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Full length article

Quantifying total lifetimes of consumer products: Stochastic modelling accounting for second-hand use and establishing an open-collaborative database

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ABSTRACT

Data on the total product lifetimes, which is much needed in the fields of sustainability and circularity assessment, is currently sparse and challenging to measure. To meet such data and methodological needs, the first information system of its kind has been developed as part of this research. While an online portal collects and stores consumer reports on use and disposal patterns for various electronics owned and used, the harvested survey data was automatically fed into a novel stochastic model that allowed estimating the total lifetimes and durability of the different products considering the impacts of second-hand use. This was done without reliance on auxiliary market statistics and costly facility-based analysis while preserving a satisfactory degree of accuracy. Additionally, the structure of the collected data allows for measuring the effects of the different circular practices (repair, reuse, recycling, etc.) on product longevity which is of specific interest to researchers and policymakers.

1. Introduction

Unsustainable levels of consumption are increasingly driving environmental challenges at a global level. Goods accounted for 15% of the total humanity's Ecological Footprint in 2022, and the latter far exceeds the planet's bio-capacity (WWF, 2022). These environmental impacts are associated with diverse stages of a product's life cycle such as manufacturing-related carbon emissions or waste-related water pollution (Hertwich, 2011).

One of the systematic approaches to mitigate such impacts is to extend the lifespan (lifetime or longevity) of consumer durables (Cooper, 2005; van Nes and Cramer, 2006). Prolonging product lifetimes is often suggested as means of increasing material efficiency through 'slowing the flows' and is seen in the core of the circular economy concept (Cooper, 2020). While several causes of product obsolescence have been observed, the technological type of obsolescence relates to the durability and reliability of consumer goods (Hennies and Stamminger, 2016; van Nes and Cramer, 2006). Accordingly, extended product durability is considered to be one of the pillars of business' eco-efficiency (Stigson et al., 2006). However, most corporations do not target extending product durability as they are not compensated for the corresponding lack of production and sales (Nazzal et al., 2013) apart from businesses that pursue servitization models (Vendrell-Herrero et al., 2021). Meanwhile, durability-related considerations do affect consumers' purchase choices (Floyd et al., 2014). Still, while it appears reasonable to empower consumers with accessible and reliable information on the durability of various goods, brands, and models, such information services are hardly available. Warranty and repair databases have been used as one source for such statistical estimations where claims frequency data related to different product brands are compared (Suzuki et al., 2008; Tecchio et al., 2019). However, such data analyses are susceptible to sampling bias and are barely available to the public. The average inter-purchase time data analysis has been proposed as a measure of product and brand durability (Ching et al., 2020). However, additional motivations to purchase a product replacement apart from technical failure and physical wear and tear (*functional obsolescence)* such as the aesthetical depreciation of a functional product (*psychological obsolescence*) also exist, and were surveyed and reported in existing studies (Woidasky and Cetinkaya, 2021)

At the same time, geographically and time-referenced data on

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product lifespan is important in the fields of material flow and stock analysis, life cycle assessment, as well as in marketing applications (Murakami et al., 2010). Four types of methods that differently use market statistics data, discard surveys, or yearly use surveys to estimate the lifespan distributions of commodities are currently distinguished in the scientific literature (Oguchi et al., 2010). Only the discard surveys (either through consumer questionnaires or at the treatment facility) do not require extensive shipment statistics or multi-year surveying to estimate the total lifespan. Yet, the consumer discard surveys usually estimate the *possession span* of an average owner instead of the total *domestic service lifespan* that includes all the owners of a product given the second-hand markets (Oguchi et al., 2010; Steffens, 2001). Meanwhile, surveys at the waste treatment facilities appear to be quite time and cost-intensive (U.S. EPA, 2008). Finally, the attempts to deliver actual and comprehensive databases are extremely limited. At the time of this work, the only similar attempts identified were the LiVES database that has been last updated 11 years ago (Murakami et al., 2010) and the International Service Life Database for buildings which has been discontinued (Daniotti et al., 2010).

In this work, we tackle these data issues in three ways. Firstly, a novel consumer survey-based method for product lifetimes estimation is presented. It is based on Markov chains theory and, in contrast to the existing methods, allows estimating various lifespan types including the important total service lifespan without reliance on auxiliary market statistics and laboratory or waste facility-based analysis. The possibility to use Markov chains to model and explore material lifecycles has been proposed before (Afrinaldi, 2020), but has never been applied to estimate the lifetimes of consumer goods. Secondly, an open-collaborative online information system that collects consumers' reports on the life-cycle data of the goods they have owned and used has been developed. The collaborators are supposed to be attracted to the platform as it analyses the previously harvested data and provides real-time rankings on the most durable product brands and models on the market with their average lifetimes. The database collects data for various years, regions, and use phases of the reported commodities, evaluating and presenting the impacts of various circular behavioral approaches such as repair and reuse on product longevity. Finally, a consumer survey has been conducted using the developed web portal for a number of consumer electronics to initiate the database and present the first findings to be used by the abovementioned stakeholders. Additionally, the study concludes with scientific and policy insights on product lifetimes extension, durability, and hibernation and disposal behavior.

2. Methods

2.1. Definitions

Commodity durability has been measured in various ways. First of all, durability can be assessed either based on time or usage perspectives, for instance, years in service versus total mileage for vehicles (Suzuki et al., 2008). Furthermore, it can be measured via laboratory analysis ("Which?," 2022) or statistically from observations, with the latter approach considered to be more realistic as it allows to account for the environmental conditions of usage (Suzuki et al., 2008).

The *durability* of a product is defined as its capacity to last performing its functions over a period of time (Maitre-Ekern and Dalhammar, 2016). Similarly, in the European standard EN 45,552:202,036, durability is defined as the 'ability to function as required, under defined conditions of use, maintenance and repair, until a limiting state is reached' (Dalhammar et al., 2021). In accordance with this definition, in this paper, it is measured using the expected time from the initial purchase of a new product until its first failure (TUFF): the total *durable span*. The failure can be either minor (limited usability) or major (not usable anymore) and any of them counts towards TUFF. We show that such a measure, given survey data for the newly purchased and later failed product, allows for accurately representing the relative reliability of brands and models.

As for the *total product lifespan* (lifetime) or TPL, we use the existing definition of the (domestic) service lifespan: the time between the purchase by the very first owner and the time when the product is ready for the end-of-life (EoL) management (Oguchi et al., 2010; U.S. EPA, 2008). This is different from the possession span that relates to a single owner only. In this paper, we assume the shipment span (time between production completion and the first purchase) as zero. Such total product lifespan, hence, will include the procession spans by each owner along the product's life cycle. By definition, the expected durable span is not longer than the expected total lifespan of a product.

2.2. Model

One of the achievements of this work is the novel stochastic approach that, in contrast to existing methods, allows estimating the TPL based merely on a single (non-repetitive in time) consumer survey. Here, we introduce the proposed computational model and the corresponding data structure.

Considering the product's service life cycle, we distinguish four possible ownership prototypes until the product is *discarded* into the EoL management stream by the last owner. Type (0) is the single ownership kind where the first user becomes the product's last user and discards it either in designated recycling or regular waste treatment services. Type (1) is the kind of ownership where the first user purchases a new commodity and later passes it on to the second owner either giving it away or selling it. Type (2) implies intermediate ownership between the previous and the subsequent owner of a used product (repeated reuse). Type (3) is the ownership that is scoped by the very last user who receives a used product and discards it into the EoL management in the end. The following Fig. 1 illustrates this model including the definitions introduced above.

Additionally, in the model, we consider that products can be returned to the retailer that additionally increases their total lifetime depending if they are later refurbished for re-selling or directed to the EoL management.

Simultaneously, we distinguish five conditions the products can be possibly in: new, new - refurbished, used (functional), used - minor malfunction (limited experience), and used - major malfunction (not usable). Here we use the term refurbished as an umbrella term for refurbished, comprehensively refurbished, and remanufactured products as defined by the International Resource Panel (Nasr et al., 2018).

Such model of the product life cycle between its initial shipment and the EoL management can be presented in the form of a Markov chain that is defined as a discrete set of states (Z), the initial state *N*, and a sequence of random variable *X* in *Z* such that the transition probability p_{ki} of occurrence of the next state *i* is defined only by the current state *k* and is given in matrix *P* (Feldman and Valdez-Flores, 2010). In our case, we consider the following space of states: R (retail), N (new product reaches first owner – the initial state), S (second-hand product received by new owner), and E (the EoL state at the moment of discard). Additionally, we assign a set (T) of weights t_{ki} to the edges to represent for how long on average does the product stay in the state *k* before transiting to *i*. This is represented in the following Fig. 2.

Using the theoretical framework of Markov processes, the TPL can be, then, calculated as an expected *hitting time* h_N to reach the final (absorbing) state E from the initial state N (Chen and Zhang, 2008). The following system of linear equations has to be considered where p_{ik} is a transition probability from state *i* to state *k* and t_{ik} is the average time span between states *i* and *k*:

$$h_i = \sum_{k\in Z} p_{ik}(h_k + t_{ik})$$

Solving the system will deliver the expected total lifespan (h_E).

The durable span can be obtained in an analogous way where the absorbing state is replaced with the 'failure' state F, state S state is

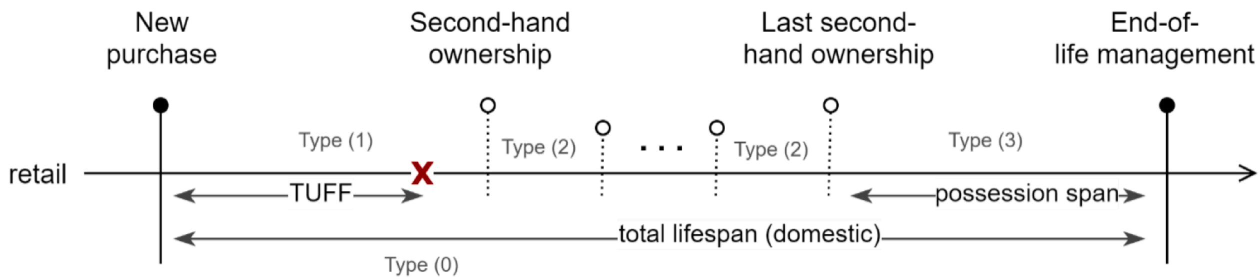

Fig. 1. Product service life cycle model along with the four types of ownership, durable span (TUFF), possession span, and the total product lifespan (TPL).

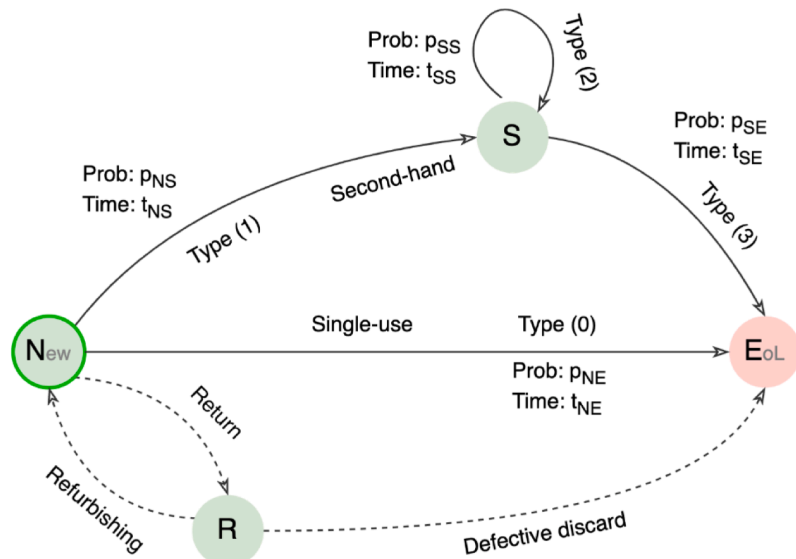

Fig. 2. Markov chain describing the proposed stochastic model of product service life cycle. N is the initial state of a new product, E is the final state of a product entering its EoL, S is the state of switching to a new second-hand owner, and R is the state of being returned to retail. Additionally, transition probabilities and weights are given. The dotted line denotes the product return path that was not considered in the calculations.

redefined as 'second-hand product received by a new owner without failure during last use', R is redefined as 'returned product without failure during its first use', and *P* and *T* are adjusted accordingly. In these terms, TUFF can be calculated as an expected hitting time to reach the final (absorbing) state F from the initial state N while solving the corresponding system of linear equations. For simplicity, in the following work, we estimate TUFF based only on data for new products that have been discarded (Type 0 ownerships).

2.3. Data requirement

To be able to estimate the PLT and the TUFF for different products using the proposed model, data on the average length of different phases of ownership and use (the average time span between states, t_{ik}) has to be estimated along with the likelihood of switching between these ownership phases for an average product (transition probability from state i to state k, p_{ik}). Collecting consumer reports can be used to obtain these average values. The comprehensiveness of the proposed model allows for avoiding restricting the survey participants as reports related to any phase of the product lifecycle (ownership types 0 to 3) are in the end contributing to the more accurate *P* and *T* estimation.

Data on the average time that each ownership phase lasts is calculated as a mean value for all the possession spans reported within such ownership type (0 – 3). Based on the statistical analysis theory of representative samples, to make sure that such values are accurate with a margin of error of 10%, at least 68 consumer reports have to be collected for each ownership type (confidence level of 90% and unlimited population assumed).

The values for the transition probabilities for an average product are then calculated as the relative difference between the number of respondents reporting such transitions during their consumer experience with a specific type of product. To make sure, such ratios are accurate with a margin of error of 10%, at least 68 reports have to be collected for each state from which several transitions are possible (states N and S). By definition, the total sum of such alternatives equals one: $p_{NS} + p_{NE} + p_{NR} = 1$ and $p_{SE} + p_{SS} = 1$.

Transition probabilities for products that have been returned to retail (state R) do not relate to the consumer experience. These might be sourced from retail statistics suggesting which share of the returned product are refurbished for reselling versus discarded into the EoL management.

Finally, temporal data on repair and failure occurrences during possession spans has to be obtained to accurately estimate the durable span or TUFF.

2.4. Web-platform and the database

The Product Lifetimes & Durability Portal has been developed to achieve both, the data harvesting and data sharing purposes of the presented work (Amatuni, 2023). The portal is two-sided in the sense that it provides one page that collects reports from respondents that adheres to the previously described model for the selected product type, and the other page that presents the consumers and practitioners with the relevant lifetime and durability results and rankings. The reports are envisioned to be collected from target surveys and benevolent contributors who are interested in the information provided in return. In the former case, the respondents have to add a unique survey ID to their report so that data collected in that way can be distinguished from the rest of the database. All the stochastic model-based analyses are automatically performed on the fly on the backend and are immediately presented back to the user after any additional input to the database.

The following temporary data is collected through consumer reports: the times when the product was obtained, repaired, failed (if), and finally passed on or discarded in the EoL management. Additionally, data on *hibernating* or *storage* time (Murakami et al., 2010; Thiébaud-Müller et al., 2018), that is the time span when the product is still in possession but not in use, is harvested. It has been argued that such 'dead stocks' create a significant barrier to efficient material flows within circular economies (Wilson et al., 2017). There has been recent work on estimating the share of hibernating versus in-use household electronics (Baldé et al., 2021), yet, data on average hibernation time is scarce.

Additionally, the following non-temporal data is collected through the reports: product brands and models, geographical data, method of product disposal, and consumer's subjective evaluation of how expensive the product is to support the corresponding analysis.

2.5. Survey setup

To verify the validity of the proposed model and to exemplify the usability of the designed portal and resulting data, a survey-based experiment has been conducted for a number of consumer electronics. In particular, respondents through paid Amazon Mechanical Turk (MTurk) service have been recruited to submit data (through the portal) regarding their experience with 11 categories of major consumer electronics as ICT and consumer electronics contribute up to 80% of the total e-waste (Forti et al., 2018). In total 1469 individual product reports have been submitted, and after cleaning these based on attention checks and duplicate data, 1037 reports were considered for analysis. Only products that are not used or owned anymore were asked to be reported. Reports that describe products that are not in use (but still in possession) were used to assess the durability of products as they contain valuable data on the history of possible failures. Product return and refurbishment transactions were not considered in this survey. Simplified assumptions were made for some products and specific second-hand phases where data availability was limited (see Appendix A). Additionally, outliers were removed from the reports.

3. Results

3.1. Overview

For 11 categories of consumer electronics, four possession spans have been estimated separately based on the corresponding reports, and then the TPL has been estimated considering all ownership phases using the presented stochastic process model.

Additionally, two durability measures for each product category have been calculated. The first measure calculates average TUFF only for the product reports that had failed at some point (including the ones reported still in possession), thus answering the question of 'how quickly does the average product fail if it fails'. To make this more meaningful, this value is provided along with the share of products that failed during their possession span at all (type 0) - the *failure rate.* The second measure, *adjusted* TUFF, calculates average TUFF based on product reports that ended their possession span and were discarded, hence, answering the question of 'for how long is this type of product expected to be in possession without failure'. The adjusted TUFF measure (in contrast to regular TUFF) takes into account products that did not fail as well. This prevents situations in which durability estimates based on possibly rare failed products create an impression that an average product from that category will function as long as regular TUFF suggests. Here, for the products that never failed, adjusted TUFF is equal to the product's possession span, and for the product that did fail, adjusted TUFF is equal to regular TUFF After averaging across all product reports, this adjusted durability measure ranges from 0 (not expected to last at all) to TPL (expected to last without failure for at least as long as TPL) allowing more representative durability measure.

Only results for five commodities with a statistically representative number of data points (at least 68 reports in total for four possession types) are presented in the paper and are validated against existing data on electronics lifetimes from United Nations University (Forti et al., 2018). See Appendix B for the complete set of results for all the equipment surveyed.

3.2. Survey outcome and analysis

Out of all product reports analyzed, 40% of the products are not in use yet still in possession suggesting a high volume of hibernating stocks. The overall distribution of the ownership phases reported for products (not in possession) is presented under the following Fig. 3:

It can be seen that the majority of participants discard their new purchases (either through recycling or a regular waste stream), however, a significant number of products enter the second-hand market (sold or given away). In particular, 55% of newly purchased electronics are discarded by the end of the first possession span without a chance for a second life. Such ratios for various products were used to obtain the transition probabilities from N -> E and N -> S. It can be also concluded that about 54% of the second-hand products switch the owner for the second time. These ratios were used to obtain the transition probabilities from S -> S and S -> E.

The following Table 1 lists five products with the corresponding average estimations for the first possession span, second-hand possession span, last possession span, the total lifespan (TPL). When compared with the existing theoretical values for the total service lifespan in the non-EU OECD countries found in the report by the United Nations University (Forti et al., 2018), the average relative deviation error of our approach is only 9%. Additionally, data on average hibernation time is given. There has been no intermediate ownership of Type 2 reported for printers, thus, we assumed zero possession span for such.

The following Table 2 presents results for the durable spans of the covered electronics based on two measures 290 introduced above (TUFF and adjusted TUFF). Additionally, we present findings on the origins of 291 possible failures and reported recycling rates.

4. Discussion

4.1. Product lifetimes

It can be seen that, for all products, the average length of all four types of possession spans gradually decreases which confirms natural expectations of products lasting shorter while switching more owners. Yet, while decreasing, the length of all the phases is long enough to contribute to considerably longer TPL. On average, TPL is extended by 34% through the introduction of the second-hand phases compared to the single-owner possession type (0) that is often considered instead. Based on data collected, on average, 38% of newly purchased products enter the second-hand phase after the end of their first possession span. At the same, 58% of electronics that enter the second-hand phase are discarded in the EoL management after the end of their second possession by the second owner. Across equipment categories, an average product switches between 1.7 owners before its EoL.

While observing product lifetime extension as estimated TPL is longer than an average possession span, we would like to refrain from concluding that second-hand markets do necessarily cause such extension. It is not evident from the data collected that in absence of such markets, first owners of the newly purchased products would not use

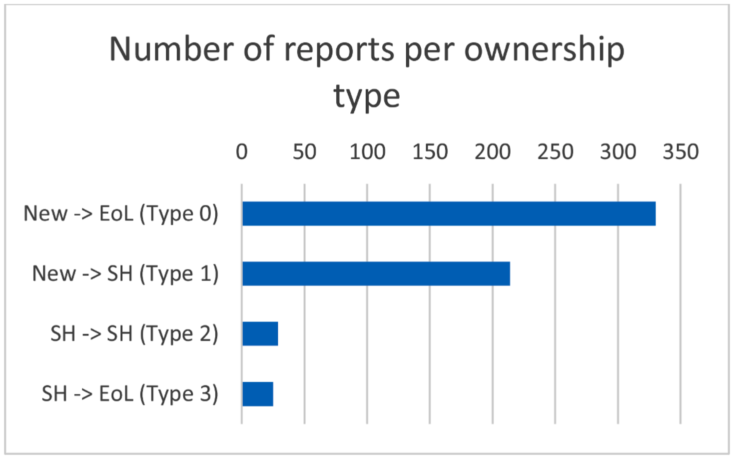

Fig. 3. Distribution of submitted product reports between different ownership types. SH stands for second-hand.

Table 1
Lifetime-related results for the product reports collected. Estimated four types of possession spans along with the modelled TPL (total product lifetime) are given. UNU – United Nations University report's resulting average years for the corresponding products (Forti et al., 2018). Unit - years.

Product	Type 0 possession span.(N -> EoL)	Type 1 possession span.(N -> S)	Type 2 possession span (S -> S)	Type 3 possession span (S -> EoL)	TPL	Total lifespan (UNU)	Hibernation time	Reports
Desktop PC	7.6	6.0	4.8	6.2	11.6	9.2	1.4	141
Laptop computer	6.1	4.6	2.8	2.6	7.7	7.8	1.0	132
Printers (incl. scanners, etc.)	5.4	4.0	0.0	5.9	7.1	7.6	1.2	94
Mobile phones (smartphones)	3.7	2.9	1.0	2.5	4.7	5.1	0.9	102
TV (Flat Panel Display)	7.0	6.1	3.4	2.6	9.4	9.7	0.4	78

Table 2
The durability measures of different consumer electronics. TUFF is defined as 'time until the first failure'. The adjusted TUFF takes into account all the reported products, not only the ones that failed. Failure rate - share of products that failed during their first possession span. Unit - years.

Product	Failure rate	Durable span of failed (TUFF)	Durable span of discarded (adjusted TUFF)	User caused failure	Mixed residual waste (not recycled)
Desktop PC	70%	6.6	6.5	7%	34%
Laptop computer	88%	4.5	4.9	13%	28%
Printers (incl. scanners, etc.)	69%	4.9	4.9	5%	51%
Mobile phones (smartphones)	72%	3.1	3.1	36%	50%
TV (Flat Panel Display)	82%	6.5	6.5	9%	30%

them for longer while not being able to re-sell them. On the contrary, there is existing evidence of consumers discarding products more quickly after being exposed to an attractive offer (Jaeger-Erben et al., 2021). At the same time, it is not evident which share of consumers obtaining used products, would purchase new products in the absence of second-hand alternatives. Such rebound effects of the circular economy have yet to be assessed quantitatively prior to any claims of environmental benefits (Makov and Font Vivanco, 2018).

4.2. Product durability

Durability of different types of products was measured (based on Type 0 possession reports only) as the expected time until the first failure using two proposed measures that in the result did not differ significantly (see the Overview subsection of the Results). Based on our results, the failure rates of electronics vary a lot starting from printers that fail in 69% of cases of their ownership span and ending with laptops that fail in 88% of cases. It is evident that portable devices such as laptops and smartphones are more prone to user-caused failures, yet, across electronics, such causes are rather infrequent and happen in 14% of failure cases. Moreover, the majority (71%) of reported failures are major (being not usable anymore), or 54% of all possessions. Relatively high failure rates observed suggest, firstly, that obtained values for TUFF can be used to assess the expected functional possession time for an average newly purchased product, and, secondly, that mechanical failure precedes the majority of discard decisions.

4.3. Hibernation time and disposal behaviour

Conducted surveys allowed us to assess the average hibernation time of different electronics (based on new products after their first possession span only). Between 51% and 73% of electronics hibernate for at least a month prior to their disposal (discarding or passing on) while the average hibernation time per possession ranged between half a year to a year and a half. Out of the listed electronics, TVs tend to be disposed of the quickest which is reasonable to expect due to their size and difficulty of storage. This is in line with the recent study by Baldé et al. (2021) where the lowest hoarding rates were observed for the products that are larger in size. Otherwise, devices tend to hibernate for a significant share of their life and policies and practices that promote more efficient circularity are suggested (Wilson et al., 2017). At the same time, only 40% of the hibernating products have a major failure while the rest have mostly minor failures suggesting the high repair potential of hibernating electronics and corresponding repair-facilitating policies. This is in line with existing findings that only around 40% of obsolete laptops are not operational (Woidasky and Cetinkaya, 2021). Finally, our data analyses showed that a significant portion of electronics (39% on average) is not recycled properly when discarded by their EoL. Such discard practices can contribute to valuable material loss and contamination of the waste streams and ecosystems. Hence, future policy interventions and circular incentives have to be accompanied by wider information campaigns on regional formal recycling possibilities.

The following figure summarizes the expected domestic use cycle of a single product averaged across five product categories (see Fig. 4). In particular, possible pathways (and their probabilities) between different user types prior to the discard decision are presented. We believe that such probabilistic data could serve as a basis for a complete mass balance based stock and flow models in future studies on the material implications of reuse (that this diagram does not tackle).

4.4. Limitations

While the authors believe this study contributes significantly to the methods and data harvesting potential in the field of product lifetime extension, we have to acknowledge several limitations of this work.

Firstly, our surveys have been conducted using the paid MTurk service which has been shown to be at least as representative as other methods for recruiting subjects (Loepp and Kelly, 2020). Additionally, we have followed important tips on validity scanning and data filtering previously suggested for Mturk users (Chmielewski and Kucker, 2020). In our study, respondents were mostly from the USA (80%), Turkey (5%), and Brazil (5%). Hence, our findings should not be generalized given observations in the existing studies that lifetimes can vary significantly between countries (Dunant et al., 2021; Forti et al., 2018; Thiébaud-Müller et al., 2018). Yet, we have to mention that similarly to the reference values by the United Nations University for the non-EU OECD Member States, most of our respondents are from high-income countries, partially conformity between our product lifetime estimates.

Secondly, several assumptions have been made. We assumed that respondents did not have preferences over which type of ownership to submit reports about, hence, resulting ratios between different possession phases are considered to represent rates between real consumption decisions (see Data requirement subsection). Yet, it has been previously shown that, in such surveys, some consumers might not accurately recall the purchase date, and that conducting longitudinal research in future studies would allow to address such limitations (Wieser and Tröger, 2016). It has to be acknowledged that, even though some of the existing lifetimes estimation approaches rely on market statistics or repetitive surveys (i.e. *approaches 2 and 3 described by* Oguchi et al. (2010)*, they are less susceptible to such memory-related uncertainties as consumers are surveyed exclusively on in-use products.* Additionally, it was found challenging to collect enough reports on the decisions after the state S (whether consumers prefer to pass on or discard the existing second-hand product), and more data on these ratios have to be located in the future as assumptions made on limited data were made for this state. Moreover, we did not include the product return path in the calculations of the TPL in this study, while such cases could have shortened the average value. Yet, it is assumed that return cases are rather rare.

Finally, we have mentioned that durability (TUFF) values were calculated based on single-use products only (Type 0 ownership). Accounting for the second-hand markets, as it was done for TPL values, would deliver more realistic TUFF values. Additionally, while resulting brands and models' longevity rankings are present at the portal, the number of reports collected is not enough to make confident claims. Similar observation on higher sample size requirements for more valid brands-specific comparison of repair needs has been reported by Woidasky and Cetinkaya (2021). Here, the issue of data collection is seen as a matter of time given that the new method, the database, and the web portal presented in this paper are completed already.

5. Conclusions

To conclude, this study contributes to scientific knowledge and the field of sustainability in general in three ways.

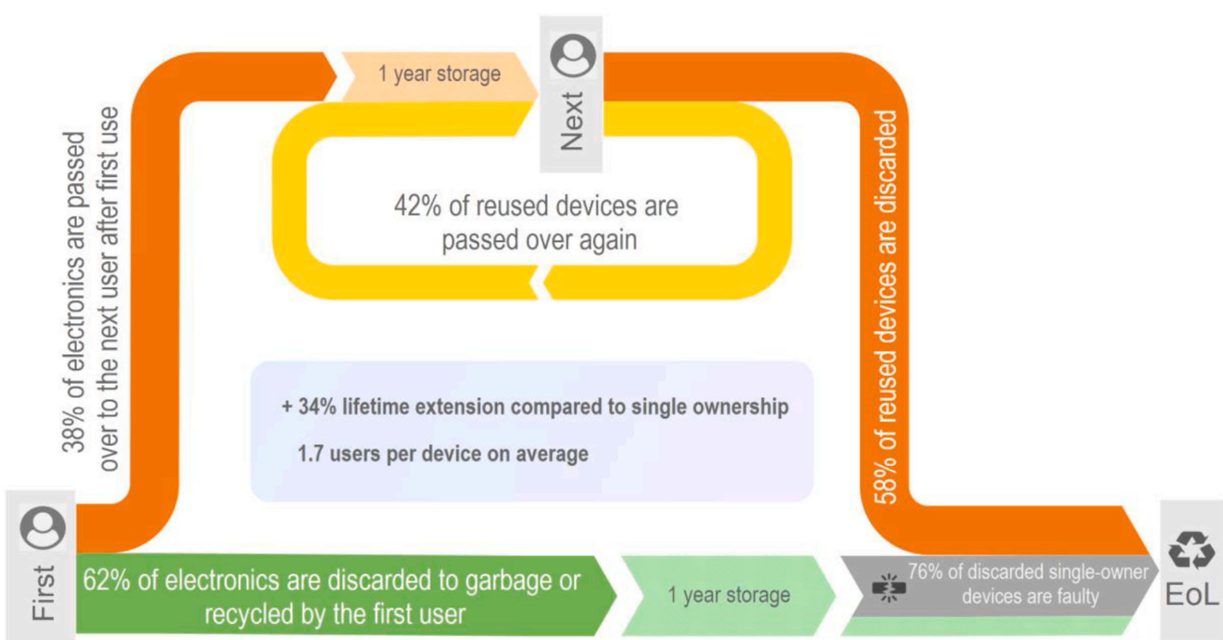

Fig. 4. Overview of a single product's domestic use cycle based on conducted surveys (averaged across five electronics categories). Arrows describe possible pathways of a device between its First, Next (users), and the final discard decision (garbage or recycling) or the End of Life (EoL). The pathways have different width based on the relative shares (transition probabilities) between different user types (states). Additionally, the shares of devices that were reported faulty or hibernating (faded arrows) by the end of their first possession are depicted.

Firstly, the proposed stochastic model, for the first time, allows estimating the total lifespan of electronics (including the second-hand and re-use practices) based on consumer surveys only, without conducting facility-based discard surveys or using unreliable and limited market data. Estimates for the total product lifetimes (TPL) of five electronic products deviated on average by 9% from the existing reference values showcasing a potentially high degree of accuracy (relative to the uncertainty in the reference study by the United Nations University).

Secondly, extensive reports from more than a thousand consumers have been collected to establish an initial seed for an open-collaborative database on product lifetimes and durability (Amatuni, 2023). Such accurate and accessible data is required by the scientific community working on the applications of material flow, lifecycle, and circularity assessment, yet, still limited. To our knowledge, for the first time, data on average lifetimes of different ownership stages (including second-hand use) has been assessed for different consumer electronics. On average, introduction to the second-hand cycle increases total product lifetime by 34% as, on average, 1.7 owners are estimated per product in that case compared to single-use behaviour.

Finally, the same web portal, which has been developed to collect consumer reports and that presents the resulting database, provides the durability assessment of different products along with their brands and models. Products can be kept and used for a different amount of time, yet, for which portion of that time they can be expected to be functionally reliable (expected time until first failure) is a different measure that, to our knowledge, has been for the first time systematically surveyed. A high circular (repair and reuse) potential of a significant share of hibernating (not in use) products has been observed as only 40% of such were reported as hard to repair (major failure). These findings suggest a significant potential for repair-facilitating interventions such as the recent 'right to repair' policy proposed by the European Commission ("Proposal for a Directive on common rules promoting the repair of goods," 2023). Yet, a significant number of major (hard to repair) product failures precede discard decisions (54% of possessions) suggesting the need for future policy interventions to consider improved electronics durability as well.

Discussion on the major findings and limitations of the study were presented in the corresponding sections. The idea of attracting scientists and consumers to the developed web portal to collect more product reports might be yet the most challenging one to overcome since it will likely depend on extensive advertisement of these achievements in a wider community.

Spotlights

- Current information on product lifespans is highly limited while being critical for material circularity assessment.
- For the first time, consumer electronics' total product lifetimes were measured accounting for possible reuse.
- Accurate estimates were possible without using market statistics and expensive lab tests, only through surveys.
- Total lifetime is 34% longer compared to single-use behavior. An open-collaborative lifetimes database is established.
- Larger scale surveys will allow more accurate estimates facilitating various sustainability-oriented stakeholders.

CRediT authorship contribution statement

Levon Amatuni: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Validation. **Tales Yamamoto:** Conceptualization, Methodology, Validation. **Cornelis Peter Baldé:** Validation, Writing – review & editing. **Christian Clemm:** Writing – review & editing. **José M. Mogollón:** Funding acquisition, Writing – review & editing, 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.

Data availability

Data has been linked through the Mendeley Data service.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.resconrec.2023.107103.

References

Afrinaldi, F., 2020. Exploring product lifecycle using Markov chain. Procedia Manufacturing, pp. 391–398. https://doi.org/10.1016/j.promfg.2020.02.196.
Amatuni, L., 2023. Product lifetimes & durability portal [WWW Document]. URL https://lt-platform.web.app/(accessed 2.11.23).
Baldé, C.P., Iattoni, G., Xu, C., Yamamoto, T., 2021. Update of WEEE collection rates, targets, flows, and hoarding-2021.
Chen, H., Zhang, F., 2008. The expected hitting times for finite Markov chains. Linear Algebra Appl. 428 https://doi.org/10.1016/j.laa.2008.01.003.
Ching, A.T., Erdem, T., Keane, M.P., 2020. How much do consumers know about the quality of products? Evidence from the diaper market. Japanese Econ. Rev. 71, 541–569. https://doi.org/10.1007/s42973-019-00030-x.
Chmielewski, M., Kucker, S.C., 2020. An MTurk crisis? Shifts in data quality and the impact on study results. Soc. Psychol. Personal. Sci 11, 464–473. https://doi.org/10.1177/1948550619875149.
Cooper, T., 2005. Slower consumption: reflections on product life spans and the "throwaway society. J. Ind. Ecol. https://doi.org/10.1162/1088198054084671.
Cooper, T., 2020. Slower cycles: an essential characteristic of the circular economy, in: the circular economy in the European Union: an interim review. Springer International Publishing, pp. 99–116. https://doi.org/10.1007/978-3-030-50239-3_9.
Dalhammar, C., Milios, L., Luth Richter, J., 2021. Increasing the lifespan of products. Policies and consumer perspectives.
Daniotti, B., Lupica Spagnolo, S., Chevalier, J.L., Hans, J., Chorier, J., 2010. An international service life database: the grid definition for an actual implementation of factor methods and service life prediction. CIB 2010 World Congr. https://doi.org/10.13140/RG.2.1.2457.1369/1.
Dunant, C.F., Shah, T., Drewniok, M.P., Craglia, M., Cullen, J.M., 2021. A new method to estimate the lifetime of long-life product categories. J. Ind. Ecol. 25, 321–332. https://doi.org/10.1111/JIEC.13093.
EPA, U.S., 2008. Elaectronics Waste Management in the United States: Approach 1. EPA, U.S.
Feldman, R.M., Valdez-Flores, C., 2010. Applied probability and stochastic processes, applied probability and stochastic processes. https://doi.org/10.1007/978-3-642-05158-6.
Floyd, K., Freling, R., Alhoqail, S., Cho, H.Y., Freling, T., 2014. How online product reviews affect retail sales: a meta-analysis. J. Retail. 90, 217–232. https://doi.org/10.1016/j.jretai.2014.04.004.
Forti, V., Baldé, C., Kuehr, R., 2018. E-waste Statistics: Guidelines on Classifications, Reporting and Indicators, 2nd edition. United Nations University, IAS-SCYCLE.
Hennies, L., Stamminger, R., 2016. An empirical survey on the obsolescence of appliances in German households. Resour. Conserv. Recycl. 112, 73–82. https://doi.org/10.1016/j.resconrec.2016.04.013.
Hertwich, E.G., 2011. The life cycle environmental impacts of consumption. Econ. Syst. Res. https://doi.org/10.1080/09535314.2010.536905.
Jaeger-Erben, M., Frick, V., Hipp, T., 2021. Why do users (not) repair their devices? A study of the predictors of repair practices. J. Clean. Prod. 286, 125382 https://doi.org/10.1016/J.JCLEPRO.2020.125382.

Loepp, E., Kelly, J.T., 2020. Distinction without a difference? An assessment of MTurk Worker types. Res. Polit. 7 https://doi.org/10.1177/2053168019901185, 205316801990118.

Maitre-Ekern, E., Dalhammar, C., 2016. Regulating planned obsolescence: a review of legal approaches to increase product durability and reparability in Europe. Rev. Eur. Comp. Int. Environ. Law. https://doi.org/10.1111/reel.12182.

Makov, T., Font Vivanco, D., 2018. Does the circular economy grow the pie? The case of rebound effects from smartphone reuse. Front. Energy Res. 6 (39) https://doi.org/10.3389/fenrg.2018.00039.

Murakami, S., Oguchi, M., Tasaki, T., Daigo, I., Hashimoto, S., 2010. Lifespan of commodities, part I: the creation of a database and its review. J. Ind. Ecol. 14, 598–612. https://doi.org/10.1111/j.1530-9290.2010.00250.x.

Nasr, N., Russell, J., Bringezu, S., Hellweg, S., Hilton, B., Kreiss, C., von Gries, N., 2018. Redefining value the manufacturing revolution, international resource panel. https://doi.org/10.13140/RG.2.2.31020.00640.

Nazzal, D., Batarseh, O., Patzner, J., Martin, D.R., 2013. Product servicing for lifespan extension and sustainable consumption: an optimization approach. Int. J. Prod. Econ. 105–114. https://doi.org/10.1016/j.ijpe.2012.10.017.

Oguchi, M., Murakami, S., Tasaki, T., Daigo, I., Hashimoto, S., 2010. Lifespan of commodities, part II: methodologies for estimating lifespan distribution of commodities. J. Ind. Ecol. https://doi.org/10.1111/j.1530-9290.2010.00251.x.

Proposal for a Directive on common rules promoting the repair of goods [WWW Document], 2023. . Eur. Comm. URL https://commission.europa.eu/document/afb20917-5a6c-4d87-9d89-666b2b775aa1_en (accessed 4.25.23).

Steffens, P.R., 2001. An aggregate sales model for consumer durables incorporating a time-varying mean replacement age. J. Forecast. 20, 63–77. https://doi.org/10.1002/1099-131X(200101)20:1<63::AID-FOR758>3.0.CO;2-D.

Stigson, B., Madden, K., Young, R., Brady, K., Hall, J., 2006. Eco-efficiency learning module. World Bus. Counc. Sustain. Dev. 231.

Suzuki, K., Alam, M.M., Yoshikawa, T., Yamamoto, W., 2008. Two methods for estimating product lifetimes from only warranty claims data. In: Proceedings - The 2nd IEEE International Conference on Secure System Integration and Reliability Improvement, SSIRI. https://doi.org/10.1109/SSIRI.2008.59, 2008.

Tecchio, P., Ardente, F., Mathieux, F., 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.

Thiébaud-Müller, E., Hilty, L.M., Schluep, M., Widmer, R., Faulstich, M., 2018. Service lifetime, storage time, and disposal pathways of electronic equipment: a Swiss case study. J. Ind. Ecol. 22, 196–208. https://doi.org/10.1111/jiec.12551.

van Nes, N., Cramer, J., 2006. Product lifetime optimization: a challenging strategy towards more sustainable consumption patterns. J. Clean. Prod. 14, 1307–1318. https://doi.org/10.1016/j.jclepro.2005.04.006.

Vendrell-Herrero, F., Vaillant, Y., Bustinza, O.F., Lafuente, E., 2021. Product lifespan: the missing link in servitization. Prod. Plan. Control 1–17. https://doi.org/10.1080/09537287.2020.1867773.

Which? [WWW Document], 2022. URL https://www.which.co.uk/(accessed 12.15.22).

Wieser, H., Tröger, N., 2016. Exploring the inner loops of the circular economy: replacement, repair, and reuse of mobile phones in Austria. J. Clean. Prod. 172, 3042–3055. https://doi.org/10.1016/j.jclepro.2017.11.106.

Wilson, G.T., Smalley, G., Suckling, J.R., Lilley, D., Lee, J., Mawle, R., 2017. The hibernating mobile phone: dead storage as a barrier to efficient electronic waste recovery. Waste Manag. 60, 521–533. https://doi.org/10.1016/J.WASMAN.2016.12.023.

Woidasky, J., Cetinkaya, E., 2021. Use pattern relevance for laptop repair and product lifetime. J. Clean. Prod. 288, 125425 https://doi.org/10.1016/J.JCLEPRO.2020.125425.

WWF, 2022. Living planet report 2022: building a nature-positive society, A Banson Production.