application for mechanical recycling is outlined in the abstract or title.

Non-sensor-based characterization methods and methods that cannot be directly applied to inline or online characterization are not considered as they are not suitable for inline SBMC in sorting and processing plants (see Section 2). Such methods include (semi-)manual methods, non-inline laboratory measurements (e.g., microscopes), sensors that strictly require a 1D singulation of the material flow, or manual positioning (e.g., handheld devices).

Furthermore, applications of sensors at the waste segregation or collection level were excluded, as the material presented to the sensor units in these applications differ from online and inline applications in sorting and processing plants (e.g., 1D singulation and material presentation), cf. Section 2.2.2. Applications of sensors for waste segregation and collection have, among others, been reviewed by Hannan et al. (2015).

3.3.3. Selection process

For publications identified by the search strategy (cf. Section 3.2), a multi-stage selection process (cf. Fig. 2) was conducted. Firstly, the titles of all search results were screened, and publications not meeting the selection criteria were excluded. Secondly, the abstract and keywords of all non-excluded publications were checked, and publications not meeting the selection criteria were further excluded. Thirdly, full copies of all non-excluded publications were obtained and checked against the inclusion and exclusion criteria. In case of uncertainty, a copy was sent to a second reviewer and discussed within the review team.

Due to the full-text search and lack of filters in Google Scholar, we observed a large number of hits for each search string (17,400 – 19,400 hits per search string, 144,500 hits in total). As Google Scholar sorts the search results by relevance and screening all 144,500 titles was practically infeasible, we limited the title screening in Google Scholar to the first 300, i.e., the most relevant, results. The limit of 300 publications was chosen because (i) we did not find additional publications in our scope after screening the first 200 search results, and (ii) we observed a similar number of hits for Web of Science and Scopus with the title and abstract specific search terms (cf. Fig. 2).

3.3.4. Included and excluded publications

In total, $n = 11{,}607$ publications were found by applying the eight search strings. $n = 10{,}720$ publications were excluded during title screening. From the remaining $n = 887$ publications, $n = 377$ publications were excluded during abstract screening. After removing $n = 309$ duplicates (publications that match multiple search strings), a total of $n = 201$ publications were selected for review. Unfortunately, $n = 4$ of these $n = 201$ publications were unavailable, despite all efforts devoted (search all available databases, search journal/publisher page, contact corresponding authors directly via ResearchGate and e-mail). $n = 108$ publications were considered out of scope during the full review. Applying the forward and backward searches revealed another $n = 217$ publications after abstract and title screening, of which $n = 113$ met the selection criteria after full review and were included in the review. The final dataset obtained $n = 198$ publications, as summarized in Fig. 2.

3.4. Quality assessment

For each publication, a quality assessment (QA) was performed by answering the following four QA questions for each included publication:

QA 1. Is the publication an original research article (i.e., did the publication conduct an experiment or propose a new method/concept)? *Yes (1 P), No (0 P).*

QA 2. Did the publication reference related work and contextualize the findings within existing research? *Yes (1 P), Partly (0.5 P), No (0 P).*

QA 3. Are the applied methods clearly described (e.g., applied sensor (s), measurement settings, applied preprocessing techniques and ML algorithms)? *Yes (1 P), Partly (0.5 P), No (0 P).*

QA 4. Are the results clearly described and discussed (e.g., quantitative assessment of achieved prediction results)? *Yes (1 P), Partly (0.5 P), No (0 P).*

Extensive pre-review discussion ensured a consistent calibration of all reviewers. Uncertainties and edge cases were discussed and jointly decided within the review team. By summing up the scores of all four QA questions, an overall QA score was obtained. The final review considered publications with overall QA scores greater than 3.

3.5. Data extraction

To answer the research questions, a data extraction form was developed (Table 5), based on which the relevant data was extracted.

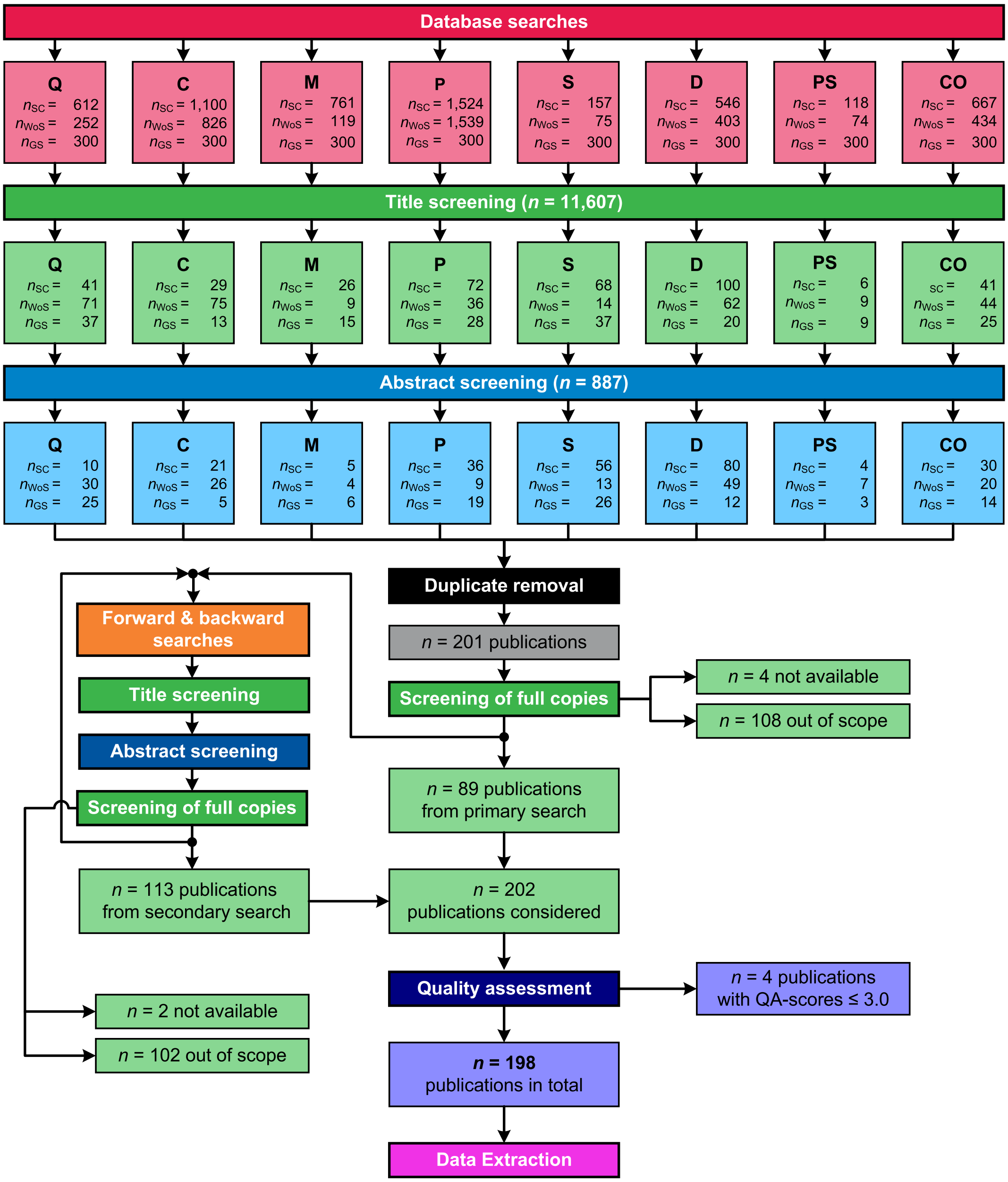

Fig. 2. Included and excluded publications. SC: Scopus, WoS: Web of Science, GS: Google Scholar; Q, C, M, P, S, D, PS, CO: search string abbreviations introduced in Table 4.

For each publication, a unique identifier was used to connect the extracted data to the bibliometric *meta*-information. Data extraction was performed by one reviewer and checked by a second reviewer. Ambiguities or discrepancies during data extraction were discussed within the review team.

As some authors published two or more independent investigations in one publication, while others split such results into multiple publications, a potential weighting bias could occur in subsequent data analysis. Furthermore, combining multiple independent investigations into one publication complicates data extraction and analysis. To minimize such biases and ensure a sophisticated data analysis, we decided to split up publications containing multiple independent experiments into separate *investigations* during data extraction and assess them independently from each other during data analysis (Section 4). Thus, one publication can contain one or multiple investigations. Examples of such publications include, e.g., publications that reported a series of investigations for different sensors, material flows, or scales (e.g., laboratory experiments followed by scale-up to industrial level) in independent experiments.

4. Results and discussion

After data extraction, the final obtained dataset contains $n = 267$ investigations from $n = 198$ publications. As a reference for the reader, we summarize all publications sorted by applied sensors and investigated material flows in Table 6. As shown in Fig. 3a, the number of reported investigations increases super-linear from $n = 2$ investigations in 2000 to $n = 65$ investigations in 2021. More than half of all investigations (155 of 267, 58.1%) were published between 2019 and 2021.

4.1. Material flows and classes

In total, $n = 17$ different material flows were studied by the

Table 5
Description of the developed data extraction form for the systematic literature review.

Field	Description
Sensor	Type of applied sensor, including multi-sensors (cf. Table 3).
Investigated materials	List of investigated materials (e.g., ["PET", "PE", "PP"]).
Material flow	Material flow from which the investigated sample originated (e.g., WEEE or MSW).
Virgin samples	Whether virgin materials were used as sample material (see Section 3.3.1).
Investigation method	Used investigation method (e.g., spectra description, classification, sensor-based sorting, material flow monitoring).
Investigation level	Whether the investigation was applied at the pixel, particle, material flow, or process level (cf. Section 2.3.1).
Investigation scale	Measure for scale and technological readiness level (TRL) (International Organization for Standardization, 2013) of the investigated technology: *concept*: formulation of (unproven) concepts (TRL 0–2), *lab scale*: basic research and laboratory-scale prototypes (TRL 2–4), *industrial-scale*: research at an industrial scale or industrial-scale prototypes (TRL 5–8), *plant scale*: investigations in plant scale (TRL 6–9).
Applied ML algorithm(s)	List of applied ML algorithms (excluding non-ML algorithms and static [preprocessing] algorithms).
Best ML algorithm	Best performing ML algorithm (highest *score* on test data).
Score type	Type of score (e.g., accuracy, F1-score, R^2-score; cf. Section 2.3.2).
Score	Score value on test data (aggregated as macro-average; cf. Section 2.3.2.1).
Intended application(s)	List of intended applications from the publication.
Quality assessment	Answers to QA questions, upon which the QA score is calculated (cf. Section 3.4).

investigations in our dataset. Table 7 summarizes the investigated material flows and introduces their abbreviations.

4.1.1. Investigated material flows

As shown in Table 7, about a third of all investigations focused on plastics (32.6%), followed by WEEE (11.2%), and CDW (10.1%). SBMC on public datasets such as *TrashNet* (Yang and Thung, 2016) and *Huawei garbage classification challenge cup* (Huawei, 2019) was examined by only 16 of 267 investigations (6.0%); the majority of researchers generated the sensor data for the investigation itself.

As shown in Fig. 3a, the focus of the investigations in our dataset has shifted over time. For example, while investigations on publicly available *datasets* started in 2019 and doubled or more since then, no new investigations on the material flow *paper* have been reported in our dataset since 2015. To quantify which material flows have gained or lost relative importance, we calculated for each material flow its relative frequency among (a) all investigations in the last five years (2016 – 2021) and (b) the years before (2000 – 2016). By comparing both relative frequencies, we observe that investigations on *datasets* (+9.8 percentage points [pp] increase in relative frequency), *plastics* (+5.2 pp) and *waste* in general (+5.2 pp) have gained relative frequency, while investigations on *paper* (-13.3 pp), *ASR/ELV* (-8.0 pp), and *CDW* (-6.3 pp) have lost relative frequency.

4.1.2. Investigated material classes

In total, 594 unique material classes (including subgroups such as high-density (HD)- and low-density (LD)-PE) and 321 unique material groups (after summarizing material classes to material groups, e.g., summarizing LDPE and HDPE to PE) have been reported. By analyzing the correlation (simultaneous occurrence) between the 20 most frequently studied material classes in Fig. 3b, we identify two groups of investigations.

The first group focuses on the classification of different polymers. Here, the classification often takes place on the pixel level and based on NIR data. The focus of the first group is often on plastic waste streams or plastics in other material flows (e.g., LWP or WEEE). Material classes frequently investigated by this group are also among the most frequently investigated pixel-level material classes (PP, PE, PET, PS, and PVC), see Fig. 3c.

The second group focuses on the discrimination of more general waste classes. Here, the classification often takes place at the particle level and with deep learning classification models on VIS-RGB data, e.g., from public datasets. Material classes frequently investigated by this group are also among the most frequently investigated particle-level material classes (plastics, paper, glass, metal, and cardboard), which correspond to the material classes of *TrashNet* (Yang and Thung, 2016), see Fig. 3d.

In contrast to the pixel and particle level, significantly less material groups are mentioned at the material flow level (Fig. 3e), which is likely caused by the few investigations published so far (see Section 4.2.1).

4.2. Characteristics and investigation levels

Fig. 4 summarizes the investigated characteristics and investigation levels by investigations in our dataset.

4.2.1. Investigation levels

As shown in Fig. 4a, investigations in our dataset have so far focused almost exclusively at the pixel and particle level with 123 (46.1%) and 133 of 267 (49.8%) investigations, respectively. Only $n = 11$ (4.1%) investigations addressed the material flow level, and we identified no investigations at the process level (cf. Section 2.3.1). For all three investigation levels, the number of investigations increases super-linear over time (Fig. 4a). Applying the trend analysis of Section 4.1.1 (2000 – 2015 vs. 2016 – 2021) shows a relative increase of investigations at the particle (+5.9 pp) and material flow (+3.4 pp) level compared to a relative decrease of investigations at the pixel level (-9.3 pp).

We assume two main reasons can explain the large discrepancy between the number of investigations at the pixel and particle vs. the material flow level. First, precise predictions at the pixel and particle level are often needed as a basis for investigations at the material flow level (cf. Section 2.3.1 and Fig. 1); thus, investigations at the pixel and particle level need to be conducted first. Second, pixel- and particle-based analysis finds a broader application than material flow-based analysis: As elaborated in Section 2, industrial applications in the past three decades have primarily focused on SBS (Feil et al., 2021), which requires pixel- and particle-based material classification, while other SBMC applications at material flow level have only emerged in recent years (see Section 4.4).

While the increased share of material flow-based investigations might indicate an increased research interest in SBMC applications beyond SBS, the increased share of particle-based investigations is likely caused by an increased application of deep learning classification algorithms in recent years (see Section 4.4.1), which are often directly applied to images (LeCun et al., 2015), i.e., particles (Kroell et al., 2021b).

4.2.2. Investigated characteristics

Investigations in our dataset almost exclusively focused on iMFCs. eMFCs have in our dataset only been investigated by Feil et al. (2019) and Curtis et al. (2021) in terms of volume flows and we identified no investigations on the determination of mass flows in our dataset.

Regarding iMFCs, investigations have so far mostly focused on material classification (207 of 264 investigations, 78.4%). Despite the practical relevance of PSDs derived in Section 2.1.3, only $n = 3$ investigations studied the determination of particle sizes at the particle (Hoffmann Sampaio et al., 2021; Kandlbauer et al., 2021) and material flow level (Di Maria et al., 2016).

As shown in Fig. 4c, the variety of investigated characteristics has

Table 6
Overview of the 198 publications in scope of the review arranged by applied sensors (columns) and addressed material flows (rows).

	VIS-RGB	VIS-HSI	VNIR-HSI	NIR	MIR	FTIR	thermal	RAMAN	THz	3DLT	multi-sensor
ASR/ELV	(Chen et al., 2021b; Li et al., 2021b; Wang et al., 2019a)	–	(Barnabé et al., 2015; Serranti et al., 2011)	(Barnabé et al., 2015; Serranti et al., 2011; Zhao and Chen, 2015)	–	–	–	–	–	(Koyanaka et al., 2013; Koyanaka and Kobayashi, 2010)	(Barnabé et al., 2015)
CDW	(Anding et al., 2013; Chen et al., 2021a; Davis et al., 2021; Di Maria et al., 2016; Gokyuu et al., 2011; Hoffmann Sampaio et al., 2021; Hoong et al., 2020; Lu et al., 2022a; Zhuang et al., 2019)	–	(Serranti et al., 2011)	(Bonifazi et al., 2018b, 2017, 2015; de Groot et al., 2002, 2001; Ku et al., 2021; Luciani et al., 2015; Serranti et al., 2015b; Serranti et al., 2012a, 2011; Trotta et al., 2021; Vegas et al., 2015; Xiao et al., 2020; Xiao et al., 2019a, Xiao et al., 2019b)	–	–	–	–	–	(Ku et al., 2021; Xiao et al., 2020)	(Ku et al., 2021; Xiao et al., 2020)
LWP	(Kroell, 2021)	–	–	(Chen et al., 2021f; Chen et al., 2021c; Chen et al., 2021e; Chen et al., 2020; Curtis et al., 2021)	–	–	–	–	–	(Feil et al., 2019; Kroell, 2021)	(Kroell, 2021)
MCW	(Kandlbauer et al., 2021)	–	–	(Curtis et al., 2021; Möllnitz et al., 2021)	–	–	–	–	–	(Curtis et al., 2021)	–
MSW	(Bobulski et al., 2021; Kiyokawa et al., 2021; Li and Chen, 2020; Mustaffa et al., 2019; Yu et al., 2020; Zhang et al., 2019)	–	–	(Hryb, 2015; Hu et al., 2013; Möllnitz et al., 2021; Serranti et al., 2015; Serranti et al., 2012b; Zheng et al., 2018)	(Rozenstein et al., 2017)	–	(Gundupalli et al., 2017b)	–	–	(Feil et al., 2019)	–
WEEE	(Hayashi et al., 2019; Lu et al., 2022b)	Picón et al., 2012; Picón et al., 2009)	(Barnabé et al., 2015; Candiani et al., 2017)	(Barnabé et al., 2015; Beigbeder et al., 2013; Bonifazi et al., 2020a; Bonifazi et al., 2020b, 2020c; Candiani et al., 2017; Palmieri et al., 2014; Wu et al., 2020)	(Jacquin et al., 2021; Signoret et al., 2020a; Signoret et al., 2020b; Signoret et al., 2019a, 2019b)	(Protopapa et al., 2021; Taurino et al., 2010)	(Gundupalli et al., 2018)	(Protopapa et al., 2021)	–	–	(Barnabé et al., 2015; Candiani et al., 2017)
Glass	(Krcmarik et al., 2019)	–	(Bonifazi and Serranti, 2006)	(Bonifazi and Serranti, 2006)	(Serranti et al., 2006)	(Farcomeni et al., 2008)	–	(de Groot et al., 2002)	–	–	(Bonifazi and Serranti, 2006)

(*continued on next page*)

Table 6 (*continued*)

	VIS-RGB	VIS-HSI	VNIR-HSI	NIR	MIR	FTIR	thermal	RAMAN	THz	3DLT	multi-sensor
Landfill	–	–	–	(Küppers et al., 2019b)	–	–	–	–	–	–	–
Metals	(Díaz-Romero et al., 2021)	–	–	–	–	–	–	–	–	(Díaz-Romero et al., 2021)	(Díaz-Romero et al., 2021)
Paper	(Rahman et al., 2015; Rahman et al., 2012a; Rahman et al., 2012b; Rahman et al., 2011; Rahman et al., 2010; Rahman et al., 2009; Shan et al., 2014)	(Ramasubramanian et al., 2005)	–	(Borel et al., 2007; Tatzer et al., 2005)	–	–	–	–	–	–	–
Plastics	(Fang et al., 2021; Küppers et al., 2020; Özkan et al., 2015; Peršak et al., 2020; Ramli et al., 2008; Scavino et al., 2009a; Scavino et al., 2009b; Tachwali et al., 2007; Tan et al., 2021; Wang et al., 2019b; Zulkifley et al., 2014)	(Arenas-Vivo et al., 2017; Kuřitka et al., 2020; Rafi Ahmad, 2000; Safavi et al., 2010; Woidasky et al., 2020)	(Brunner et al., 2015; Fomin et al., 2017; Fomin and Kargel, 2019; Gruber et al., 2019; Gruber et al., 2018; Maris et al., 2012; Serranti et al., 2010; Serranti and Bonifazi, 2010)	(Alassali et al., 2018; Barcala et al., 2004; Bonifazi et al., 2021; Bonifazi et al., 2018a; Calvini et al., 2018; Cucuzza et al., 2021; Duan and Li, 2021; Galdón-Navarro et al., 2018; Kulcke et al., 2003; Küppers et al., 2021; Küppers et al., 2019c; Küppers et al., 2019a; Leitner et al., 2003; Li et al., 2019; Michel et al., 2020; Moroni et al., 2015; Moroni and Mei, 2020; Pieszczek, l., Daszykowski, M., , 2019; Serranti and Bonifazi, 2010; Tachwali et al., 2007; Ulrici et al., 2013; van Engelshoven et al., 2019; Vázquez-Guardado et al., 2015; Wahab et al., 2006; Xia et al., 2021a; Yang et al., 2020; Zhu et al., 2019)	(Becker et al., 2017; Kassouf et al., 2014; Signoret et al., 2020a,2019a ; Vázquez-Guardado et al., 2015; Zinchik et al., 2021)	(Bae et al., 2019; da Silva and Wiebeck, 2017; Jiang et al., 2021; Michel et al., 2020; Roh et al., 2018; Serranti and Bonifazi, 2010)	–	(Bae et al., 2019; da Silva and Wiebeck, 2017; Roh et al., 2017; Roh and Oh, 2016; Serranti and Bonifazi, 2010)	(Küter et al., 2018)	–	(Serranti and Bonifazi, 2010; Tachwali et al., 2007)
Textile	(Furferi and Governi, 2008; Zhou et al., 2021)	(Furferi and Governi, 2008)	(Blanch-Perez-del-Notario et al., 2019)	(Cura et al., 2021; Li et al., 2021a; Liu et al., 2020; Mäkelä et al., 2020; Zhou et al., 2019)	–	(Riba et al., 2020)	–	–	–	–	–
Waste	(Altikat et al., 2022; Chen et al., 2021g; Fatovatikhah et al., 2021; Gondal et al., 2021; Guo et al., 2021; Kumar et al., 2021;	–	–	(Serranti et al., 2011)	–	–	–	–	–	–	–

(*continued on next page*)

Table 6 (*continued*)

	VIS-RGB	VIS-HSI	VNIR-HSI	NIR	MIR	FTIR	thermal	RAMAN	**THz**	**3DLT**	**multi-sensor**
	Liang and Gu, 2021; Ma et al., 2020; Masand et al., 2021; Pieper et al., 2018; Salmador et al., 2008; Toğaçar et al., 2020; Vo et al., 2019; Wang et al., 2020; Zhang et al., 2021; Zheng and Gu, 2021)										
Wood	–	–	(Kobori et al., 2008)	(Jin et al., 2020; Kobori et al., 2017; Kobori et al., 2008; Mauruschat et al., 2016; So et al., 2004; Tsuchikawa et al., 2003; Tsuchikawa and Yamato, 2003)	–	–	–	–	–	–	(Kobori et al., 2008)
Dataset	(Adedeji and Wang, 2019; Ahmad et al., 2020; Fu et al., 2021; Huang et al., 2021; Huang et al., 2020; Mao et al., 2021; Masand et al., 2021; Melinte et al., 2020; Patrizi et al., 2021; Qin et al., 2021; Rajak et al., 2020; Shi et al., 2021; Vo et al., 2019; Zhang et al., 2021; Zheng and Gu, 2021)	–	–	–	–	–	–	–	–	–	–
Virgin	(Maier et al., 2019; Rybarczyk et al., 2020)	–	–	–	–	–	–	–	–	–	–
None	(Ata et al., 2005; Maier et al., 2021)	–	–	–	–	–	–	–	–	(Mattone et al., 2000)	–

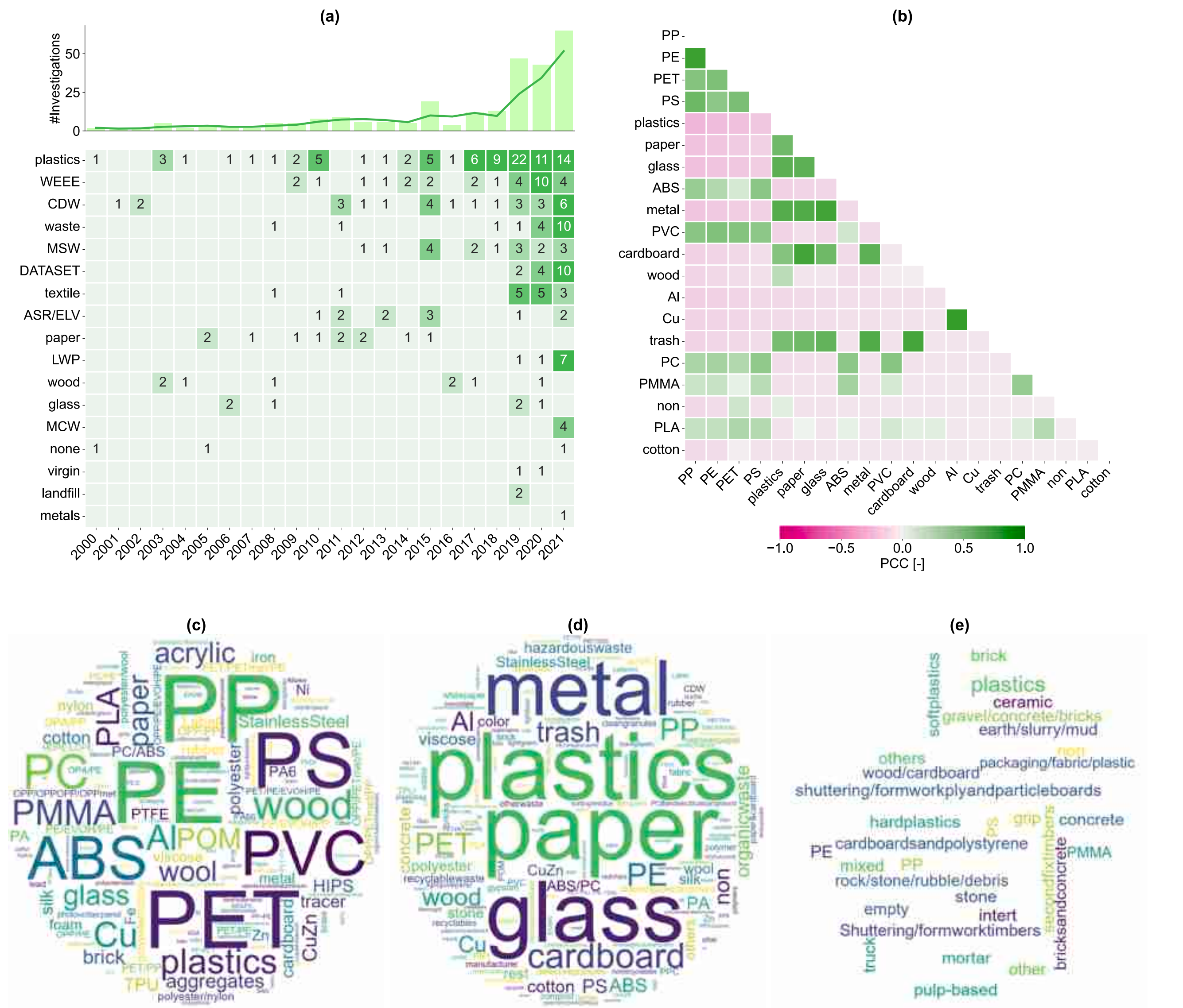

Fig. 3. Material flows and material classes. (a) Material flows and total investigations per year; (b) correlation between the 20 most frequent (top 20) material classes; (c-e) word clouds (Mueller et al., 2018) of investigated material classes (font size proportional to frequency) on the (c) pixel, (d) particle and (e) material flow investigation level. ABS: Acrylonitrile butadiene styrene, HIPS: High Impact PS, PA: Polyamide, PBT: Polybutylene terephthalate, PC: Polycarbonate, PE: Polyethylene, PET: Polyethylenterephthalate, PMMA: Polymethylmethacrylate, POM: Polyoxymethylene, PP: Polypropylene, PPS: Polyphenylene sulfide, PS: Polystyrene, PVC: Polyvinylchloride, PVDF: Polyvinylidenfluoride, SBR: Styrene-butadiene rubber, TEEE: Thermoplastic elastomer-ether-ester, TPE: Thermoplastic elastomers, TPU: Thermoplastic polyurethane, TPU: Thermoplastic polyurethanes; BC: Beverage carton, PPC: Paper, paperboard and cardboard; Al: Aluminium, Au: Gold, Cu: Copper, CuZn: Brass, Fe: Iron, Ni: Nickel.

expanded over time, especially over the last five years. Until 2015, researchers in our dataset have focused on a total of six different characteristics: material identification, i.e., the determination of *material classes* (since 2001), *material compositions* (since 2004), and *material flow compositions* (since 2011); the identification of *tracers* (since 2000) and *colors* (since 2005); and image *segmentation* (since 2000). Starting in 2016, newer publications widened the scope of investigated characteristics subsequently to *PSDs* (Di Maria et al., 2016), *presentation iMFCs* (Pieper et al., 2018), mechanical properties (*melt viscosity* and *tensile strength*) (van Engelshoven et al., 2019), *sub material classes* (van Engelshoven et al., 2019), *volume flows* (Feil et al., 2019), *particle sizes* (Kandlbauer et al., 2021), *particle masses* (Kroell et al., 2021a), and *grasping parameters* (Ku et al., 2021).

When comparing the relative frequency between characteristics for material and color identification (*material class*, *material composition*, *material flow composition*, *color class*) and all other characteristics in 2000 – 2015 vs. 2016 – 2021 (cf. Section 4.1.1), we observe a relative decrease of investigations on material and color classification (-9.1 pp) and a simultaneous increase of investigations on other characteristics (+9.1 pp).

A likely explanation of the large share of material (as well as color and tracer) classification investigations in our dataset is the outstanding importance of material and color classification for SBS, to which much research has been devoted in recent years (Gundupalli et al., 2017a). In contrast, the expansion of the addressed characteristics and the higher relative shares of other characteristics indicates a more widened use of sensor data for advanced SBS and other SBMC applications.

4.2.2.1. Investigated characteristics at different investigation levels. As shown in Fig. 4b, the investigated characteristics differ per investigation level. Publications in our dataset have so far reported four groups of characteristics (see braces in Fig. 4b): (i) purely pixel-based, (ii) pixel- or particle-based, (iii) purely particle-based, and (iv) purely material-flow-

Table 7
Overview on investigated material flows.

Material flow	Abbreviation	#Investigations	%
Plastics	–	87	32.6%
Waste from electrical and electronic equipment	WEEE	30	11.2%
Construction and demolition waste	CDW	27	10.1%
Waste (not further specified)		18	6.7%
Mixed solid waste	MSW	17	6.4%
Dataset	–	16	6.0%
Textile	–	15	5.6%
Automotive shredder residue/end-of-life vehicles	ASR/ELV	11	4.1%
Paper	–	11	4.1%
Lightweight packaging waste	LWP	9	3.4%
Wood	–	8	3.0%
Glass	–	6	2.2%
Mixed commercial waste	MCW	4	1.5%
None (no material flow addressed)	–	3	1.1%
Landfill	–	2	0.7%
Virgin test material	–	2	0.7%
Metals	–	1	0.4%
	Σ	267	100.0%

based characteristics.

4.2.2.2. Investigated characteristics for different material flows. While material classification has been investigated for all identified material flows (except for *virgin* and *none*), many other characteristics have so far been investigated for only few material flows (Fig. 4d). For example, the prediction of particle sizes and PSDs has only been researched for CDW and MCW (Di Maria et al., 2016; Hoffmann Sampaio et al., 2021; Kandlbauer et al., 2021); particle mass prediction has only been studied for LWP waste (Kroell et al., 2021a); mechanical material properties have only been predicted for plastics (van Engelshoven et al., 2019) in our dataset. The highest number of unique characteristics have been investigated for plastics (8 of 16 characteristics, 50.0%).

4.3. Sensors

As shown in Fig. 5, ten different optical sensors were applied in total: NIR, VIS-RGB, VNIR-HSI, MIR, 3DLT, Fourier-transform infrared spectroscopy (FTIR), VIS-HSI, RAMAN, THz, and thermal sensors, with the VIS-NIR range being addressed most frequently (234 of 282 mentioned sensors, 83.0%). Comparing the relative frequency of sensors from 2000 – 2015 and 2016 – 2021 (cf. Section 4.1.1) shows that especially VIS-RGB sensors have been increasingly applied in recent years (+14.6 pp).

Fig. 5a shows that within the theoretical wavelength ranges of each sensor (cf. Table 3), sensors in the investigations were operated at specific wavelength ranges to varying extents: For example, NIR sensors theoretically covering the wavelength range from 780 nm to 2500 nm, have increasingly been applied in between 1000 nm and 1700 nm, which results from the high market share of sensors in a lower wavelength range but at the same time sufficient distinct spectra of commonly applied materials.

Multi-sensors offer the possibility of combining advantages and compensating disadvantages of different sensors; however, only 15 of 267 (5.6%) investigations in our dataset applied multi-sensors. One reason for this may be the increased technical effort required to merge the data from multiple sensors (early or late sensor fusion). The 15 multi-sensor investigations have so far focused on the combination of NIR, VNIR, 3DLT, and VIS-RGB sensors.

4.3.1. Applied sensors for different characteristics

The 16 different characteristics presented in Section 4.2 can be abstracted into three distinct tasks: (i) material identification, (ii)

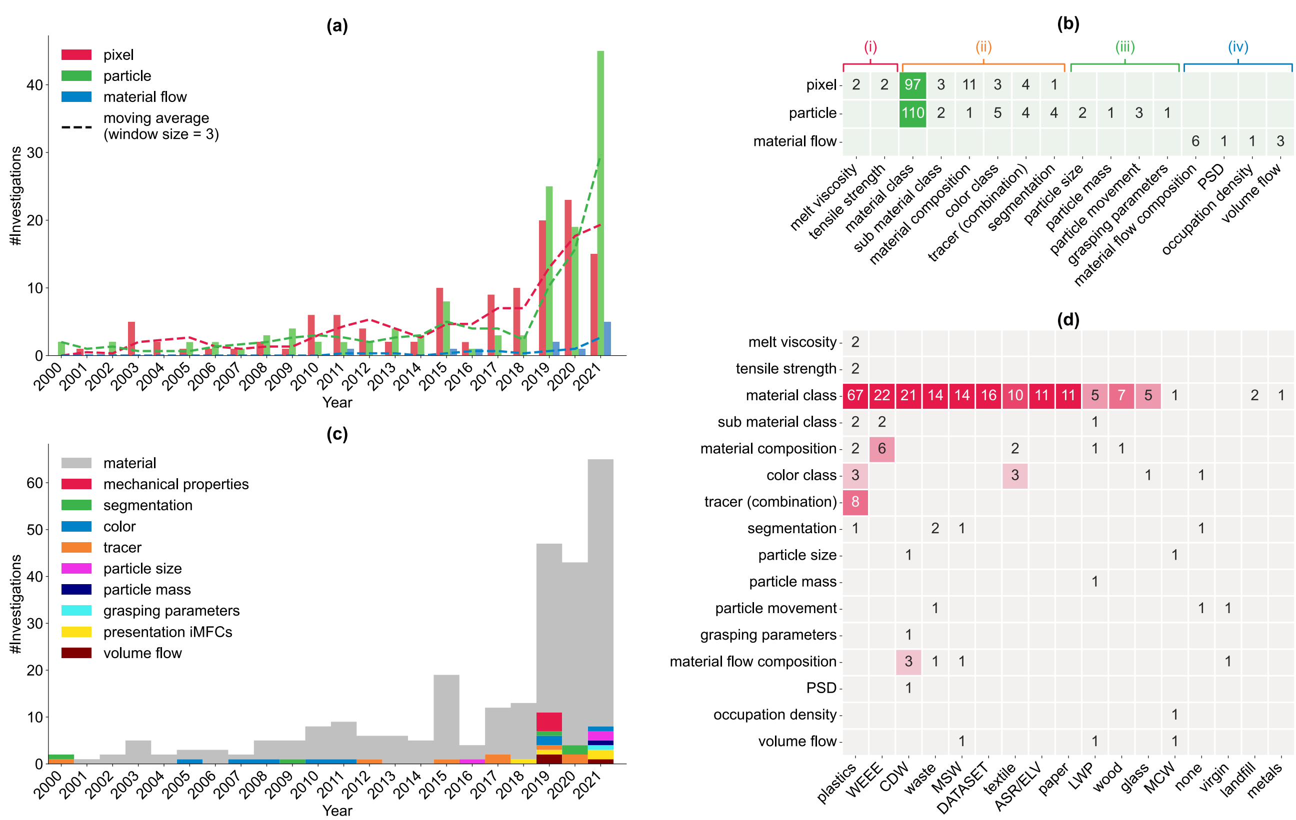

Fig. 4. Characteristics and investigation levels. (a) Investigation levels per year; (b) investigated characteristics per material flow, (i) purely pixel-based, (ii) pixel- or particle-based, (iii) purely particle-based, (iv) purely material-flow-based characteristics; (c) investigated characteristics (aggregated) per year; (d) investigation levels per material flows (see Table 7 for abbreviated material flows).

Fig. 5. Sensors. (a) Addressed wavelength ranges (kernel density estimation), (i) full optical wavelength range (100 nm – 1 mm) in logarithmic scale*, (ii) zoom in on VIS-NIR range; (b-f) investigated sensors per (b) investigation level, (c) year, (d) characteristic, (e) material classes (top 20), and (f) material flow. *two THz-investigations from (Küter et al., 2018) focus on the lower THz range (84 GHz to 96 GHz) and are not shown in [a] for better readability.

segmentation and measurement, and (iii) prediction of material properties.

4.3.1.1. Material identification. Material identification can be performed at the pixel, particle and material flow level. At the **pixel level**, predominantly sensors in the IR range (NIR, MIR, and FTIR) have been applied (Fig. 5b). Especially for common plastics and other IR-active materials, NIR-based material classification has been developed to such an extent that classification accuracies of more than 99% have been achieved in many applications (e.g., Duan and Li, 2021; Jin et al., 2020; Li et al., 2021a; Palmieri et al., 2014; Zheng et al., 2018).

Partly for this reason, research interest has shifted to newer classification applications in the NIR wavelength range in recent years. Examples for such new applications are the discrimination of LDPE and HDPE (Bonifazi et al., 2018a), increasing classification depths (e.g., packaging types) (van Engelshoven et al., 2019), investigations of mixed NIR spectra such as multilayer plastics (Chen et al., 2021f; Chen et al., 2020), classification of new materials such as bioplastics (e.g., Chen et al., 2021e; Moroni and Mei, 2020), and investigation and prediction of aging or degradation processes based on NIR spectra (e.g., Chen et al., 2021c; Chen et al., 2021e).

In addition to NIR, fundamental vibrations in the MIR range open new sensor-based characterization opportunities. Besides an early study by Serranti et al. (2006) focusing an the detection of ceramic glass contaminants with MIR, investigations on MIR have been increasingly conducted since 2014 (Fig. 5c). In contrast to NIR, most MIR investigations (10 of 13, 76.9%) are limited to a pure description of the spectra data and classifications based on MIR has so far only been reported by Kassouf et al. (2014), Jacquin et al. (2021), and Zinchik et al. (2021) with classification accuracies between 92% and 100%. The low share of classification investigations based on MIR might be attributed to the lower technological maturity of MIR compared to NIR. Furthermore, MIR investigations to date have focused almost exclusively on plastic identification with the exception of the aforementioned investigation by Serranti et al. (2006) (detection of ceramic glass contaminants) and an investigation by Rozenstein et al. (2017) (PET, PE, PVC, PP, PLA, PS, cardboard, paper, and wood). Moreover, the focus of MIR investigations is often on technical polymers or carbon black plastics (cf. Table 6), for which the classification based on NIR can be difficult or even technical impossible. In addition, advanced material characterization (e.g., investigation of aging effects) represents an application field of MIR (Signoret et al., 2020b).

In contrast to the pixel level, VIS-RGB and 3DLT sensors are particularly used at the **particle level** (cf. Fig. 5b). Two main reasons for the increased application of VIS-RGB sensors at the particle level are (i) the low investment cost compared to other sensors and (ii) the possibility of transferring RGB-based deep learning algorithms (especially CNNs) from other research fields (e.g., autonomous driving) to the waste management sector. 3DLT sensors, in contrast, can measure the 3D shape of particles, which can be used as a feature for the prediction algorithm (e.g., Koyanaka et al., 2013; Koyanaka and Kobayashi, 2010; Mattone et al., 2000). Another way to identify materials at the particle level is to aggregate pixel-based classification results for example by majority voting (argmax) or the use of number of pixel-based classifications as a particle-based classification feature (e.g., Bonifazi et al., 2021; Chen et al., 2021f). This occurs mainly for sensors in IR range and VIS sensors; for example, Chen et al. (2021f) has defined a threshold (70%) of correct pixel-based classification share as a correct particle prediction.

Like the particle level, classification results from different sensors of the pixel and particle level can be aggregated at the **material flow level** (e.g., Curtis et al., 2021; Serranti et al., 2015). Alternatively, direct predictions can be made at the material flow level, which have been investigated so far with CNNs based on VIS-RGB data by Lu et al. (2022a) and Davis et al. (2021).

4.3.1.2. Segmentation and measurement. A second task involves the 2D or 3D measurement of particles and material flows. The starting point for all 2D measurements are *binary images* that divide the sensor data into foreground and background at the **pixel level**. Depending on the sensor used, the segmentation can be based on different features, e.g., color or brightness from VIS-RGB data (e.g., Maier et al., 2021), intensity or dynamics of NIR spectra (e.g., Curtis et al., 2021), or height information from 3DLT sensors (e.g., Kroell et al., 2021a). Starting point for all three-dimensional measurements are 3D heightmaps, for example from 3DLT data.

At the **particle level**, binary images (2D) or heightmaps (3D) can be used to localize or measure individual particles. The localization of particles is of high relevance for SBS processes, in order to sort individual particles using coordinate-precise air pressure bursts (e.g., Maier et al., 2021; Pieper et al., 2018) or with mechanical grippers (e.g., Ku et al., 2021; Xiao et al., 2020). In addition, 2D and 3D particle dimensions form the basis for predicting other particle properties such as particle size (Kandlbauer et al., 2021) and particle mass (Kroell et al., 2021a) or can be an (additional) input for material classification (see Section 4.3.1.1).

Table 8
Overview of investigated ML algorithms.

Abbr.	Algorithm	#Investigated	#In best	Reference
PCA	Principal component analysis	73	24	(Karhunen, 1998)
CNN	Convolutional neural network	47	42	(Lecun et al., 1998)
PLS	Partial least squares	46	37	(Wold et al., 1989)
kNN	k nearest neighbors	36	20	(Altman, 1992)
SVM	Support vector machine	32	17	(Cristianini and Shawe-Taylor, 2013)
LDA	Linear discriminant analysis	28	13	(Tharwat et al., 2017)
ANN	Artificial neural network	25	13	(Wang, 2003)
DT	Decision tree	12	2	(Grajski et al., 1986)
QDA	Quadratic discriminant analysis	10	3	(Hastie et al., 2009b)
RF	Random forest	9	5	(Breiman, 2001)
Fuzzy	Fuzzy based algorithm	7	5	(Perfilieva, 2006)
SAM	Spectral angle mapper	5	2	(Kruse et al., 1993)
SIMCA	Soft independent modelling by class analogy	5	2	(Wold and Sjöström, 1977)
GMM	Gaussian mixture models	4	0	(Figueiredo and Jain, 2002)
CVA	Canonical variate analysis	3	0	(Tofallis, 1999)
SCC	Spectral cross-correlation	2	2	(Koenig, 1999)
GA	Genetic algorithm	2	1	(Holland, 1992)
BN	Bayesian network	2	0	(Holmes and Jain, 2008)
CBR	Case based reasoning	1	1	(Chen et al., 2008)
CRF	Conditional random field	1	1	(Lafferty et al., 2001)
CT	Complementary troubleshooting	1	1	(Xiao et al., 2019a)
DBC	Dissimilarity-based classifier	1	1	(Pekalska and Duin, 2000)
ICA	Independent component analysis	1	1	(Hyvärinen and Oja, 2000)
MAP	Maximum a posteriori estimation	1	1	(Gauvain and Lee, 1994)
ViT	Vision transformer	1	1	(Dosovitskiy et al., 2020)
DNA computing	–	1	0	(Adleman, 1998)
GPC	Gaussian process classifier	1	0	(Rasmussen and Williams, 2008)
LEMAP	Laplacian Eigenmaps	1	0	(Belkin and Niyogi, 2002)
Linear	Linear regression	1	0	(Fahrmeir et al., 2013)
MLR	Multinomial logistic regression	1	0	(Hosmer and Lemeshow, 2000)
NC	Nearest centroid	1	0	(Hastie et al., 2009a)
RDA	Resemblance discriminate analysis	1	0	(Koch, 2014)
SOM	Self-organized map	1	0	(Kohonen, 1998)
SVD	Singular value decomposition	1	0	(Boardman, 1989)
	Σ	368	199	

At the **material flow level**, 2D binary images can be used to quantify material flows in terms of area flows or occupation densities (e.g., Curtis et al., 2021; Küppers et al., 2021; Küppers et al., 2020); whereas 3D(LT) measurements allow the determination of volume flows (Curtis et al., 2021; Feil et al., 2019).

4.3.1.3. Prediction of material properties. Since material properties such as mechanical properties or material colors are usually not influenced by particle shapes or sizes, these can be measured directly at the **pixel level**. In our dataset, mechanical properties such as melt viscosity and tensile strength have so far only been predicted based on NIR data for plastics by van Engelshoven et al. (2019).

Information on color classes is (obviously) extracted in the VIS wavelength range (Fig. 5d). The $n = 8$ investigations on color classification in our dataset, predominantly applied VIS-RGB sensors (6 of 8 investigations, 75.0%), but also VIS-HSI have been applied (2 of 8 investigations, 25.0%). Among the $n = 8$ color classification investigations, $n = 5$ investigations (62.5%) conducted classifications at the **particle level** to reduce the influence of, e.g., labels, colored bottle caps, or contaminates (Ata et al., 2005; Krcmarik et al., 2019; Tachwali et al., 2007; Wang et al., 2019b; Zhou et al., 2021).

4.3.2. Applied sensors for different material flows and classes

Fig. 5e shows the application of optical sensors for different material classes. As introduced in Section 4.1.2, two groups can be identified: Sensors in the IR range (especially NIR) are often applied to plastics (e.g., PP, PET, PE, PS), while VIS-RGB sensors find increased applications for the broader material classes (glass, paper, metal, cardboard, trash) of *TrashNet* (Yang and Thung, 2016).

Regarding material flows (Fig. 5f), two effects play a role: First, for material identification (Section 4.3.1.1), the application of different sensors follows their suitability for identifying different material classes, e.g., NIR sensors are often applied for material flows that contain higher amounts of polymers (e.g., plastics, LWP, and WEEE), while VIS-RGB sensors are often applied for broader material identification (e.g., *TrashNet*) or classification of different paper grades (e.g., "old corrugated cardboard", "old newsprint", or "white paper"), mainly by optical characteristics (Rahman et al., 2014). Second, for characteristics based on segmentation and measurements (Section 4.3.1.2) the characterization is independent from the contained material classes. For these characteristics, VIS-RGB or 3DLT are often used due to their low investment cost or their ability to perform 3D measurements, respectively. Fig. 5f shows a superposition of both effects: While NIR sensors are mainly used for plastic-rich material flows, other sensors (e.g. VIS-RGB and 3DLT) find a wide range of material flow applications. The selection of sensors is therefore not necessarily based at the material flow itself, but rather on the characteristics and material classes of interest, as well as the suitability of the respective sensors for their combination.

4.4. ML algorithms

In our dataset, 204 of 267 (76.4%) investigations studied ML algorithms to extract characteristics from the acquired sensor data. For 188 of 204 (92.2%) investigations, details on the studied ML algorithm(s) were given, which are the focus of this section (hereinafter referred to as *ML investigations*).

Table 8 summarizes the 34 unique ML algorithms investigated by ML investigations in our dataset, introduces their abbreviations, and gives reference to further details for each ML algorithm. In addition, four investigations developed *custom* ML algorithms, i.e., ML algorithms that were developed for the investigation itself (Di Maria et al., 2016; Koyanaka and Kobayashi, 2010; Li et al., 2019; Zhang et al., 2019). Among all investigated ML algorithms, PCA ($n = 73$ investigations), CNN ($n = 47$), PLS ($n = 46$), kNN ($n = 36$), and SVM ($n = 32$) were studied most often.

Furthermore, 45 of 319 (14.1%) studied algorithms were ensembles of multiple algorithms (e.g., PCA + PLS). Most ensembles composed two algorithms (42 of 45 ensembles, 93.3%) and combined PCA as a preprocessing step with other ML algorithms (37 of 45, 82.2%).

Fig. 6 gives an overview of ML algorithms investigated more than once. As shown in Fig. 6a, the frequency at which different ML algorithms were applied has changed over the years. While some algorithms (e.g., ANN and LDA) have been studied since the early 2000s, other algorithms (e.g., SVM and RF) have been investigated since 2013. Especially for CNNs, which were studied since 2018 by investigations in our datasets, a steep increase in the number of investigations (2.5-fold increase or more per year) can be observed.

4.4.1. Investigated ML algorithms for different prediction tasks

Each prediction task can be broken down into (i) a sensor that defines the input to the ML algorithm, as well as (ii) an investigation level and (iii) a characteristic that define the model output.

4.4.1.1. Investigated ML algorithms for different sensors. As shown in Fig. 6c, most ML algorithms have been applied to data from various sensors. However, while CNN (37 of 43 CNN investigations, 86.0%), kNN (15 of 34, 44.1%), and SVM (14 of 28, 50.0%) algorithms were most frequently applied to data from VIS-RGB sensors, PCA (38 of 53, 71.7%) and PLS (40 of 45, 88.9%) algorithms were most frequently applied to NIR data, which might be traced back to their dimensionality reduction capability for highly correlated spectral data.

4.4.1.2. Investigated ML algorithms for different investigation levels. From 34 unique ML algorithms, 23 and 25 algorithms have been investigated on the pixel and particle level, respectively (see Fig. 6b). Since PCA and PLS are capable of dimensionality reduction, they have been often applied on the pixel level (48 of 58 [82.8%] and 39 of 45 investigations [86.7%], respectively), e.g., to process high-dimensional data from hyperspectral sensors such as NIR sensors. In contrast, CNNs have found increased application on the particle level (39 of 46, 84.8%) due to their suitability for image classification. On the material flow level, researchers have so far applied CNNs (Davis et al., 2021; Lu et al., 2022a), ensembles of CNNs and SVMs (Chen et al., 2021a), and custom algorithms (Di Maria et al., 2016).

4.4.1.3. Investigated ML algorithms for different characteristics. Although most ML algorithms are suitable for a wide range of predictions (Marsland, 2014), Fig. 6d shows that most algorithms have so far been applied to material classification, which can be attributed to the high number of material classification investigations (cf. Section 4.2). Besides material identification, ML algorithms have only been investigated in occasional case studies for other characteristics. In fact, of $n = 288$ possible algorithm-characteristic combinations, only $n = 46$ (16.0%) have been investigated.

4.4.2. ML prediction scores

In total, 167 of 188 (88.8%) ML investigations in our dataset reported the achieved test score of the best-performing ML algorithm. As depicted in Fig. 6f, the reported test scores range from 49.1% to 100.0%. 133 of 167 (79.6%) ML investigations report test scores of 90% or higher. On average, higher best test scores are reported on the pixel level (mean: 95.4%) compared to the particle level (mean: 91.3%). Only three investigations reported test scores on the material flow level (68.4% – 94.0%), which do not allow further statements due to the small sample size.

When analyzing the development of test scores over time (Fig. 6e), for both the pixel ($p = 0.048$) and particle level ($p = 0.015$), a slight increase of the reported test scores can be observed. At the pixel level, reported test scores increased about 0.21% per year; at the particle level, test scores increased steeper with about 0.41% per year.

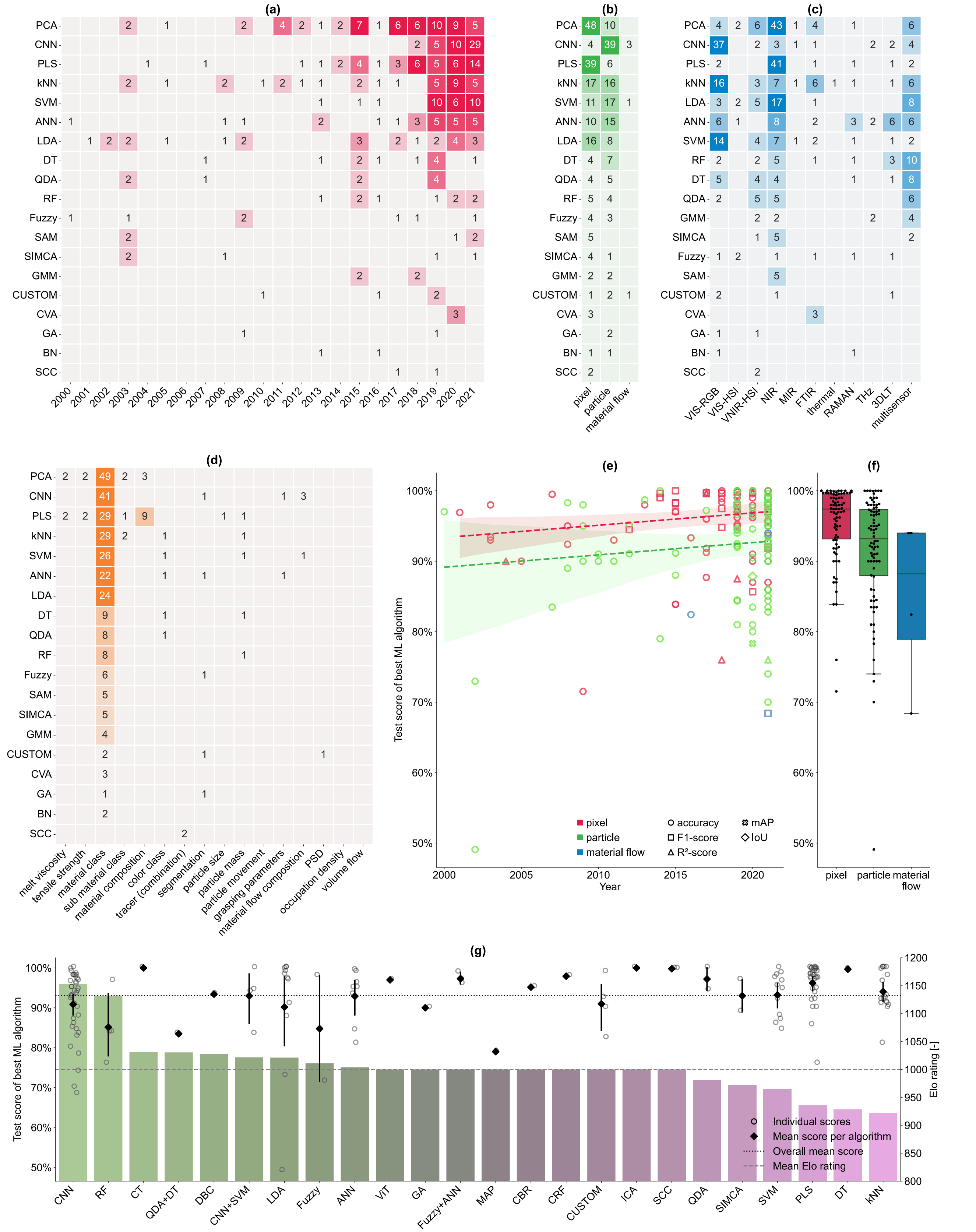

Fig. 6. Investigated ML algorithms* (a) per year, (b) per investigation level, (c) per sensor, and (d) per characteristic; (e) test scores of best-performing ML algorithms per year and investigation level; (f) test scores per investigation level; (g) Elo rating and test scores of best-performing ML algorithm combinations per investigation. *for better readability, only ML algorithms investigated more than once are depicted (see Table 8 for frequency and abbreviations).

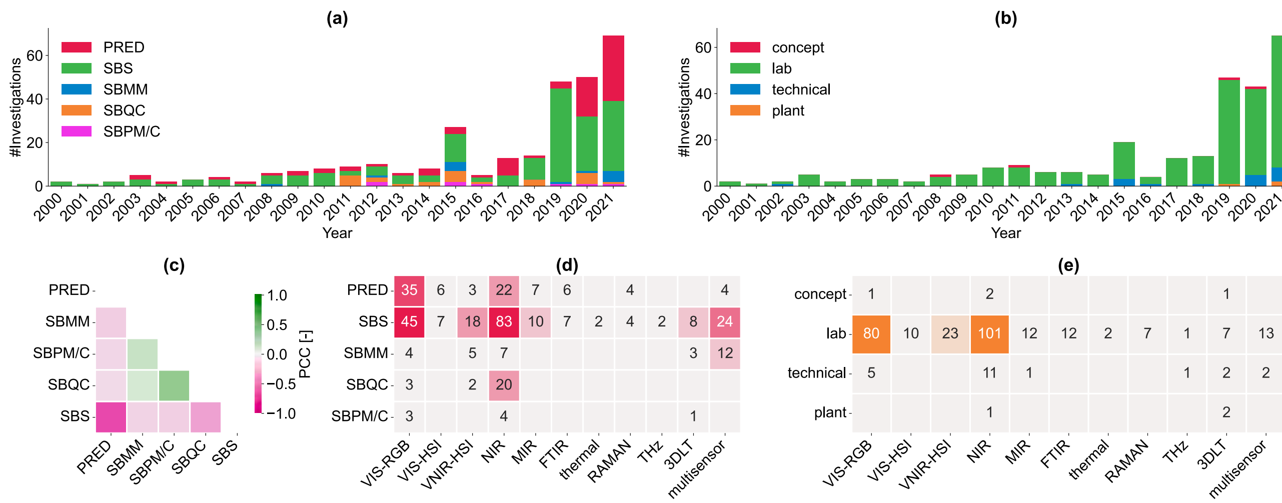

Fig. 7. Applications and investigation scales. (a) Applications per year; (b) investigation scales per year; (c) correlation (simultaneous occurrence) between different applications; (d) applications for different sensors; (e) investigation scales per sensor. PCC: Pearson correlation coefficient.

However, these results must be interpreted with great caution as several biases could distort the reported test scores. For example, (i) researchers are incentivized to publish only sufficient test scores (publication bias); (ii) most predictions are based on different datasets and are therefore only comparable to a very limited extent (if at all); (iii) different types of test scores (e.g., accuracy and R^2-score) cannot be directly compared; and (iv) different investigations may use different implementations and hyperparameter settings.

From 34 investigated ML algorithms, 22 algorithms of the were reported once or more as the best-performing ML algorithm or as part of a best-performing ML ensemble (cf. Table 8). Among the best-performing ML algorithms, CNN ($n = 42$), PLS ($n = 37$), PCA ($n = 24$), kNN ($n = 20$), and SVM ($n = 17$) algorithms were most often reported.

However, the frequency at which ML algorithms are reported as the best performing ML algorithms is not sufficient to draw conclusions about the suitability of different ML algorithms for SBMC. First, ML algorithms studied more often have a higher probability of being the best-performing ML algorithm (cf. Table 8). Second, ML algorithms, which are less often compared to other ML algorithms, have a higher probability of being reported as the best-performing ML algorithm.

To overcome these limitations, we propose an alternative method to assess the suitability of different ML algorithms for SBMC: The Elo rating system (Elo, 2008), which is a method to calculate relative skill levels of different players that is used in zero-sum games such as chess and football.

In our Elo implementation, we model each investigation as pairwise *matches* between the tested ML algorithms and the best-performing ML algorithm within each investigation. All algorithms start with an initial Elo rating of 1,000. After each match, the winning algorithm takes points from the losing algorithm, and both Elo ratings are updated. The transferred points after each match are based on the difference between both Elo ratings, which makes the rating system self-correcting. If a higher-rated algorithm wins a match against a lower-rated algorithm, fewer points will be transferred compared to a match in which a lower-rated algorithm wins against a higher-rated algorithm since a win in the first case is more likely than in the second case (Elo, 2008). Therefore, ML algorithms of higher suitability will achieve higher Elo ratings than algorithms of lower suitability.

Fig. 6g summarizes the Elo ratings and the achieved test scores of the 25 different ML algorithms (ensembles) that were reported as best-performing ML algorithms (ensembles) by the investigations in our dataset (excluding PCA[2]). As a result, we observe high Elo ratings for CNN (Elo-score: 1153.1, 14 [matches won]: 1 [match lost]) and RF (1132.0, 17:4). In contrast, low Elo ratings are observed for PLS (935.8, 0:5), DT (928.0, 3:9), and kNN (922.4, 7:14).

In conclusion, the calculated Elo ratings indicate a high suitability of CNN and RF algorithms for SBMC and confirm the observed outperformance of CNN in comparison to other traditional ML algorithms observed in other research fields. However, these results must be interpreted with great caution, as outlined above and in Section 4.7.

4.5. Applications and investigation scales

Fig. 7 summarizes the envisioned applications by investigations in our dataset and the scales at which the investigations were conducted.

4.5.1. Envisioned applications

In total, we identified six different applications envisioned by the publications in our dataset. Table 9 defines the envisioned applications and introduces their abbreviations.

As shown in Fig. 7a, SBS applications have been mentioned since the beginning of the period under review (2000 – 2021) and by the majority of investigations (cf. Table 9). Starting in 2003, the first investigations on PRED applications were published followed by SBMM (2008), SBQC (2011), and SBPM/C applications (2012). When comparing the relative share of applications mentioned between 2011 – 2021 (last ten years) and 2000 – 2011 (cf. Section 4.1.1), we observe that SBMC research has been expanding from SBS applications (-18.6 pp) towards SBQC (+9.7 pp), PRED (+3.6 pp), SBPM/C (+3.1 pp), and SBMM (+2.3 pp) in recent years.

Fig. 7c indicates that the identified applications can be clustered into three groups: (i) SBS; (ii) PRED; and (iii) SBMM, SBQC, and SBPM/C.

[2] Note that we chose to exclude the PCA algorithm from our Elo evaluation because PCA is commonly used for explanatory data analysis or preprocessing (high frequency among investigated ML algorithms), but has less application in final model prediction (low frequency among the best-performing ML algorithms), which would systematically bias the Elo evaluation towards other algorithms.

Table 9
Overview and definition of envisioned applications by the publications in our dataset; *SBPC or SBMM*.

Abbr.	Name	Description	Target level	Example	#Mentions	Mention share
PRED	Prediction	Prediction of material or material flow characteristics from sensor measurements.	Pixel, particle, material flow	Classification of polymers based on NIR spectra.	81	30.3%
SBS	Sensor-based sorting	Particle-wise sorting of material flows based on predicted characteristics from sensor measurements through actuators.	Particle	Sorting PET bottles out of LWP waste.	174	65.2%
SBMM	Sensor-based material flow monitoring	Sensor-based measurement of MFCs through SBMC over a period of time and evaluation of measured MFCs or comparison with a target or reference value.	Material flow	Sensor-based monitoring of the input material composition in a sorting plant.	13	4.9%
SBQC	Sensor-based quality control	Comparison of MFCs acquired through SBMC with predefined quality criteria.	Material flow	Sensor-based monitoring of the purity of preconcentrates in a sorting plant.	25	9.4%
SBPM	Sensor-based process monitoring	Monitoring of characteristics or indicators acquired through SBMC at the process level.	Process	Sensor-based monitoring the screening efficiency of a drum screen.	8*	3.0%*
SBPC	Sensor-based process control	Adjustment of actuators based on characteristics or indicators through SBMC at the process level.	Process	Setting the shaft speed of a pre-shredder based on the measured output volume flow.	8*	3.0%*

* During data extraction, we observed that it is difficult to identify if authors intended an SBPM or SBPC application (since both applications require similar technological prerequisites), which we thus unified to SBPM or SBPC (abbreviated as SBPM/C) in the following.

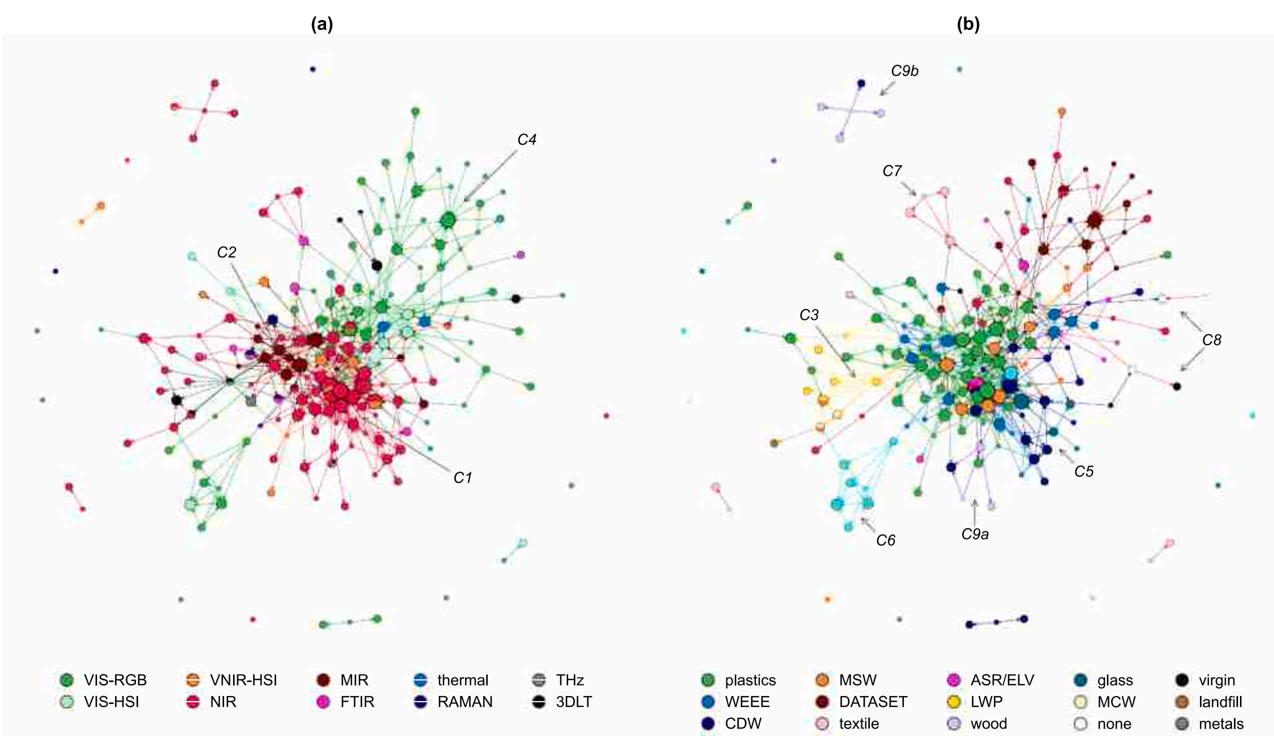

Fig. 8. Citation network between the 198 publications in our dataset colored by (a) applied sensors and (b) addressed material flows. Vertices: publications, edges: citations, pie: relative frequency of respective among a publication, vertex size: #citations among the 198 publications in our dataset.

While applications that require data analysis on the material flow level (SBMM, SBQC, or SBPM/C) are positively correlated with each other, SBS and PRED applications tend to be envisioned independently, which might be traced back to different researchers targeting for different applications.

As shown in Fig. 7d, the envisioned applications differ significantly in terms of investigated sensors. While NIR-sensors find more frequent applications in SBS ($n = 83$ mentions on NIR vs. $n = 45$ mentions on VIS-RGB [1.84:1]), VIS-RGB sensors are more frequently investigated for PRED applications ($n = 22$ mentions on NIR vs. $n = 35$ mentions on VIS-

RGB [0.63:1]).

4.5.2. Investigation scales

As shown in Fig. 7b, most investigations in our dataset were conducted on laboratory scale (242 of 267 investigations, 90.6%), followed by investigations on technical (n = 18, 6.7%) and plant scale (n = 3, 1.1%). In addition, n = 4 investigations (1.5%) were classified as novel concepts (Feil et al., 2019; Salmador et al., 2008; Serranti et al., 2011; Wu et al., 2020).

Besides an early investigation by de Groot et al. (2002), investigations on a technical scale in our dataset have been reported frequently since 2013 (Beigbeder et al., 2013). Comparing the relative shares of different investigation scales between 2000 – 2015 and 2016 – 2021 (cf. Section 4.1.1) shows an increasing trend towards higher TRL levels in recent years: While the relative frequency of concepts (-2.1 pp) and investigations on lab-scale (-4.1 pp) decreased, more investigations were published on a technical (+4.7 pp) and plant scale (+1.4 pp).

As shown in Fig. 7e, all ten optical sensors in our dataset have been studied extensively on the laboratory scale. On a technical scale, however, the investigated sensors in our dataset reduces to NIR (n = 11), VIS-RGB (n = 5 investigations), 3DLT (n = 2), MIR (n = 1), THz (n = 1), and multi-sensors (n = 2). Moreover, investigated sensors at the plant level are currently limited to NIR (Curtis et al., 2021) and 3DLT (Curtis et al., 2021; Feil et al., 2019).

In summary, we observe that most reviewed investigations have taken place at the laboratory scale, which can be explained mainly by the type of reviewed literature (peer-reviewed journal articles). However, researchers have made significant efforts towards upscaling to plant scale. While SBS with many sensors is already state-of-the-art (Chen et al., 2021d; Gundupalli et al., 2017a; Sarc et al., 2019), SBMC methods rapidly evolve towards plant scale maturity. So far, NIR and 3DLT have been proven to be suitable for SBMM at plant scale (Curtis and Sarc, 2021; Feil et al., 2019).

4.6. Collaboration and networks

To determine how interconnected research on SBMC is (RQ 6), we evaluate two types of connections in the following subsections: Citation networks (Section 4.6.1) and co-authorship networks (Section 4.6.2). Both connections will be visualized as graphs. In the citation network, the modeled graph consists of publications (vertices) and citations (edges) between them. In the co-authorship network, the modeled graph consists of authors (vertices) and co-authorships (edges) between them.

For visualizing both graphs, we will determine the vertex positions through the force-based graph drawing algorithm of Hu (2005), implemented in *graph-tool* (Peixoto, 2014). In force-based graph drawing, the edges are modeled as mechanical springs that pull connected vertices together, while repulsive electrical forces of the vertices push vertices away from each other. Vertex positions are initialized randomly and then iteratively updated to minimize the system's energy until an equilibrium is reached. In this way, more connected vertices are closer together in the final graph than other vertices, enabling us to identify relationships between different publications and authors visually.

4.6.1. Citation networks

Fig. 8 shows the resulting citation network of the 198 publications in our dataset. To interpret the resulting graph, all vertices (publications) are visualized as pie charts with the different sensors (Fig. 8a) and material flows (Fig. 8b) of the underlying investigations defining their color and share (e.g., a publication containing one NIR and one VIS-RGB investigation would result in a 50% NIR and 50% VIS-RGB pie).

In total, we identified n = 497 citations among the 198 publications in our dataset. On average, publications in our dataset cited/got cited from n = 2.5 other publications from our dataset. The three most cited vertices within our dataset are Serranti et al. (2011) [n = 23], Ulrici et al. (2013) [n = 18], and Serranti et al. (2012a) [n = 17].

The majority of publications (174 of 198, 87.9%) belong to a large subgraph (shown in the center of Fig. 8a and b), which contains 98.2%

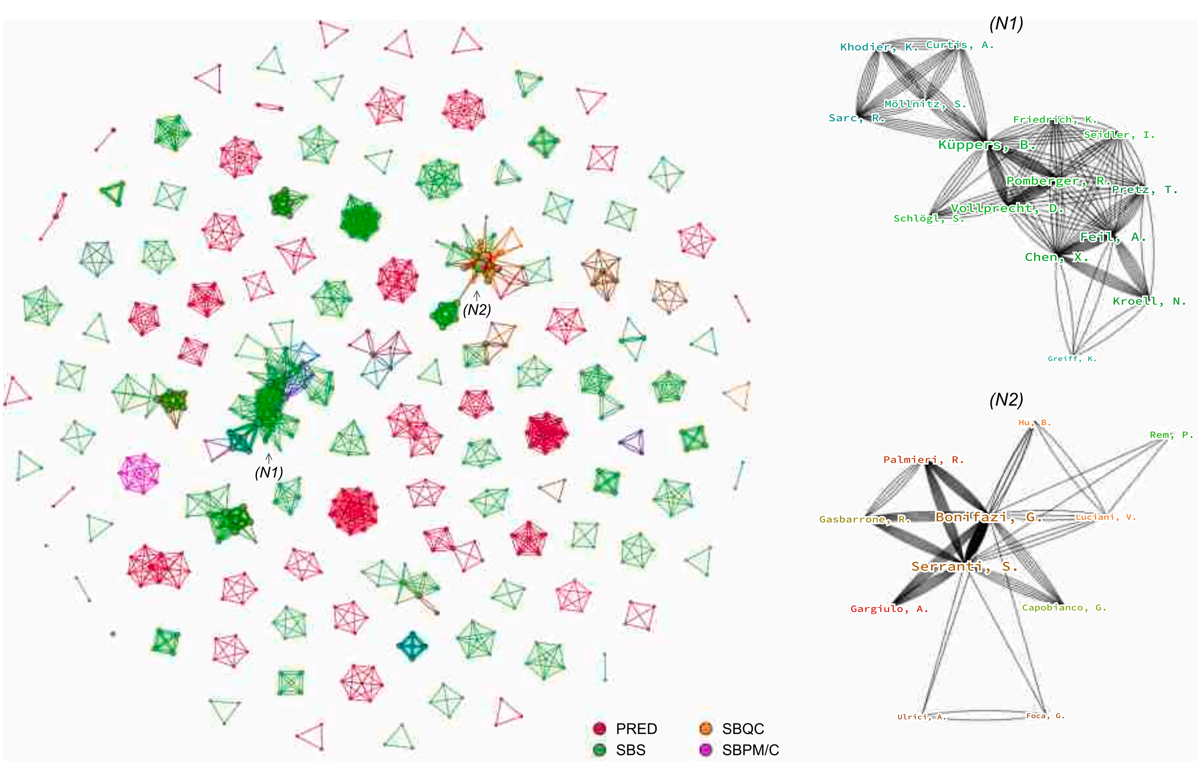

Fig. 9. Co-Authorship Network of the 611 authors from 198 publications in our dataset. (N1) largest and (N2) second-largest co-authorship subnet (for clarity, only authors with two or more total publications are shown in N1 and N2).

(n = 488) of all citations. When we calculate the shortest paths between all publications within this subgraph (considering both citations and references), we observe that it takes, on average, 2.7 intermediate publications to reach any target publication from any source publication (min: 0, median: 3, maximum: 7), which indicates a strong interconnection of this subgraph. In contrast, we identify 15 subgraphs isolated from the main subgraph containing between $n = 1$ and $n = 5$ publications each (shown at the borders of Fig. 8).

When analyzing both colored citation graphs, we observe that publications with similar sensors (Fig. 8a) or material flows (Fig. 8b) often cite each other and are thus located closer to each other. Five broader clusters can be identified that are closely connected to the main citation network: publications that focus on the material flows plastics and MSW and apply NIR sensors (*C1*), publications on plastics and WEEE with MIR sensors (*C2*), NIR publications on LWP (*C3*), VIS-RGB publications on public available datasets or waste classification in general (*C4*), and mostly NIR publications on CDW and glass (*C5*). In contrast, publications on paper based on VIS sensors (*C6*), NIR and FTIR publications on textile (*C7*), material-independent publications (*C8*), and investigations on wood (*C9a*, *C9b*) are less connected to the main citation subgraph.

In accordance with the findings of Section 4.3, we see that the (main) citation network is largely dominated by two research communities focusing (a) on the application of NIR (and MIR) sensors for a more nuanced identification of (mostly) plastics (*C1*, *C2*) and (b) the application of CNNs for more general waste classification especially on public datasets.

4.6.2. Co-authorship networks

Fig. 9 shows the co-authorship graph, in which vertices are colored based on the envisioned applications. In total, the co-authorship graph contains n = 611 different authors (vertices) and n = 2,472 co-authorships (edges). In contrast, to the citation network, the co-authorships network is significantly less connected with n = 111 co-authorship networks in total, ranging from $n = 1$ to $n = 33$ authors per group (mean: $n = 5.5$).

As shown in Fig. 9, the largest co-authorship network (*N1*) in our dataset contains a total of $n = 33$ authors (for clarity, only authors with two or more total publications are shown in the detailed views of Fig. 9), which can be traced back to researchers from the RWTH Aachen University (Germany) and Montanuniversitaet Leoben (Austria). Fig. 9.N2 shows the second-largest co-authorship network (*N2*) with $n = 28$ authors, which can be traced back to researchers from the Sapienza University of Rome (Italy).

In summary, two main conclusions can be drawn from Section 4.6. First, individual co-authorship networks are often focused on a limited number of applications. Second, despite extensive citation within our dataset (Fig. 8), research collaboration often ends at the boundaries of single or a few universities or research groups (Fig. 9). Therefore, research across university and research group boundaries has likely the potential to provide new impulses for SBMC research. Readers may find related researchers by the overview given in Table 6.

4.7. Limitations

Despite all efforts devoted, this study has three major limitations. First, as the review has focused on peer-reviewed journal articles in the English language, non-peer-reviewed publications such as conference proceedings and non-english literature have not been included, which may add systematic errors to the obtained findings. For example, most recent findings from conference publications as well as industrial research results are not represented in the review, which may result in an underestimation of the state-of-research or reached TRL levels. Here, a systematic literature review on non-peer-reviewed and/or non-English language literature could complement the present study.

Second, the focus of this review was on dry-mechanical recycling of non-hazardous waste streams. However, it is likely that sensor-based characterization methods already exist for virgin materials or hazardous wastes that could be transferred to the waste management sector. Here, an additional review focusing on transfer from other industries (with more advanced levels of digitalization) could be of great value.

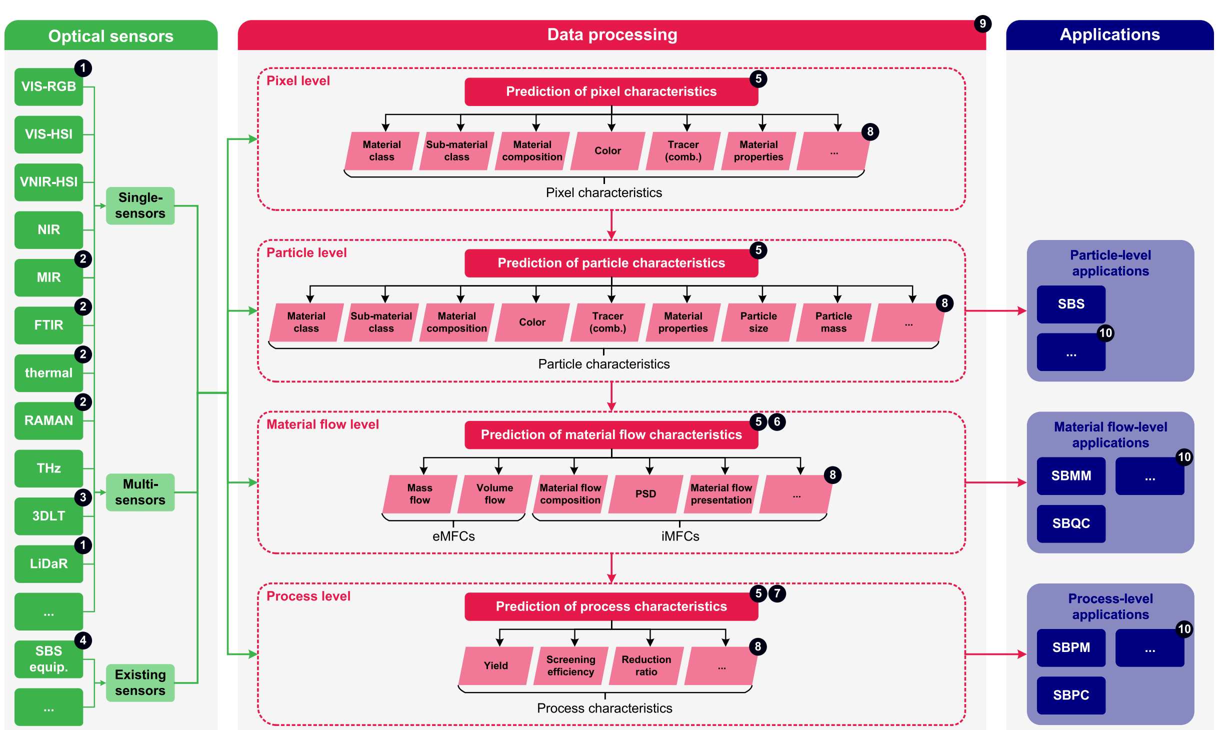

Fig. 10. SBMC data processing pipeline and future research potentials. Research potentials 1–10 (in circles): Future research potentials as outlined in Section 5 (Research potential i corresponds to Section 5.i).

Third, although our ML algorithm comparison based on Elo ratings ensures that only algorithms on the same datasets and for the same tasks are compared, several effects could still distort the comparison. (i) The fact that each investigation makes a pre-selection of algorithms to be investigated could lead to systematic biases, e.g., a better performing algorithm might exist but was not considered in the respective study. (ii) The Elo rating does not consider how large the prediction difference is between individual algorithms. Especially in the case of very small differences, random effects (e.g., splitting of training and test data) can impact on the comparison. (iii) The algorithm comparison may be affected by different implementations or hyperparameter optimizations among the respective investigations. (iv) It should be noted that our Elo implementation compares ML algorithms across different prediction tasks within our dataset and does not , e.g., differenciate between classification and regression tasks. Thus, it is still possible that despite an overall low Elo rating, certain algorithms are better suited for certain tasks than algorithms with overall higher Elo ratings. Therefore, our evaluations only provide evidence for particularly well-suited SBMC algorithms, but do not replace a direct algorithm comparison in primary studies.

5. Future research potentials

Based on the obtained overview of existing SBMC publications and existing SBMC methods in Section 4, several future research potentials can be derived. In Fig. 10, we integrate the insights from Section 4 into an SBMC data processing pipeline that illustrates how data from different sensors can be used to extract characteristics at different investigation levels and what applications emerge from these characteristics. Using the framework provided by Fig. 10, we identify $n = 10$ future research opportunities, which we discuss in more detail in the following subsections (one potential per section; Section 5.i referrers to research potential i in Fig. 10).

5.1. Utilizing low-cost sensors

Modern sorting plants often produce ten or more output material flows; several dozen material flows are often conveyed between individual separation units inside the plant. To realize the research vision of automated and adaptive process control in next-generation sorting plants (Section 1.1), it is likely that a significant part of these material flows has to be monitored by SBMC methods in the future to obtain a full picture of the process state and enable a precise process control for optimal sorting results. Many existing sensor technologies have rather high unit costs, making exhaustive process monitoring economically unfeasible.

Possible strategies to reduce these investments costs comprise (i) the use of existing sensors (see Section 5.4), (ii) positioning additional sensors at strategically useful locations, and (iii) reducing the investments cost per sensor. Regarding reducing the investment cost of sensors for eMFCs (especially volume flows), we see large potential in light detection and ranging (LIDAR) sensors, which could measure volume flows at a significantly lower cost compared to state-of-the-art 3DLT sensors (Nordmann and Pfund, 2020). Regarding iMFCs, we see great potential in VIS-RGB sensors, which could substitute 3DLT sensors where 2D particle measurements are sufficient (e.g., Kandlbauer et al., 2021) or other sensors when combined with advanced ML algorithms such as CNNs (e.g., Chen et al., 2021a; Davis et al., 2021; Lu et al., 2022a).

5.2. Upscaling and utilization of emerging sensor technologies

In addition, potential improvements could be achieved by further upscaling emerging optical sensor technologies such as THz and MIR, which have proven to solve intractable problems such as sorting carbon-black plastics in the past (e.g., Küter et al., 2018; Rozenstein et al., 2017; Signoret et al., 2020a, Signoret et al., 2019a, Signoret et al., 2019b). For example, a more detailed characterization with MIR sensors could enable the identification of specific plastic additives, the prediction of application-specific material properties of post-consumer recyclates (van Engelshoven et al., 2019), or quantify aging effects (Signoret et al., 2020b), which can be challenging in the NIR range (e.g., Chen et al., 2021c).

These predicted characteristics could be utilized in advanced SBS and SBQC and contribute to higher-quality material recycling (e.g., additives like flame retardants could damage the quality of the plastic recyclate). As these emerging sensor technologies have so far predominantly been applied to plastics, the extension to other use cases such as the discrimination of different waste wood categories, a more nuanced paper sorting, or SBS in CDW recycling could contribute further to an improved material circulation.

5.3. Improvement of 3D(LT) detection

As discussed in Section 4.3.1, 3D sensors are of great value for measuring volume flows (3DLT and LIDAR) and individual particles (3DLT) in SBMC. However, many problems in applying 3DLT sensors for SBMC are still under-researched. For example, many post-consumer material flows contain transparent materials such as PET bottles or glass, which can only be detected to a limited extent using 3DLT because the laser beam (depending on transparency and surface contamination) penetrates the transparent material and cannot be measured at the particle's surface. Regarding volumetric flow measurement, 3DLT and LIDAR sensors often overestimate or underestimate the volumetric flow through cavities or overshadowing, respectively, or it is unclear how the "true" volumetric flow is even defined in such cases.

5.4. Utilization of existing sensor equipment and data streams

As mentioned under Section 5.1, there is great potential in using existing sensor data in sorting plants. Many modern sorting plants contain several SBS units. Since the material flow on the acceleration belts/chutes of existing SBS equipment is presented as a singled monolayer, and the existing sensors classify the material flow, either way, the use of sensor data from existing SBS units offers great potential for material flow monitoring. SBS manufacturers are already recording this data and making it available to their customers (e.g., TOMRA Systems ASA., 2022a). However, challenges in this area are mainly of a technical and organizational nature. Since the data is primarily used for SBS, material flow information (e.g., area-related material flow compositions) is usually stored in an aggregated form and cannot be evaluated and used in more detail for other SBMC applications. In addition, sensor data often have material-specific weights, and individual reference spectra are stored for the sorting recipe, which can be very different if they are saved desirably for, e.g., SBMM applications. Besides, recipes often change over time (due to SBS unit maintenance), complicating the data analysis. A simple technical solution would be to split the sensor data stream into an SBS and an SBMM data stream immediately after acquisition so that the sensor data can be analyzed at high resolution without affecting the actual sorting task (and vice versa).

5.5. Open-access datasets and further utilization of deep learning methods

CNNs have so far achieved impressive classification results on VIS-RGB datasets of post-consumer wastes (e.g., *TrashNet* [Yang and Thung, 2016] and *Huawei garbage classification challenge cup* [Huawei, 2019]; see Section 4.4.2). However, the public datasets available are quite different from the reality in many industrial sorting plants. For example, in sorting plants, particles usually must be identified on (dirty) conveyor belts, whereas the particles in, e.g., *TrashNet* were created in front of mostly homogeneous, white, and clean backgrounds. In addition, waste collection and preconditioning particles in sorting plants are

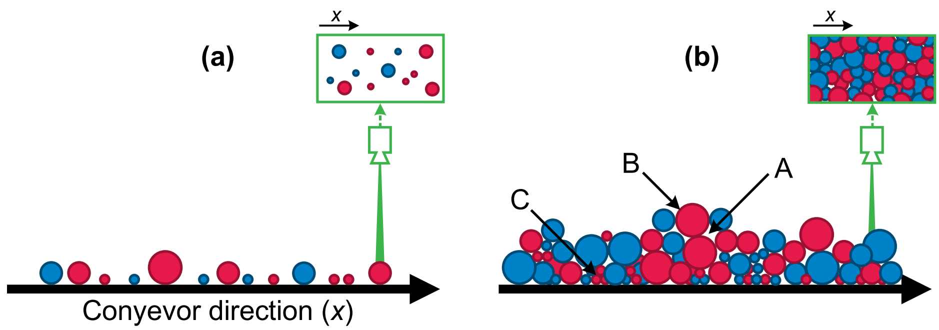

Fig. 11. Presentation of material flows as (a) singled monolayer and (b) multilayered bulks to SBMC sensors. A. hallow spaces, B. large particles aggregate on top, C. smaller particles accumulate on the bottom.

often covered with dust, ash, or dirt, exist as agglomerates with other materials, or are often heavily deformed or partially damaged by waste collection or preconditioning processes. Additionally, modern sorting plants often sort according to other and more nuanced material classes than the ones used in *TrashNet*.

ML researchers could largely profit from open-access datasets of post-consumer or post-industrial waste closer to real-world sorting plants' reality. Open access could help exploit datasets once generated through elaborate labeling more intensively by many researchers. For example, Lu et al. (2022a) report that it took $n = 10$ annotators "a month of hard work" (Lu et al., 2022a, p. 4) to label their dataset of $n = 5{,}022$ images for semantic segmentation, yet, the dataset has only been investigated by the authors themselves.

Furthermore, CNNs could be applied to predict other characteristics such as particle sizes and masses, as stated earlier (Kroell et al., 2021a). To date, the prediction of particle sizes and masses has been mostly conducted on manually engineered particle features (e.g., Kroell, 2021), which might not be optimal for the given prediction task. Here, CNNs could be of great value since the extracted features are learned by the model itself and might thus be adapted better to the specific prediction task. Since CNNs can be trained on any type of data array, CNNs could be applied to other types of sensor data at the pixel and particle level. First investigations following this approach have already presented promising results (e.g., Gruber et al., 2019; Jiang et al., 2021; Liu et al., 2020; Xia et al., 2021a; Zinchik et al., 2021). Especially transfer learning techniques (Alom et al., 2019) could help to utilize existing CNNs models for SBMC applications.

5.6. Development and demonstration of sensor-based characterization methods at the material flow level

As discussed in Section 4.2, characteristics have so far been predicted only occasionally at the material flow level. Several research gaps need to be overcome to enable a reliable extraction of iMFCs.

First, all existing optical sensors create area- or volume-based measurements. As elaborated detailed in (Kroell et al., 2021a), most applications in waste management require mass-based MFCs. Therefore, a transformation of the area- or volume-based sensor measurements into mass-based MFCs is necessary, which so far has been researched only briefly for a limited set of material flows (Krämer, 2017; Kroell et al., 2021a; Serranti et al., 2015; Weissenbach and Sarc, 2022; Weissenbach and Sarc, 2021).

Second, outside SBS units, material flows in sorting and processing plants are often not transported as a singled monolayer (Fig. 11a) but as multilayered bulks (Fig. 11b) with materials touching or overlapping each other. When particle-based characteristics (e.g., PSDs) shall be determined in such an unfavorable material flow presentation, adapted segmentation algorithms need to be developed first. Here, we see great potential in the application of semantic instance segmentation algorithms based on deep learning such as U-Net (Ronneberger et al., 2015), Mask R-CNN (He et al., 2017) and DeepLabv3+ (Chen et al., 2018). Pixel-based derivable characteristics such as the material flow composition can be derived by analyzing the surface of the investigated material bulk (e.g., Curtis and Sarc, 2021). However, segregation errors, e.g., through granular convection ("Brazil nut effect") (Rosato and Prinz, 1987) (Fig. 11b) or different material densities, might result in high uncertainties when only considering the bulk surface. Here, extensive research is required to understand and quantify these effects on SBMC at the material flow level.

Third, little research has been conducted regarding the measurement of volume flows (see Section 5.3) and the transformation of volume to mass flows (Curtis and Sarc, 2021). Likewise, significant research gaps exist in the prediction of PSDs on conveyor belts (cf. Section 4.2).

Fourth, there is no consensus at which time intervals SBMM data should be aggregated or smoothed and how material flow fluctuations should be quantified best (Curtis et al., 2021; Feil et al., 2019). While there are rather clear prediction metrics on the pixel and particle level (see Section 2.3.2), first investigations on the targeting on a prediction of iMFCs show that there are yet no clear metrics to assess the prediction performance on the material flow level (e.g., Kandlbauer et al., 2021).

5.7. Development and demonstration of sensor-based characterization methods at the process level

As discussed in Section 4.2.1, we have not identified peer-reviewed investigations on the process level yet. However, such investigations would be of high value since they would enable SBPM or even SBPC in nearly real-time. From our initial experience (Kroell et al., 2022), it appears that SBPM is technically feasible, and the prediction accuracy depends especially on the prediction at the material flow level. Compared to other investigation levels, the challenge at the process level is that several sensors have to be used simultaneously as process evaluation usually consists of at least two different material flows (see Section 2.1.3). Once a precise characterization of the material flow level is possible, the process assessment can be performed relatively straightforward, e.g., based on the indicators presented in Section 2.1.3. We assume that case studies on performance assessments on the process level for mechanical unit operations frequently applied in sorting and processing plants would be of great value for a better process understanding. These insights could be helpful, for example, regarding the parameterization or modeling of individual unit operations or entire sorting or processing plants.

5.8. Extraction of new characteristics

Besides the characteristics listed in Section 2.1 and Section 4.2, new characteristics could be envisioned that could help to improve material circulation further. For example, differentiating food and non-food packaging through VIS-RGB data and CNNs could greatly value advanced SBS and SBQC. Furthermore, as mentioned in Section 5.2, MIR or NIR sensors combined with CNNs could be used to classify more nuanced material classes (van Engelshoven et al., 2019) or, e.g., additives or hazardous substances in plastics. Especially the detection of application-orientated interfering substances through deep learning could be of great value for improving the quality of produced preconcentrates and secondary raw materials as, e.g., demonstrated by the detection of PE cartages in PE preconcentrates (STEINERT GmbH, 2020; TOMRA Systems ASA, 2022b) or waste wood sorting (TOMRA Systems ASA, 2022b).

5.9. Upscaling to plant scale

As shown in Section 4.5.2, most investigations in our dataset have so far been conducted on a laboratory or technical scale. Subsequent upscaling is necessary to reach higher TRL levels and bring the investigations from laboratories into applications that generate actual ecological benefits. Despite a higher number of unknowns, there is high potential in investigations at plant scale, since only under real-world conditions, unexpected challenges such as dust, vibrations, interfering substances, blockages, material overlay, and surface adhesions occur (Parrodi et al., 2021), which need to be overcome to reach higher TRL levels.

5.10. Development of new business models around SBMC

In addition to the long-term use of the material flow data obtained by SBMC for automatic and adaptive process control (see Section 1.1), new business models could contribute to increased material circulation along the way.

Downstream of a sorting plant, material flow data of preconcentrates could be utilized in processing plants to adapt, e.g., process parameters to different input compositions. Based on the measured material flow characteristics, SBQC and dynamic pricing models for preconcentrates could be possible. Improved SBS and an in-depth knowledge of material flows could help produce higher quality secondary raw materials for demanding applications.

Upstream of a sorting plant, input material flow data could be used to optimize waste collection and recycling-friendly production. For example, input material flow data could be used to monitor separate waste collection in different collection areas, e.g., to make public campaigns for separate waste collection more effective. In addition, material flow data could help to evaluate the recyclability of different products or packaging and provide feedback to product designers or to assess the environmental performance of individual products more accurately.

Ultimately, SBMC methods could contribute to greater transparency of mechanical recycling processes and the anthropogenic material cycles in which they are embedded. Currently, this transparency is largely lacking due to time-consuming and costly plant assessment and sorting analysis. SBMC methods can help to close this data gap, leading to more transparency and a better decision-making basis.

6. Conclusions

Focusing on optical sensors and machine learning algorithms for sensor-based material flow characterization in dry-mechanical recycling of non-hazardous wastes, this article systematically reviewed 267 investigations from 198 peer-reviewed journal publications published between January 2000 and October 2021.

The review demonstrates that applications of optical sensors and machine learning algorithms have received increased attention in recent years, with more than half of the investigations published in 2019 – 2021. The reviewed investigations addressed various material flows, especially plastics. Whereas most investigations presented analysis of sensor data at the pixel or particle level, less than 5% of all investigations conducted analyses at the material flow level, and we identified no investigations at the process level.

We identified ten different sensors among the wavelength range under review (100 nm and 1 mm), with the visible to near-infrared range being studied most often. While investigations with VIS-RGB sensors often focused on identifying broader material classes with CNNs, NIR and MIR sensors were most often used for plastic classification at the pixel level.

In the reviewed publications, a total of 34 different ML algorithms have been investigated to predict characteristics from sensor data, with PCA, CNN, and PLS being applied the most. CNNs in particular have been increasingly applied since 2018: the number of CNN investigations in our dataset doubled or more each year and became the most frequently applied machine algorithm in our dataset by 2021. A comparison of the reported test scores of different ML algorithms based on Elo ratings indicates that the predictive performance of CNN and RF models might be higher than that of other ML algorithms. While applications initially focused on only sensor-based sorting, a trend has emerged toward new applications including sensor-based material flow monitoring, quality control, and process monitoring/control over the past 10 years.

Our literature review revealed significant research gaps in the field of sensor-based material flow characterization demonstrating that little research has been conducted at the material flow and process level. In particular, research has yet to focus on the conversion of area-based sensor data into mass-based material flow characteristics as well as the prediction of material flow characteristics in the case of overlapping material flow presentation (multilayered bulks). Furthermore, more than 90% of all investigations were conducted on laboratory scale, with considerable upscaling potential. Future research can especially focus on further applications of deep learning methods, on advanced exploitation of low-cost sensor systems such as VIS-RGB, and on a broader application of new sensor technologies (e.g., MIR and THz) for new and more nuanced material characteristics.

The combination of increasingly better and cheaper optical sensors with advanced data analysis methods such as deep learning will probably make it possible to characterize material flows with sufficient accuracy at plant scale in the next few years. Together with developments in remotely controllable actuators and intelligent process control algorithms, next-generation sorting and processing plants could not only sort and process materials better, but also provide valuable material flow information for the entire value chain. In conjunction with other circular economy strategies, these developments could significantly close anthropogenic material cycles and help to transition the world toward sustainable development.

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CRediT authorship contribution statement

Nils Kroell: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration, Funding acquisition. **Xiaozheng Chen:** Methodology, Validation, Investigation, Data curation, Writing – review & editing, Funding acquisition. **Kathrin Greiff:** Supervision, Writing – review & editing, Funding acquisition. **Alexander Feil:** Supervision, Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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