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Second-hand smartphones reduce carbon emissions, yet shorter use times limit actual gains

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Product reuse advances circular economy by reducing material demand. However, environmental assessments often assume reused products fully replace new ones, or they overlook market changes and shortened lifespans driven by resale and repurchase opportunities. This study presents an empirically based analysis of the second-hand smartphone market and its cumulative effects on manufacturing demand and carbon emissions. Integrating consumer survey data and product lifetime estimates in a stock-and-flow model, we find that in the United States, each second-hand transaction currently extends smartphone use time by 40%, displaces 0.40 new devices, and that circular consumption results in a 34% lower annual carbon footprint. With 25% of consumers purchasing used phones, production demand and carbon emissions are lowered by 15% and 14%, respectively. Yet, shortened use times offset nearly half the potential gains. If reuse became the norm, manufacturing demand could decline by one-third, revealing both the promise and the limits of reuse.

The demand for consumer goods requires large amounts of primary raw materials and energy (a third of the global material consumption[1] and up to 36% of the total industrial sector energy use[2]) while generating an alarming amount of waste[3] containing valuable metals[4]. Material production for consumer goods alone accounted for 8% (3.7 Gt) of the global carbon emissions in 2015[1].

Product reuse, defined here as the resale or transfer of products down to the next user within a second-hand market, prolongs the lifespan of existing products and represents a central strategy for the circular economy[1]. Reusing goods increases the total product use time (period between the initial purchase of a new product by the first owner and its disposal by the last owner) and, as a result, reduces manufacturing rates of new goods and the related environmental pressures[5,6]. However, consumer behaviour regarding second-hand products is highly variable and interdependent[7]. As second-hand markets grow and attract more users[8], they delay new purchases for some, while enabling more frequent purchases for others[9,10]. Consequently, in the absence of comprehensive market data and integrated analyses of diverse consumer groups, the cumulative reduction in manufacturing demand due to the second-hand market has often been assumed rather than understood and has therefore remained highly speculative[10].

The impacts of the second-hand market on consumption are twofold: it promotes multiple product-use cycles while delaying new product purchases, and simultaneously, it might substantially shorten the average use time for owners exposed to resale opportunities. Furthermore, second-hand products can enter previously unreachable markets, increasing the total market size. The cumulative (i.e., considering all users) effect of second-hand consumption on production can be represented by measuring the resulting displacement rate (per instance of reuse), which is the ratio of the total number of displaced new products to the required number of equivalent second-hand products consumed on the market[11]. In an ideal scenario, this ratio can reach a value of 1, where each instance of reuse substitutes for a new purchase and also doubles the product's lifespan, thereby fully preventing the production of a new unit. However, these ratios remain highly uncertain. In existing assessments of the environmental benefits of secondary consumer electronics, lifetime extension has usually been established based on expert opinion[12–15] or assumed to be perfect, implying that each used product displaces a new product on a one-to-one basis[8,16]. Yet, various unintended consequences, such as the *circular economy rebound* effect[17] can reduce the expected benefits of reuse. It has been suggested that, due to the complexity of such market effects, studies based on comprehensive empirical data are needed to assess the actual benefits of reuse[17].

Hence, in this study, we present an empirical analysis of the overall effects of the second-hand market on the production of new consumer products. Focusing on the case of smartphone reuse in the United States of America (U.S.), we use survey and market data to model the flow of both new and second-hand smartphones. By comparing two market scenarios (the current market with reuse and the reference market without reuse), we

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quantify the impacts of reuse on product lifetimes, manufacturing demand, and associated carbon emissions. We capture such carbon reduction from reuse at both the individual and cumulative market levels. Our study accounts for two key rebound effects that are often overlooked: (1) shortened product use times, where consumers use savings from buying or selling second-hand goods to replace products more frequently, thereby increasing overall consumption[9,10]; and (2) imperfect substitution, in which second-hand goods enable access for consumers who might not otherwise own that extra product at all, thereby expanding the total market rather than displacing new production[17]. We find that while circular consumption leads to a 34% lower annual carbon footprint for an average smartphone user participating in product reuse, second-hand consumption is far from the previously assumed 100% material displacement. Additionally, we assess the maximum potential for production and emissions reduction through reuse, considering potential widespread adoption and limitations in product longevity. If reuse became the norm, manufacturing demand could decline by one-third. These findings aim to inform more effective circular policies for carbon reduction.

Results

Current impact of the second-hand market and the associated rebound effects

We find that the existing second-hand market in the U.S. increases the average total product use time by 17% and reduces the demand for new smartphones by 15% (Fig. 1). This reduction is driven by 19% of consumers who make their smartphones available for reuse after the first use cycle, and 25% who obtain second-hand phones. Of these reused devices, approximately three-quarters are discarded after one reuse cycle, while one-quarter is passed on to a subsequent user for another cycle of reuse. As a result, a lower-than-assumed displacement rate of 0.40 is observed as about 6 new units are avoided annually (reduction of production volumes from 37 to 31 units per 100 users) by 13 second-hand purchases (with 9 later discarded and 4 passed down again to the next user). We also found that, on average, devices that go through reuse (i.e., circular use) have 2.4 users during their life and 1.8 times longer total use time compared to linear devices.

We also measure the scale of the two rebound effects that impact the rates of smartphone consumption. Only 2% of respondents reported that they would not purchase any phone at all in the absence of the second-hand alternative (when, likely, second-hand devices are obtained as spares), suggesting a rather negligible imperfect substitution effect, as most second-hand purchases substitute new purchases[17]. At the same time, if no shortening of the product use time due to resale and reuse would occur, the resulting displacement rate would be about perfect (1) and the annual carbon footprint of an average user would be 5.3 instead of 7.9 kg CO_2e (a unit that expresses the impact of all greenhouse gases in terms of carbon dioxide equivalent), suggesting that the direct rebound effect[17] (an increase in smartphone replacement frequency due to reuse opportunity) notably diminishes the actual reduction of the current manufacturing rates.

Cumulative carbon emission reductions due to lower manufacturing demand, the circular economy rebound, and the impacts stemming from additional logistic movements in the second-hand market are depicted in Fig. 2. While the U.S. second-hand market enables the avoidance of 14% of production-related carbon emissions due to the prolonged use of fewer manufactured smartphones, an additional 10% decrease could happen if users did not shorten their ownership spans due to reuse or resale opportunities (direct rebound effect). A 1% increase is due to impacts associated with the logistics of transferring used phones between subsequent users.

Maximum potential of reuse

The maximum potential of smartphone reuse as a widespread social practice was assessed by modelling a market scenario in which all consumers prioritize purchasing second-hand devices, and all new devices are offered for reuse after their first use cycle. In this idealized scenario, the total reduction in production is constrained by the maximum durable lifespan of devices in circulation. Given existing estimates for smartphones durability[18], we considered two hypothetical cases in which smartphones are used on average for a total of either 4 or 5 years, 25% and 56% higher compared to the current average of 3.2 years, after which they are discarded. Under these assumptions, widespread reuse could reduce production volumes by an additional 20% or 36%, respectively, relative to current demand levels (Fig. 3).

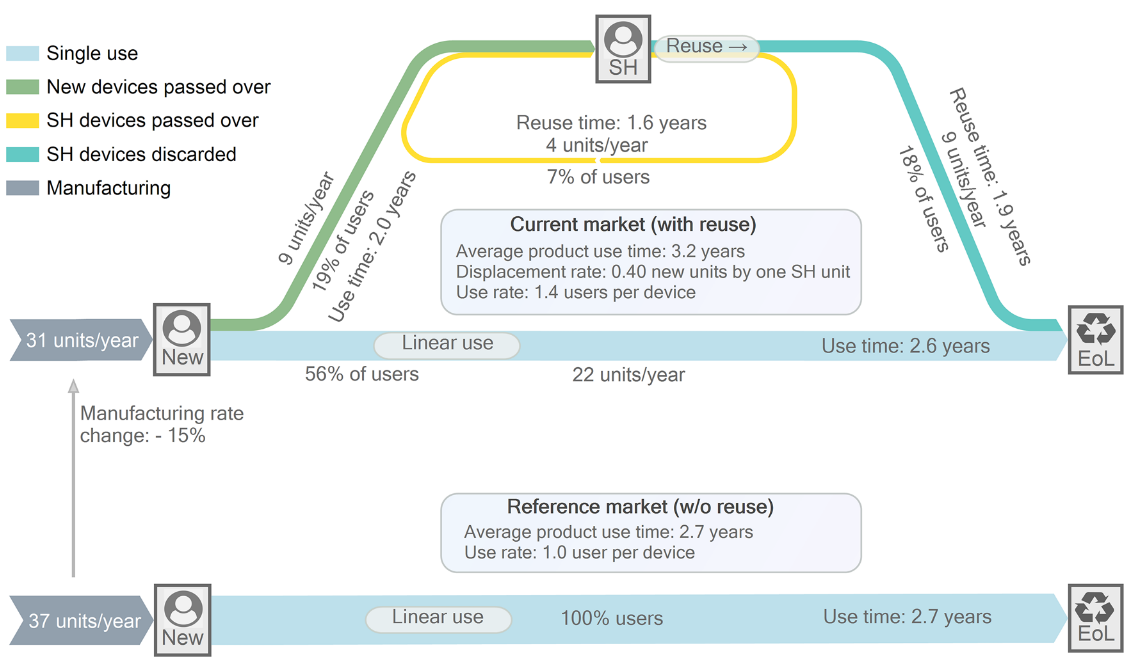

Fig. 1 | Smartphone consumption markets with and without reuse. Two Sankey diagrams depict the total new annual smartphone demand (grey flows) and four consumption (coloured) flows of New and Second-Hand (SH) products until devices reach their end-of-life (EoL) for two cases: current market (top) and reference market without reuse (bottom). Results are given per 100 users. Sizes of the flows are proportional to the number of units used in one year. Use rate specifies number of owners per average device lifetime.

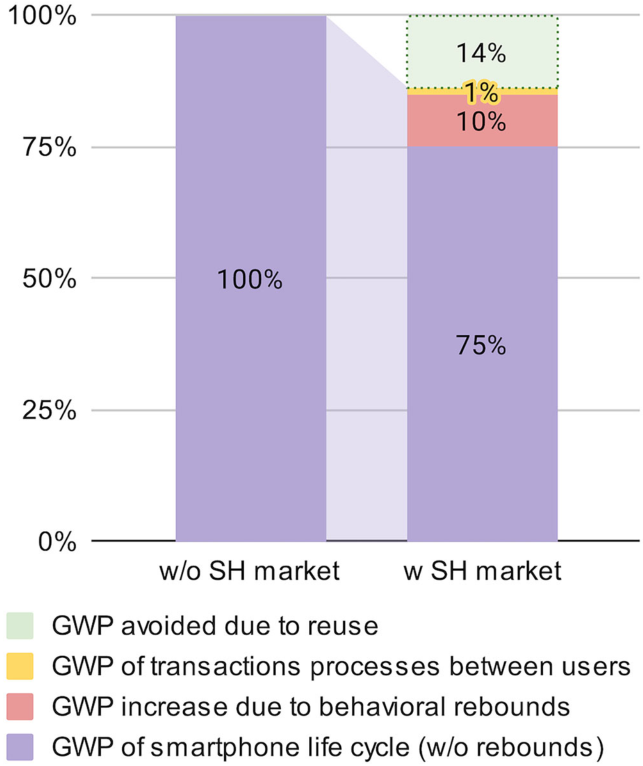

Fig. 2 | Global warming potential (GWP) reduction from smartphone reuse. SH = second-hand. CER = circular economy rebound (incl. direct rebound and imperfect substitution effects). GWP of a smartphone life cycle includes only non-operational phases.

Resulting carbon footprint comparison

Finally, we distinguished the carbon footprint of consuming circular (devices being reused during their life cycle) versus linear devices. We found that current circular users switching from linear to circular consumption reduce their average individual annual impact by 34% (considering equal use time-based impact allocation between consequent device users) from 11.9 to 7.9 kg CO_2e per year. Also, current circular smartphone users have 41% lower carbon footprint compared to current linear consumers (7.9 versus 13.5 kg CO_2e per year). Yet, the annual footprint of circular devices is much higher compared to linear devices if the total device's impact is allocated to the first user only (18.5 kg CO_2e per year). The analysis here considers the global warming potential (GWP) associated with new phone manufacturing, its refurbishment, and additional shipment between consumers, along with the expected total use times of circular versus linear devices (see Table 1).

Discussion

Allocating savings from reuse

For many energy-efficient consumer electronics, such as smartphones, the environmental impacts related to the non-operational phases (e.g., raw materials provisioning and manufacturing) dominate the total life-cycle burden (excluding communication services)[8]. For such products, reuse offers the potential to extend the total service lifespan and partially displace new production, lowering the life-cycle carbon emissions. While most studies assumed no rebound effects and a linear decrease of primary manufacturing due to reuse (a displacement rate of 1)[10], this study reveals a notably lower production displacement rate of 0.40 new devices avoided per each second-hand purchase.

Given that observed lifetime extension, material savings, and the corresponding carbon reduction are the results of a simultaneous resale decision of the initial new device user and the decision of the following user who re-purchases that device, there is no universal way to allocate the benefits to one or the other. In other words, there is no objective way to determine which consumer in the use chain is more responsible for the environmental burden. Similarly, comparing the footprints of new versus second-hand purchase decisions without context on their end-of-use fates and prior cycles might be challenging. Hence, in our results (see Table 1), we present two impact allocation approaches: (1) a conventional allocation to the first user, where second-hand purchases are considered carbon-neutral; and (2) a time-based, arguably more objective, equal allocation among all users of the device. The latter way to allocate production-related impacts is based on the share of the use time by each owner (regardless of whether the user is the first or last user of the device) over the total use time of the device by all users. This way, the annual footprint of average linear consumption can be contrasted with that of multi-use device consumption based on the difference in their total use times, hence allowing us to determine carbon savings behind alternative consumption habits.

Using the suggested time-based allocation, we find that devices that go through the reuse cycle (the upper flows of the current market scenario under Fig. 1) have an average of 2.4 uses with 1.8 longer total use time, compared with linear devices (the lower flow of the current market scenario). As a result, the consumer who is part of the reuse cycle (irrespective of whether they use a new or second-hand smartphone) will have a material burden equivalent to consuming 0.56 linear devices, not nearly as material neutral as often assumed.

Insufficient substitution and direct rebound dictate an imperfect displacement rate

While the imperfect or insufficient substitution effect[17] describes *what* kind of products second-hand purchase decisions substitute (i.e., whether such a product would even be purchased in the absence of second-hand alternatives), the displacement rate[11] describes *how much* displacement occurs in the result—the number of new devices displaced by existing second-hand devices on the market. An imperfect displacement rate is an expected result given insufficient substitution, shortening use time, and other rebound effects[17]. The displacement rate, for instance, can be notably lower than one even in the case of a perfect substitution (i.e., all second-hand purchase decisions would be new product purchases otherwise) due to the shorter use time and more frequent replacement of devices due to savings enabled by reuse (direct rebound effect).

Here, based on empirical data, we show that the imperfect substitution effect in the U.S. is almost negligible (98% of consumers would purchase new devices without second-hand options) and, at the same time, observe a rather low resulting displacement rate of 40%. These two measures were hardly distinguished in the existing literature. Only one existing study accounted for the imperfect substitution effect based on a substitution survey (as 58%) and expert opinion (as 5%)[15]. However, the study did not account for changes in the duration of product use, and it assumed a perfect displacement when second-hand devices are purchased instead of new ones. That study also considered the re-spending of monetary savings on extra consumption (mostly indirect—i.e., other product categories). Our analysis does not consider indirect rebound effects, as it focuses solely on changes in smartphone demand. However, the overall environmental benefits of reuse would likely be even lower if such effects were considered.

Environmental rebound and policy implications

We present findings that the practice of product reuse leads to lower environmental savings than is generally assumed[8,16]. This calls for prioritizing consumption-slowing strategies (e.g., repair and extended use), in line with a recent study that showed the biased overshadowing of the 'Reduce' pillar of the circular economy ('Reduce, Reuse, Recycle') by actually less efficient recycling-oriented strategies[19].

While this study did not assess the total carbon impact of all rebound effects (e.g., indirect or wider economy effects), it captured the magnitude of the circular economy rebound effect on manufacturing rates. The environmental rebound effect (ERE[20]) lowers possible carbon savings by 41% as consumers shorten product use times. This finding substantiates existing

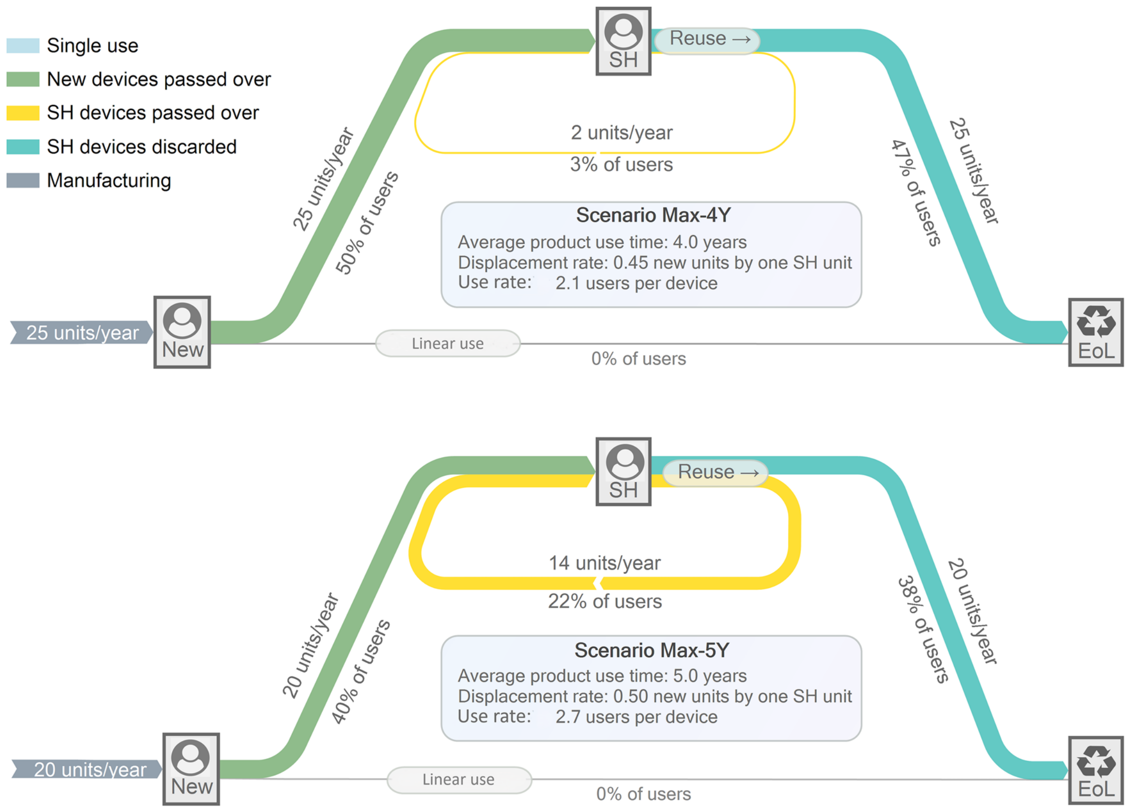

Fig. 3 | Hypothetical smartphone consumption markets under widespread reuse. Sankey diagrams depict the total new annual smartphone demand (grey flows) and four consumption (coloured) flows of New and Second-Hand (SH) products until devices reach their end-of-life (EoL). Hypothetical markets with the widespread reuse practice. Two cases for the maximum durable lifespan of devices in circulation: 4 and 5 years. Results are given per 100 users. Sizes of the flows are proportional to the number of units used in one year. The use rate specifies the number of owners per average device lifetime.

Table 1 | Annual non-operational carbon footprint of smartphone consumption patterns

Market	Current				Reference	Maximum reuse
Consumer type	Linear use	Circular use	Circular use	Circular use	Linear use	Circular use
Assumptions		Impacts allocated to the 1st user	Impacts equally allocated	Hypothetical behaviour without rebounds	Hypothetical linear behaviour by currently circular users	Hypothetical behaviour, everyone practices circular use
Total use time [years]	2.6	2.0	4.6	6.9	2.9	5.0
Users per life	1	-	2.4	2.3	1	2.7
GWP [kg CO_2e per device]	34.6	36.4	36.4	36.2	34.6	36.7
Footprint [kg CO_2e per year of use]	13.5	18.5	7.9	5.3	11.9	7.3

Annual non-operational (i.e., use-related impacts excluded) carbon footprint of various smartphone consumption patterns. Equal allocation of impacts under the current market assumes use time-based allocation regardless of whether you are the first or the following user of the circular device, in contrast to allocating full environmental burden to the first purchaser. Linear use in the reference market relates to the hypothetical footprint of those currently consuming circular devices in the absence of reuse. Hypothetical circular consumption without rebound assumes users would not shorten their possession spans.

claims on the importance of curbing negative consequences of behavioural change while developing the circular economy[21]. Furthermore, our study shows the sensitivity of such environmental assessments to the underlying assumptions about product use times and illustrates the need to base analysis on empirical data.

Even though the U.S. second-hand market extends the use time of an average smartphone by 17% - from 2.7 up to 3.2 years (see Fig. 1), linear and circular devices reach notably different total use times (2.5 and 4.6 years, respectively) by the end of their life (EoL) and, ideally, require distinct approaches facilitating eco-efficiency. The lifetimes of circular devices (28% of the total annual devices reaching EoL) are already close to the existing estimates for smartphones durability[18] and require efficient material recovery strategies[3]. At the same time, linear devices (70% of the total annual devices reaching EoL) would benefit the most from reuse facilitating strategies well-described in the existing literature[22]. Moreover, as the majority of phone replacements happen due to perceived performance loss[23], a shift in focus toward promoting more durable designs and longer-lasting products that perform as expected is needed. Hence, our findings suggest that while there is further potential to grasp, it requires corresponding interventions. The forthcoming EU proposal for Ecodesign for Sustainable Products Regulation can promote such sustainable production.

Limitations and outlook

Among several limitations, our conclusions primarily apply to the U.S., where most survey participants reside, while reuse behaviour can be sensitive to regional consumption patterns. Moreover, based on recent U.S. mobile cellular subscription rates[24], we have assumed one device in use per consumer. However, consumers may use spare devices in addition to their main ones. Additionally, even though possible refurbishment practices were considered within our calculations for the GWP, we assumed the refurbishment rate after end-of-use device collection (for second-hand devices only) based on existing literature. Such rates could be improved in future studies with more detailed surveys for the end-of-use decisions of new devices as well, accounting for the sensitivity of the results to this parameter The self-reported nature of responses also involves recall bias. Moreover, we did not collect respondents' age, which may influence consumption behaviours. However, MTurk samples have been shown to be broadly representative compared to other online recruitment methods[25], which partly mitigates this concern. Future studies could strengthen representativeness by including age and larger samples and could examine consumer demographics to better assess the potential and limits of reuse measures. Our model assumes a uniform smartphone type, whereas in reality reuse is dominated by high-end models with greater recirculation potential, and the resulting material flow diagrams would differ significantly across brands. Similarly, the implications of our findings are product-specific and cannot be directly applied to other consumer goods. Finally, this study assumed a snapshot of a steady market in the long term, where supply equals the demand with no delays, even though in reality, various market fluctuations occur.

To conclude, while finding evidence of primary production and related carbon emission reduction caused by electronics reuse on a market scale, this study measures and reassesses previous hypothetical claims. We show that, per year of use, circular smartphones have 59% of the environmental burden of new ones, second-hand market decreases overall production-related carbon emissions in the US by 14%. The potential of reuse is currently limited by premature device performance loss, low user acceptance, and rebound effects from shorter use times linked to second-hand opportunities. Yet, significant untapped potential remains, as most people do not release their end-of-life devices for reuse. We estimate that widespread adoption could reduce production volumes by a third. Institutionalizing reuse practices could therefore yield even greater reductions in carbon emissions and raw material demand.

Methods

The actual market-level impact of reuse is assessed by comparing total manufacturing demand in the current U.S. smartphone market, where reuse is present, with a counterfactual scenario in which reuse is absent and reported[26] longer product use times are realized (reference market). In this reference scenario, each consumer purchases a new smartphone, and each device is used by only a single owner over its full lifespan. To describe such markets, we use a stock and flow model (see Step 1 below) that describes the annual flow of consumer goods between various types of consumers, from manufacturing until the discard into waste. Product use times (possession spans) and ratios between different user group sizes are two critical inputs to our material flow model, as it determines both the total duration of smartphone use and the total demand for new manufacturing.

Hence, to provide an evidence-based estimation of the cumulative impact of the second-hand market (reuse) on the average lifetime of smartphones, the manufacturing rates, and the associated carbon emissions, we have modelled the current (Steps 2–3) and the reference (Step 4) market scenarios integrating (1) existing survey data on primary and secondary smartphone lifetimes and user consumption preferences[27]; (2) market data on lifetime changes related to smartphone reuse[26]; and (3) our additional consumer survey data on average product storage times and actual product substitution decisions. Balancing the model (i.e., the supply flows of new and used devices match their demand flows), we calculate values for the corresponding consumer group sizes, their annual unit consumption, the average product use time (total lifetime minus idle storage time), and the primary manufacturing rate required to satisfy market's demand (Step 5). Finally, we quantified the environmental impacts stemming from the reduction in manufacturing rates driven by the second-hand market (Step 6). See Supplementary Tables 1 to 6 for the full description of the calculations used and results obtained. The numerical assessment that underlies this study was divided into the following steps.

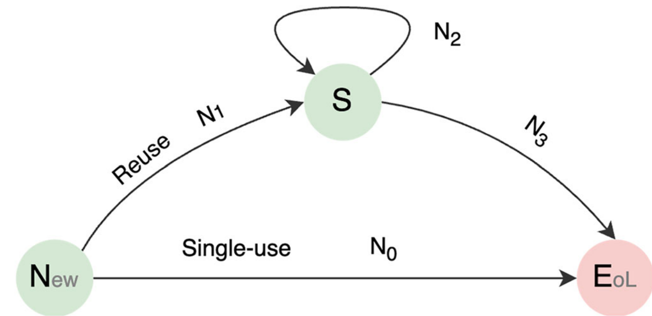

Fig. 4 | Stochastic product service life cycle across four consumer types. Markov chain describing the stochastic model of product service life cycle between four consumer types, adapted from Amatuni et al. (2023).

Step 1: Market-level stock and flow model of reuse

First, we defined a stock and flow model that describes the annual flow of primary and secondary electronics (from manufacturing to disposal as waste) between four consumer types (linear use; buy new and resell; buy used and resell; buy used and discard). Each consumer segment is defined by its size and the annual flow (consumption rate). For the basis of our model, we used the existing stochastic Markov chain-based product lifetimes model developed by Amatuni et al. in the earlier work[27]. We depict its adaptation for our purposes in Fig. 4.

Four user types were identified depending on their consumption pattern and interaction with the second-hand market. They are labelled as N_0 through N_3 in that work and are described as follows: N_0 - Linear use: Acquire new, use, dispose; N_1 - First use: Acquire new, use, resell; N_2 - Interim use: Acquire used, use, resell; N_3 - Last use: Acquire used, use, dispose.

In this study, we adjust that model and consider the smartphone market from a stock and flow perspective instead. Stocks are four user groups of corresponding sizes N_i. Each group is also characterized by its average smartphone use time (LT_i) and the average ownership span that includes hibernation after use (idle stored devices not in use). The yearly material outflow of end-of-use (EoU) devices from each consumer group (stock) is equal to $f_i = \frac{N_i}{LT_i}$ and adheres to the mass balance assumption – smartphone consumption (sum of all inflows) equals EoU outflow. Only user types N_0 and N_1 consume new products. Hence, the total annual manufacturing rate M in a market with a population P (sum of N_0 through N_3) can, therefore, be expressed as:

$$M = \frac{N_0}{LT_0} + \frac{N_1}{LT_1} \tag{1}$$

Also, we define:

$$c_1 = N_0/N_1 \tag{2}$$

parameter that defines which share of the population discards new devices after use instead of enabling reuse.

$$c_2 = N_2/N_3 \tag{3}$$

parameter that defines which share of the population discards second-hand devices after use instead of passing them over for reuse.

$$c_3 = (N_0 + N_1)/(N_2 + N_3) \tag{4}$$

parameter that defines which share of the population purchases new devices instead of second-hand.

Finally, we set the total size of the population as 100 consumers (normalized population size for ease of presentation and comparability):

$$P = \sum_i N_i = 100, \tag{5}$$

and define the mass balance equation:

$$f_1 + f_2 = f_3 \tag{6}$$

the total annual consumption of second-hand devices equals its EoU outflow.

Here, we solve the system of linear equations (SLE): (2), (3), (5), (6) for four unknown group sizes N_i given the inputs: the average use time for each group LT_i, reported consumer preferences over reuse (c_1, c_2), and the population size P.

Then, we can calculate the total manufacturing demand using (1). The resulting yearly average per-capita material (unit) requirement of smartphone consumption is expressed as: M/P.

We also estimate the expected total lifetime of the average smartphone on the market using the theory of Markov chains given (1) the product transition probabilities between three states (see Fig. 4) defined as ratios between resulting outflows f_i rather than the corresponding user group sizes N_i as it was in the original study, and (2) the weights for each use phase (edge) defined by the average use times LT_i .

Step 2: Collecting existing data for the current market scenario

To prepare SLE input parameters for the current scenario, which approximates the current market situation, we first collected existing data on smartphone use times (LT_i) and ratios between different user group sizes (c_1 and c_2). These were sourced from the existing academic publication, where online surveys from the year 2022 identified the average possession and storage times of primary and secondary electronics for four aforementioned user types in the U.S.[27]. The difference between the means of the two (possession and storage) spans reported in the original survey gave us the estimate of the use time. Parameters c_1 and c_2 were based on the number of corresponding EoU reports in the original survey (173 respondents, around 80% of whom were from the U.S.). Apart from product disposal (e.g., recycling) and passing over to the next user, some reports also included cases of product returns, hibernating products not in use, and other EoU cases for which additional assumptions were made. For returned products (7% of reports), we assumed a 50% reuse rate. For hibernating not-in-use products (30% of reports), we assumed a 4% reuse rate based on the earlier study that revealed that the hibernation period usually exceeds the use span itself and that only 11 in 288 respondents hibernate with the intention to pass over or sell their device later[28]. The rest of the cases of product returns and hibernation, and also reports that mentioned "Other" as their EoU fate - were all assumed to reach their end-of-life (EoL).

Step 3: Collecting new data for the current market scenario

We also conducted an additional survey that improved data accuracy related to consumer groups that reuse existing devices (N_2 and N_3). Specifically, 108 additional EoU consumer reports from the year 2023 through the paid Amazon Mechanical Turk (MTurk) service were analysed for such purposes. The service has been shown to be at least as representative in the US as other subject recruitment methods[25]. In addition, we applied recommended practices for validity checks and data filtering, as outlined for MTurk users[29]. In particular, we have collected more detailed data for second-hand product possession and hibernation times and relative user group sizes (parameter c_2). Through this additional survey, we also assessed the share of devices that are collected for refurbishment by the end of their reuse (assuming a 50% refurbishment rate after collection based on consulted expert opinion) and analysed the direct rebound effect (shorted use time factor) for the group N_2 in case they would need to purchase and discard new devices instead. The full survey data is made available through data repository (see Data availability statement in the end). As only not-in-possession devices were surveyed, we also assumed that these are only 45% of all EoU decisions as reported by earlier study[30], and applied the 4% reuse rate for hibernating devices as it was reasoned above.

We examined the statistical uncertainty in the input parameters for the current market scenario, to be able to later conduct sensitivity analysis for our results in Step 5. To evaluate the uncertainty in the average use times (defined as product lifetime minus hibernation time), we compared the mean reported lifetimes and mean reported hibernation times of our sample. We estimated the error of their difference using Welch's t-test, which does not assume equal variances between the two distributions, and derived a 95% confidence interval and margin of error for the resulting average use time. To evaluate the uncertainty in the consumer reuse preference parameters c_1, c_2 (ratios between the number of respondents who said they discard their smartphone after use and the number who said they pass it on or resell it), we calculated a confidence interval using the log-ratio (delta method). In this approach the ratio is transformed to a logarithmic scale, the statistical error is estimated from the two counts, and the result is then converted back. Finally, we propagated the 95% confidence intervals of the survey parameters through the model to assess the resulting uncertainty in outputs (consumer group sizes, total manufacturing demand, and total use times) for the current market (see Table 2). See Supplementary Tables 1 and 3 for a full description of the uncertainty analysis performed.

An informed consent to participate in the study was obtained from all the participants and the Ethics Review Committee of the Faculty of Science at Leiden University reviewed our research.

Step 4: Collecting data for the reference market scenario without reuse

As has been shown by previous studies, assuming no behavioural change and rebound effects caused by the possibility of participating in the second-hand market can be misleading. Hence, it would not be correct to assume that in the reference scenario (hypothetical market without reuse), all users would use devices for the same length. Yet, no primary data can be collected for such fictitious scenario in which no second-hand market exists. Hence, to calculate the total manufacturing demand $M_B = \frac{N_0'}{LT_0'}$ in the reference scenario where $N_0' = 100$, $N_1' = N_2' = N_3' = 0$, we should determine the alternative (longer) product use times for all the consumer groups, since, in the absence of the second-hand market, everyone would purchase new and dispose of devices by the end of their use instead.

Hence, we have (1) assessed the extent of the imperfect substitution effect, asking consumers in the additional survey above about their alternative choice in the absence of the second-hand market (98% would purchase new device instead), and (2) collected data on the behavioural change (direct rebound effect) defining smartphone longer use times in case if reuse or resale is impossible based on the existing market research[26]. Based on this existing market data, users of type N_1 would use their phones longer by 33 % if resale was not possible, and user of type N_3 would use their phones longer by 62 % if buying used was not possible. To estimate such rebound effect for the user group N_2 (both, buying and resale are not possible), we used our additional survey to find out about hypothetical alternative use times if linear new devices were the only option, which resulted in 114% longer use. All three use-time multipliers were applied to LT_1, LT_2 and LT_3 to estimate LT_i' in the absence of a second-hand market. Finally, LT_1', LT_2', and LT_3' were combined with the original LT_0 from the current market scenario to estimate

Table 2 | Stock-and-flow model inputs and outputs for smartphone markets with and without reuse

Consumer types	Relative user type occurrence ($P = 100$)	Average use time - LT_i [years]	Average hibernation time - HT_i [years]	Annual smartphone consumption - f_i [units per 100 users]
Current market scenario				
N_0	56 [48, 64]	2.6 [1.82, 3.31]	1.0 [0.63, 1.29]	22.0 [14.4, 35.1]
N_1	19 [15, 23]	2.0 [1.33, 2.60]	0.9 [0.51, 1.28]	9.5 [8.6, 11.1]
N_2	7 [5, 10]	1.6 [1.23, 1.90]	0.1 [0.08, 0.16]	4.2 [3.7, 5.1]
N_3	18 [17, 20]	1.9 [1.51, 2.35]	0.2 [0.09, 0.20]	9.5 [8.6, 11.1]
M_A	31 [23, 46] units/year per 100 users			
Total use time	3.2 [2.2, 4.4] years			
Total SH use time	4.6 [3.3, 6.1] years			
Reference market scenario without reuse				
N_0	100	2.6 -> 2.7	1.0	36.9
N_1	0	2.6	0.9	0
N_2	0	3.4	0.1	0
N_3	0	3.1	0.2	0
M_B	37 units/year per 100 users			
Total use time	2.7 years			
Total SH use time	-			

Current market scenario - the smartphone use and hibernation times by each user type (see Step 3) and the resulting relative consumer group sizes and annual consumption flows from the stock-and-flow model balancing. Reference market scenario without reuse - the prolonged smartphone use and hibernation times by each user type (see Step 4) in case if they would have to switch to linear consumption and the resulting average use time of the whole population (2.7 years) with the corresponding annual new consumption. Values for the current market are means with 95% confidence intervals in brackets.

the modified $LT_0{}'$ in the market where everyone ($N_0{}' = 100$) practices linear behaviour instead. As a result, M_B can be estimated.

Step 5: Estimating manufacturing demand for two scenarios

Given data inputs and equations from the stock and flow model defined above, the resulting consumer group sizes, the annual flows of smartphones through them, their average use and hibernation times, and the required rates of new product manufacturing were obtained for each scenario separately and are presented in Table 2.

Step 6: Estimating the environmental impact of reuse

Finally, we estimated the resulting environmental impacts associated with the observed manufacturing rate reduction caused by the second-hand market. In particular, the changes in global warming potential (GWP) were assessed by multiplying the annual manufacturing rate M with the GWP factor G related to the non-operational life cycle stages of a single smartphone and adding additional impacts related to reuse transactions (E_{shipment}) and refurbishment ($E_{\text{refurbishment}}$).

$$E = M * G + E_{\text{shipment}} + E_{\text{refurbishment}} \tag{7}$$

The value G is derived from existing research[14] that estimated the non-operational (i.e., materials, production and distribution, excluding end-of-life treatment) life cycle GWP of a reference smartphone to be 34.6 kg CO_2e assuming manufacturing in China. Whether a second-hand phone is reused domestically in the U.S. or exported abroad, the resulting use-time extension is assumed to lower global demand for smartphone manufacturing. Operational (use-related) impacts arising from smartphone use (e.g., emissions from provisioning of electricity for battery charging) are not included, assuming that use patterns are identical in both scenarios and differences in energy efficiency between new and used phones are negligible. As smartphones evolve rapidly, we use this GWP value as a representative estimate of embodied emissions rather than a fixed number.

No data on the share of smartphones that undergo treatment (repair, refurbishment) in between possession spans by users was identified in the literature. Instead, this data was obtained based on our user survey. Among users who purchase second-hand smartphones (groups N_2 and N_3), 22% stated purchasing their phone in refurbished condition. Also, 12% stated that, after their possession span, they had their device donated, traded in, or sold off to a business, such as a refurbishment operator, manufacturer, or retailer. Assuming a 50% refurbishment rate at collection, this allows to estimate that 11% of all N_2 reuse transactions include the refurbishment process. Therefore, out of 13.7 annual second-hand phone transactions per 100 users, 2.6 involve refurbishment: 11% out of N_2 flow plus 22% out of N_1 flow. The resulting $E_{\text{refurbishment}}$ is obtained by multiplying the number of transactions involving refurbishment with the emission factor of 3.41 kg CO_2e reported for a single smartphone refurbishment[14]. The shipping-related impact E_{shipment} is estimated by multiplying the annual number of reuse transactions (13.7) by the emission factor sourced from ecoinvent 3.6 database (0.475 kg CO_2e based on the assumption of a 0.5 kg parcel shipped by land using a light commercial vehicle for a 500 km distance)[31].

Finally, dividing the per-device non-operational impact (combined with the expected number of shipments and refurbishment) by the total use time under different scenarios, we compared the annual carbon footprint of the circular vs linear device consumption (see Table 1).

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

All data supporting the findings and figures of this study are provided in the Supplementary Tables 1-6, which include a full description of the calculations performed and the results obtained. The raw data collected from our smartphone reuse online consumer survey is openly available at the Mendeley Data repository (https://doi.org/10.17632/r3929wws92.1)[32].

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Author contributions

L.A. conceived the study, designed the research, conducted the analyses, and led the writing of the manuscript. C.C. contributed to data collection, validation, and assisted in the analysis for the carbon footprint. B.S. provided advice on the research design and contributed to manuscript editing. A.T. provided guidance on research framing, policy relevance, rebound effects taxonomy and contributed to manuscript revisions. J.M.M. co-supervised the study, supported the interpretation of results, and contributed to writing and revising the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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