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Article

Keywords:

Posted Date: July 24th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10399538/v1

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Additional Declarations: No competing interests reported.

Inferring First and Second Use Lifespan Indicators for Household Appliances from Peruvian Survey Data

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ABSTRACT

The circular economy aims to keep materials in use and reduce disposal in landfills. In this context, household appliances at the end of their life cycle can become a source of recoverable materials. Estimating this potential requires information on appliance useful life, including possible second-use phases through resale, donation, storage, repair, or reuse. This exploratory study provides, to our knowledge, the first nationally representative model-based assessment of household appliance longevity and reuse patterns in Peru from 2008–2024. We apply an EM–Weibull mixture model to National Household Survey (ENAHO) data, where appliance retirement and transfer dates are not directly observed. We estimate population-weighted first-use and second-use indicators for 12 appliance categories and identify three ownership diffusion patterns: rapid saturation, essential goods, and obsolescent devices. The results provide empirical evidence on appliance lifecycle patterns in Peru and illustrate how mixture models can be used to infer lifespan dynamics from limited survey data.

1 Introduction

The lifespan of a household appliance (HA) can be defined as the interval from purchase to final disposal[1], including possible phases of secondhand use, repair, or storage before reaching end of life[2–4]. This definition is important for assessing environmental impacts[5] and product-use patterns. HA lifespan depends on technological, social, and environmental factors. Household characteristics and high initial costs may be associated with longer lifespan[1]. Wear from use is relevant, especially in devices with mechanical parts[4]. Consumer preferences influence lifespan through the relation between expected and actual durability and through the novelty criterion, which is associated with demand for devices with better performance[6]. Repair feasibility also affects whether a product is repaired or discarded, depending on cost, fault type, and technical complexity[7,8].

Unlike some consumer goods, such as tires and medical supplies, HAs can have a "second life" in which reuse, repair, and refurbishment extend their total useful life[9,10]. Second use is motivated by financial, environmental, social, and emotional factors[11]. From an economic perspective, resale, leasing with refurbishment, and related business models can keep products in circulation for longer periods[12,13]. Extending the total life cycle can also contribute to preserving natural resources and reducing demand for raw materials[14–16]. However, these practices may face barriers such as storage of unused devices in households, quality risks in secondhand goods, and technological obsolescence[9,16,17].

Among the challenges described above, planned obsolescence, as a type of technological obsolescence, helps explain why products may be discarded before or at the end of their useful life. Obsolescence goes beyond physical degradation and includes product quality, technological change, consumer expectations, and social preferences[1,6,18]. Planned obsolescence is relevant because it has been described as a commercial strategy to stimulate sales[1]. This idea remains debated: some authors question whether obsolescence is always a deliberate attempt to increase sales[4], while other studies report cases of planned obsolescence[19], discuss its environmental impacts[20], and examine its relationship with consumer rights[21].

Once HAs reach the end of their life cycle and become electronic waste (e-waste), urban mining becomes relevant. Urban mining is defined as the management of stocks present in the technosphere to recover resources while conserving resources, protecting the environment, and generating economic benefits[22]. This concept is related to the circular economy and the 3R approach, reduce, reuse, and recycle, which seek to keep materials extracted from the lithosphere within the technosphere for as long as possible[9,10,23]. Urban mining is based on value recovery through secondary raw materials, often with lower costs and energy consumption than conventional mineral extraction[24]; environmental protection through mitigation of pollutants such as heavy metals and reduction of degradation associated with traditional mining[10]; and social sustainability through the transformation of informal recycling into formal employment[10,25]. In this sense, urban mining links resource recovery, environmental protection, and social sustainability within a circular economy framework.

As an environmental and economic strategy, urban mining offers advantages and challenges. It can provide natural resource savings by using e-waste as a source of metals instead of primary mining[16], and it can achieve higher extraction yields than

conventional mining for some materials[15,23,25]. It can also reduce heavy metal pollution and the environmental impacts of conventional mining[17], while supporting job creation and poverty reduction[26,27]. However, urban mining faces bottlenecks caused by low collection rates[16,17], difficulties in material recovery due to low concentrations in e-waste[28], and risks linked to informal recovery practices that harm the environment and human health[25,29]. Additional barriers include the need for adequate regulation, reliable data, and appropriate e-waste collection[9], as well as raw material price volatility and dependence on subsidies[24]. Taken together, these benefits and limitations show that urban mining is a relevant circular economy strategy.

Regarding the recovery of valuable materials, HAs are a source of resources that can be recovered through urban mining. Base metals represent a significant share of their weight and value; iron and steel predominate, followed by non-ferrous metals such as copper and aluminum[15,17,30]. In smaller quantities, but with high economic value, HAs may also contain precious metals such as gold, silver, and palladium[10,16,17,28,31], industrial metals such as lead, tin, and zinc[10,31], rare earth elements such as neodymium, lanthanum, cerium, praseodymium, and terbium[17], and other elements such as tantalum, niobium, antimony, gallium, germanium, and indium[9]. Battery-powered appliances may contain critical raw materials and strategic minerals, such as lithium and cobalt[16]. Non-metallic materials include polymers such as polypropylene, polystyrene, and acrylonitrile butadiene styrene[30]. However, these appliances may also contain hazardous substances, including mercury[17,23], lead and cadmium[17,28], and arsenic, beryllium, and chromium[17]. Overall, this composition emphasizes the dual role of HAs at the end of their useful life: they are both a secondary source of valuable materials and a waste stream requiring environmentally sound management.

In this context, HAs are relevant products for circular economy analysis because they contain valuable materials such as metals, rare earth elements, and polymers. Their lifespan depends not only on operating technology, but also on obsolescence, consumer expectations, repair, reuse, and replacement practices that can create a second life. However, official household surveys often record ownership and acquisition information, not disposal, resale, donation, or transfer dates. Therefore, the main objective of this research is to estimate model-based useful-life indicators, during primary and secondary use, for HAs reported in ENAHO. This work addresses the lack of direct retirement and transfer information by using acquisition-year data to infer latent use patterns, and it provides a preliminary stage for estimating the potential of HAs as a source of valuable materials at the end of their life cycle.

2 Method

2.1 Lifespan

In the literature, several notions of lifespan coexist, ranging from the time between acquisition and first divestment by the original owner, known as first-use lifespan, to the interval from acquisition until formal entry into a waste management system, or to the period until functional or economic obsolescence[5]. These definitions hinder comparability across studies. For example, Amatuni et al. report a first-use lifespan of 6.1 years for a color television[32], while UNU's global assessment yields 9.7 years by combining primary, secondary, and tertiary use phases[33]. We therefore adopt an operational framework that distinguishes two quantities: first-use lifespan, defined as the time from acquisition to first divestment, and second-use lifespan, defined as the time from transfer to the secondary market, through resale, donation, or prolonged storage, to final retirement. Because retirement dates are not directly observed in ENAHO, these quantities are inferred as model-based components, not measured as complete lifetime records.

2.2 Official data sources

The National Household Survey (ENAHO), conducted by the Instituto Nacional de Estadística e Informática (INEI), uses a stratified, multistage design and survey weights to produce national household estimates of appliance ownership[34]. Between 2008 and 2024, the annual surveys used in this study include more than 530,000 household interviews[35–37]. ENAHO Module 18 records household equipment ownership, the number of units owned, and the acquisition year of the newest unit[38]. We use this acquisition year to compute the observed age of each appliance at the survey date. This variable does not identify disposal, resale, donation, or transfer dates. Previous work used ENAHO Module 18 to estimate first-use lifespans for television equipment in Peru with Kaplan–Meier and parametric survival models[39]. The present study extends this use of ENAHO from television equipment to multiple HA categories and separates first-use and second-use patterns as unobserved components. For this study, we retain appliances reported without interruption from 2008 to 2024 and align them with the United Nations University (UNU) Waste Classification keys (Table 1)[33]. This matching provides a consistent set of appliance categories across survey years.

2.3 Data Scarcity

Although ENAHO's sample is large and nationally representative, its temporal information for lifespan estimation is limited. Module 18 records one time-related variable per appliance: the acquisition year of the newest unit currently owned[38]. It does not record resale, donation, informal export, retirement, or physical discard. Moreover, when multiple units of the same type

Table 1. Household appliances according to ENAHO (2008–2024).

Appliance category	Appliance	UNU key[33]
Audio	Radio	0403
Audio	Sound system	0403
Computers	Desktop computer	0302
Computers	Laptop	0303
Video	Black-and-white TV	0407
Video	Color TV	0407
Video	DVD player	0404
Video	VCR (videocassette)	0404
Home appliances	Blender	0201
Home appliances	Electric iron	0201
Home appliances	Sewing machine	0201
Home appliances	Washing machine	0104
Home appliances	Refrigerator/Freezer	0108
Home appliances	Microwave oven	0114

coexist in a household, ENAHO records only the most recent acquisition. We therefore define an operational condition of **data scarcity**, in which the only longitudinal signal for an appliance is its current stock and latest acquisition year, with no direct observation of end-of-use, end-of-life, or secondary transactions. Under these circumstances, conventional survival techniques require assumptions that cannot be verified directly in ENAHO: the Kaplan–Meier estimator requires observed event times and censoring information[40], and a single-component Weibull survival model cannot separate overlapping first-use and second-use patterns when only age in use is observed[41]. This motivates a latent-component model instead of a direct event-time survival model. Therefore, the estimates reported in this study should be interpreted as model-based lifespans under data scarcity, not as direct observations of individual appliance retirement events.

2.4 EM–Weibull mixture model

A single observed age t_h may describe either a device in its *first-use* phase or one already transferred to *second-use*; consequently, a one-component Weibull model cannot separate these two unobserved use histories. Let $h = 1,\ldots,H$ index appliance observations and $j \in \{1,2\}$ index the unobserved component. We therefore represent observed appliance ages with a two-component Weibull mixture, with

$$\theta_1 = 1-\pi, \quad \theta_2 = \pi, \quad \theta_1+\theta_2 = 1,$$

where component 1 is interpreted as the first-use component, component 2 as the second-use component, and π as the model-based population share assigned to the second-use component. Conditional on component membership j, the observed age is represented by a Weibull component with scale $\lambda_j > 0$ and shape $\rho_j > 0$:

$$f_j(t \mid \lambda_j,\rho_j) = \frac{\rho_j}{\lambda_j}\left(\frac{t}{\lambda_j}\right)^{\rho_j-1}\exp\left[-\left(\tfrac{t}{\lambda_j}\right)^{\rho_j}\right], \tag{1}$$

$$S_j(t \mid \lambda_j,\rho_j) = \exp\left[-\left(\tfrac{t}{\lambda_j}\right)^{\rho_j}\right]. \tag{2}$$

The survey records the current age of the newest unit, defined as

$$t_h = \text{SurveyYear}_h - \text{AcquisitionYear}_h.$$

For each observation, $t_h \geq 0$ is measured in years. Because acquisition year is recorded annually, t_h is treated as an annual age proxy. Because ENAHO does not directly record the retirement, disposal, resale, donation, or transfer date of each appliance, t_h is not a complete lifetime observation. It is the observed age of an appliance still present in the household at the survey date. We therefore use the two-component mixture to decompose the observed age distribution into two latent components interpreted as first-use and second-use patterns. This choice avoids introducing event indicators that are not observed in ENAHO. The survival form in Eq. (2) is reported for interpretation as the right-tail probability of the fitted observed-age distribution, while the likelihood below is based on the observed-age density.

Thus, the contribution of observation h under component j is

$$u_{h,j} = f_j(t_h \mid \lambda_j, \rho_j).$$

With ENAHO sampling weight $w_h > 0$, the weighted likelihood contribution is

$$L_h = \sum_{j=1}^{2} \theta_j u_{h,j},$$

and the weighted observed-data log-likelihood is

$$\ell_{\text{obs}}(\pi, \lambda_1, \rho_1, \lambda_2, \rho_2) = \sum_{h=1}^{H} w_h \ln L_h.$$

Because the use-phase label $Z_h \in \{1,2\}$ is unobserved, we maximize ℓ_{obs} with a weighted expectation–maximization (EM) algorithm[42,43]. Here, $Z_h = 1$ denotes assignment to the first-use component and $Z_h = 2$ denotes assignment to the second-use component.

E-step. Given the current parameter values at iteration m, compute for $k = 1, 2$:

$$u_{h,k}^{(m)} = f_k\left(t_h \mid \lambda_k^{(m)}, \rho_k^{(m)}\right),$$
$$Z_h^{(m)} = \sum_{k=1}^{2} \theta_k^{(m)} u_{h,k}^{(m)},$$
$$\gamma_{h,j}^{(m)} = \frac{\theta_j^{(m)} u_{h,j}^{(m)}}{Z_h^{(m)}}.$$

Here, $\gamma_{h,j}^{(m)}$ is the estimated probability that observation h belongs to component j, conditional on the observed age and the current parameter values.

M-step. For each j and $h = 1, \ldots, H$, define

$$a_{h,j} = \ln f_j(t_h \mid \lambda_j, \rho_j).$$

Then update:

$$Q_j(\lambda_j, \rho_j) = \sum_{h=1}^{H} w_h \gamma_{h,j}^{(m)} a_{h,j},$$
$$\pi^{(m+1)} = \frac{\sum_{h=1}^{H} w_h \gamma_{h,2}^{(m)}}{\sum_{h=1}^{H} w_h},$$
$$(\lambda_j^{(m+1)}, \rho_j^{(m+1)}) = \arg\max_{\lambda_j, \rho_j} Q_j(\lambda_j, \rho_j),$$

where the last maximization is solved numerically for the two Weibull parameters of each component.

Initialization and convergence. To reduce dependence on a single starting point under our data-scarce framework, we generate each initial mixing proportion by sampling

$$\pi^{(0)} \sim \text{Uniform}(0.05, 0.95), \quad \rho_j^{(0)} = 1, \quad \lambda_j^{(0)} = \bar{t},$$

where $\bar{t}$ is the weighted mean observed age. We augment these starts with a deterministic grid of $\pi^{(0)} \in \{0.10, 0.20, \ldots, 0.90\}$. We perform 100 total starts (random + grid), run the weighted EM algorithm to convergence—until changes in ℓ_{obs} and in the parameters fall below $\varepsilon = 10^{-6}$[43]—and then select the parameter set with the highest observed-data log-likelihood. This procedure provides a reproducible initialization strategy and reduces the risk of selecting a poor local maximum.

Lifecycle metrics. Upon convergence $(\hat{\pi}, \hat{\lambda}_j, \hat{\rho}_j)$, we compute the estimated second-use share and component means as

$$\widehat{\pi} = \frac{\sum_{h=1}^{H} w_h \gamma_{h,2}^{(\text{final})}}{\sum_{h=1}^{H} w_h},$$

$$\mu_j = \hat{\lambda}_j \Gamma\Big(1 + \tfrac{1}{\hat{\rho}_j}\Big), \quad j = 1,2.$$

Under the component convention used here, μ_1 is the model-based mean of the component interpreted as first use and μ_2 is the model-based mean of the component interpreted as second use. This EM–Weibull mixture uses the acquisition-year variable, the survey weights, and the two-component assumption to infer appliance life-cycle indicators, including the estimated share of appliances assigned to a second-use component π, the mean of the first-use component μ_1, and the mean of the second-use component μ_2. These quantities should be interpreted as model-based indicators under latent-use assumptions, rather than as direct observations of individual appliance retirement or transfer events.

Algorithm 1 EM–Weibull Mixture Algorithm

Input: observed ages t_h and survey weights w_h.
Draw multiple initial parameter sets $(\pi^{(0)}, \lambda_j^{(0)}, \rho_j^{(0)})$.
repeat
  E-step: compute $\gamma_{h,j}^{(m)}$, the estimated component-membership probabilities.
  M-step: update π and (λ_j, ρ_j) by maximizing Q_j.
  Check convergence of ℓ_{obs} and the parameters; if not met, set $m \leftarrow m+1$.
until parameter changes $< \varepsilon$
Compute $\widehat{\pi}$ and μ_j.

3 Results and Discussion

ENAHO penetration data show that gas stoves and Colour TVs reach high ownership levels, while the model-based estimates suggest longer in-use ages for some appliance categories. In contrast, legacy media devices follow a declining ownership pattern, with possible relevance for recycling planning. Figure 1 compares the annual penetration rates of twelve household appliance categories in Peruvian households with the model-based population-weighted age estimates for those same appliances over 2008–2024, and Table 2 reports descriptive Pearson correlation coefficients between penetration and estimated age. The penetration trajectories show three descriptive patterns. First, gas stoves and Colour TVs reach high ownership levels: both cross the 70 % threshold in 2016 and stabilize between 75 % and 86 % by 2024. Second, technologically obsolescent devices such as DVD players and VHS recorders decline: DVD penetration peaks early in the period before falling below 10 % by 2024, while VHS ownership declines from over 20 % to near zero, consistent with the shift away from physical media reported in other markets[44–46]. Third, stable-ownership items such as blenders, irons and radios fluctuate around long-run averages near 55–60 %, suggesting continued household use; meanwhile, refrigerators and personal computers grow modestly yet remain below the levels observed for gas stoves and Colour TVs (see Fig. 2).

Table 2. Per-appliance Pearson r between penetration (%) and population-weighted model-based age, 2008–2024.

Category	Appliance	r
Audio	Radio	−0.90
Audio	Sound System	−0.95
Computers	PC	+0.74
Home appliances	Clothes Washer	+0.53
Home appliances	Blender	−0.30
Home appliances	Microwave Oven	−0.34
Home appliances	Gas Stove	−0.63
Home appliances	Refrigerator/Freezer	−0.87
Home appliances	Electric Iron	−0.95
Video	Colour TV	+0.71
Video	VCR (VHS)	−0.68
Video	DVD Player	−0.92

Next, we examine how these penetration dynamics correspond to model-based in-use ages. The estimates group appliances into four descriptive age ranges. VHS recorders show the highest average, with 12.6 ± 1.9 years of in-use service. In the long-age range (8–10 years), refrigerators (9.45 years), radios (8.52 years), irons (8.08 years), sound systems (7.98 years) and

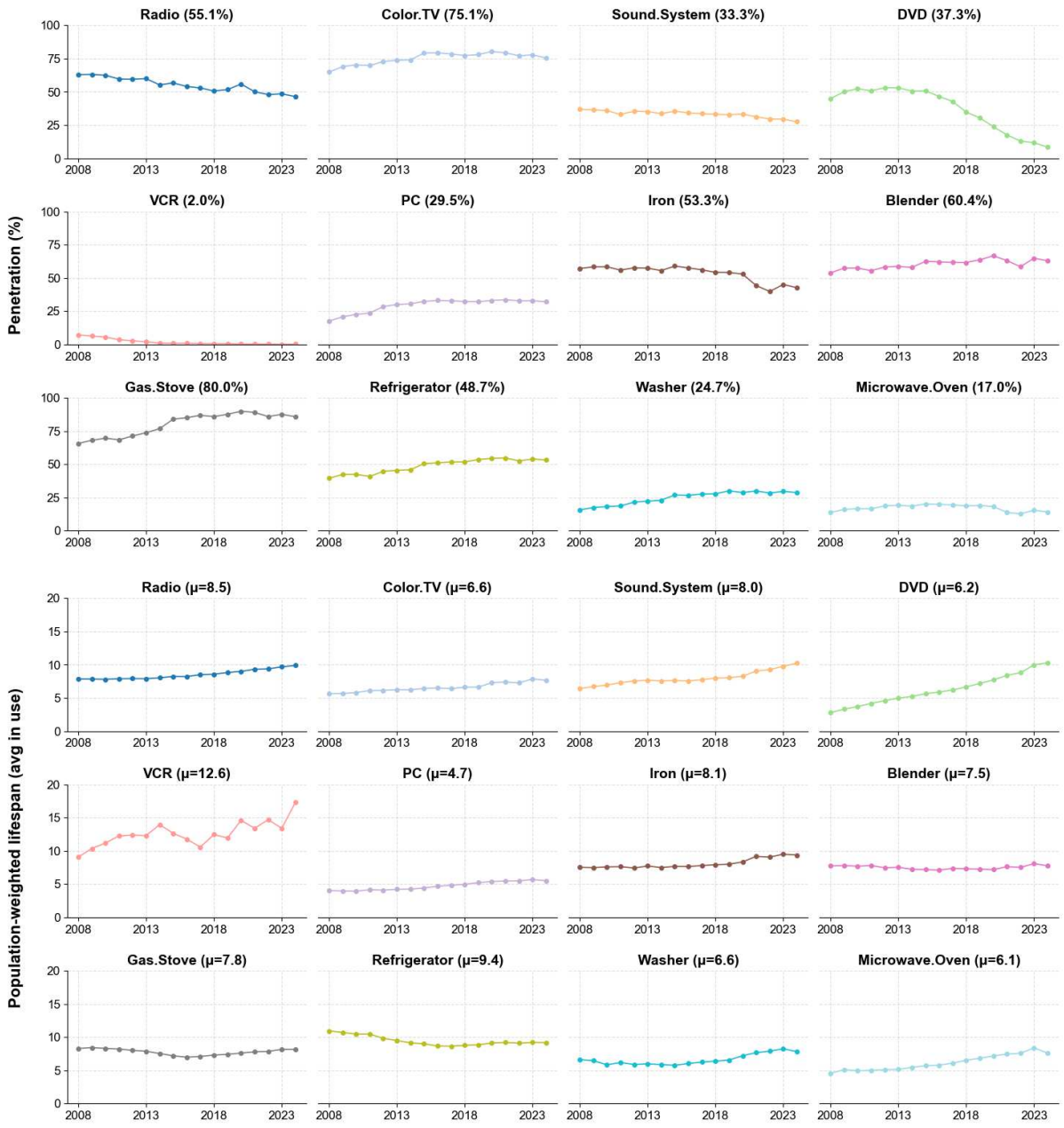


Figure 1. Penetration percentage of selected household appliances in Peruvian households (2008–2024) (top) and population-weighted model-based age in use (bottom). The numbers in parentheses indicate the average value of each metric over the study period: mean penetration percentage (%) and mean age in use (years).

gas stoves (7.77 years) form a group of products with higher model-based ages; refrigerator estimates shorten by 1.8 years, while sound-system and radio estimates lengthen by 3.8 years and 2.1 years, respectively. The medium-age range (6–8 years) includes clothes-washers (6.62 years), Colour TVs (6.58 years), DVD players (6.21 years) and microwave ovens (6.13 years), among which Colour-TV and PC estimates increase by 2.0 years and 1.5 years. Personal computers remain the lowest-age category, averaging 4.73 years despite this upward trend; prior studies show that ICT lifespans vary by setting, use pattern, and storage behavior[5,47,48].

Pooling the appliance-year series yields a modest negative correlation between penetration and model-based age ($r = -0.25$). These descriptive correlations do not imply causality. Appliance-level coefficients suggest two broad patterns. Categories with increasing penetration, personal computers (+0.74), Colour TVs (+0.71) and washers (+0.53), show positive correlations, consistent with, but not direct evidence of, the interpretation that households may retain higher-performance or higher-cost

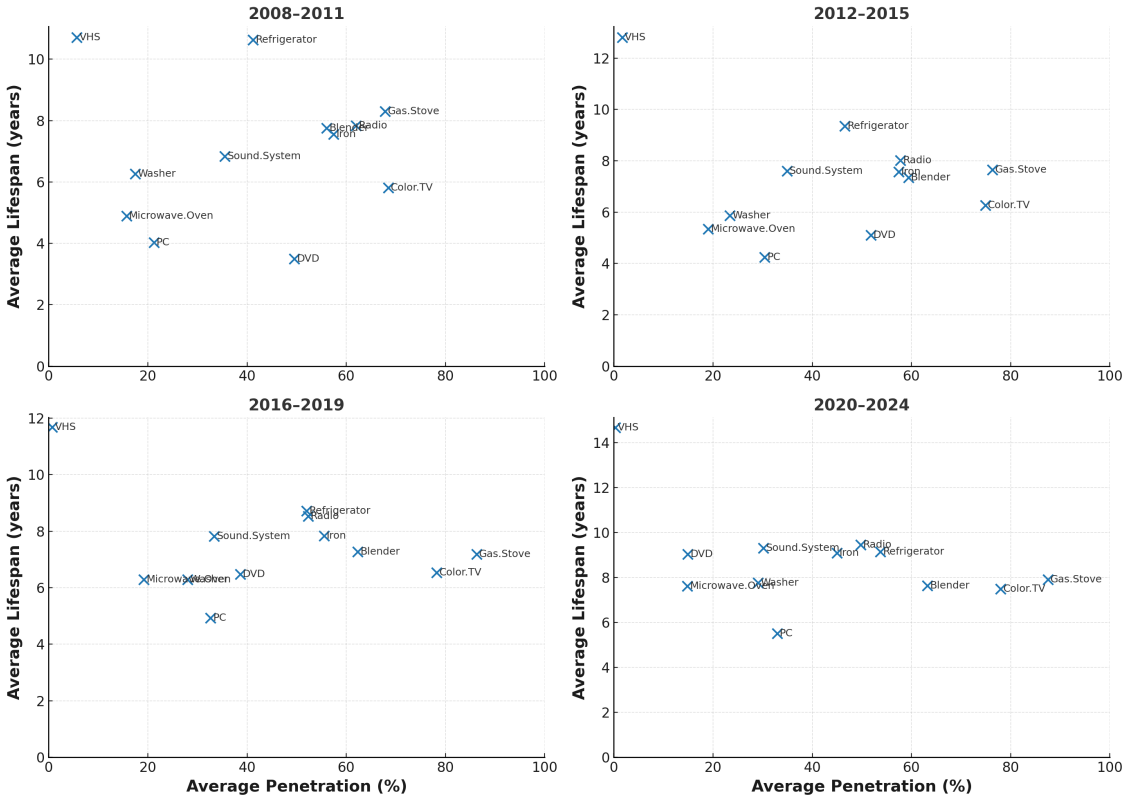


Figure 2. Relationship between average penetration (%) and average model-based age in use (years) of household appliances, segmented into four-year intervals. Each point corresponds to an appliance, labeled at its respective coordinates.

appliances longer once their functional needs have been met[47,49]. In contrast, obsolescent or low-cost items, DVD players (-0.92), irons (-0.95), radios (-0.90), sound systems (-0.95) and gas stoves (-0.63), exhibit negative correlations, consistent with literature on perceived obsolescence, repair decisions, and relative price declines[1,50]. These findings suggest that some major appliance categories may approach high ownership levels while extending in-use age, whereas the decline of legacy media devices may indicate a possible concentration of end-of-use flows if retained devices exit use within a short period.

From the mixture model, the population-weighted mean age in use can be written as $\mathrm{E}[T] = (1-\pi)\mu_1 + \pi\mu_2$, where μ_1 denotes the mean of the first-use component, μ_2 denotes the mean of the second-use component, and π is the model-based share of appliances assigned to the second-use component. Although this single summary metric is useful for comparing average in-use ages across appliance categories, it masks two separate sources of variation: changes in the fraction of units assigned to the second-use component, captured by π, and changes in the component means, captured by μ_1 and μ_2. To describe these patterns, we disaggregate the overall mean into its two unobserved components. Figure 3 plots the estimated second-use share $\widehat{\pi}$ over time, while Figure 4 shows the component-specific mean ages. Under data scarcity, where only current age and most recent acquisition year are observed, these mixture-model estimates provide a quantitative description of ENAHO's appliance use patterns. On average, first-use component means ($\widehat{\mu}_1 \approx 10.6$ years) exceed second-use component means ($\widehat{\mu}_2 \approx 4.3$ years) by a factor of roughly 2.5, but the relative weight of each term varies by product and survey year. These values should be regarded as indicative approximations, conditional on the mixture assumptions, rather than direct measurements. This two-component decomposition describes which appliances are more strongly assigned to the first-use component and which are more strongly assigned to the second-use component.

From 2008 to 2024, the estimated first-use share, $1-\widehat{\pi}$, decreases in eight of the ten categories with sufficient recent penetration; the largest decreases occur in **refrigerators** (-34.8 pp), **gas stoves** (-34.5 pp) and **electric irons** (-28.2 pp). By 2024, more than 60% of the observed stock of gas stoves, blenders, irons and Colour-TV sets is assigned by the model to the second-use component, whereas radios remain nearly unchanged (-2.6 pp). Personal computers exhibit a distinct pattern: after a peak in the estimated second-use share during 2020–2021, they settle at roughly 45% by 2024. VHS and DVD players are excluded due to negligible recent penetration (Figures 1 and 2).

As analogous evidence from high-income markets, recent work for Norway reports lifetime contractions for some large appliances, but not uniformly across products[4]. German and U.S. studies indicate that low-cost small appliances and rapidly



Figure 3. Heatmap of the estimated second-use proportion $\widehat{\pi}$ for selected household appliances in Peru (2008–2024). Rows are appliance types; columns are survey years.

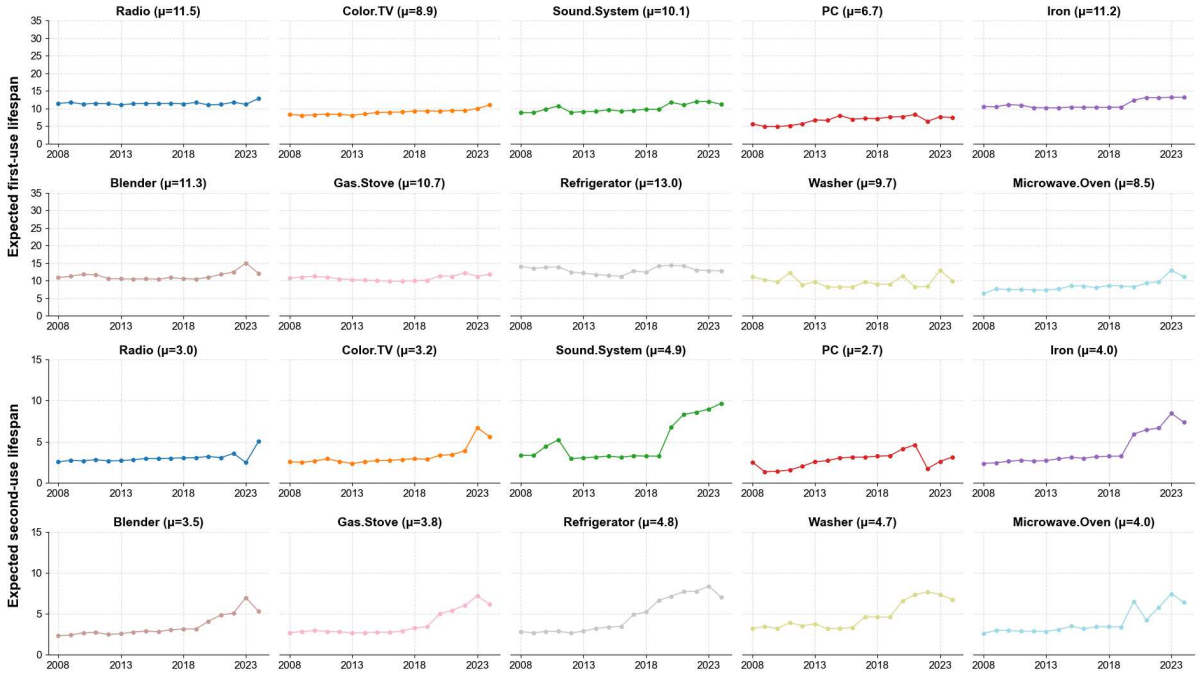


Figure 4. Model-based first-use component mean (top) and second-use component mean (bottom) for selected appliances in Peruvian households (2008–2024). Parentheses show the mean value in years over the study period.

improving electronics are often replaced before failure in contexts involving perceived obsolescence, repair decisions, and falling prices[1,51].

The onset of COVID-19 in 2020 coincided with a ~ 20 pp median increase in the estimated second-use share; microwaves and irons increased by $+29$ pp, and gas stoves by $+24$ pp. While a partial decrease occurred in 2021, the estimated second-use

share stabilized roughly 22 pp above the 2019 baseline through 2024. Studies in Canada and Portugal report COVID-period changes in household waste flows and recycling patterns[52,53]. However, ENAHO does not directly observe whether households deferred purchases, resold appliances, donated them, stored them, or discarded them. Thus, the estimated increase should be interpreted as a model-based change in second-use assignment during the pandemic period, particularly for kitchen appliances and small electrics, rather than as direct evidence of specific household behaviors. Radios and PCs returned close to pre-pandemic estimated second-use levels.

Extending the two-component perspective, Figure 4 shows that most appliances have gradually lengthened their first-use component mean (μ_1) since 2008. Descriptive linear slopes are largest in microwave ovens and sound systems, at roughly $+0.26$ years per calendar year, or about 4.2 additional years over 2008–2024. Irons follow at $+0.18$ years per calendar year and personal computers at $+0.17$ years per calendar year, whereas gas stoves rise more modestly ($+0.05$ years per calendar year); washers (-0.02 years per calendar year) and refrigerators (≈ 0 years per calendar year) change little.

Second-use component means (μ_2) diverge more sharply. **Refrigerators show the largest increase** ($+0.40$ years per calendar year). A larger-increase group, sound systems ($+0.38$ years per calendar year), irons ($+0.34$ years per calendar year) and washers ($+0.29$ years per calendar year), comes next, followed by a moderate-increase group comprising microwave ovens ($+0.25$ years per calendar year), gas stoves ($+0.25$ years per calendar year) and personal computers ($+0.11$ years per calendar year). These slopes are descriptive changes in the model-based component means. Taken together, the trajectories are consistent with longer first-use durations being relevant to the timing of entry into secondary markets and expected end-of-use flows.

4 Limitations and Uncertainty

ENAHO does not observe disposal, retirement, resale, donation, or transfer dates. Consequently, the model does not recover complete appliance histories. Instead, it decomposes the observed age distribution into two unobserved components interpreted as first-use and second-use patterns. These components are statistical groups inferred by the model and are not directly labeled in the survey data. Lifetime estimates may therefore be biased if the observed age of the newest unit differs systematically from the age structure of all units in use. Additionally, our analysis relies on a single, self-reported acquisition year for each category, the most recent purchase, which introduces two further concerns. First, excluding older, still-active units narrows the observed age distribution, potentially biasing the estimated mixture weight π and the first-use share $1-\pi$. Second, inaccuracies in respondent recall, particularly for purchases over five years old, may introduce measurement error in t_h, affecting the estimated component means (μ_1, μ_2) and mixture weight π. These limitations mean that first-use and second-use quantities should be interpreted as model-based estimates, not as directly observed appliance histories. Future research can address these limitations by incorporating external e-waste collection data, validating reported acquisition dates against external records, explicitly modeling measurement error within the EM framework, or using longitudinal data to track appliance histories.

5 Conclusion

In this paper, we provide a quantitative analysis of ownership patterns and model-based reuse indicators for household appliances in Peru over the period 2008–2024. By fitting a two-component EM–Weibull mixture model to national survey data, we represent first-use and second-use patterns as latent components and estimate the model-based share of units assigned to second use. Our results indicate divergent penetration and model-based age patterns across appliance categories: goods such as Colour TVs and personal computers exhibit sustained diffusion and moderate increases in model-based age, with positive correlations between market penetration and in-use duration; in contrast, legacy media devices (DVD players, VHS recorders, radios) show declines in ownership and negative correlations, which may indicate a future concentration of end-of-use flows. The EM–Weibull decomposition suggests that the mean first-use component ($\mu_1 \approx 10.6$ years) is, on average, more than twice as long as the mean second-use component ($\mu_2 \approx 4.3$ years), although the fraction of units assigned by the model to the second-use component (π) varies by product and survey year. The COVID-19 period coincided with a ~ 20 pp increase in the estimated second-use share, which settled at ≈ 22 pp above its 2019 baseline, mainly for microwaves, irons, and gas stoves. These findings underscore the importance of component-specific lifecycle analysis in contexts of limited data and offer policy-relevant indications for circular-economy planning. Longer first-use durations are relevant to the timing of end-of-use flows, while reuse-channel planning may be especially relevant for appliances affected by rapid obsolescence.

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Author contributions statement

P.C.-F. contributed to conceptualization, methodology, formal analysis, software, validation, investigation, writing–original draft, writing–review and editing, and visualization. M.G. contributed to conceptualization, methodology, formal analysis, validation, investigation, writing–original draft, and writing–review and editing. All authors reviewed the manuscript.

Data availability statement

This study uses publicly available microdata from the Encuesta Nacional de Hogares (ENAHO), produced by the Instituto Nacional de Estadística e Informática (INEI), Peru. The ENAHO databases and documentation are available through the INEI Microdatos portal: https://proyectos.inei.gob.pe/microdatos/.

Code availability

The code used to clean the ENAHO microdata, harmonize appliance categories, estimate the EM–Weibull mixture model, and generate the tables and figures is available at https://github.com/PedroChumpitaz/RCR25-Lifespan.

Additional information

Funding: The authors received no specific funding for this work.

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Competing interests: The authors declare no competing interests.