Journal of Cleaner Production xxx (xxxx) xxx

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Exploring 14 years of repair records – information retrieval, analysis potential and data gaps to improve reparability

Eduard Wagner [a, *], Ellen Bracquené [b], Melanie Jaeger-Erben [a]

[a] TU Berlin, Reseach Center for Microperipheric Technologies, Gustav-Meyer-Allee 25, 13355, Berlin, Germany
[b] KU Leuven, Department of Mechanical Engineering, Celestijnenlaan 300A Box 2422, 3001, Leuven, Belgium

ARTICLE INFO

Article history:
Received 31 May 2020
Received in revised form
18 November 2020
Accepted 23 November 2020
Available online xxx

Handling editor: Cecilia Maria Villas Bôas de Almeida

Keywords:
Digitalisation
Repair
Data potential
Circular Economy
Digital transition

ABSTRACT

The digital transition generates data that can enable and support the optimisation of products and accelerate the circular economy adoption. However, the potential of this digital transition to support product reparability has not yet been fully explored. Therefore, this study aims to provide fundamental knowledge on potential opportunities and limits of repair data for specific repair applications relevant to different stakeholders. An unfiltered dataset was obtained from an independent repair shop and an explorative data analysis approach was applied to clean, visualize and analyse the data. The applied data cleaning techniques are scalable and adaptable to other repair dataset which would reduce cleaning efforts significantly.

The potential benefits of the repair data was investigated through three specific applications. First, the analysed repair data enabled the identification of priority parts based on (1) failure modes occurrence, (2) increasing failure modes occurrence over time and (3) low repair success rates. Second, the data analysis showed that repair costs can be lowered by increasing repair time for deeper component disassembly and replacement but using less expensive material (new component vs part). Third, the potential of repair data to improve the symptom-based diagnose was demonstrated. It allows to establish a step-wise diagnose process, especially for symptoms with high repair time variation and failure mode probabilities. Such an approach is expected to significantly reduce labour time and therefore repair costs.

Recommendations are derived for future data collection on target repair parameters and necessary data quantities. Harmonising classification systems, improving data recording processes and using a centrally provided product model databases will make the target repair parameter extraction more viable and increase the potential benefits from data pooling.

1. Introduction

Electronic waste (e-waste) is a fast growing waste stream with over 10 million tonnes generated in Europe each year (Baldé et al., 2017). Reparability is a useful strategy to reduce waste generation by extending product lifetimes and postponing the need and manufacturing of a new product (Ardente and Mathieux, 2014; Bocken et al., 2016). However, repairing modern electronic equipment is becoming increasingly difficult for independent repairers or consumers. Obstacles are across legal, technical or economical categories: lack of appropriate repair information, lack of access to and high costs of spare parts, rapid change of product design and difficulty to disassemble products for repair without breaking the housing forcefully (RREUSE 2015; Svensson et al., 2018).

Information and data availability play a critical role in the digital transition and in current political agendas in Europe such as the "New Circular Economy Action Plan", the "Green New Deal" and the "European Digital Strategy". These policies aim to improve data availability on product characteristics to empower users with reliable, comparable and verifiable information on repair and dismantling possibilities (EEB 2018; EC, 2020a; 2020b). Product lifecycle data (including repair data) used for diagnostics, maintenance and prognostics of components and products is fundamental to prolong product lifetimes and reduce transaction costs (Ellen MacArthur Foundation, 2016).

Repair related data are mainly generated within two periods which has consequences in terms of data ownership, availability and content. First, within the product warranty period,

* Corresponding author.
E-mail address: eduard.wagner@tu-berlin.de (E. Wagner).

https://doi.org/10.1016/j.jclepro.2020.125259
0959-6526/

manufacturers have access to data from their own after-sales repair services and they can utilize this data for product design improvement and spare part provision strategy (Blischke et al., 2011). Second, in the post-warranty period, repair data is generated mostly by small independent repair shops (3 employees in average in Germany, 2017) resulting in heterogeneous data structure and scattered datasets. Therefore, data collection efforts for post-warranty data is significantly higher (Poppe 2014; Bundesamt, 2017).

Nevertheless, post-warranty data is of great importance to better understand the reparability of failed products. Other researchers have also identified a lack of relevant post-warranty repair data (Monier et al., 2016; Tecchio et al., 2019). While generic data is sometimes available through review studies, detailed primary repair data are rare and accessibility is still limited, hindering the analysis on the potential application (Alfieri et al., 2019; Tecchio et al., 2019). Vice versa, without economic incentives and little knowledge about the benefits and usage options, sharing data is less attractive (Hammer et al., 2017).

The overall goal of this study is to provide knowledge on the potential opportunities and limits of data from post-warranty repair. The raw dataset is used to describe cleaning efforts, data gaps and derive measures for improvement. Furthermore, the data analysis and discussion is structured by the following selected applications:

(1) **Priority parts identification:** Prioritisation of parts is commonly done by analysing failure frequency and trends of individual parts as well as economic and environmental aspects. They are commonly identified for eco-design preparatory studies used by EU legislation (Bennett et al., 2017; BIO by Deloitte, 2013). In addition, manufacturers use quantitative data of failure modes to forecast the type and amount of spare parts needed (Jack et al., 2000) and to minimize related additional costs for production, storage, management and logistics (Huang et al., 2007). The need for long term statistics to identify priority parts becomes more relevant due to the recently revised Eco-design regulations, including requirements for manufacturers to provide product repair information and spare parts for at least 10 years after purchase (EC, 2019).

(2) **Minimal repair strategy**: Repair services, offered by manufacturers or independent repair shops, aim to increase cost efficiency by targeting a minimal repair strategy that balances repair time and repair depth. Indeed, replacing (smaller) components instead of entire parts can reduce the material cost but, at the same time, it will increase the repair time as it requires more disassembly steps (Tadj et al., 2011). According to Blischke et al., producer warranty strategies also include imperfect repair strategies to limit repair cost (Blischke et al., 2011). This cost optimisation problem is often tackled by analysis of data on failure modes, product age, usage and material cost (Varnosafaderani and Chukova, 2012).

(3) **Symptom-based diagnosis support**: Repair shops as well as self-repairing users are faced with increasing product variety, changes of product design and technology. The rising complexity of product put on the market requires new repair skills and increases the necessary experience to identify failure modes based on symptoms. In general, failure diagnostics is time consuming and can heavily influence the repair cost due to associated labour cost. The effect of rising complexity and labour costs is reflected in a decrease of repair jobs (Monier et al., 2016). Similar challenges are indicated by 39% of EU citizens, who throw things away as it is difficult or too expensive to get them repaired (TNS 2014). In a behavioural study on "Consumers' engagement in the Circular Economy", up to 25% of EU citizens have indicated availability of spare parts and information as important aspects (Cerulli-Harms et al., 2018). Provision of self-repair tools as the currently developed online tool for failure diagnosis could facilitate the reduction of barriers and may make repair more viable, though lacks on large scale repair data (Open Repair Alliance 2020).

By these three applications, this study aims to demonstrate the potential value for stakeholders, in particular repair shops, to further incentivise data sharing and overcome limited data accessibility for further data sampling. To this end, following research questions should be answered:

- To which degree can the case study data be used for the selected application cases?
- Which data gaps are preventing a further analysis and to gain benefits, in particular for repair shops?
- Which data quantities are necessary to analyse on brand and model specific failure modes?

2. Material and method

The explorative data analysis approach applied in this study is commonly used for empirical exploration of historic datasets to provide fundamental knowledge for hypothesis generation and formulate data induced recommendations, instead of statistical hypothesis testing. Furthermore, the authors combine this approach to practical steps from knowledge discovery in database (Marbn et al., 2009): the characterisation of the repair process and available raw data to evaluate the quality of the sampling process (2.1), the data preparation (2.2), data analysis towards repair related application cases (2.3) and data pooling scenarios (2.4). In a next step (2.5), case study boundaries and results are discussed against selected data quality criteria.

2.1. Raw data characterisation

The raw data obtained from a German independent repair shop included 30174 repair records on out-of-warranty repairs collected from 2003 to mid-2017 (about 2155 cases per year, neglecting 2017). Although they repair both small and large household appliances, the main activity of the repair shop concerns large household appliances such as washing machines (WM) which usually requires to carry out repairs on site (at the customer house). The different repair steps defined by the repair shop are described in Table 1. In addition, a sample record from the raw dataset is given in the right column to illustrate the raw data quality and cleaning efforts.

The repair starts with an initial remote troubleshooting (usually a telephone call). For each customer inquiry, a record is generated with initial parameters including personal and geographical information, worker and device. Next, a technicians is sent on site to further investigate symptoms and failure mode. Although the technicians has foreseen repair activities based on the initial symptoms descriptions of the customer, sometimes an additional visit may be required which significantly influences the repair cost. During the on-site visits, brand/model, symptoms, failure modes, labour time and total repair costs are noted by hand on paper and later digitally transferred to the comment field of the digital repair record. However, the information recorded in the comment field uses a coding system which requires further data preparation

Table 1
Aggregated repair steps that are relevant to data recording. Example values show parameters, structure and values (right column).

Repair step	Process description	Format	Example raw data record	
1. Remote troubleshooting	Description given by customer (personal information, device category, brand, symptom); Initial technical diagnose and economical estimation on total repair costs;	Electronically recorded (structured)	Date	12.05.2015
			Location	m-i
			Distance	2
			Distance cost	45
			Worker	j
			Device	w
2. On site diagnosis & repair	Professional diagnosis and repair on-site (in case of positive customer decision)	Electronically recorded from handwritten notes made on site	Comment	j w siem pna p4 0,25h 60 15.05.2015

before repair information can be extracted.

2.2. Data preparation and text structuring

The data preparation of the raw data towards the application scenarios included the following steps: (1) structuring the comment field by extracting parameter, (2) calculating not directly available parameters and (3) excluding unnecessary parameters or errors (eg. missing ID number). The unstructured text in the comment field, shown in Table 1 is converted into structured data in order to facilitate further analysis. This conversion is done by a natural language processing technique called ‘named entity extraction’. Entities, here also referred as parameters, from the example in Table 1 are: repair worker (j), device category (w), brand (siem), symptom (pna), failure category (p), repair action (4), labour time (0,25h), total repair costs (60), date of repair (15.05.2015).

The proprietary coding system consists of 26 failure mode categories for parts with 38 subordinated components, 18 symptoms and 7 repair action categories with 18 subordinated repair actions. For each entity or parameter of the comment field, rule based extraction algorithm and dictionaries (look-up tables) have been established including the proprietary coding system (see Annex A.1 and A.2). The data preparation script followed the search rule: if (text in comment field) includes (code from dictionary) extract (code). Finally, the cleaned dataset presented in section 3.1 consists of 12951 records, considering a record to be complete with majorly available (above 11000) parameters: ID, date, symptom, failure mode, repair action, total repair time, total repair cost.

2.3. Data analysis for the selected repair data application

The three potential repair data applications (introduced in chapter 1) for data analysis include the target parameters that match with the available parameter from the dataset: date, brand, symptom, failure mode, repair action (incl. not repaired), total repair cost. Supplementary data as environmental or lifetime data is out of scope as available data and data gaps are focused. The selected applications are relevant to different stakeholders, demonstrating individual interests:

Manufacturer and legislator: The first application is to use available repair data to identify priority parts. Priority parts are subject to high failure rates and/or critical for the product to deliver the main desired function (Bracquené et al., 2018). The target parameters to identify priority parts are failure mode, repair success rate (repair action) and temporal distribution (date). The priority parts are identified with the combined criteria of highest absolute occurrence of failure modes, increasing failure modes over time and lowest repair success rates.

Repair businesses and manufacturer: the second application analyses the repair strategy for different failure modes. The repair data is used to analyse the trade-off between labour cost (repair time) and material cost (spare part purchase). In other words, does the cost for longer repairs (eg. for replacing components with more disassembly steps) balance out with lower material cost (avoiding the purchase of new spare parts)? For this analysis, the repair actions in the dataset are clustered into three categories “using no material or maintenance material”, “replacing component or part” and “not repaired” (Table 4 in annex A.2.). The total repair cost is aggregated from two available parameters: labour cost and material costs. Different repair strategies are visualised by average repair costs and failure modes for each repair action.

Repair business and self-repair community: The third application explores the potential of the repair data to support symptom-based failure diagnose. Different failures modes can cause the same symptoms which greatly increases the difficulty of remote troubleshooting and on-site failure diagnose. Based on the repair data, the likelihood of different failure modes is visualised for each recorded symptom. To indicate benefits in terms of time savings, the average repair time per failure mode is presented, showing variations in repair time for a specific symptom, for example “not draining”.

2.4. Evaluating the potential benefits of large-scale datasets

Data sharing holds potential for gathering critical data amounts for new repair data application or improving the accuracy of the obtained correlations and results. The potential benefits are demonstrated for a particular use case where the level of detail for the repair data analysis is increased. First the amount of data required to achieve the targeted improvement is estimated. Second, the feasibility of pooling sufficient data to realize the aimed data use case is evaluated.

The dataset obtained in this study from one repair shop only enabled data analysis at product level and brand level. The dataset was not able to capture sufficient repair information at specific model level. Indeed, the high variety of available models in the market requires high amounts of data that can hardly be provided by one repair business. To calculate the necessary data quantity, two scenarios are established, based on different model variety assumptions in the market. The first “maximum variety” scenario includes all available models that are currently available, based data from a price comparison platform, showing currently 1412 different WM models (67 brands, released between 2015 and 2020) (idealo, 2020). The second scenario assumes that most households own popular or common models (pareto principle). Data for this "common-brand" scenario is based on the consumer oriented product testing organisation Stiftung Warentest, comparing 84 different WM models (of 20 most common brands between 2015 and 2019) (Warentest, 2020).

Furthermore, the feasibility to collect the necessary data quantities from repair businesses is evaluated. The expected generated records per year and employeeis estimated based on the available case study dataset. This estimation is then extrapolated to the German repair sector assuming 3 employees per company with the same repair focus (household appliances). Data is taken from the statistical report (Bundesamt, 2017) in Germany, counting 1133 companies with 3503 employees performing repair on electrical household and garden devices.

2.5. Data quality discussion

In chapter 4, the boundaries of the case study are discussed qualitatively for the results (chapter 3) on data preparation and application analysis. Data quality evaluation metrics are adapted from ISO 25012 (Rafique et al., 2012; ISO/IEC 25012, 2008): information accuracy (correctness), currentness, credibility, completeness, consistency and portability (homogenisation). We discuss the metric completeness towards data gaps for the applications (fit-for-purpose).

3. Results

3.1. Analysis of the dataset

Table 2 gives an overview of the target repair parameters and provides insights in their availability after cleaning the dataset. While some parameters are directly registered or could be derived by applying text structuring rules, others are indirectly available by calculation. Furthermore, the target repair parameters are clustered in different categories from (Blischke et al., 2011) which are adapted towards electronic product repair process (column "parameter cluster").

After data cleaning, 12951 WM repair records are available (925 cases per year) of which 10300 are successfully maintained or repaired, 1651 not successfully repaired, 1000 with no failure or no repair action necessary (eg. typically releasing child lock or resetting an WM error code). In addition, repair records for other device category are also available: dishwasher (7403), tumble dryer (2039), refrigerators (1026) and vacuum cleaner (375). While the product category is always recorded, the specific brand of the product was only registered for more than half of the repair cases. Nevertheless, a significant amount of records were found for 10 different brands.

Identifying specific WM models is very challenging and was only retrieved in about one of 20 cases (5%). This is mostly due to small repairs or restoration that did not require any brand or model specific material. Furthermore, extracting model information out of the comment field is challenging, as a structuring rule could not be applied (models did not have a specific position in the comment field and an extensive dictionary containing all available model names would be necessary). In those cases where the model description was recorded, the repair worker also estimated the product age.

In some cases, repair parameters are aggregated in the data record which hampers the data analysis. For example, although the total repair time is directly recorded, no breakdown is provided for failure diagnostic and disassembly time. In addition, before 2014, the total repair cost (invoiced to clients) included material, labour, travel and spare part cost. Since 2014, the travel and labour cost are recorded separately. However, the spare part price can still not be accurately calculated as the remaining cost may include other costs such as storage, overhaul and profit margin.

3.2. Repair data application

3.2.1. Identification of priority parts

To provide quantitative data and evaluate few existing field data from literature, failure modes are compared to results by (Tecchio et al., 2019) (data in Annex). Fig. 1 shows multiple and single

Table 2
Categorisation of generic target parameter and (in-)directly available parameter in this case study. Specific characteristics are commented.

Parameter cluster	Target repair parameter	Directly available parameter	Indirectly available parameter	Comment	Number of records (WM)
Product related	Product category	X			100% (13292)
	Brand	X		Available after cleaning	56,08% (7456)
	Model			Could not be extracted automatically	<5%
Product status related	Age	X			<5%
	Number of repairs				–
	Energy consumption				–
	Symptoms	X		Available after cleaning	97,43% (12951)
Customer related	Usage intensity				–
	Operating mode				–
	Maintenance				–
Repair related (technical)	Total repair time	X			99,39% (13212)
	Re- and disassembly time			Included in labour time	–
	Spare part availability	X			100%
	Specific tool or diagnose software	X			100%
	Repair action	X		Available after data cleaning	97,43%
	Failure mode	X		Available after data cleaning	99,39%
Repair related (economical)	Total repair cost	X			98,13%
	Labour cost		X	Before 2014 aggregated into total repair cost	45,96% (6111)
	Spare part cost		X	Aggregated into total repair cost	45,96%
	Travel cost		X	Before 2014 aggregated into total repair cost	45,96%
	Shipping cost				–

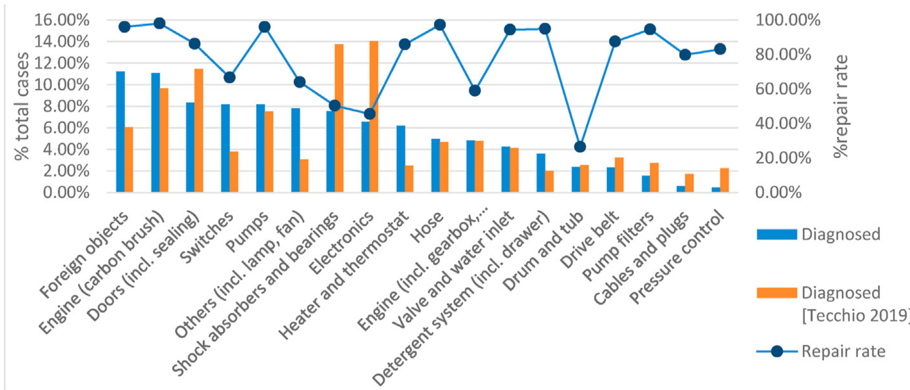

Fig. 1. Classification and comparison of failure mode distribution 2003–2017 to (Tecchio et al., 2019).

failure modes merged into the proposed classification system of Tecchio et al.. The relative contribution of each failure modes to the total repair cases are shown for both studies, repair rates are shown for this study only.

The failure modes are grouped into 18 categories, showing significant distribution with the top failure mode "foreign object" on the left side with 1266 repair cases, decreasing to 53 cases for pressure control on the right side. Major differences between both studies can be seen for electronics (−7,5%), shock absorber and bearings (−6,2%), foreign objects (+5,8%), switches (+4,4%) and heater and thermostat (+3,7%). In 15 failure categories, the successful repair rate is over 80%. Least successful failure modes match with Tecchio et al. with similar repair rates: drum and tub (26,4% compared to 27%), electronics (45,5% compared to 49%) and shock absorbers and bearings (50,4% compared to 47%). Splitting up the cluster, shock absorbers show 86%% and bearings 33% repair rate.

For the identification of failure modes of increasing concern, Fig. 2 represents the trends of failure modes, shown by their annual distribution. From 2003 to 2016, an increase in failure modes can be seen for electronics (from 1,9%–12%), shock absorbers (from 1,5% to 4,9%) and heater and thermostats (from 3,1% to 10,1%). We identify electronics as main priority parts, as they show a rapidly increasing occurrence, low repair rates and considerable amounts. Furthermore we consider heaters and thermostats as well as shock absorbers as priority parts with better repairability. Drum and tubs and bearings are of concern due to low repair rate while their trend for occurrence is decreasing.

3.2.2. *Minimal repair strategy*

Fig. 3 ranks repair actions from left to right by increasing complexity and material use: starting from maintenance and restore without the need for part replacement (left) up to unsuccessful repairs (right). In addition, three different categories of replacement are defined: (1) small component, (2) used part

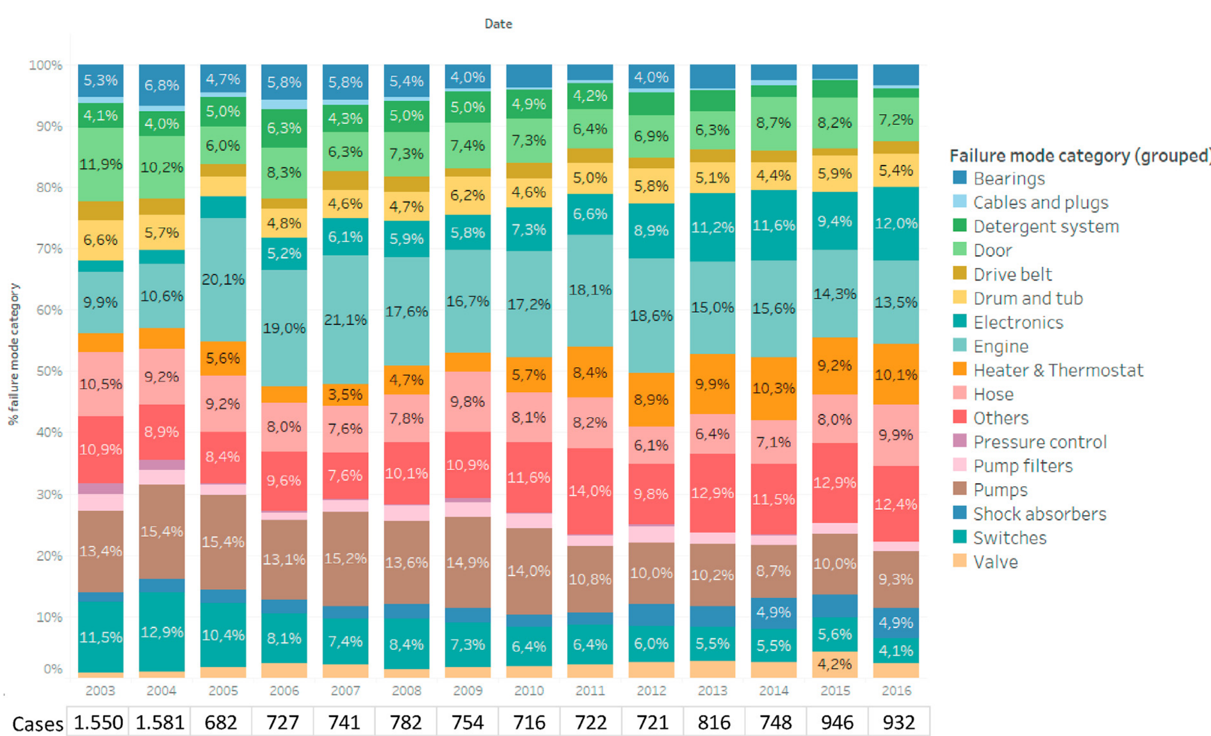

Fig. 2. Trends of failure modes for years 2003–2016. Distribution of failure modes shown per each year. Absolute number of cases are shown above for each year.

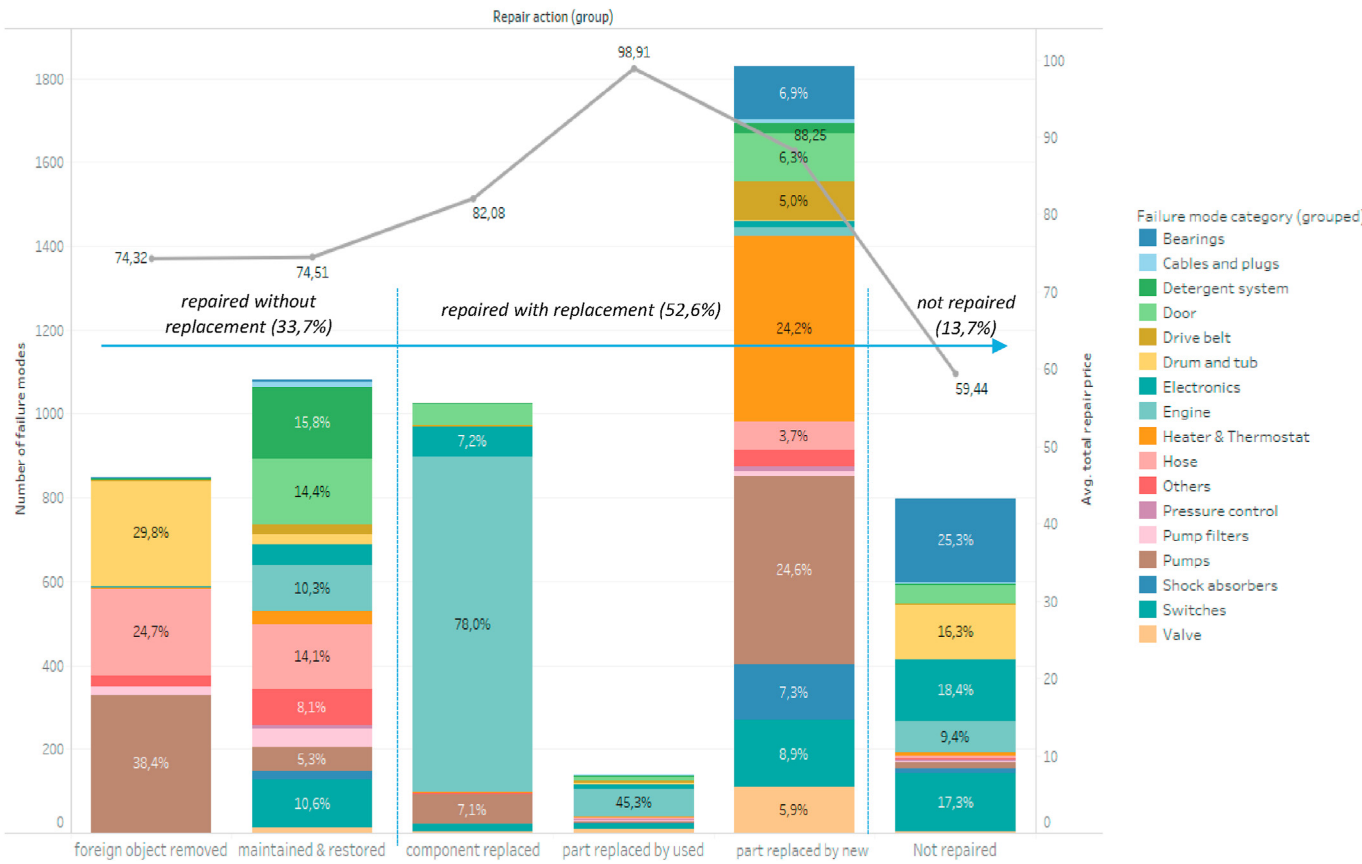

Fig. 3. Failure mode categories and average cost per repair action, ranked from left to right by increasing complexity and material use (assumed).

(harvested and stored by repair shop from end-of-life WMs) and (3) new spare part purchase. Furthermore, the graph shows average costs per repair action to understand price and repair relationship. For this analysis, only single failure modes (total 6206) are considered and the breakdown per single failure mode is indicated by colours.

A significant amount of repairs (1929 cases) were successful without any replacement. In these cases, the problem was solved by either removing foreign objects (849 cases) or maintaining and restoring components (1080 cases). For most repairs (2975 cases), however, components or parts were replaced. While new spare parts were used in 1828 cases, many repairs were limited to component replacement (1025 cases) such as carbon brushes within engines and electronic board components (resistance, triacs, diodes, transformers). For a few cases (122), failed parts were replaced by used parts replacing engines (42,4%), switches (10,1%) and electronics (10,1%). These parts are harvested from end-of-life WMs because purchasing new engines and electronic boards would make the repair economically unviable. In addition, switches are often unavailable on the spare part market. Nevertheless, this repair action, repairing with used parts, has the highest average costs (98,91 Euro) due to high labour cost (repair time) and storage costs. Unsuccessful repairs are dominated by bearings (25,3%), electronics (18,4%), switches (17,3%), drum and tubs (16,3%) and engines (9,3%). In addition, costs for non-repairable devices arise from travel and labour (diagnose) costs (about 60 Euros on average).

Overall, the results show that investing more time to minimize material usage is viable. Over one third of cases are done without material usage with significant less costs. Component replacement is specifically viable for engines and electronic boards because exchanging the entire part is too expensive. Even though repair with used parts is most expensive, it is a solution for failure modes that would otherwise be unrepairable.

3.2.3. Symptom-based diagnostic support

Fig. 4 shows failure mode categories that were diagnosed for each symptom. Only single failure modes are considered for direct symptom correlation. The two most common symptoms, not draining and not rotating, are caused in over 50% by a single part: pumps and engines, respectively. For example, not draining, as the most common symptom, results majorly from defect pumps (54%) followed by hose (18%), others (9%) and engine (5%) while the probability of the other failure modes is beneath 5%.

On the one hand, some symptoms are clearly associated with a major single failure mode representing over 50% of cases. On the other hand, other symptoms are induced by different failure modes of similar probability. In this case, search on the different possible failure modes might be more time intensive. This allows to estimate which symptoms are more likely for correct or quick diagnosis.

The potential variance of repair times per symptom is shown in Fig. 5 for the most common symptom “not draining”. The zero axis for repair time is set to the dominant failure mode pumps with an average repair time of 0,9 h.

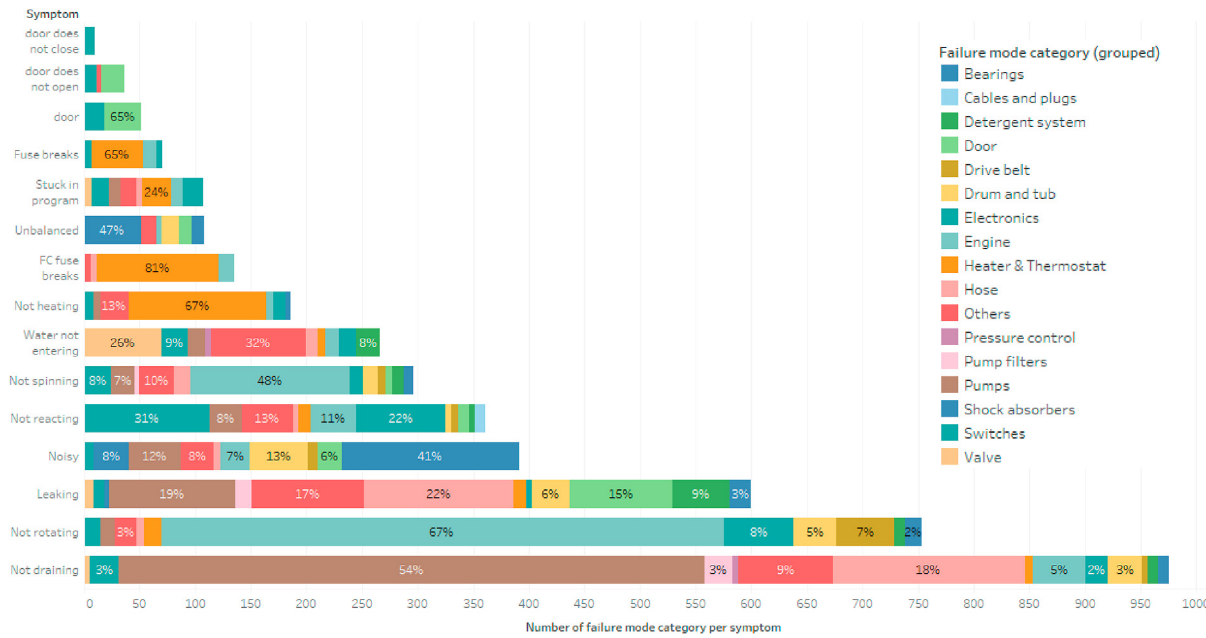

Fig. 4. Relative distribution of failure mode category per symptom.

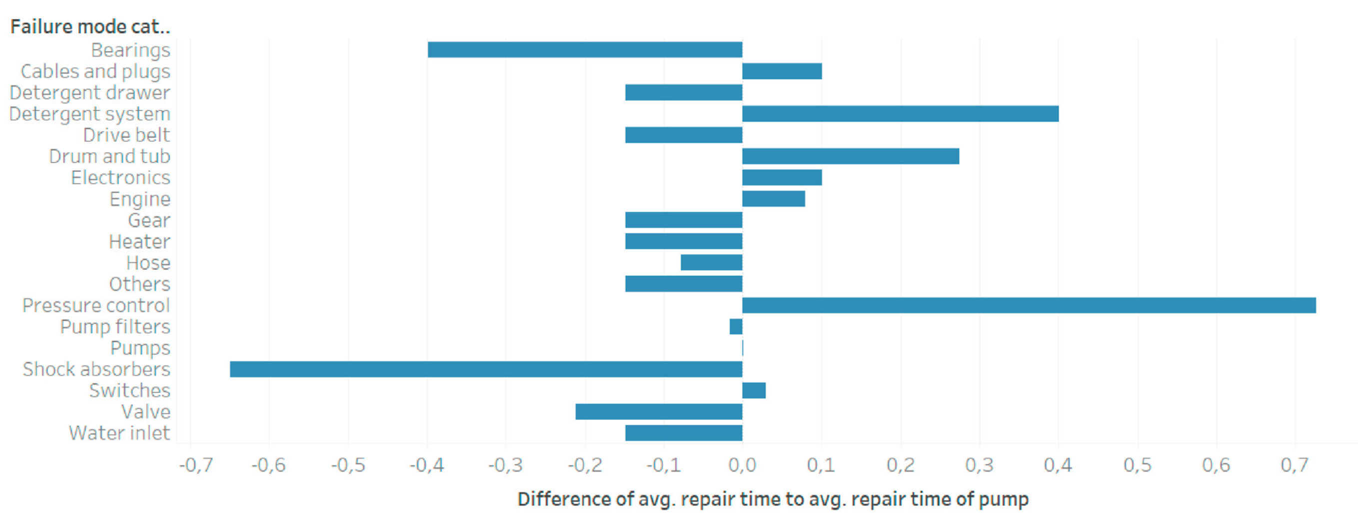

Fig. 5. Variance of repair times of different failure modes for the symptom "not draining".

Assuming a scenario where pressure control was not the correct diagnosis (taking 0,75h), the second diagnose pump (0,9h) adds up to a total labour time of 1,65h. It has to be mentioned that single failure mode consideration implies a full repair, including opening, part exchange and closing of the device. If the first diagnosis was not accurate, second diagnosis and repair might be shorter.

The potential relevance for brand and model specific analysis to further support failure diagnostic can be seen in Fig. 6, representing distribution of failure modes per brand. In most cases (5667), no brand was specified. With less than 10 cases, Panasonic and Hanseatic are not shown but included in the overall average of all brands (left bar, "All"). Each brand shows major individual deviation from the overall average. For Siemens, engines (25%) and heater and thermostats (14%) are above 10% from the overall average. Slight deviations above the overall average are also observed for Bauknecht electronics (+4%) and AEG detergent systems (+6%). For Miele, the cases are more evenly distributed over the different failure mode categories resulting in all failure rates below 15%. Other brands show less than 120 cases respectively less than 8 cases per failure mode on average.

The analysis of (un-)successful reparability rates per brand and failure modes is limited due to data constraints. Assuming that at least a sample of 50 cases is required to be considered relevant, several brands and failure modes are cut off. Not specified brands show unsuccessful repairs for a wide range of failure mode categories: bearings, doors, drum and tub, electronics, engines and switches. For specified brands, only electronics show relevant cases for not successfully repairs, resulting is a higher overall reparability rate of 83% compared to 75% for unspecified brands.

3.3. Extrapolation of necessary data quantities for model specific analysis

The necessary data quantities by means of records per scenario

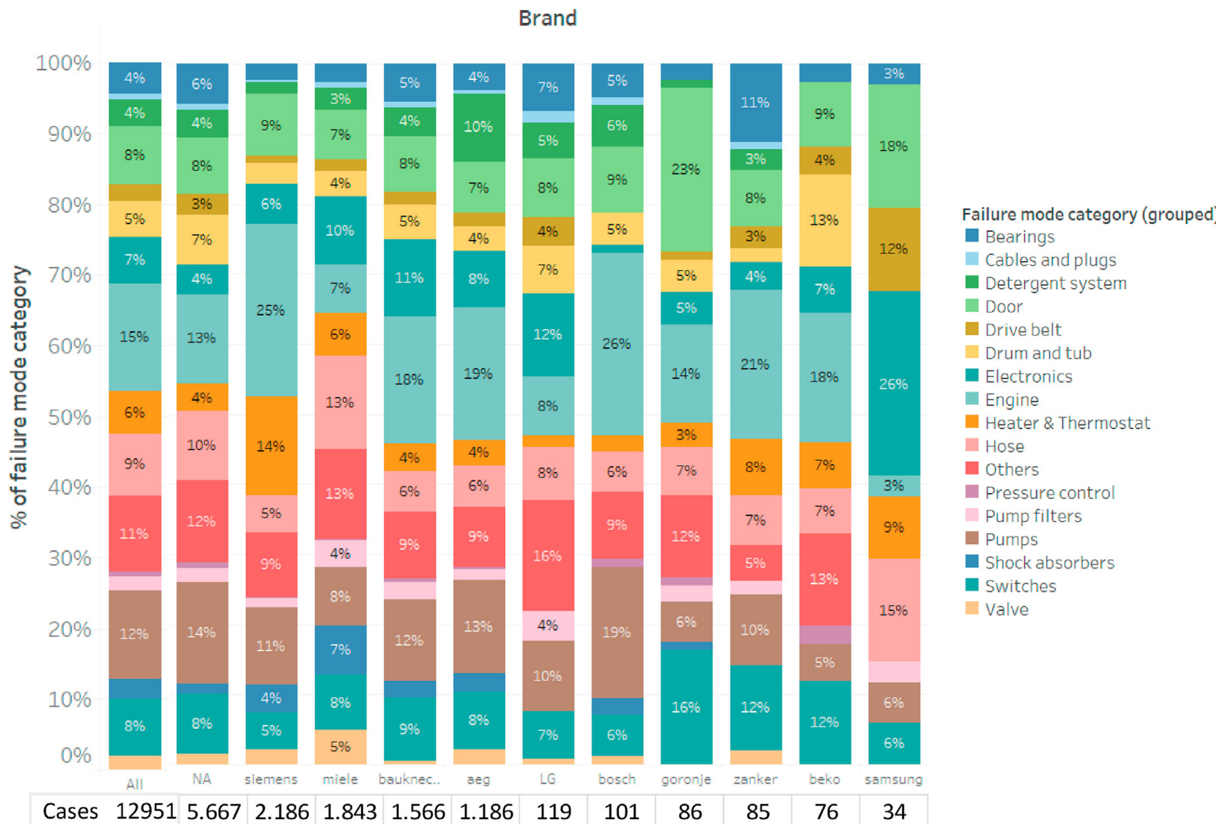

Fig. 6. Failure mode distribution per brand. Absolut number of cases are shown above for each brand.

($n_{records(scenario)}$) is calculated for correlations between model and different parameter (i) for an assumed minimum of 50 cases per model (n_{cases}). Background data (n_i) for correlating parameter (i) is taken from this case study: 17 failure mode categories, 18 symptom categories, 6 repair action categories. The maximum variety scenario ($n_{models(max)}$) is based on 1412 assumed models while the common-brand scenario is based on 84 models ($n_{models(common)}$).

$$n_{records(scenario)} = n_{models(scenario)} \cdot n_{cases} \cdot n_{i,correlating\ paramter}$$

The necessary repair businesses needed to gather data quantities are calculated as follows: first, this case study dataset was generated by about 231 cases per year and employee (scaled from the average of 925 cases per year by 4 employees). Multiplied by three for average number of 3 employees per repair business in Germany will generate about 693 records per year and repair business. In accordance with data for model variety, a 5 year time span is assumed for repair data collection. This adds up to 3465 cases recorded in an average repair business with 3 employees within 5 years.

$$n_{repair\ businesses(scenario)} = \frac{n_{data\ required(scenario)}}{3465}$$

Germany counts 1133 registered repair businesses for household appliances in 2017 (Bundesamt, 2017). Assuming harmonised datasets, model specific data can be gathered for the threefold parameter correlation model-symptom-failure and model-failure mode-repair action for the "common brand" scenario. This is not an unrealistic scenario, as the "Vangerow GmbH" repair company alone operates 700 repair shops in this field in 2014 (Poppe 2014).

4. Discussion

4.1. Discussion on data preparation

The obtained raw dataset contains repair statistics collected during 14 years from 2003 till mid-2017. While newer records are available, this historic batch was preferred for this study to show a range of data preparation methods and data gaps that need to be considered when applying the analysis to other similar datasets. The repair shop that provided the dataset is operating since 1983 and uses long established classification schemes, making the recorded parameter credible and relevant for data analysis. The conversion from handwritten text to digital record was checked for correctness and consistency by unique ID (double entries) and plausibility like negative numbers and outliers.

Text structuring has been successfully applied by establishing

	$n_{records(max)}$	$n_{repair\ businesses(max)}$	$n_{records(common)}$	$n_{repair\ businesses(common)}$
Model –Failure mode	1.200.200	346	71.400	21
Model - symptom - failure mode	21.603.600	6.235	1.285.200	371
Model – failure mode – repair action	7.201.200	2.078	428.400	124

algorithms and dictionaries. The method and algorithms used in this study for data cleaning are adaptable and scalable to other studies facing text structuring and/or proprietary coding. As benefits can be derived from gathering more data from multiple sources the application of this method to other historic datasets make the initial efforts more viable.

The raw dataset recorded a number of entities that aggregated multiple targeted repair parameters. For example, the spare part cost (merged with other material costs) and disassembly time (merged with diagnostic time) could not be derived from the available dataset.

In addition, recording inconsistencies are observed. For example, in many cases, the specific product model and/or brand specifications were not recorded. Furthermore, extracting the recorded model information out of the comment field is challenging due to missing structure or lists with available models in the market. To enable a more detailed analysis at product model level, it is necessary to compile a comprehensive lists of product models to make recording more convenient and harmonic.

4.2. Discussion on potential data applications and data gaps

In order to compare the case study data to literature, it was necessary to harmonize the failure mode categories which indicates further potential for harmonising classification systems. Although repair rates and failure mode trends of the analysed dataset are mostly in accordance with literature, deviations on the absolute amount of cases were observed. The varying amount of absolute cases could be induced by several external factors. For example, failure modes which are assumed difficult to repair by the repair shop such as electronics, shock absorbers and bearings may not be recorded. Reason for this is, that the repair shop does not recommend to repair a device if its residual value is expected to be low, by means of high expected repair costs (difficult repair), future repair costs and lifetime expectancy. This indicates recording inconsistencies between repair shops that need to be harmonised if multi-source data is merged. The varying numbers indicate the necessity for larger data samples. The used classification system aggregates related parts, that shows significant differences if analysed separately. For example there are twice as much cases and about 25% higher repair rate for shock absorbers compared to bearings.

Sufficient data is available for symptom based analysis even for less common symptoms as “unbalanced” or “fuse brake”. The data analysis demonstrated clear benefits for the repair shop by revealing symptoms with highest repair time differences and probabilities of occurrence. Furthermore, the ranking of failure modes for each symptom enables a step-wise diagnose process - if the first and most likely failure mode was not correct the device can be checked for second dominant failure modes related to this symptom. In addition, symptoms are identified that show higher probability for false diagnose. This allows to reduce false diagnose, diagnose (disassembly) time as well as for more accurate planning of necessary spare parts for on-sites visits, reducing travel time and costs significantly.

Data gaps are present for model specifications as it is an important parameter for precise characterisation of failure modes and repair viability. Especially for priority parts as electronics, a model specific analysis on the electronic components will reveal possibility for minimal repair decisions. Model specific data increases the preciseness of symptom-failure distributions and repair time estimations and makes successful repair more likely, also to non-experts as this reduces complexity for diagnose.

Spare part prices is another missing parameter for in-depth analyse of repair viability for specific components that are cheaper than entire parts but require more repair time due to higher degree of disassembly. A more precise analysis on the time savings requires data on disassembly time for each failure mode that is difficult to record in a standardised way in the daily repair process as it is subject to the employee skills and presence of tools.

Though not within the scope of this study, the dataset allows investigations on component specific failure modes and repair actions (eg. door hinges tightened). Furthermore, an investigation is possible and suggested to evaluate employees as an external influence to failure mode and repair time. Such an analysis could be useful to identify learning potential for individual employees.

The calculations of necessary data quantities for model specific correlations is based on the assumed scenarios and background data taken from this study as available data from other sources is limited. The assumption that other repair businesses generate similar amounts of records remains uncertain. Furthermore, the assumption is made that all sources use harmonic classifications and can be merged. A first indication that post-warranty repair dataset from independent repair shops are comparable is given by the comparison to Tecchio et al. showing similar data amounts and used classification. However, further validation is required.

5. Conclusion

Essential learning came out of gathering and processing the historic raw data obtained from an independent repair shop. Although the initial data cleaning efforts are relatively high for structuring parameters, the used method including the established algorithms in this case study are adaptable and scalable for other studies facing similar text structuring (entity recognition) or decoding problems. Recording inconsistencies between repair shops might hinder the valorisation or fusion of historic datasets from different sources. For this, the repair process needs to be carefully characterised towards the target repair parameters. In particular, troubleshooting or diagnosis needs to be recorded even if no costs occurred. Furthermore, brands and model should be recorded, even if no brand or model specific material was used. Although brand parameters were extracted from the current dataset, unfortunately, model parameters were not retrieved due to limited availability and efforts required to create a model dictionary. However, gathering more datasets and applying the used approach makes the extraction of model parameters potentially viable in future. Other identified missing parameters are product age and use intensity which are currently barely registered and, when available, they are usually estimated by the customer or repair worker. These rough estimations can lead to inconsistencies making historic dataset inadequate to provide reliable data for these parameters while newer machines can be provided with a usage counter which could greatly improve the quality of future datasets.

In the first application, the data allowed to identify priority parts by combining absolute amount of failure cases, failure mode evolution, and repair success rates. Electronics, heater and thermostat and shock absorbers are parts that are often associated with failures and their failure modes occurrence is rapidly increasing. In addition, the electronic parts are associated with low repair rates. Therefore, these three parts are qualified as high priority parts for washing machines. The analysed repair data is found useful to identify concerning parts eg. for eco-design legislation. However, supplementary data on product age or usage would allow for lifetime modelling and make recommendations more valuable.

Second, the economic viability of different repair strategies highlight the importance of minimal repair efforts. The results show that additional time for deeper component disassembly balance out with lower spare part costs, resulting in lower total repair cost. Furthermore, recorded information on spare part type (new or used) provided evidence for the economic viability of replacement with used parts for expensive parts like engines and electronics. This evidence base might be used against restrictions to harvest parts from electronic waste before recycling. Spare part price information is usually sensitive data, tough when recorded the contribution of repair time and material costs to economic viability could be analysed in more detail. Such data would also be useful for proposed French repair cost index by (HOP 2020) that reflects the most expensive spare part price of a specific device in relation to its current market price.

Third, the results shows that most symptoms are dominated by one or two failure modes which allows for a step-wise diagnosis process. In addition, the repair data enabled the identification of symptoms with highest repair time variations and potential highest benefits for supporting low-skilled users or employees. A support tool for self-repair could use and operationalise this data for customers. As disassembly time was not recorded, failure mode specific time savings could not be calculated. This parameter is further subject to the employee's skills which the dataset allows to analyse but was not within the scope of this study.

Closing the gap on model specific data could enable in-depth analysis and increase data relevance for the repair data applications. In particular, the minimal repair strategy determination and symptom-based diagnosing would benefit critically from model data availability. Based on two scenarios, it was calculated that model specific data on failure modes can be collected realistically for common brands from 21 repair businesses. Further correlation of failure modes to specific repair actions and to symptoms, requires data from 124 to 371 repair businesses, respectively. The numbers are based on the assumption that datasets between repair businesses are harmonised.

Based on the identified repair parameter data gaps, it is recommended for future data collection to align recording processes and use a centrally provided, harmonised product model database and classification systems. Minimal data gathering should at least include the following parameters: ID, repair date, product brand, model, age or usage cycles, failure symptom(s), failure mode(s), repair action(s), total repair time, total repair cost and spare part costs. Quality assurance eg. by random sampling, double checking notes or electronic error/plausibility validation by recording software can significantly reduce cleaning efforts and increase data quality.

Finally, this study provides important insights on the potential value and benefit of analysing repair data for the data provider and other stakeholders. These benefits can serve as incentives to share and harmonize (post-warranty) repair data for establishing the necessary evidence base to support future policies that enable repair effectively.

CRediT authorship contribution statement

Eduard Wagner: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Visualization. **Ellen Bracquené:** Validation, Writing - original draft, Writing - review & editing, Authorship. **Melanie Jaeger-Erben:** Supervision.

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.

Acknowledgments

The authors would like to thank Heinrich Jung, the repair shop owner of Blitzblume-Ingelheim Haushaltsgerätereparatur for providing the data and sharing business insights during and beyond this study.

This research was conducted within the research group "Obsolescence as a challenge for sustainability" (Obsoleszenz als Herausforderung für Nachhaltigkeit—OHA), funded by the German Federal Ministry of Education and Research (BMBF) in the context of the Research for Sustainability programme.

A.Annex

A.1. Data cleaning

A main challenge arise from unstructured data in the raw data set. Following entry gives an estimation on the nature of raw data: Repair case #8699 „Zanker old nr (not rotating) engine gets stuck, brushes o.k. tacho o.k. probably E (engine) def. discourage from rep. because E too expensive … please bring it gentle to the customer that rep. is not viable. "[1]

A rule based python script was written for structuring the parameters that were merged in the text in the comment field:

(1) Based on a proprietary coding system from the repair shop, a dictionary was established including abbreviations and meanings for symptoms, product category, failure modes, brands and repair actions.
(2) Each entry from the dictionary was used to search for in the comment field.
(3) If a search result was positive, the identified value was structuring by extracting and assigning the value to the designated parameter.
(4) The above steps were performed for symptoms, product category, failure modes, brands and repair actions.

Records with missing parameters were neglected. In total over 30000 unstructured comment fields were searched by 832 failure codes and repair codes (A-Z multiplied by numbers 0–31), 20 most frequent symptoms and 10 brands. The mid-step dataset resulted in 9 additional columns with mentioned parameters (multi failure modes and multi symptoms), adding up to a table of total 19 columns, multiplied by over 30000 entries.

A.2. Classification of failure mode categories and repair actions

Failure mode categories are split into parts and components (Table 3). In total, 25 failure mode are available as part categories.

[1] German original: „zanker alt dn Motor läuft stockend, Kohlen i.O. Tacho i.O. wahrscheinlich E def. von Rep. abraten da neue E zu teuer … wenn sie anruft bring ihr schonend bei, dass die Rep. nicht mehr lohnt! w331 b9g3 850Umd. me13 bau 8270 alt von Born 23.12.2006 0,"

Table 3
Classification of failure modes by parts and components for washing machines, aligned to classification of (Tecchio et al., 2019).

Failure mode categorisation of this study		Failure mode categorisation (Tecchio et al., 2019)
Part	Component	Part
Pressure control	pressure control, flow meter	Pressure control
Cables and plugs		Cables and plugs
Detergent drawer	pressure switch vessel/water bag, ion exchanger unit, lid salt container, insert for dispenser case, water switch	Detergent system
Detergent system	Air trap	
Pump filters		Pump filters
Valve		Inlet valves
Water inlet		
Drive belt		Drive belt
Shock absorbers	spring, spring strut, cap for spring strut, friction damper	Shock absorbers and bearings
Bearings	bearing flange, shaft seal, bearing and seal set	
Door	hinges, handles, locks, other	Doors
Door seals	door seals, o-ring, tension rings	
Drum, Tub	tub rip, tub seal, balance weight	Drum and tub
Heater		Heater and thermostat
Thermostat		
Electronics	resistance, triacs, diodes, transformers, other electronic board components	Electronics
Others (No failure detected, no action necessary)		Others
Lamp		
Fan		
Hose	Inlet hose, drain hose, hose clamp, hose weight, air exhaust hose	Drain system
Switches (starting relais, heating contractor, reed relais)	Button, switch toggle	Switches
Pumps (circulation, drain, lye pumps)	pump seals, pump impeller, gasket sets	Pumps
Engine	Carbon brushes	Carbon brushes
	Tachogenerator	Engine
Gearbox	Drum pulley, motor pulley, drive belt tensioner, gear part	
Condensator		
(part specific repair action)		Foreign objects

Table 4
Repair actions performed and recorded by the repair shop. Reasons for not repaired are recorded. Other detailed actions descriptions (not bold) within the are not recorded.

Repair action
Foreign object removed, machine reset
Component maintained: cleaned, decalcified, lubricant added
Component restored: tightened, adjusted, enabled;
Component restored: glued, sealed, soldered, isolated;
Component restored: bypassed, disconnected, reconnected;
Component replaced
Part replaced by used spare part
Part replaced by new spare part
Not repaired: Spare part not available (anymore), repair technically not feasible (difficult failure detection/opening of device), repair economically not viable, customer decision not to repair

For each part up to 9 components are defined. Each part and component is uniquely coded and available in the dataset. This study defines parts as functionally unique units within products system. Parts consists of several components (sub-system).

Table 4 gives an overview of the registered repair actions, clustered into categories that were used by the repair shop.

As data related terms differ in meanings between disciplines, this study uses terms as follows: Data records are defined as “information created, received, and maintained as evidence and as an asset by an organization, in pursuit of legal obligations or in the transaction of business” (ISO 15489—1:2016). Parameters or attributes describe one characteristic to define a problem or observation. Variables are operationalized attributes with assigned individual values.

A.3. Coding system and failure mode categorisation

For detailed but quick repair case documentation, a multi-dimensional coding system is used to shorten device category, symptoms, failure mode diagnose and repair action. The device category is shortened by lower case letters (a-z).[2] The failure mode diagnose is encrypted by capital letters for and numbers, documented within a coding system. It horizontally formed by part category (A-Z) and vertically by further differentiation by (21-29)[3]. Repair action take same part category letters while using numbers (3—19). Special cases are shortened by (X1-X30). Category “Others” include device explained and no repair action necessary as this indicates usability.

[2] Eg washing machine (w), dish washer (d), fridge (k).
[3] Eg. E22 shortens E-Electronic and 22-Component on PCB.

Failure category	Diagnosed	Percentage of failure category	Percentage of failure category [Tecchio et al., 2019]	Diagnosed [Tecchio et al., 2019]
Foreign objects	1266	11,2%	6,0%	572
Engine (carbon brush)	1250	11,1%	9,7%	914
Doors	941	8,3%	11,5%	1086
Switches	922	8,2%	3,8%	359
Pumps	921	8,2%	7,5%	711
Others (incl. lamp, fan)	881	7,8%	3,1%	291
Shock absorbers and bearings	854	7,6%	13,8%	1301
Electronics	740	6,6%	14,0%	1328
Heater and thermostat	698	6,2%	2,5%	237
Hose	561	5,0%	4,7%	445
Engine (incl. gearbox, condenser)	545	4,8%	4,8%	452
Valve and water inlet	478	4,2%	4,1%	391
Detergent system (incl. drawer)	406	3,6%	2,0%	191
Drum and tub	268	2,4%	2,5%	240
Drive belt	264	2,3%	3,2%	307
Pump filters	174	1,5%	2,7%	260
Cables and plugs	66	0,6%	1,7%	162
Pressure control	53	0,5%	2,2%	212

A.4. Metadata characterisation

The value based meta data quality assessment methodology by (European Data Portal 2020) is used to characterize the underlying case study data set.

Findable	- Keyword usage: repair time, repair symptom, washing machine, dishwasher, failure mode, repair action, repair costs - Categories: sustainability, repair - Geo search: Germany - Time based search: 2003–2017
Accessibility	- Access URL: Eduard.wagner@tu-berlin.de - Download URL: n.a. - Download URL accessibility: n.a.
Interoperability	- Format: excel - Media Type: text - Use of controlled vocabulary (EDP GitLab repository): n.a. - Non-proprietary: n.a. - Machine readable: n.a. - DCAT-AP: n.a.
(Re-) Usability	- Licence Information: n.a. - Licence vocabulary: n.a. - Access restrictions: n.a. - Access restrictions vocabulary: - Contact Point: Eduard.wagner@tu-berlin.de - Publisher: not yet published
Contextuality	- Right: Blitzblume-Ingelheim Haushaltsgerätereparatur, Heinrich Jung - File Size 23 MB - Date of issue: 12. 12. 2017 - Modification data: 07.04.2020

References

Alfieri, Felice, Cordella, Mauro, Sanfelix, Javier, 2019. Analysis and Development of a Scoring System for Repair and Upgrade of Products. Final Report. Publications Office of the European Union (EUR, 29711), Luxembourg.

Ardente, Fulvio, Mathieux, Fabrice, 2014. Environmental assessment of the durability of energy-using products. Method and application. J. Clean. Prod. 74, 62–73. https://doi.org/10.1016/j.jclepro.2014.03.049.

EC, 2019. New rules make household appliances more sustainable. https://ec.europa.eu/commission/presscorner/detail/en/IP_19_5895.

EC, 2020a. The European green deal. Communication from the commission to the EUROPEAN parliament, the EUROPEAN council, the council, the EUROPEAN economic and social committee and the committee OF the regions. https://ec.europa.eu/info/sites/info/files/european-green-deal-communication_en.pdf,zuletzt.geprüft.am.03.04.2020.

EC, 2020b. A new circular economy action plan - for a cleaner and more competitive Europe. Communication from the commission to the EUROPEAN parliament, the council, the EUROPEAN economic and social committee and the committee OF the regions. https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52020DC0098&from=EN,zuletzt.aktualisiert.am.04.04.2020,zuletzt.geprüft.am.04.04.2020.

Baldé, C.P., Forti, V., Gray, V., Kuehr, R., Stegmann, P., 2017. The Global E-Waste Monitor 2017. Quantities, Flows, and Resources. International Telecommunication Union, Geneva.

Bennett, M.J., Boyano, A., Espinosa, N., Villanueva, A., 2017. Follow-up for the Preparatory Study for the Ecodesign and Energy Label for Household Washing Machines and Household Washer Dryers. Hg. v. Publications Office of the European Union. JRC.

BIO by Deloitte, 2013. Material-efficiency Efficiency Ecodesign Report and Module

to the Methodology for the Ecodesign of Energy-Related Energy Related Products (MEErP): Stakeholder Consultation.
Blischke, Wallace R., Karim, M. Rezaul, Murthy, D.N.P., 2011. Warranty Data Collection and Analysis. (Springer series in reliability engineering), London: Springer. http://site.ebrary.com/lib/alltitles/docDetail.action?docID=10490509.
Bocken, Nancy M.P., Pauw, Ingrid de, Bakker, Conny, van der Grinten, Bram, 2016. Product design and business model strategies for a circular economy. Journal of Industrial and Production Engineering 33 (5), 308–320. https://doi.org/10.1080/21681015.2016.1172124.
Bracquené, Ellen, Brusselaers, Jan, Dams, Yoko, Peeters, Jef, Dewulf, Wim, 2018. Repairability criteria for energy related products Study in the BeNeLux context to evaluate the options to extend the product life time Final Report. https://www.benelux.int/files/7915/2896/0920/FINAL_Report_Benelux.pdf.
Bundesamt, Statistisches, 2017. Strukturerhebung im Dienstleistungsbereich - reparatur von Datenverarbeitungsgeräten und Gebrauchsgütern - fachserie 9 Reihe 4.6 - 2017. https://www.destatis.de/DE/Themen/Branchen-Unternehmen/Dienstleistungen/Publikationen/Downloads-Dienstleistungen-Struktur/reparatur-gueter-2090460177004.pdf?__blob=publicationFile,zuletzt.geprüft.am.28.05.2020.
Cerulli-Harms, Annette, Porsch, Lucas, Suter, James, Rodriguez Diaz, Adriana, Peroz, Timothé, Vermeulen, Jurgen, et al., 2018. Behavioural Study on Consumers' Engagement in the Circular Economy. Luxembourg: Publications Office of the European Union. Final report. https://ec.europa.eu/info/sites/info/files/ec_circular_economy_final_report_0.pdf,zuletzt.geprüft.am.18.05.2020.
EEB, 2018. The EU Product Environmental Footprint (PEF) Methodology. What can it deliver and what not? An NGO viewpoint. EEB. http://eeb.org/publications/80/product-policy/89544/briefing-on-the-eu-product-environmental-footprint-methodology.pdf,zuletzt.geprüft.am.07.04.2020.
Ellen MacArthur Foundation, 2016. Intelligent assets. Unlocking the circular economy potential.
European Data Portal, 2020. Metadata quality assurance. https://www.europeandataportal.eu/mqa/methodology?locale=en,zuletzt.geprüft.am.07.04.2020.
Hammer, Cornelia, Kostroch, Diane, Quiros, Gabriel, 2017. Big data: potential, challenges and statistical implications. In: Staff Discussion Notes, vol 17, p. 1. https://doi.org/10.5089/9781484310908.006, 6.
HOP, 2020. 50 mesures pour une consommation et une production durables. https://www.halteobsolescence.org/wp-content/uploads/2019/03/Livre-Blanc.pdf,zuletzt.geprüft.am.29.05.2020.
Huang, Hong-Zhong, Liu, Zhi-Jie, Murthy, D.N.P., 2007. Optimal reliability, warranty and price for new products. IIE Trans. 39 (8), 819–827. https://doi.org/10.1080/07408170601091907.
idealo, 2020. Waschmaschine preisvergleich. https://www.idealo.de/preisvergleich/ProductCategory/1941oE2oJ0.html,zuletzt.aktualisiert.am.28.05.2020,zuletzt.geprüft.am.28.05.2020.
ISO/IEC 25012, 2008. Software engineering — software product quality requirements and evaluation (SQuaRE) — data quality model. https://www.iso.org/standard/35736.html,zuletzt.geprüft.am.07.04.2020.
Jack, Nat, van der, Duyn Schouten, Frank, 2000. Optimal repair–replace strategies for a warranted product. Int. J. Prod. Econ. 67 (1), 95–100. https://doi.org/10.1016/S0925-5273(00)00012-8.
Marbn, scar, Mariscal, Gonzalo, Segovi, Javier, 2009. A data mining & knowledge discovery process model. In: Julio Ponce und Adem Karahoca (Hg.): Data mining and knowledge discovery in real life applications. InTech, Rijek, Crotia.
Monier, Véronique, Tinetti, Benoît, Mitsios, Andreas, Trigo, Prado, Alvaro de, Ax, Christine, Medhurst, James, 2016. Study on Socioeconomic Impacts of Increased Reparability of Increased Reparability. Publications Office, Luxembourg. Final report.
Open Repair Alliance, 2020. Open Repair Data Standard v0.1. https://docs.google.com/document/d/1zR7GO2Jot_1g7QFPNo5R9wgEFXYo9CiyByM264BAsB4/edit#,zuletzt.aktualisiert.am.07.04.2020,zuletzt.geprüft.am.07.04.2020.
Poppe, Erik, 2014. Reparaturpolitik in Deutschland. Zwischen Produktverschleiß und Ersatzteilnot. SUSTAINUM, Berlin.
Rafique, Irfan, Lew, Philip, Maissom Qanber Abbasi, Li, Zhang, 2012. Information quality evaluation framework: extending iso 25012 data quality model. https://doi.org/10.5281/ZENODO.1072956.
RREUSE, 2015. Improving product reparability. Policy options at EU level. http://www.rreuse.org/wp-content/uploads/Routes-to-Repair-RREUSE-final-report.pdf,zuletzt.geprüft.am.29.05.2020.
Svensson, S., Richter, J.L., Maitre-Ekern, E., Pihlajarinne, T., Maigret, A., Dalhammar, C., 2018. The Emerging 'Right to Repair' Legislation in the EU and the U.S. CARE Innovation. Vienna. Austria.
Tadj, Lotfi, Ouali, M.-Salah, Yacout, Soumaya, Ait-Kadi, Daoud, 2011. Replacement Models with Minimal Repair. Springer-Verlag London Limited (Springer series in reliability engineering), London. http://site.ebrary.com/lib/alltitles/docDetail.action?docID=10460761.
Tecchio, Paolo, Ardente, Fulvio, Mathieux, Fabrice, 2019. Understanding lifetimes and failure modes of defective washing machines and dishwashers. J. Clean. Prod. 215, 1112–1122. https://doi.org/10.1016/j.jclepro.2019.01.044.
TNS, 2014. Attitudes of Europeans towards Waste Management and Resource Efficiency. [Brussels]: [European Commission] (Flash Eurobarometer, 388).
Varnosafaderani, Sima, Chukova, Stefanka, 2012. A two-dimensional warranty servicing strategy based on reduction in product failure intensity. Comput. Math. Appl. 63 (1), 201–213. https://doi.org/10.1016/j.camwa.2011.11.011.
Warentest, Stiftung, 2020. Waschmaschinen im Test - 84 Modelle (Frontlader, Toplader, Waschtrockner). Stiftung Warentest. https://www.test.de/Waschmaschinen-im-Test-4296800-tabelle/suche/,zuletzt.aktualisiert.am.28.05.2020,.zuletzt.geprüft.am.28.05.2020.