Artificial Intelligence in Product Identification and Evaluation: Insights from Expert Interviews

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Abstract

Modern industries face complexity with diverse products and shorter lifecycles, shifting towards circular economy principles for value preservation and profitability. Artificial Intelligence (AI), specifically Machine Learning and Deep Learning, is considered for efficient product identification and evaluation in reverse logistics and prior to remanufacturing. However, the industrial viability of AI in this context remains to be determined. This research explores potential applications, challenges, technologies, and implementation aspects through expert interviews. The gained insights clarify the effectiveness of AI in product management within reverse logistics across diverse sectors.

1 Motivation

An increasing variety of products and ever-shorter lifecycles characterize the modern industry. Simultaneously, there is a growing societal interest in sustainable economic practices, exemplified by renewable energies, environmentally friendly resources, and recycling. This presents significant challenges across the entire global value chain. Consequently, a shift from traditional linear business models to a circular economy has been observed in recent years. Many companies aim to enable value preservation, resource conservation, and simultaneous profit growth [1]. This is achieved, in part, through the return and processing of used or defective products and components. Mainly done manually, the initial inspection of these products requires clear identification and determination of their condition, posing a highly complex process due to the diverse values, characteristics, and conditions of the often variant-rich goods. However, this process yields low-value creation, necessitating the selection of large quantities of products for refurbishment. A flexible and intelligent approach is required to address this dilemma, capable of independent application to various components [2]. One approach involves using Artificial Intelligence (AI) through Machine Learning (ML) and Deep Learning [3].

Currently, there are only sporadic applications of AI-based product identification and evaluation within the circular economy context, making the potential and necessity of industrial implementation still being determined. The anticipated benefits are consequently challenging to estimate, and the required procurement and implementation costs initially pose risks for companies. Additionally, acceptance of AI applications in reverse logistics may be open to question, potentially due to a lack of competence and willingness within companies.

The objective of this work is a practice-oriented exploration of the potential for industrial implementation. This goal is achieved through a qualitative analysis of expert interviews, evaluating potential application areas for product identification and evaluation in process-oriented challenges, improvement potential, and introduction aspects. This approach allows for a well-founded assessment of the deployment potential of AI-based product identification and evaluation for reverse logistics in various application domains. Section 2 discusses the interview preparation and analysis method applied for this work. Afterward, the gained insights are presented in section 3, and a conclusion is drawn in section 4.

2 Interview preparation and analysis

For interview preparation, research and market analysis were conducted to identify potential companies highlighting the circular economy, remanufacturing, or reverse logistics on their websites. Thirty-three companies were described based on use cases and product portfolios. Multiple potential interviewees were identified and prioritized for each company. Semi-structured questionnaires were created based on market analysis and literature review, attached in Annex 1. An interview protocol was documented during the interviews, and audio recordings were transcribed after the interviews in two stages to evaluate them. Transcription was initially done by machine and then manually corrected in the second stage to rectify transcription errors. After transcription and evaluation, the contents were translated into English.

Transcript evaluation follows Mayring's Qualitative Content Analysis to suit the opinion-oriented data. This method reduces extensive text to relevant statements [4]. We developed a category system for comparing expert statements, facilitating a targeted response to the research objective [4]. Using a combined deductive-inductive approach, we maintained focus while incorporating new aspects. MAXQDA software aided the analysis. Evaluation occurred in two steps: 1) Initiating textual analysis marked relevant statements, expert knowledge, possible quotes, and paraphrased opinions, and 2) Classifying relevant passages into the category system. The following section presents these classifications thematically, outlining the study's results.

2 Insights from Expert Interviews

This section outlines the expert interview results based on the deductively inductively formed category system, including 12 main categories and 23 subcategories. Three overarching thematic areas are discussed, with the first focusing on the potential deployment of AI-based product identification and evaluation. This is analyzed within the framework of the EIBA system. Each thematic area begins with category definitions, followed by a comparative presentation and interpretation of experts' core statements. Noteworthy remarks are italicized quotes from respondents identified by interview codes, like I1 (Interview 1), representing specific segments and product categories. The following table clearly maps respondents' affiliations to contextualize their statements and draw meaningful conclusions.

Table 1: Interview overview

Interviewee	Segment	Product Category
I1	Re-Commerce	Consumer electronics
I2	Remanufacturing	Construction machinery, Maritime
I3	Re-Commerce	Consumer electronics, Media
I4	Catering	Food
I6	E-Commerce	Fashion
I7	Remanufacturing	Electronics

The following sections examine how product identification and evaluation are implemented in the experts' companies. The process flow is detailed, emphasizing identification, evaluation, classification, and the covered product portfolio. Challenges in the process and the potential of AI-based product identification and evaluation to address them are discussed. Lastly, the introduction and use of AI-based product identification and evaluation are explained, focusing on optimal usage, key decision factors, resources, and potential barriers from the experts' viewpoint.

3.1 State-of-the-art product identification and evaluation

This category includes the current process for handling returned goods in the surveyed application areas. The identification, evaluation, and classification processes are examined in more detail within this context. Furthermore, the covered product portfolio is addressed. Most experts mentioned highly standardized process workflows, primarily done manually by employees. Employees are often assisted by software that stores manually recorded information and guides the processing flow.

I1: *"We have developed software that conducts standardized data collection for each device in various condition categories. This encompasses aspects from packaging to the external appearance of a product. [...] we addressed this through technologies and also through what we call a user interface, which is available to the workforce in the warehouse. It allows standardized data collection for the different requirements of categories and products."*

I7: *"The system we have already assumes a certain standardization of the process steps. [...] it's like an electronic work plan that needs to be followed. You cannot skip a step, and afterward, you can precisely see what has been examined. And what results are obtained in each step."*

Only I3 reports on an automated processing process where only 25% of the activities are performed by humans. This includes cleaning the products while machines take over the evaluative tasks. However, this is more of a particular case, as other company locations have a higher proportion of manual work, and other companies in re-commerce are significantly more manual in their setup.

Regarding the process steps relevant to this study, it is evident that identification, evaluation, and classification of returned products and components are conducted in all surveyed application areas. However, there is a heterogeneous picture in terms of the manifestation and complexity of each step. According to experts, identification is typically done through the serial number with a visual process. Only I3 reports reading product information through software for phones, tablets, and MacBooks. In medical technology, identification occurs through a legally mandated 2D barcode, which is crucial for product processing approval. I4 mentions an AI-based system identifying returned food through photo comparison with a database. I3 notes that over 50 percent of trade volume is already automated but accounts for only 10 percent of the product portfolio. While most areas involve only initial product or component identification, I2 reports an additional identification at the part level through an automated optical system.

According to the experts, the evaluation of returned goods is almost exclusively done manually. Only I3 reports optical error detection through an AI system that compares photos with a database to identify scratches, for example, on mobile phones. However, this is only feasible for a portion of the product portfolio, as other categories are manually evaluated. The importance of an evaluation that is as objective as possible is also emphasized. I1 and I7 describe a software-assisted manual evaluation.

I3: *"What we have found throughout the entire process is that the identification of damage is the key point because when you involve humans, it becomes subjective. We conducted tests [...] with a set of our best-trained graders, who are our quality assurance experts. In the normal process, without them knowing it, we repeatedly distributed the same devices throughout the shift from morning to evening. And believe it or not, in the evening, they rated the same devices much lower than in the morning."*

In addition to visual evaluation, most experts discuss a functional assessment (I1, I2, I3, I7). I3 also mentions an evaluation of accessories. Statements regarding the complexity of the evaluation vary significantly among the experts. I2 describes a simple assessment to keep the hurdle for returning used components low. In contrast, I3 refers to an elaborate evaluation with 280 checkpoints in the automated and 70 checkpoints in the manual process. I6 and I7 emphasize that the criteria are product-specific.

Four experts report a classification of products and components based on the preceding evaluation. The classification aims to target the processing of returned goods, especially by sorting out economically non-recoverable objects early. Statements regarding the complexity of the decision-making process differ. I7 explains that a decision is made after each evaluation stage on whether to proceed with a component or to sort it out and scrap it. A similar process is described by I2, where classification occurs only after the initial evaluation. The core criteria of the evaluation serve as the basis for decision-making. I6 outlines a three-stage classification into saleable (A), refurbishable (B), and to-be-sorted-out (C) products. The decision is subjective and made by trained employees considering product-specific classification criteria. I1 describes similar classification levels, incorporating additional information such as market value, demand, and repair costs based on the condition assessment. A self-learning ML algorithm makes the decision. I1 emphasizes the minimization of the error rate achieved.

I1: *"We have developed software that conducts standardized data collection for each device in various condition categories. [...] Based on this data, we decide on the further fate of the device by enriching it with additional information, such as market value, repair costs, demand, and other factors – essentially, everything one can imagine, and at this point, we are moving already towards the realm of self-learning algorithms."*

Regarding the covered products and components, all experts describe broad product portfolios with a very high diversity of variants. I1 lists 3,500 products in the field of consumer electronics with 8,000 to 9,000 variants. For I3, there are about 30,000 electronic products, specifically *"[...] everything from smartphones, tablets, MacBooks, and Mac Minis, digital cameras and accessories and lenses, etc., video game consoles from PS to Xbox, etc., smartwatches from various manufacturers, so everything from Apple to Garmin."* I6 estimates the portfolio at approximately 1 million item numbers, with about half in the fashion sector. I2 breaks down the product portfolio into components such as combustion engines, hydraulic pumps, hydraulic motors, transmissions, and winches for the construction machinery, cranes, mining, and maritime sectors. In total, several thousand variants are covered in remanufacturing. I7 describes that the focus is less on repairing entire components than refurbishing circuit boards for patient monitors. The portfolio includes over 1,000 variants.

3.2 Current Challenges and Potential for Improvement

This category considers current challenges within the previously analyzed processes of identification, assessment, and classification. Regarding these challenges, the potential of the EIBA system for AI-supported product identification and evaluation is discussed.

Experts point out various challenges. For I6 and I7, the most significant challenges lie in the limited capacities for processing returned goods. I6 concludes that an increase in process speed is necessary to handle high return volumes efficiently. I7 advocates for a decision-making process that takes into account the expected workload. Returns that do not meet the requirements should be sorted out early.

Additionally, optimal resource planning and resource-oriented personnel planning are seen as challenges. I6: *"The biggest challenge is speed. We don't have enough capacity; we have too many returns. We are never fast enough to reintegrate everything that is returned back into the sales process at 100 percent."*

I1 and I2 see a challenge in the manual design of processes. I1 adds the subjectivity of humans as well as the diversity of the product portfolio. The desired standardization of methods is the most significant challenge of these issues. For I2, there needs to be more quality-oriented pricing for used parts. I1: *"Certain decisions need to be made. Can the product be rented again, does it require specific refurbishment or repair, or is it beyond repair? Yes, and the biggest challenge is how to standardize something that is currently manually inspected by people. It's a relatively manual process, and it is very subjective."*

The optical evaluation is considered the greatest challenge by I3. I3: *"Optical assessment, definitely, optical assessment. For us at the moment, since we don't have a learning system in regular operation, it means that a new rule set has to be developed for each new product or variation. [...] Then, one of my employees scans them all, and the scans are processed one after the other. He adjusts the rule set accordingly and says, 'Okay, this would still work, that would still work.' You can imagine, you know how many different product variants there are."*

I4 identifies system networking as the current most significant challenge. I4: "*The concept of a circular economy would, for example, involve this waste system where I collect data that, in turn, has an impact on my ordering behavior. I believe the biggest challenge is to connect the systems with each other, so that everything communicates together. Otherwise, I have some data in one pot, some data in another, and they're just standing around. They should probably be connected in many areas, and then a result should come out of it."*

A positive outlook emerges in relation to the potential of AI-based product identification and assessment derived from the described challenges. Five out of the experts describe specific applications to enhance the existing process. I3 and I6 see identification through the AI system as advantageous. I3 can envision using the AI system to identify products that have been exclusively manually recorded. I6 sees potential in order-specific identification of returns. I3 and I7 see potential in AI-based assessment. I7 describes its use in assessing the condition of circuit boards, particularly regarding their integrity. Immediate classification based on the evaluation is also noted as beneficial.

Furthermore, optical pre-inspection holds the potential for early sorting out non-processable components, improving the efficiency of subsequent processes. I3 describes a possible assessment of products currently inspected manually as meaningful. I4 considers less the mere identification of food than an integrated derivation of recommendations based on defined cases. Additional information, such as delivery weight and weather conditions, should also be considered. I1 sees the most significant potential of AI-based product identification and assessment in its use as a market standard. Instead of individual competitive advantages, I1 values the benefit for the entire market as more critical to achieving both sustainable and economic goals.

3.3 Incorporation and Utilization of AI-Based Product Identification and Evaluation

This category addresses relevant aspects of introducing an AI-based product identification and evaluation system. Initially, the optimal use from the experts' perspective is discussed. Essential decision factors and necessary resources for the introduction and sustainable utilization are described. Finally, potential barriers to the introduction are explored.

All surveyed experts have a concrete idea of the optimal use of the AI system. I2 and I7 consider integration into existing technical infrastructure, such as inventory and documentation systems, crucial. I2 describes that deriving patterns and trends from identification and assessment could serve as a meaningful basis for customer negotiations. I7 sees automated documentation of assessment results and integration into the existing documentation system as advantageous. Experts I3 and I6 highlight the use of the system at the beginning of the process chain as an optimal use case. I3 explains: *"[...] the perfect scenario would be a machine opening the package for me, also related to hygiene, and immediately identifying what's inside and how good or bad it looks."* I6 describes a similar scenario: *"You can start the returns processing with it and then install a switch afterwards... "*. While I2 sees potential only in efficiency improvement in pure identification and evaluation, I7 emphasizes: *"[...] one thing that should also be automated are investigations that you otherwise have to laboriously do visually or something like that, and that take a long time."*

I3 emphasizes the avoidance of subjectivity and errors in identification and assessment as an economically important factor. I3: *"[...] The optimal use would really be, like a dream: the items are placed on a conveyor belt by DHL, a robot cuts it open, scans it, indicates which conveyor belt, and then I proceed with further processing, possibly even with another device where I go over it again and perform a fine scanning because I only looked at it roughly before and might have cleaned it in between. That would be really cool!"*

I6 describes the relief of employees and the capacity of subsequent process steps through early sorting of returned goods. I4 confirms that maximum support for workers is the optimal use and a possibility to enhance process efficiency. Like I6, I2 also addresses capacity and states: *"[...] If, of course, you can make clearer predictions about capacity, how fast you would need to be or should be if you have benchmarks, that would certainly help."* I1 is confident that an increase in the degree of automation provides the optimal use and a foundation for further innovations. I1: *"For our use case, that would certainly promote an acceleration of automation and probably also offer completely new possibilities for innovation. I would reflect the same on the entire market. Standardization and usable technology, linked with legislation that can address these issues, would innovate the market and significantly promote the sustainability segment as well."*

Most experts consider the cost and performance of the system as the most crucial factors for implementing AI-based product identification and assessment. Regarding the system's performance, I1, I4, and I6 differentiate between the quality of results and the processing productivity. I3 and I7 perceive scalability across the product portfolio as a crucial decision factor. I3 explains: *"It doesn't help me if I have a learning algorithm that I have to train for every new phone or for every color of phones."* Validation of the system is considered necessary by I1 and I7. Other factors from the experts' perspective include technical availability and the ability to integrate into the existing company infrastructure. I4: *"A classic cost-benefit analysis. We are also always dependent on our customers because, in the end, they pay for it or at least contribute to the funding. And if it turns out that we can improve certain processes, streamline them, and increase quality through this, it's optimal."*

Regarding the necessary resources for the introduction and sustainable use of the AI system, the experts agree that suitable personnel is primarily essential. I2, I3, and I4 particularly emphasize this concerning IT expertise. I2 highlights the need to build knowledge for system operation within the company through training. I7 even sees this as a necessary prerequisite. In addition to efforts in the IT area, I4 considers the related interfaces as another vital personnel resource, such as procurement or inventory management. I7 emphasizes the use of external personnel for the introduction.

Another important aspect, according to I3 and I4, is financial resources. I3 refers explicitly to the costs of technology, hardware, and personnel. On the other hand, I2 considers financial means to be secondary. Another resource, according to I3, is the training set, precisely its scope and quality. I3: *"The other thing is the quantity and quality of the test set, the training set [...]. You just have to have the opportunity, and I see it as a great benefit if there is cooperation between a company or a research institution that has the technology and knowledge, and on the other side, someone like us, a re-commerce provider, who says 'Yes, come, I send 2,000 phones through every day. How many do you want?'"*

A mixed picture among the interviewed experts is assessed regarding possible barriers. I1 and I7 address the necessary system validation in the context of the industry- and company-specific requirements. I3 explains that the length of the project and the potentially limited experience should be taken into account. I2 sees the consolidation and regular updating important component information as a possible barrier.

I3: "[...] We can't ask anyone [...], and that's the point I find most critical, and everything else follows from that. You can quickly run out of money in the process if the results are not correct, and if you don't have the basic requirements with enough objects to learn or test the whole thing, then you also have a problem."

A much-discussed aspect and potential barrier is the workers' acceptance of using the AI system. Most experts agree that this is not a critical barrier. I2 and I3 are confident that it would even be well-received. I4 and I6 see employee acceptance as given, provided that the introduction and impacts are communicated clearly. I7 compares that employees are already working with IT systems and are accustomed to them. I1 is more skeptical about unanimous acceptance and refers to demographic factors such as generation, nationality, and region.

4 Conclusion

Expert interviews on product inspection provided valuable qualitative insights into the potential of using AI and ML for product identification and evaluation. Challenges identified included high manual labor, subjective decision-making, variant complexity, and capacity issues. The performance profile indicated that AI-based solutions effectively address these challenges, a view supported by experts. Integration into existing infrastructure (remanufacturing), minimizing subjectivity and errors, and improving planning (re-commerce) and capacity relief (e-commerce) were highlighted as optimal applications. Human acceptance was not seen as a barrier. While half of the experts currently use similar technologies, the EIBA system stands out for its integrated product identification and evaluation and AI-based capabilities.

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Annex 1: Questionnaire

Location and date of the interview	Duration of the interview	Ident. -No.

Topic: Examination of the performance and potential of innovations with artificial intelligence in product identification and evaluation

Objective: Assessing the potential use of artificial intelligence-based product identification and evaluation for specific applications and industries

Interview opening & introduction	▪ Expression of gratitude for participation ▪ Brief self-introduction ▪ Explanation of the approximate interview process ▪ Confirmation of the consent statement ▪ Optional: Organizational questions for the interviewee ▪ A brief introduction to the topic ▪ The objective of the interview

Introductory questions	**Background (Start of interview)**	▪ What is your current position and responsibilities? ▪ What experiences have you had with applications of Artificial Intelligence (AI), personally and professionally? ▪ To what extent is AI already used for business processes in your company? ▪ What do you associate with AI-based identification and evaluation in the context of the circular economy?
	Industry overview	▪ Can you tell me about your experiences in your industry and how it has developed in recent years? ▪ What are the biggest challenges in reverse logistics that companies in your industry are currently facing? ▪ What growth opportunities do you see in your industry? What growth prospects do you see in your industry through reverse logistics? ▪ In your opinion, what trends or technologies do you think will influence your industry in the coming years?
Guiding questions	**Challenges and impact**	*Introduction of the AI system for the identification and evaluation of products, which was developed as part of the EIBA project. The EIBA system is explained based on its structure and expected performances.* **Question 1:** In what context does the identification and evaluation (inspection and sorting) take place in your company? **Follow-up:** Can you describe the current process flow? What is the diversity of the products being processed? What are typical products? How are products currently identified? How are products inspected/evaluated? Are there guidelines/standards for inspection? What are typical criteria for inspection? How are products currently classified? Are there distinct quality levels? Which tasks are performed by employees? Why are the processes performed manually? What are the environmental conditions like? **Question 2:** What are the biggest challenges of the current process? **Question 3:** How could the EIBA system contribute to improving the process?
	Substitution	**Question 4:** Is a technology comparable to the EIBA system already in use in your company, or are you aware of a similar technology?

	Follow-up: How do you perceive the EIBA system in comparison? **Question 5:** In your view, what are the differences between the presented EIBA system and comparable technologies or current processes?
Applications and requirements for implementation	**Question 6:** In your opinion, what could be an optimal use of the technology? **Follow-up:** Which functions should the EIBA system cover to be sustainably successful in your process? **Question 7:** What factors would you consider in the decision to introduce the EIBA system? **Question 8:** In your opinion, what resources (e.g., personnel, financial, etc.) are required for a successful implementation and sustainable use of the EIBA system? **Follow-up:** Can you think of any requirements or adjustments that you consider particularly important for successfully introducing the EIBA system? **Question 9:** In your opinion, what are the biggest barriers that could arise during the introduction of the EIBA system? **Follow-up:** How would you assess the acceptance of the workers in the event of introducing the EIBA system?
Outlook	**Question 10:** Can you think of additional potential uses or applications for the EIBA system that may not be immediately apparent?
Conclusion	▪ Summary of the discussed aspects ▪ Do you have any final comments or suggestions? ▪ Do you have any remaining questions?