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# The Total Cost of Ownership Score: Unifying Repair with Durability and Improving Objectivity, Completeness, and Scalability

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***Abstract*—This paper introduces the Total Cost of Ownership Score (TCOS) as a comprehensive framework for evaluating and improving product repair, durability, and maintenance all together on a uniform scale. The scoring procedure, implemented through a spreadsheet, calculates a product's total cost of ownership per year based on likelihood of failure modes, repair costs per failure (parts, labor, and other), likelihoods of repair successes, and cost of replacing the product if repairs fail. Because costs and repair times vary substantially based on many factors, and likelihoods of device failures and repair successes are stochastic by nature, the uncertainties are large and must be displayed in final scores. However, preliminary results indicate that even with large uncertainties, the TCOS provides meaningful product comparisons and hotspot identification. The advantages of the TCOS include scoring quantitatively in units that both consumers and businesses understand and value, to drive market behavior; vast reduction of subjective judgments in scoring; measuring durability and repair on the same scale; universal applicability, enabling legislation or policy to scale across products easier; and enabling legislation to allow innovation rather than prescribing designs. The TCOS's two challenges are that the data required is not publicly available for most products, so it requires empirical product testing; and further development / negotiation is required to decide what standard assumptions can be applied as shortcuts to shrink the scope of empirical testing.**

***Keywords—Repair scorecard, durability scorecard, Repair policy, reparability index, circular economy***

## I. Introduction

Repair is extremely important for the circular economy, as it is one of the most energy and resource efficient ways to keep products in service longer [1]. Because of this, European policies are pushing requirements for product repairability, such as the Circular Economy Action Plan [2] and the Waste Framework Directive [3]. This requires ways of scoring product repairability that are objective (repeatable and fair), complete (measure all relevant aspects), easy to apply to many product types across whole industries, influence purchasing behavior, and also influence product design toward better repairability. They should also consider when products are durable and do not need repair.

Subjectivity is a problem because all of today's repairability scorecards are qualitative checklists. For example, one of the best and most widely used repair scorecards today is the French Repairability Index (FRI). FRI was introduced by the French government in 2019, with mandatory labeling for a few product categories in 2021. To score a product with it, an assessor (whether it is the manufacturer, a government agency, or a third party assessor) fills out a checklist with varying points for different qualitative aspects to semi-quantify them (e.g., rate number of disassembly steps on a scale of 1 – 4; rate the types of fasteners on a scale of 1 – 3; check if firmware can be reset, as a yes/no; etc.) Then the semi-quantitative points are weighted into an overall product score from 1 to 10.

In these scores, assessors must decide whether they are scoring for professional repairers or amateurs at home, they must score fastener types and firmware as mentioned above, sometimes decide how visible fasteners are, etc. FRI is not unique; as mentioned above, it is one of the best. An assessment of today's major scorecards (FRI, iFixit, ONR 192102, AsMer by Benelux, RSS by JRC, and EN 45554) found that all of them have significant problems with subjectivity [4], so different people scoring the same product can create very different scores [5].

Some subjective aspects are often argued about, such as "bundling": whether modules should be bigger (including more components, thus more expensive and higher environmental impact, but faster to replace because of simplified disassembly) or smaller (less cost and environmental impact, but more time to replace), and these arguments often have no one right answer.

Completeness is another problem. Qualitative checklists must anticipate and have points for every aspect of product repairability, from modularity and fastener types to types of tools required, special skills required, and more. No existing scorecard considers all such aspects, and several of them miss many such aspects [4].

Because of scorecard incompleteness, products can sometimes score well without actually being repairable [6]. Because they are weighted averages of different factors (e.g., disassembly steps, part availability, etc.), a bad score in one area is a small percent of the total score, even if it prevents

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repair entirely. For example, the inability to disassemble a product to its priority parts only lowers FRI scores by ~5%, JRC scores by ~18%, and iFixit scores by ~33%. Spare parts more expensive than buying a new product leave JRC scores unchanged, lower FRI scores ~20%, and lower iFixit scores ~12% [7].

Even if scorecards did completely consider all aspects, they must also weigh them against each other fairly, to give credit for designs that best enable repair. Such priorities vary greatly between product categories. Thus, every product category must have its own painstakingly-crafted scorecard, making it difficult and expensive for policymakers to scale repair scorecards across all industries, especially when industries fight with legal challenges to scorecard credibility. This is why FRI only legally scores a few product categories: smartphones, laptops, televisions, washing machines, and lawnmowers. Difficulty scaling across industries means difficulty influencing purchasing behavior and product design at scale.

Today's scorecards are also not easy for non-experts to understand, which further limits their ability to influence purchasing behavior. As mentioned above, FRI, iFixit, and all other scorecards give a numeric score, such as on a scale of 1 to 10. But what does it mean to score a 4 rather than an 8? Is it twice as repairable, ten times more, or 10% more? And what would it mean to be twice as repairable? We could not find any published academic studies of whether the general public understands these scores or how much influence they have on purchasing decisions, if any.

Finally, existing repair scores do not grade product durability, and thus cannot differentiate between products that are easy to repair but break frequently versus products that are hard to repair but never break. This was a justified part of industry opposition to repair scorecards; both durability and repair are needed to keep products in use longer [8]. Professional repairers have also asked for this information [9]. Designing for durability and repairability sometimes conflict with each other; today's scorecards cannot help manufacturers or policymakers decide between design tradeoffs, at what threshold repairability becomes more or less preferable to durability for each product type. FRI is not unique in these aspects; as mentioned earlier, it is one of the best and most widely-used scorecards.

Our goals in this project were to explore whether it was possible to fix these problems with a new kind of scorecard that could offer better objectivity, completeness, and ease of scaling across many product types, while also increasing influence on purchasing behavior and product design, and balancing durability versus repair.

The solution that was developed attempted to fix these problems by quantifying the time and money required to repair product failures, then displaying the results as an average cost of ownership in €/year, including the annualized total cost as well as the annualized cost to repair, further broken down into annualized costs of parts, labor, and failure to repair. This paper describes how the tool was developed, and shows example cases performing a sensitivity analysis of how well the scorecard does or does not fulfill the goals, including what other problems it may raise.

## II. Methods

Quantifying the annualized costs of failure and repairs required building an equation including as many factors as possible, without overwhelming the assessor, for optimal completeness. Then it required conventions on how assessors should fill in the numbers to maximize objectivity. Then it required building a calculator tool for assessors to enter data into and receive a score from. Finally, example assessments were performed to test the tool in a sensitivity analysis.

The equation, conventions for entering numbers, and calculator were all developed through an iterative process involving analyses of existing scorecards and other repair literature; building the calculator; conducting user tests and interviewing experts, including three professional telephone and household appliance repairers and a repair policy engineer at iFixit; and improving prototype equations, number entry conventions, and calculator interfaces based on the testing. This iterative approach led to the creation of seven versions of the tool, each incorporating feedback gathered throughout the development process. This nonlinear process is summarized below by topic in the following sections.

### *A. Building the equation*

The equation was chosen to quantify economic cost and time, but not environmental impacts such as carbon footprint or more comprehensive life cycle assessment (LCA) metrics, for seven reasons: First, because economic costs are universally understood, unlike carbon footprints or more comprehensive LCA scores like ReCiPe millipoints. Second, because economic costs are well known to be extremely motivating, strongly affecting purchasing decisions for consumers, companies, and other institutions (often companies and government have rules requiring purchase decisions based on cost). Third, LCA data is rarely available publicly from companies on a component-by-component level, especially rarely using methodologies consistent across different companies, much less across different industries. Fourth, LCAs are time and money intensive for government or other third-party assessors to perform. Fifth, while economic costs of spare parts do not correlate strongly to environmental impacts of the parts, there is usually a reasonable correlation. Sixth, by contrast with LCA data, cost and time data is usually already tracked and often public (at least in the case of spare parts, and often for whole repair operations); where it is not yet tracked, companies are more motivated to collect it than LCA data. Seventh, where it is not tracked or published, it is far easier for companies, governments, or third parties to gather than LCA data.

These seven factors together suggested that a scorecard counting only economic costs per product lifetime would be far easier to calculate and a reasonable proxy of environmental impacts per lifetime. Of course, this proposition should be tested by performing LCAs and circularity assessments of several products while comparing their scores on this new scorecard versus others such as FRI. However, before such tests can be run, the scorecard must first be developed.

The method used to build the equation was iterative, intertwined with conventions for numeric data gathering and the calculator interface, as mentioned above. However, it began by listing all variables that significantly affect the cost of repair (e.g., spare part cost, tool cost, disassembly time, the hourly cost of labor for professional repair, etc.) The list of variables was primarily based on analyses of existing scorecards and other repair literature [4], [5], [10], [11], [12], [13], including studies of repair failures [14]. Iterations also incorporated feedback from the expert repairer interviews.

We required all variables to be generically applicable to any product category, from electronics to furniture to clothing to housewares, so the same equation could be applied universally. The reason for this is to enable policies to scale up quickly and easily across any or all industries. Details specific to certain product categories appear in the data entry.

Once variables were listed, the equation was built by deductive reasoning and validating it in two ways: First, ensuring that the correct units always resulted from the operations on the variables chosen (e.g., labor cost in €/hr multiplied by repair time in hours results in units of €, and multiplying that by the probability of success does not change the units). Second, by entering many test values to verify that the equation's resulting score followed logical trends (e.g., if the input of spare part cost rises, the output of total cost of ownership should rise proportionally).

### *B. Developing data entry conventions*

Conventions for data entry were iteratively developed alongside the equation and case study, as mentioned above, for consistency across products. They were informed by FRI and iFixit scorecards, the interviews with expert repairers. They were developed with the assumption that scoring any product would require several empirical product teardowns or equivalent repair simulations (ideally 5 or 10 teardowns by at least two different independent parties for statistical validity), plus manufacturer durability tests to determine probabilities of common failure modes. However, even in the most perfect circumstances of manufacturers measuring all failure rates, repair costs, and repair success rates, some questions remain. For example, if repair success rates depend on documentation availability, tool availability, and other such variables, they must be consistently scored for all products.

To avoid the subjectivity of existing scorecard checklists, these questions are handled in two ways: First, by including uncertainty in the calculations, so every variation can be included within best-case and worst-case scores. Second, we developed prototype rules for how to enter data for common situations where different interpretations are possible.

Uncertainty was included so that the scorecard can show when data input variations cause minimal difference in outcomes for decision-makers (either purchasers or companies redesigning product for better repair), and so that when there is too much variation to make decisions, the scorecard helps highlight which data requires more certainty (e.g., in spare part costs, failure rates, or other).

The prototype data entry rules for how to count the cost of common situations started based on conventions from existing scorecards and other repair literature cited above in the equation-building section (e.g., if no documentation is available for a repair, conservatively assume a zero percent success rate for that repair). These rules were tested iteratively with the equation and calculator using the case study phones described below. The case study provided sensitivity analysis across several scenarios.

The scoring conventions are listed in Results, but should be reviewed and further iterated by a larger consortium of repair experts, manufacturers, and policymakers to achieve a broad-based consensus before becoming policy.

Unfortunately, we could not find publicly available data with thorough rigorous statistics on failure rates, disassembly / reassembly times, and spare part costs for most product types. However, many companies have this data for many product categories due to warranty claims, which cost companies significant money and whose data are used to improve spare part provision strategies and product design [15].

The scenarios we tested in the case study were smartphones because iFixit gave us access to their data on spare parts sales for various phones. This was used not only for spare part prices, but also to estimate failure rates. To estimate probability of successful repair, ideally assessments would perform many instances of the same repair to gather empirical statistics, but likely this will only need to be done for a small percentage of repairs, with the rest using estimates including significant uncertainty. For this study, we estimated probabilities based on iFixit online repair guide difficulty ratings, with significant uncertainty used.

In other cases where empirical data was deemed too difficult to obtain (e.g., quantifying repair success rates by performing hundreds of the same repairs and counting failures), we built systems for existing qualitative assessments from FRI to be translated into quantitative estimates. These estimates were assigned uncertainties of at least ±20%, but further research should investigate them.

Because this scorecard quantifies durability and repairability economically, it was largely focused on professional repair. However, self-repair was deemed important to consider and reward, so a convention was set for when repairs become fast and easy enough to be counted as self-repair.

As with the equation, we strove to have all data entry conventions be generically applicable to any product category, not product-specific, but due to time limitations, we only tested it with a case study of smartphones. Future research should test it with a wide a variety of different product types, and iterate as needed.

Part of the goal of this scorecard system is for companies and policymakers to amass a large shared database of empirical data on actual costs and times to repair products, rather than today's guesswork. However, we recognize that today, many manufacturers (and all government or third party assessors) do not have data on all failure rates, costs, and repair times, especially for new highly novel products. To accommodate this, we built an alternative method for estimating missing data in the scorecard, based on qualitative FRI checklist assessment methods. These outputs were assigned a higher uncertainty in the calculator, due to their sourcing from qualitative checklists.

### *C. Developing the Excel calculator*

We decided to create the calculator as a Microsoft Excel spreadsheet rather than a custom software platform for three reasons: First, Excel is ubiquitously available worldwide, enabling our calculator to be zero cost to users; even those without Excel itself can open the spreadsheet in other free programs such as Google Drive. Second, Excel is ubiquitously understood worldwide, reducing the learning curve for potential users. Third, Excel spreadsheets are user-editable, meaning users have potentially infinite ability to improve and refine the interface, or expand the calculations, which they could not do with purpose-built software. This opens up the calculator to future development. When or if it is adopted for official government labeling, a locked version will be created.

As mentioned above, the calculator was developed iteratively in concert with the equation and data entry conventions, requiring seven iterations. It began based on FRI and iFixit checklist systems, and iterations also incorporated feedback from the expert repairer interviews. The spreadsheet design iterations included separating different data entry stages into different worksheets versus combining them all into one sheet; changing the number of steps in the process by grouping data entry fields differently; calculating uncertainty by entering best-case and worst-case values or by entering average values with percent errors; various forms of graphing the resulting scores; and more.

### *D. Choosing and estimating case study examples*

The iterative process of developing data entry conventions was supported by a case study for sensitivity analysis, performing estimated assessments of several different smartphones with the total cost of ownership score and comparing results to the products' FRI and iFixit scores. As noted earlier, smartphones were chosen because of the availability of some empirical data on failure rates from iFixit.

Data on overall repair costs were sourced mostly from interviews with local professional phone repair shops—this was deemed the highest quality data, as it included not only spare part and labor costs, but any incidentals such as amortized cost of special tools and workplace real estate costs. Where such data was not available from professional repairers, it was supplemented by online searches for spare part costs and repair times, usually via https://www.ifixit.com or https://www.consumentenbond.nl.

The case study performed sensitivity analysis by comparing four phones from different manufacturers against each other in one scenario where they all have the average phone lifetime in Europe; then for two phone models, we also tested two more scenarios each, where data was available to show longer lifetimes than average. Data for the case study phones came from retail, spare part, and repair prices advertised online by both the manufacturers and third-party repair shops, alongside the published FRI scores and iFixit scores for the phones. However, significant data for each phone was unavailable and had to be estimated, most notably failure rates of components and exact average lifetimes.

The sensitivity analysis was divided into four scenarios: Scenario 1 examined four phones, selected for a wide range of price and repairability, and assumed they all have the 21-month average service life for all phones in Europe, according to Counterpoint [16]; with uncertainty, this meant the lifetimes were all entered as 2 years best-case and 1.5 years worst-case. Costs of spare parts were found online, or if they were not available, those repairs were assumed not viable (see rules for data entry). Published probabilities of failures were not available for any phones, but iFixit shared data on failure rates from customers ordering replacement parts; this provided probabilities relative to each other, but not an absolute percentage for all failures in each phone. This was fixed using Cordella's [17] report that 47% of failures occurred within the initial two years of usage, so the probability of each failure from iFixit data was scaled down by 45% best-case and 49% worst case for all phones in S1.

For scenario 2, only the iPhone 12 Pro Max and Fairphone 3 were assessed, due to their better data availability than other phones and the expected variation in repairability between them. Rather than the average 21 month lifetime, we used actual lifetimes of 4.5 years for the iPhone [18] and 5.5 years for the Fairphone [19], each with an uncertainty of ±0.5 year. In the absence of data on how failure rates change over time, we tested better and worse variations. This scenario assumed the total number of failures (and thus repairs) over the lives of the phones was the same as in scenario 1's short lifespans, a very optimistic assumption.

Scenario 3 was the variant of scenario 2 testing higher failure probability. Cordella [17] noted that for average phones, after the initial two years of usage, the remaining 39% (totaling 86%) of failures transpired between the second and third year of usage. Given the documented longer lives of iPhones and Fairphones, we assumed they reach this 86% threshold not at three years but at 4.5 years and 5.5 years respectively. Since this was nearly double the scenario 2 failure rate, we considered it adequate sensitivity analysis.

Scenario 4 was a thought experiment, not using empirical data, testing the influence of self-repair on scores. It assumed the iPhone in scenario 3 met minimal requirements for being self-repairable according to the FRI checklist elements integrated into our scoring spreadsheet (scoring an "A" for necessary tools, types of fasteners, and parts availability, and "A" or "B" for ease of disassembly and documentation; see Results for details). When a repair is considered self-repairable, the cost of labor was set to zero and the probability of unsuccessful repairs were cut in proportion to the improvement in qualitative scoring of repair difficulty (as noted above). Again, this is ***not*** real product data, merely a thought experiment to see how it affected scores.

For all of these scenarios, we calculated the total cost of ownership scorecard's numeric graph of annualized costs in €/yr and the ratio of repair cost to total cost for each phone. The best case ratio of repair cost to total cost was the lowest repair cost divided by the highest total cost; the worst case ratio of repair cost to total cost was the highest repair cost divided by the lowest total cost; this gives very wide uncertainty ranges, but we preferred to err on the side of caution until more precise data is available. For the two phones with additional scenarios assessed, we also compared the cost of ownership scores to FRI and iFixit repairability scores, and translated the quantitative cost of ownership into a qualitative label.

## III. Results and discussion

This section describes the cost of ownership equation, the data entry conventions, the Excel calculator, the prototype labeling scheme, and the case study used for sensitivity analysis illustrating how altering certain input variables affects output scores.

### A. The scoring equation

The equation developed is described below, but it need not be the final equation; further refinement could be done based on broad-based stakeholder input. However, as it is, the equation combined with data entry conventions can capture all costs of a product's failures and repairs. The equation can be broken down into three parts. First, the cost of repairing an individual failure mode is displayed as (1).

$$C_{SPMi} + (T_i \cdot R_i) + C_{Oi} \tag{1}$$

Where:
$C_{SPMi}$ = Cost of spare parts & materials for operation "i" (€)
$T_i$ = Time taken for operation "i" (hrs)
$R_i$ = Labor rate for operation "i" (€/hr)
$C_{Oi}$ = Other costs (amortized tools, administration, overhead, etc.) for operation "i" (€)

Note that this entire expression can be replaced by a flat repair cost quoted by a professional repairer; such a quote will contain all this data, though it may not be transparently communicated to the assessor, the assessor may only receive a single number in €.

Note also that this equation is organized by failure mode, not by component. One failure mode may require multiple parts to be replaced, or may require no parts replacements, only labor (e.g., unclogging a filter). As such, the equation could also include preventive maintenance, not just failures, though we expect this to be such a small percentage of total cost of ownership that we did not test it.

Next, the probability of a successful repair and the repercussions of an unsuccessful one are incorporated. Then the costs of all such failures and repairs are summed into the average cost of all expected repairs, including unsuccessful repairs, are displayed as (2).

$$\sum_i^g P_i\big((100 - P_{Ri})C_{NP} + P_{Ri}(C_{SPMi} + (T_i \cdot R_i) + C_{Oi})\big) \tag{2}$$

Where:
$g$ = Total number of failure modes (#) (can limit to priority failures if desired)
$P_i$ = Probability of failure (%)
$P_{Ri}$ = Probability of successful repair (%)
$C_{NP}$ = Cost of new product (€) (retail / sale price)

Finally, the total cost of ownership per year is the previous equation plus the product's purchase price, both divided by the expected product lifetime (3).

$$\boldsymbol{TCO} = \frac{C_{NP}}{Y} + \frac{1}{Y} \cdot \sum_i^g P_i\big((100 - P_{Ri})C_{NP} + P_{Ri}(C_{SPMi} + (T_i \cdot R_i) + C_{Oi})\big) \tag{3}$$

Where:
TCO = Total cost of ownership (€/year)
Y = Expected lifetime (years)
$C_{NP}$ = Cost of new product (€) (retail / sale price)

This equation fulfills the goal of completeness, capturing all economic aspects of durability and repair for a product (as well as maintenance, though as mentioned above this was not pursued here). However, for the results to be objective, there must be a consistent choice of numbers to fill the equation with. This is provided by data entry conventions.

### B. Data entry conventions

As mentioned in Methods, the data entry conventions here should be refined and collectively agreed upon by a large consortium of repair experts, manufacturers, and policymakers to achieve a broad-based consensus before becoming policy. The prototype data entry conventions resulting from is study's user testing and feedback were as follows:

- As mentioned above, a repair cost may include all elements of spare part cost, labor rate, etc., but it may instead be a flat fee quoted by a credible professional repairer.
- To quantify uncertainty from best-case to worst-case scores, the product should be assessed using five or more empirical datasets (e.g., price quotes from five vendors, or five timed tests of the same physical disassembly) by an independent assessor. Two separate assessors would provide even more rigor, if desired.
- If disassembly / reassembly times are measured, they should include five timed trials, and should ideally include one person experienced with the product and one inexperienced person. (This might be the same person after several disassembly / reassembly cycles).
- Assessors do not need to perform separate teardowns for each failure mode, but can simply mark the times to access whatever components require replacement.
- Ideally, parts costs should be quoted from five different sources, if possible, to quantify uncertainty. Often there will only be one source, leading to zero theoretical uncertainty. However, we recommend never assuming less

than ±20% uncertainty to account for assumed variations over time and region.

- Cost of spare parts can include OEM parts and inexpensive third-party parts, if they meet OEM quality standards.
- When no spare parts are findable online in a quick Google search for public purchase, they are assumed to be unavailable and the probability of successful repair was assumed to be zero. This is conservative, but is a simple, objective, and reasonable convention.
- As with spare part sales, when no repair instructions were findable online in a quick Google search, they were assumed to be unavailable and the probability of successful repair was assumed to be zero. Empirical studies could refine this, but policymakers might wish to keep the assumption for the sake of encouraging better repair documentation.
- In the absence of empirical data, labor rates are estimated at best-case 40 €/hr and worst-case 50 €/hr; these are based on North American and European markets, and could be lowered for regions with lower cost of labor (see also later notes on labor cost).
- In the absence of empirical data, self-repairability is defined by European Standard NF EN 45554 [20], where no special tools or fasteners are required, both spare parts and repair instructions are available online with a simple web search, and disassembly is relatively easy.
- The labor rate of self-repair is set to zero €/hr. Even though the time of product owners is still valuable, they do not pay themselves, and counting the labor rate as zero encourages self-repair by providing better scores.
- While assessors would ideally calculate failure rates and repair costs for all possible failures, this is likely too time consuming / expensive, so there is a convention to only count a reasonable representation of "priority failures". Here, we added up the likelihoods of failure of the most common failures until the sum reached 85% of known failures. This is similar to AsMeR's scorecards only counting the first 75% of "priority parts" [21].
- Probabilities of failure would ideally be gathered from real customer data and/or the physical product testing that most companies already perform but generally do not publish. Lacking this data, they can be estimated based on similar parts and failures, with larger uncertainties.
- Probability of successful repair would ideally be calculated from OEM market data, but many OEMs do not perform their own repairs, thus requiring third parties such as repair shops. Small independent shops often do not track their work well enough for reliable statistics; the case studies here used data from iFixit's records of spare parts sold.
- Cost of a failed repair is the product purchase price. It assumes replacement with a new product of the same make and model.

Note that some of these values only have empirical data after a product has been on the market for some years—notably failure rates and parts costs. This may seem like a large barrier, but the percentage of products on the market that are completely new is extremely small; the vast majority of products in most industries are simply variants on previous products. After some years of gathering data on failure rates and costs for many product components / subassemblies, the database containing this data will provide initial estimates of future subassembly failure rates and costs, just as the Ease of Disassembly Metric (eDIM) [22] provides highly useful disassembly time estimates today.

Because it will take years before such an extensive database is built to provide easy estimation based on proxies, we built an alternative method for estimating missing data in the scorecard, based on qualitative FRI checklist methods. These outputs were assigned a higher uncertainty in the calculator, due to their sourcing from qualitative checklists. They are described in the calculator section, below.

### *C. The Excel calculator*

To perform the above calculations, we created an Excel spreadsheet with a relatively user-friendly interface. As mentioned in Methods, a spreadsheet was chosen over custom software for three reasons: ubiquitous free availability, ubiquitous understanding of the platform, and editability for future development, with the ability to lock it once consensus on development is achieved.

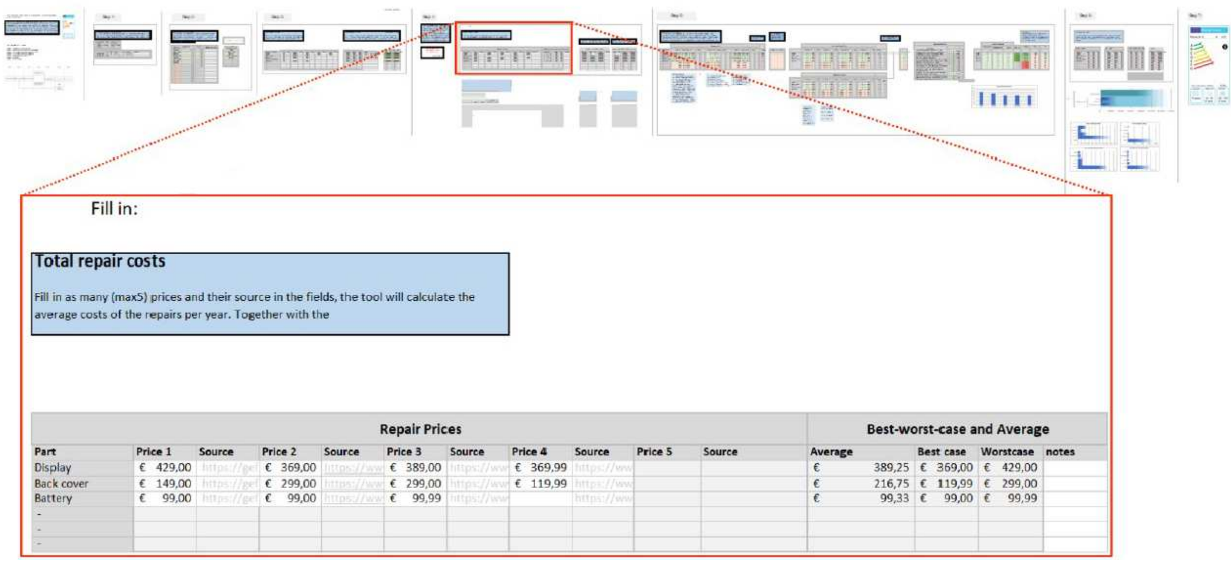
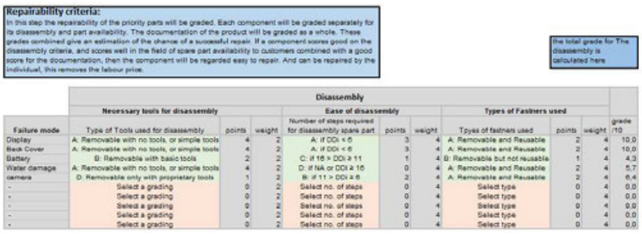



*Figure 1. Screen shot of the TCO calculator spreadsheet overview across the top, plus a detailed zoom of step four's empirical data entry on the price of repairs.*

The calculator was oriented horizontally on one single large worksheet, to enable assessors to have an overview and also for easy duplication for sensitivity analysis. See Figure 1. It leads the user through a seven step process of filling in forms, then it presents the user with cost of ownership graphs and a qualitative label design.

In the seven-step process of data entry, step one is to enter general information on the product (e.g., product make and model, expected lifetime, and such). Most of this data is directly added to the final label. Step two is to enter failure modes and frequencies. The spreadsheet calculates the 85% cutoff threshold of priority failures; it shows the assessor when that has been reached, and lists what failures to count in upcoming steps. Step three is to enter the prices of spare parts for priority failures identified in the previous step. The calculator has five sets of blanks to encourage assessors to enter five datapoints each; it calculates the average of these and tracks the highest and lowest values to determine uncertainty.

Step four has two options: A) to enter empirical data on the cost of repairs for the priority failure modes; or B) if such data is lacking, to fill out a qualitative checklist copied from FRI, which is translated into estimated costs of the repairs. See Figure 1 and Figure 2.



**Repairability criteria:**
In this step the repairability of the priority parts will be graded. Each component will be graded separately for its disassembly and part availability. The documentation of the product will be graded as a whole. These grades combined give an estimation of the chance of a successful repair. If a component scores good on the disassembly criteria, and scores well in the field of spare part availability to customers combined with a good score for the documentation, then the component will be regarded easy to repair. And can be repaired by the individual, this removes the labour price.

the total grade for The disassembly is calculated here

| | Disassembly | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Necessary tools for disassembly | | | Ease of disassembly | | | Types of Fastners used | | | |
| Failure mode | Type of Tools used for disassembly | points | weight | Number of steps required for disassembly spare part | points | weight | Tpyes of fastners used | points | weight | grade /10 |
| Display | A: Removable with no tools, or simple tools | 4 | 2 | A: if DDi < 6 | 3 | 4 | A: Removable and Reusable | 2 | 4 | 10,0 |
| Back Cover | A: Removable with no tools, or simple tools | 4 | 2 | A: if DDi < 6 | 3 | 4 | A: Removable and Reusable | 2 | 4 | 10,0 |
| Battery | B: Removable with basic tools | 2 | 2 | C: if 16 > DDi ≥ 11 | 1 | 4 | B: Removable but not reusable | 1 | 4 | 4,3 |
| Water damage | A: Removable with no tools, or simple tools | 4 | 2 | D: if NA or DDi ≥ 16 | 0 | 4 | A: Removable and Reusable | 2 | 4 | 5,7 |
| camera | D: Removable only with proprietary tools | 1 | 2 | B: if 11 > DDi ≥ 6 | 2 | 4 | A: Removable and Reusable | 2 | 4 | 6,4 |
| - | Select a grading | 0 | 2 | Select no. of steps | 0 | 4 | Select type | 0 | 4 | 0,0 |
| - | Select a grading | 0 | 2 | Select no. of steps | 0 | 4 | Select type | 0 | 4 | 0,0 |
| - | Select a grading | 0 | 2 | Select no. of steps | 0 | 4 | Select type | 0 | 4 | 0,0 |
| - | Select a grading | 0 | 2 | Select no. of steps | 0 | 4 | Select type | 0 | 4 | 0,0 |
| - | Select a grading | 0 | 2 | Select no. of steps | 0 | 4 | Select type | 0 | 4 | 0,0 |

*Figure 2. If empirical data is unavailable for step four, the calculator offers a way to estimate quantitative values from qualitative FRI-based checklists.*

Step five is to enter the probability of a successful repair and self-repairability. Like the previous step, assessors have the option to A) enter empirically-measured data; or B) if these are missing, fill out a qualitative checklist copied from FRI, which are scored from "A" (best) to "D" (worst). The latter are translated into estimated probabilities of successful repair and self-repairability. These FRI criteria include ease of disassembly, necessary tools, spare part availability, and fastener types.

Though step four and five's grading and criteria were copied from FRI, the calculator creates more accurate and reliable scores than FRI by increasing the level of detail and changing from a weighted average of checklist points to a stage-and-gate method where failure to meet any important criterion destroys the probability of that repair succeeding. The stage-and-gate method is a much more accurate way to model real repairs, as any barrier can stop a repair, whether it be lack of tools, difficult disassembly, unavailable parts, or others. The level of detail is also important: this calculator grades each priority repair separately instead of grading the product as a whole, thus avoiding unnecessarily harsh or easy scores for one difficult or easy repair.

As mentioned in the Data Entry Conventions section, the calculator's translation of qualitative checklist data to cost in €/year estimated labor times according to the number of disassembly steps, and estimated labor costs at 40 – 50 €/hr for professional repair. This assumes European or North American wages, but as later results will show, labor rates at half or even a fifth this cost would not change overall scores or priorities significantly. A repair is considered self-repairable if it scores well ("A") on necessary tools, types of fasteners used, and documentation; reasonably well on ease of disassembly ("A" or "B"); and spare part availability ("C" or above). Self-repairable operations have their labor costs set to zero.

Note that while these qualitative checklist translators are set up for a specific product category (smartphones), none of the empirical data entered in the spreadsheet is specific to a product category—that means the scorecard could be used for any type of product, from electronics to appliances to furniture to clothing, and more. These product categories are so different that no existing repair scorecards address clothing or furniture. However, data could easily be gathered on the repair costs for such products. Data on failure rates and repair success also already exist for some products by some manufacturers; while these are almost never published, the manufacturers could score their own products today.

Step six provides the user with scorecard outputs as numbers and graphs. These can be used for reporting, and they allow the assessor to reflect on how to improve the repairability of the product. Step seven draws a label that can be printed and presented with the product, in packaging or websites. This label translates the numeric results of the graphs into a qualitative grade from A to G, as with European energy labels. (More details below.)

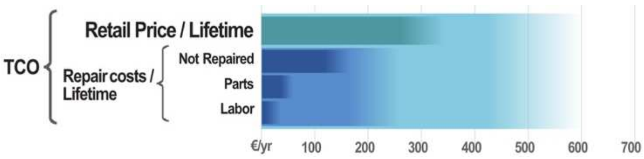



*Figure 3. Graphing an estimated TCO score for a phone.*

The scorecard's main output is Figure 3's graph, from step six, showing annualized total cost of ownership (TCO) and subdividing it to show annualized retail price and costs of repair, which is further divided into cost of parts, labor and failed repairs (average probable cost of purchasing a replacement product). As shown by the blurred ends of the graph's bars, all the data has significant uncertainty, often almost ±30%, due to estimated variance in lifetime, prices, labor rates, disassembly time, failure rates, etc. This may be typical for most products, future assessments must be done with manufacturer cooperation to see. But the uncertainty need not paralyze us—even with these uncertainties, the graph shows clear conclusions:

First, it shows the cost of failure and repair is lower than the retail price per lifetime. If it never broke, the repair costs would be zero. If it broke frequently but was fast and easy to fix, the repair score would still be low. A high (bad) repair cost comes from both breaking frequently and expensive repairs.

Figure 3 also shows the cost of labor is much less than the cost of parts or the cost of failed repairs. Thus, in this case, spare part price is a larger problem than disassembly time. For other products, it might be the opposite. Such insights can guide product design in a way that current scorecards cannot. Also note that the insignificance of labor costs in these results mean that, for this product, it does not matter whether the repair occurs in wealthy European or North American countries, or countries of the Global South with much lower labor rates; the repair score and its implications are effectively the same.

The spreadsheet's other main important output could be step seven's possible product label for consumers, in Figure 4 It lists the total annualized cost of ownership, the annualized repair costs, and the ratio between them. It then translates the ratio into a rating from A to G of how durable and repairable the product is. This is merely a prototype; an actual label should be designed in consensus with regulators and manufacturers. Any grades of A, B, C, etc. would need to vary by product category, and should be standardized by measuring and comparing all major products within each category.

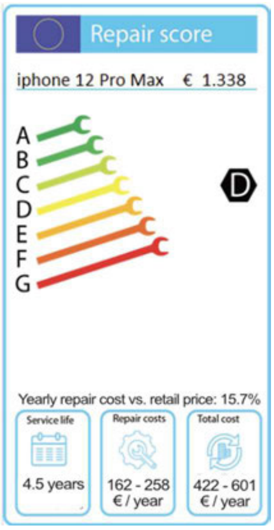



*Figure 4. A potential label design to make the cost of ownership score easily readable and comparable by purchasers.*

**Case studies**

To illustrate how scoring outputs vary with changes in data inputs, case studies were performed. As mentioned in Methods, due to a lack of sufficient industry data (especially failure rates), empirical data was supplemented with estimated data of high uncertainty. Better data would be helpful, and assessments with precise data from companies could have much more precision. However, even with full manufacturer cooperation and thoroughly tracked data, prices change over time and between regions, part availability may fluctuate, etc., so likely no assessments will ever be very precise. As before, though, uncertainty need not paralyze us. Even with high uncertainties, clear conclusions emerge when comparing product scores in Figure 5.

Figure 5 compares scores of four smartphones against each other in one scenario (S1) where they all have the average EU phone lifetime (1.5 - 2 yrs); the phones are a Google Pixel 4A, Fairphone 3+, Samsung Galaxy S21+, and iPhone 12 Pro Max. Then scenarios two and three (S2 & S3) compares the actual longer lifespans of the iPhone (4 - 5 years) and Fairphone (5 - 6 years). S2 assumed the same probabilities of failure as in S1, and S3 assumed much higher probabilities corresponding to the longer lifetimes, as described in Methods. Finally, S4 is a hypothetical score for the iPhone in S3 but self-repairable. The figure compares A. total average annualized cost of ownership (TCO) and cost of repairs, B. the ratio of repair costs to TCO, C. FRI scores, and D. iFixit scores. For easier comparison, the TCO graph is simplified from the earlier full graph, not showing the subcomponents of repair costs.

Figure 5 shows that in S1, the Pixel has roughly 1/3 the cost of the iPhone, and is within uncertainty of the cost of the Fairphone, perhaps slightly higher. This is despite the Pixel's lower purchase price (€350) versus the Fairphone (€439), because the Fairphone's low cost of repair makes it less expensive over time, on average. Of course, a sufficiently inexpensive phone (such as an Oppo) could score better than a Fairphone, even if it has poor repairability, when all phones are assumed to have this same short lifespan. But the TCO scorecard handles this in two ways: first, by also calculating the ratio of repair costs to total costs; and second, by accounting for the fact that repairable products last longer in S2, S3, and S4.

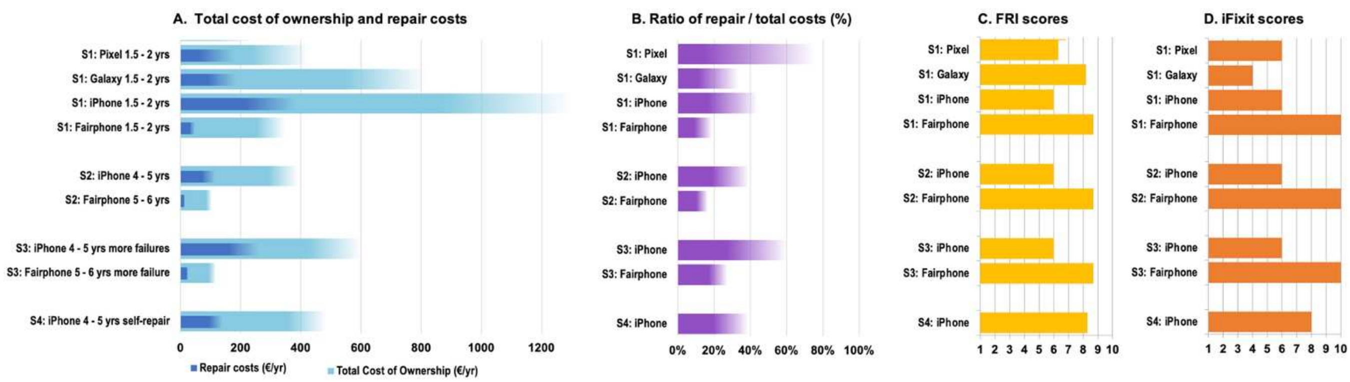



*Figure 5. Comparing TCO scores for several phones in scenario 1 (S1) and different lifetimes and scenarios (S2 – S4) for the iPhone and Fairphone.*

Comparing TCO and ratio of repair costs to total costs with FRI and iFixit in S1, the Fairphone scores best in all scorecards. The difference is that in the TCO and ratio, the differences are quantifiable—even with the uncertainties shown, the Fairphone has roughly ¼ the TCO and half the ratio of the iPhone, and less than half the TCO and ratio of the Galaxy (all roughly ±20-30%). FRI and iFixit cannot quantify these differences. This enables more informed decision-making. Also, the units of €/year are units that nearly all individuals and institutions both understand and care strongly about. We expect them to be much more easily motivated to make purchasing decisions based on such cost data than on qualitative scores like 8.7/10 or 6/10. Especially institutional purchasers (e.g., companies and governments), who buy products in large volumes and often have explicit policies capping the allowable costs of goods.

However, the TCO may unfairly penalize the iPhone for its expense, hence the calculation of the ratio of repair costs to total costs. This also shows quantitative differences, though not in €/year. Note that in FRI, the Galaxy scores much better than the Pixel and iPhone, almost as well as the Fairphone, while in iFixit it scores much worse; this shows the subjectivity of even the best existing scorecards. In the ratio of costs, these scores are all within uncertainty of each other, showing there is not a reliable difference. While this might seem less useful than a clear difference in scores, it more accurately shows there may not be a definite answer, it may depend on circumstances. (Though with better data from manufacturer cooperation, the uncertainties could likely be much reduced.)

The FRI and iFixit scores in Figure 5 do not differentiate between S1, S2, and S3, but such durability differences make a very large difference for real product owners and for environmental impacts. In S2, with actual iPhone and Fairphone lifetimes and low likelihood of failures, their TCO scores improve greatly. The Fairphone's TCO here is lower than all other phones in any scenario, and the iPhone cost is better than the Galaxy in S1, within uncertainty of the Pixel. In S3, where the iPhone and Fairphone have longer lifetimes but the higher failure and repair rates, they both have higher costs than in S2, but both are still less than half of their costs in S1. This shows how the TCO scorecard captures both repairability and durability, while existing scorecards do not.

In S4, the thought experiment (***not*** real product data) showing what if the iPhone in S3 met our minimum requirements for being self-repairable, Figure 5 shows how the TCO score improves but is still not as good as the iPhone in S2, where it has very low failure rates. This shows how the TCO scorecard captures durability even for products of the same lifespan.

Note that despite the S4 iPhone's improved repairability, the Fairphone in S3 still scores far better than it in TCO and possibly better in ratio of repair costs to total costs (though it is within uncertainty), because initial price and spare parts are less expensive, and it has much greater spare part availability, meaning a higher percent of successful repairs. This difference is not captured clearly by other scorecards, as they do not score individual repairs but lump all repairs into a single checkbox.

The ratios of repair costs to total costs remove the influence of expensive versus inexpensive products, in theory giving a purer measure of repairability and durability. However, in practice, the ratio penalizes products living so long they inevitably drive up the number of failures and thus the cost of repairs. This is because the annualized purchase price shrinks while repair costs grow. To illustrate, the Fairphone has the best ratio of all the phones assessed: even in S1 it is 10-20% (rounding to one significant figure), and in S2 it is effectively the same, with the longer life only reducing the uncertainty range slightly. The iPhone in S1's ratio of repair cost to total cost is 20-40%, but in S3 it has a ratio of 30-60%, much worse because its longer life means less €/yr for purchase cost, and its longer life on average requires more repairs. Since this ratio scores S3 worse than S1 but S3 is obviously the environmentally preferable scenario, this metric is not ideal. Future versions of the scorecard could solve this problem by adjusting repair costs over time with a discount rate, as is standard in other cost of ownership calculations. This would be easy to build into the spreadsheet, requiring no extra effort from assessors, but the discount rate would need to be agreed upon by a consortium of stakeholders, so we leave it for future work. For now, having the scorecard display both TCO and ratio of repair costs to total costs lets assessors make good judgments.

Finally, as shown earlier, the TCO scorecard graphs also inform policymakers and product manufacturers how they might improve product designs. Figure 7 shows the S3 iPhone versus the more repairable S4 iPhone; S4 has a lower total score even though product price, lifetime, and spare parts cost all remain the same, because the cost of professional labor has been eliminated and the probability of unsuccessful repair (requiring product replacement) is much lower.

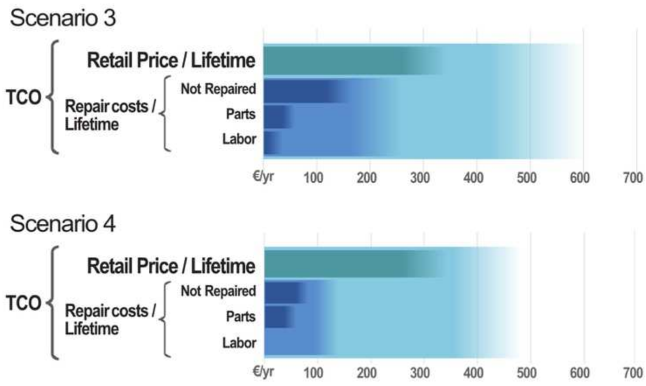



*Figure 7. Comparing theoretical TCO scores for a difficult-to-repair iPhone (above) versus an easily self-repairable one (below) with the same lifetime.*

Despite the significant uncertainties in Figure 7, it is a quantifiable economic difference, and thus can be used to make evidence-based decisions. It can quantify the value of self-repair versus professional repair, changing the current debate in the field from a qualitative moral one to a quantitative economic one.

Such comparisons could be done not only after product release, but done by designers during product development, to model the results of design decisions. For example, it could resolve the "bundling" debate, whether to cluster several components into fewer modules with faster replacement times but higher cost (and higher environmental impact) versus more modules with a lower cost but more disassembly time. There is no universal answer, but the debate could be solved product by product. Similarly, it could solve other qualitative moral debates by turning them into quantitative economic debates, such as the use of specialized tools or diagnostic equipment.

Because the TCO does not score a checklist of specific design items or services (e.g., documentation, special tools, etc.) but does include these in the score by their causal impacts on costs and probabilities of success, it can also make policy pro-innovation as well as pro-repair and pro-durability. The danger of legislating qualitative checklists is that they can freeze product designs; in the green building industry, the number one barrier to innovations in energy efficiency and materials health are existing building codes [23]. If we turn repair and durability scorecards from qualitative design checklists into quantitative scores of evidence-based impacts, it can drive both sustainability and innovation at the same time. Even if the economic impacts measured are not perfectly correlated to environmental impacts, the results above show that TCO scores track circular economy benefits much better than even the best checklist scorecards today.

## IV. Limitations

While the TCO scorecard solves many problems with existing repair scorecards, it has its own challenges. The primary limitation is that, while repair cost data are often easy to obtain, data on probabilities of failure modes and repair success rates are almost never published. Thus, manufacturer cooperation and data gathering is required for precise scoring. Though, as shown in the figures above, meaningful decisions can often still be made with imprecise data.

Another limitation is that the data entry rules need review and standardization—they should be collaboratively agreed upon by a broad consortium of policy, industry, and academic representatives. Such consortia should also decide on the qualitative grades (A, B, C, etc.) in the label version of the scorecard; these grading thresholds should be specific to each product category, as the repair costs of a smartphone are very different from those of a leather satchel or office chair. Similarly, a convention should be decided on for fair comparisons of phones of different costs and lifetimes: the TCO fairly compares phones that last longer despite greater repairs but penalizes expensive phones, while the ratio of repair costs to total costs fairly compares phones of different costs at similar lifetimes, but penalizes products lasting longer times with more repairs. Incorporating a discount rate over time into repair costs would likely be a good solution. In addition, the data visualization should also be user-tested further, to see if manufacturers and/or policymakers want the graphs simplified or further broken down into specific details.

Finally, as with all repair scorecards, other causes of obsolescence (e.g., fashion trends, or new software requiring higher performance hardware) are not included. In theory, these could be considered failure modes just like the hardware failures included here; if they were, the TCO calculation would need to be modified so that the expected product lifetime is not assumed at the start, but empirically derived from the cumulative sum of failure modes over time versus a threshold where the user would prefer to replace rather than repair or upgrade. Initial investigations have explored this, but it needs more research.

## V. Conclusion

This study developed a new scorecard for product repairability and durability, the Total Cost of Ownership Scorecard, that has several advantages over the best repair scorecards of today, specifically:

- It is quantitative, listing scores in units everyone understands and that both individuals and institutions often base purchasing decisions on (€/yr).
- It enables easy score comparison (e.g., 100 €/yr is twice as good as 200 €/yr.)
- It uses uncertainty to eliminate subjective decisions and incorporate variations in prices or other factors, including them all in best-base / worst-case values.
- It scores durability, repair, and maintenance on one scale, so can compare tradeoffs between durability and ease of repair.
- It makes legislation far easier and more affordable to scale up, using the same methodology for all product types, only setting different numbers for what good and bad scores are.
- It lets policy drive repairability while enabling innovation, by measuring results rather than checklists of design strategies.

The primary disadvantage of the new scorecard is its need for empirical data on failure rates and probabilities of successful repairs. As mentioned above, companies do often have this data but almost never publish it. Building a shared international database of product scores would also create a broad historical dataset by which to estimate failure rates of new products. Even if such a database were not publicly visible due to IP concerns, it would help product manufacturers and policymakers not only score more products, but set evidence-based priorities for where to improve durability and repairability of components.

Is this scorecard actually better than existing scorecards in a practical sense in the real world? The only way to answer this is to have several companies and/or researchers try it across many products in very different product categories. We enthusiastically encourage people to test it, and help improve it, so that together we can drive more effective repair policies and design for repair in a circular economy.

## VI. ACKNOWLEDGMENTS

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