Journal of Cleaner Production 313 (2021) 127561

Contents lists available at ScienceDirect

Journal of Cleaner Production

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

Is repairability enough? big data insights into smartphone obsolescence and consumer interest in repair

Tamar Makov [a,*,1], Colin Fitzpatrick [b,1]

[a] Department of Management, Guilford Glazer Faculty of Business and Management, Ben-Gurion University of the Negev, Be'er Sheva, Israel
[b] Department of Electronic & Computer Engineering, University of Limerick, Limerick, V94 T9PX, Ireland

ARTICLE INFO

Handling editor: Cecilia Maria Villas Bôas de Almeida

ABSTRACT

A dominant narrative surrounding smartphone lifespans suggests that their objective functional capabilities deteriorate rapidly and that if only devices were more repairable consumers would use them longer thereby reducing demand for new production and e-waste generation. Here we use a big-data approach to help unpack this narrative and examine two related yet distinct aspects: smartphone performance and obsolescence, and consumers interest in repair. Examining over 3.5 million iPhone benchmarking test scores, we reveal that the objective performance of devices remains very stable over time and does not rapidly deteriorate as common wisdom might suggest. In contrast, testing frequency varies substantially. This discrepancy suggests that factors other than objective performance meaningfully influence consumers' perceptions of smartphone functionality and obsolescence. Relatedly, our analysis of 22 million visits to a website offering free repair manuals revels that interest in repair declines exponentially over time and that repairability does not necessarily prolong consumer's interest in repair. Taken together, our findings indicate that non-technical aspects, such as mental depreciation and perceived obsolescence play a critical role in determining smartphone lifespans, and suggest that focus on the technical aspects of repairability as currently discussed by policy makers is unlikely to yield the desired extension in smartphone lifespan. We propose that sustainability advocates try to avoid narratives of planned obsolescence which might have counterproductive impacts on perceived obsolescence and consumer's' interest in repair, and instead highlight how well devices perform over time. More broadly, this work demonstrates the potential of using novel datasets to directly observe consumer behavior in natural settings, and improve our general understanding of issues such as planned obsolescence and repair.

1. Introduction

The fast pace at which consumer goods are currently replaced is thought to contrast with sustainability(Cooper, 2005). Take for example the smartphone. In major markets including Europe, the USA and China, smartphones are typically replaced within 24 months of purchase, a strikingly short lifespan compared with other consumer goods, let alone similarly expensive ones (Kantor World Panel, 2017; Troger et al., 2017). Despite their small size, smartphone production requires significant energy and material inputs. For example, the climate change impacts associated with a single iPhone 11 Pro are up to 110 kg CO_2 e (Apple, 2019). In addition, each device makes use of over 75 different elements of the periodic table (Kakaes, 2016), many of which have very low recycling and recovery rates, including a variety of precious, critical, and conflict materials (Reck and Graedel, 2012). Since most environmental impacts associated with smartphones accrue during the manufacturing phase, the case has been made that extending smartphone lifespan would reduce demand for new devices and subsequently their production (Gloser-Chahoud et al. 2019; Benton et al., 2015; Suckling and Lee, 2015; Wieser and Troger, 2018). While there is some question to what extent longer lifespans actually reduce primary production in practice (Raz et al., 2017; Makov & Font-Vicano, 2019), the common assertion among policy makers and advocacy groups suggests that prolonging the lifespans of smartphones improves resource efficiency and promotes sustainability.

Many factors influence consumers' perception of a product's desirability, obsolescence, and subsequently the choice of whether and when to replace it. While some consumers readily admit that a desire for

* Corresponding author.
E-mail addresses: makovt@bgu.ac.il (T. Makov), Colin.Fitzpatrick@ul.ie (C. Fitzpatrick).
[1] These authors contributed equally.

https://doi.org/10.1016/j.jclepro.2021.127561
Received 31 May 2020; Received in revised form 11 May 2021; Accepted 17 May 2021
Available online 27 May 2021

newness plays a key role in their replacement choices, many cite physical or technical aspects as the key drivers behind their decision to replace a device. According to the Eurobarometer report for instance, 38% of respondents said that they replaced their electronics because the old device broke, while 30% opted for replacement because the performance of their old device "had significantly deteriorated" (European Commission, 2019). Moreover, consumers often state that they are dissatisfied with the rate at which they are compelled to replace their devices and express their desire that smartphones would last longer. For instance, 56% of respondents in the Eurobarometer report stated that they would like to hold on to their current digital devices (smartphone, tablet) for at least 5 or 10 years provided there will be no severe drop in performance, while respondents in other surveys indicated that the ability to repair and upgrade could convince them to hold on to their current devices longer (Wilhelm, 2012; European Commission, 2018). These findings suggest that consumers view degraded functionality as one of the main causes for product replacement, and that repairability would make a meaningful difference towards extending the lifespan of smartphones.

Despite consumers' professed interest in repair, and wide advocacy from academics, policy makers, and activists, currently, most leading smartphone models are notoriously challenging or costly to repair. This discrepancy is taken by many as an indication that manufacturers are actively engaging in planned obsolescence.

1.1. Planned obsolescence

In recent years, the notion that manufacturers are deliberately shortening the lifespan of smartphones via technical failures has received much attention from the media, policy makers and the general public. Popularized by Brooks Stevens in the 1950's (Adamson, 2003), planned obsolescence typically refers to the practice of designing and producing durable goods which would be considered outdated within a shorter time period than technically possible. The underlining goal of planned obsolescence and designing short lived products is to keep demand for new products high even in saturated markets (Slade, 2006).

Today, with penetration rates as high as 80% or more in some countries (Silver, 2019) few would question whether leading manufacturers such as Apple and Samsung, have a vested interest in increasing smartphone sale volumes. However, while most of the public debate and policy actions related to planned obsolescence focus on technical or physical product features, the academic literature has long acknowledged that obsolescence does not stem solely from physical or functional deterioration.

As early as the 1960's Packard highlighted that perceived obsolescence, namely-consumers' perceptions of product up-to datedness, can be detached from its' objective functional capabilities (Packard, 1960). In addition to manipulating the physical durability of goods through material and design choices, producers can also encourage repetitive consumption through frequent stylistic model changes. Tapping into psychological mechanisms, visible cosmetic changes can make it easier to distinguish between older and newer models and instill consumers with a desire to purchase the newer model even when it does not provide meaningful added value in terms of functional utility (Slade, 2006; Park, 2010; Troger et al., 2017). Yet while many acknowledge that perceptions of product obsolescence might be detached from objective functional performance (defined here as the smartphone's computational power and its ability to perform operations using software), most of the public discourse, regulation, and academic research in fields such as sustainability science, industrial ecology, and green design has emphasized the functional aspects of product obsolescence and subsequently the importance of repair (van Nes and Cramer, 2005, Bocken et al., 2016). This focus is also apparent in the efforts invested in enabling and facilitating product repair and is well-articulated through the right to repair campaign (Right to Repair, 2021).

1.2. Repair

The right to repair refers to the campaign advocating for the individual rights of consumers to repair their own electronic devices rather than rely on the services offered by producers. Originating in the US, the Digital Right to Repair Coalition which later became The Repair Association, lobbies for repair friendly legislation, standards and regulations in the electronics sector. It has followed the largely successful example from the automotive sector where following legislation passed in Massachusetts which requires vehicle manufacturers to provide the same information to independent repair shops as they do for dealers, manufacturers have committed to meet the requirements of this law in all fifty states. More recently, The Right to Repair campaign in the EU has echoed its US counterpart adding a more overtly environmental emphasis (Right to Repair, 2021). The goals of the EU campaign are to achieve EU legislation that sets minimum design requirements and ensures easy disassembly and replacement of key components-starting with smartphones, laptops and other IT products. It also demands access to spare parts and repair information for repairers which are fair and inclusive and the introduction of a scoring system on repairability as part of the existing energy label for all energy consuming products.

More recently, repairability was also emphasized in the announcement of the European Green Deal in 2019 which stated that "… action plan will also include measures to encourage businesses to offer, and to allow consumers to choose, reusable, durable, and repairable products …. and curb the built-in obsolescence of devices, in particular for electronics" (European Commission, 2019).

1.3. The mental cost of product replacement

While the environmental implications of product obsolescence and replacement have largely been studied from an engineering perspective, the field of consumer behavior offers insights into consumers' decision-making process and the ways in which they reason about product replacement (Guiltinan, 2010). Using lab and field studies, researchers in consumer behavior and marketing typically rely not only on peoples' stated preferences (as reflected via surveys or focus groups), but also on revealed preferences teased out via lab and field experiments. These revealed preferences, when examined under different experimental conditions allow to investigate the underlining psychological mechanisms driving peoples' decision making and consumption choices.

Building on the idea of mental accounting (Heath and Fennema, 1996; Okada, 2001) conducted a series of experiments and found that consumers create a mental account-book for each product they buy and log the initial purchase price. Over time, and as the product is used consumers slowly depreciate the amount of utility they got from the product against the products' initial cost until they feel that they got their 'full money's worth' out of the purchase, at which point, the products' value in the mental accounting book is fully depreciated and reaches zero. Since a replacement purchase, typically involves two intertwined decisions- the purchase of a new product as well as the retirement of an older one (Roster and Richins, 2009), consumers consider not only the cost of the new product, but also the mental cost associated with retiring the older product they already own. When the incumbent product (i.e. the one consumers currently own) has a low residual value in the mental accounting book, it is easier to justify its replacement. In contrast, replacing a product before it has been fully depreciated mentally, is harder since it forces the consumer to write off the residual value as a loss in the mental accounting book. This psychological mechanism makes it easier for consumers to retire products that are not functioning properly, and search for a functional justification even when one does not really exist (Shani et al., 2020).

Despite inferences that modern society has adopted a 'throwaway culture" (Cooper, 2005), research suggests that people prefer to avoid the guilt associated with unnecessary or wasteful consumption (Bolton and Alba, 2012), and seek to justify their purchases, preferably on the basis of utilitarian and/or functional reasons (Keinan et al., 2016; Okada, 2001; Shani et al., 2020). In other words, when considering whether or not to upgrade, consumers feel the need to justify not only why they should buy a new smartphone but also why it is reasonable and/or acceptable for them to let go of their current one. Beyond use intensity and ownership duration, physical damage or functional deterioration also lower the mental accounting book value of products, making it easier for consumers to replace them (Makov & Newman 2019). Examining replacement purchases of watches, for example, Jacoby et al. (1977) demonstrate that consumers often use minor signs of wear and tear to justify the need for replacement (Jacoby et al., 1977). These results indicate that consumers inflate the importance of minor functional or cosmetic issues in order to ease the mental pain associated with prematurely retiring a functioning product. Focusing on upgrades, Bellezza et al. (2017) show that consumers tend to be more careless with their possessions when they know a newer, more desirable version is available. For example, they find that consumers are less likely to search for a lost phone when a new model comes out, or safeguard a coffee mug so it does not break when an upgrade is available. This "upgrade effect" stems from consumers' need to justify the purchase of a replacement product when they haven't gotten all 'their money's worth' out of what they already own. More recently, Shani et al. (2020) used smartphones as a case study to demonstrate that consumers can more easily justify an upgrade purchase when the new model offers functional improvements over their current device compared to when the new model offers only stylistic or aesthetic improvements. They argue that differences in functional performance between the incumbent and newer model, give consumers just cause, or a "functional alibi," to purchase a smartphone they desire yet feel wastefully guilty to buy (Keinan et al., 2016).

Considering that consumers prefer to justify replacement purchases on the basis of objective, utilitarian reasons, an alternative explanation to the survey results presented earlier could be offered. Specifically, consumers might be motivated to report that they replaced their smartphones following technical or functional issues because it helps them justify their decision to retire their old device. The strong narrative around planned obsolescence in smartphones could similarly provide consumers with a rational explanation for why they upgrade so frequently. Troger et al. (2017), report that one out of ten respondents express concern that their smartphones were reacting very slowly and that their performance was declining. Yet consumers' search for an objective (i.e. utilitarian) justification for a replacement purchase might influence their perceptions of how fast or how well their smartphone is working. Proske and Jaeger-Erben (2019) argue that since consumers' expectations of their smartphones evolve, a device would actually need to improve over time if it is to meet future functionality expectations. This gap between expected and actual functionality could potentially lead consumers to mistakenly feel that their devices are deteriorating, even if from a technical stand point their performance remains unchanged. In other words, as functionality expectations increase, consumers may start to devalue the objective performance of the smartphones they currently own.

Using Fogg's behavioral model, Ackerman et al. (2018) provide insight into consumers' perspective on product care which identifies motivation, ability, and triggers as the key factors that motivate people to undertake activities that extend products' lifetime. In this context, mental depreciation may be interpreted as the erosion of motivation. This is also evident in the work of Sabbaghi and Behdad (2018) who show that consumers' willingness to pay for repair services declines at an annual rate of 6.7%.

While the difference between perceived and objective deterioration in smartphone performance might seem trivial (after all, they would both encourage consumers to replace their devices), this distinction is important when considering which factors meaningfully affect product lifespans. Repair, for example, could help restore functionality in devices whose performance had declined due to physical deterioration. In that sense, repair limits manufacturers ability to engage in planned obsolescence and intentionally shorten the physical or technical lifespan of products. Yet repair can do very little to address perceived obsolescence. After all, it won't make an older device more fashionable and its potential to enhance devices' compatibility with the broader eco-system of evolving apps and services, which may be developed based on higher objective performance levels, is at best limited. As policymakers around the world debate the adoption of right to repair laws, gaining a better understanding of the relationship between repairability, obsolescence and product lifespans is both timely and imperative to support informed policy making.

1.4. Insights into repair in the age of big-data

In the past, data on people's attributes was limited to what researchers could collect via experiments or surveys. The data revolution of the 21st century has brought forth an unprecedented growth of large-scale datasets originating from various sources. The wide spread adoption of the internet as well as smartphone apps has transformed the types of data through which researchers can observe and analyze human behavior. Notably, the evident success of Google's search engine, demonstrates that information on what people search for online can become in itself valuable information. Access to new data sources has greatly contributed to multiple evidence-based studies in a variety of research fields including healthcare, gender studies, political science, transportation, finance, and sustainability (Stephens-Davidowitz, 2018, Makov et al., 2020; Netzer et al., 2019; Kagan et al., 2020).

Here, we make use of over 3.5 million data points gathered from a benchmarking app (see methods for more) to explore if and to what extent the objective performance of smartphones deteriorates over time, and how well it correlates with consumer's interest in smartphone functionality. In the second part of this paper, we examine visitor traffic on iFixit.com, and use this data to assess consumer's interest in repair over time and explore if and how it is affected by repairability.

We find that while the objective performance of smartphones remains fairly constant, interest in repair decreases over time. In the following sections we detail our methodological approach, the novel data sources we rely on, and our results. We future discuss the potential implications of our findings and their relevance for advocacy as well as policy making.

It is important to note that our investigation of benchmarking data and interest in repair does not aspire to provide robust evidence on casual mechanisms. Rather, our analysis is an attempt to highlight the potential of using novel datasets which offer a unique opportunity to directly observe consumer behavior in its natural setting to improve our general understanding of issues such as planned obsolescence and repair.

2. Materials and methods

2.1. Benchmarking

Benchmarking is the act of running a set of computer programs, or other operations, in order to assess the performance of an electronic device using objective metrics. A user of a device, in this case an iPhone, downloads and runs a benchmarking app which provides them with a composite score based on the range of operations performed. The benchmarking score is thus an objective measure of a phone's performance, and allows users to track the performance of their devices over time as well as compare it with the average performance across all phone models. Test scores of individual devices, are typically logged by the benchmark provider and often displayed on-line.

As such, examining benchmarking scores present a unique opportunity to examine if and how smartphone performance varies across smartphone models and over time, as well as consumers interest in the performance of their devices changes over time. To be clear, in this context, we define objective performance as being the computational power of the device and its ability to perform operations using software and does not include factors such as battery health. Objective performance is distinct from perceived (or subjective) performance whereby a user makes their own judgement on the performance of the device and may, for example, be affected by more demanding newer apps.

2.2. Performance over time

Relying on publicly displayed results from Geekbench – a leading processing (i.e. CPU) benchmarking company, we used a web crawler to compile a dataset containing 3,541,554 iPhone test results conducted using Geekbench 4 between September 2016 and May 2019 (see a description of the data in Table 1). For each test, we logged the following information: test score (single-core), iPhone model, operating system version, iPhone memory (Gb), and test date. We then examined if and how test scores within each phone model changed overtime, and whether and how they were affected by iOS version. It is important to note that Geekbench is a. As such its ability to fully reflect actual user experience is limited. For more please see discussion.

In addition, for each test we calculated the percent difference between test score and the corresponding iPhone models' benchmark score (i.e. a constant mean expected score as reported for by Geekbench). We

Table 1
Benchmarking test scores by iPhone model.

iPhone model	Overall number of tests	Share of all tests	Below benchmark range	Within benchmark range	Above benchmark range
iPhone 4s	8798	0.2%	22%	5%	73%
iPhone 5	28,794	0.8%	27%	2%	71%
iPhone 5c	9166	0.3%	27%	1%	72%
iPhone 5s	147,071	4.2%	33%	1%	66%
iPhone 6	336,525	9.5%	43%	0%	57%
iPhone 6 +	144,256	4.1%	34%	0%	66%
iPhone 6s	557,402	15.8%	35%	0%	65%
iPhone 6s +	249,433	7.1%	23%	0%	77%
iPhone 7	448,008	12.7%	22%	0%	77%
iPhone 7 +	431,010	12.2%	29%	1%	69%
iPhone 8	126,483	3.6%	33%	4%	63%
iPhone 8 +	216,810	6.1%	32%	4%	64%
iPhone SE	226,431	6.4%	24%	0%	76%
iPhone X	445,377	12.6%	32%	3%	65%
iPhone Xs	43,332	1.2%	35%	3%	62%
iPhone Xs Max	86,131	2.4%	35%	3%	62%
iPhone XR	31,199	0.9%	36%	0%	64%
Total	3,536,226		1,095,640 31%	43,263 1%	2,397,323 68%

Score (the official model mean as defined by the benchmarking app), while only 31% scored lower than 5% below the benchmark (see Table 1). In other words, most phones tested performed as well or even better than expected. Taken together, these results suggest that Batterygate is not so much a story about a manufacturer using software to degrade the performance of older models and encourage its customer base to upgrade, but rather a cautionary tale about the potential negative repercussions of poor communications around a software fix.

then examined the share of tests whose scores were more than 5% below the benchmark, and compared that to the number of tests conducted daily to shed light on the relationship (or lack thereof) between low performance and testing frequency. As a CPU benchmarking tool that tests processing speed and functionality, Geekbench's ability to fully reflect user experience in practice is limited (see discussion for more). Nonetheless, assuming that the main reason people test their phones is to check whether they are underperforming, we used testing frequency as a proxy for perceived functionality, and test scores as a proxy for objective device performance.

2.3. Interest in repair

To investigate if and how interest in smartphone repair changes over time, we examined all web traffic to pages providing free repair manuals on the iFixit.com website between October 2011 and December 2019. iFixit is one of the leading independent repair outlets, with up to 30 million unique page views per months, and is well known for its free and easily accessible repair manuals, product teardowns, and repairability rankings. Since there is no cost associated with browsing the website, examining traffic data provides a useful setting to investigate interest in repair without the need to control for other factors such as the availability of spare parts or the cost of repair. As such, examining web traffic to websites such as iFixit offers a somewhat unique opportunity to observe actual, real life behavior reflecting interest in repair, instead of relying solely on consumer surveys. Since, however there are many potential repair outlets beyond iFixit, to confirm that iFixit traffic reflected general interest in repair, we compared visitor traffic trends per model on iFixit with trends of general searches for smartphone repair on Google (e.g. "repair my iPhone 6" or "fix my Galaxy S4") and confirmed that the two were significantly correlated (see Supplementary Materials (SM), section 1.1).

Focusing on a set of pre-defined Apple and Samsung Galaxy S series smartphone models, we used iFixit's Google analytics plug-in to directly log the number of unique daily visits to each model's repair manual landing page (see Table 2). To remove some of the noise originating from daily variability and reveal the underlying trend, we then calculated the 30-day moving average for traffic to each model's repair manual webpage and used it to examine interest in repair over time.

A preliminary analysis revealed that generally, trends across smartphone models from day of launch onwards follow a similar pattern. Specifically, traffic to the repair manual webpage is initially low, then gradually increases before peaking (a point we refer to as peak interest) and entering a period of more gradual decline with a long tail off. Examining each smartphone model separately, we then defined and calculated (a) time between launch and peak interest, (b) the time it took for traffic to drop to 50% of peak and (c) the time it took for visitor traffic to drop to 10% of peak interest.

To illustrate, Fig. 1 shows the 30-day moving average for daily site visits to the iPhone 5 repair guide landing page, from its launch date in September 2012 through to January 2020. As observed in Fig. 1, overall interest in repair peaks after two years and then begins to gradually decline. Notably, landing page views increase throughout the second year even though the iPhone 5 installed base (i.e. the number of active iPhone 5 devices) remains constant as this model was discontinued in September 2013. Among other things, this suggests that traffic to the iPhone 5 manual is not merely a reflection of the installed base (i.e. the overall number of active iPhone 5 devices that are in use).

Time till peak is likely linked to sale volumes and the following increase in each model's installed base, as well as service contracts or warranty packages which typically cover the first one to two years. Given our interest in product lifespan we focused on the post peak period, and specifically the rate of decline in visitor traffic calculated from point a (peak interest) to point c (10% of peak interest).

Although the decline in visitor traffic is no doubt affected by the attrition in each models' installed base as some devices become

Table 2
Key parameters of interest in repair site traffic.

Model	Launch Year	Page Visits	Months to Peak (a)	Months to 50% (b)	Months to 10% (c)	Decay Rate (%age per month)	iFixit Score
Galaxy S7	2016	328,592	18	34	72	4.411	3
Galaxy S6	2015	641,007	12	26	56	5.250	4
Galaxy S8	2017	275,533	5	31	92	2.655	4
Galaxy S5	2014	948,711	11	31	56	5.116	5
iPhone 4	2010	4,420,538	27	54	84	4.067	6
iPhone 5s	2013	2,516,937	25	55	95	3.212	6
iPhone 4s	2011	2,471,229	36	46	78	5.417	6
iPhone 5	2012	2,688,494	25	43	77	4.419	7
iPhone 6	2014	3,447,491	25	43	78	4.149	7
iPhone 6s	2015	1,533,223	28	45	83	4.118	7
iPhone 7	2016	1,253,521	13	42.	104	2.494	7
Galaxy S4	2013	818,872	17	32	64	4.929	8
Galaxy S3	2012	852,231	20	35	66	5.003	8
Total Site Visits		22,196,379					

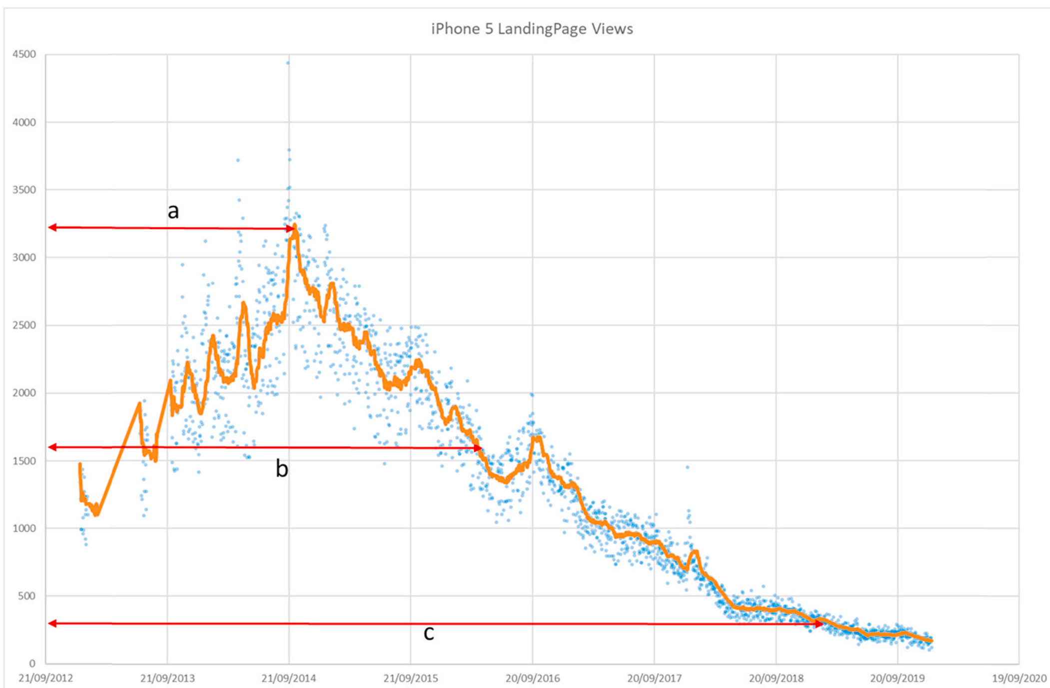

Fig. 1. iPhone 5 Repair Manual Landing Page Site Visits.

damaged beyond the point of repair, we posit that the rate of decline is also affected by the rate at which the population of owners as a whole judge their devices to be worthy of repair. As such peak traffic reflects peak interest in repair, and a tipping point of sorts, after which users gradually lose interest in repairing their devices when damaged, or have chosen to replace them altogether, until interest in repair dissipates completely. For either reason, this rate of decline in visitor traffic and interest is a reflection of mental depreciation which and psychological obsolescence.

The rate at which it declines dictates the lifespan (the longest period over which a device model may extend) and since site traffic is asymptotic, we defined the mental lifespan of devices as the time between model launch and the point at which interest in repair drops to 10% of peak interest.

In older models, where traffic had already reached 10% of its peak, we calculated the rate at which interest in repair had decayed. Confirming that the decay was best characterized by an exponential curve, we then predicted future decay for all remaining iPhone models for which data on period c was not yet available accordingly. Decay rate is thus a proxy for the speed in which a smartphone model becomes obsolete and the faster the obsolescence the higher the decay rate. Only devices which had reached their peak and had declined sufficiently to make reliable projections were included in our analysis (hence the exclusion of more recent models, e.g. iPhone 8).

To explore differences in interest in repair between brands, we examined the relationship between visitor traffic to pages of the four oldest models included in our analysis, namely iPhone 6, iPhone 5, Galaxy S4 and Galaxy S5. Specifically, we calculated the 1st difference of the 60 day moving averages of each model to smooth trends and control for autocorrelation (a common issue in time series analysis) and analyzed correlations.

3. Results

3.1. Benchmarking - functionality over time

Fig. 2, presents mean weekly test scores by iPhone model over time. Surprisingly, our results suggest that the objective performance of individual iPhone models remains mostly stable over time. This is true for both newer as well as older models included in our dataset. Consider for example the iPhone 5, which was released in September 2012 and discontinued in Sept 2013. Although all iPhone 5 devices included in our

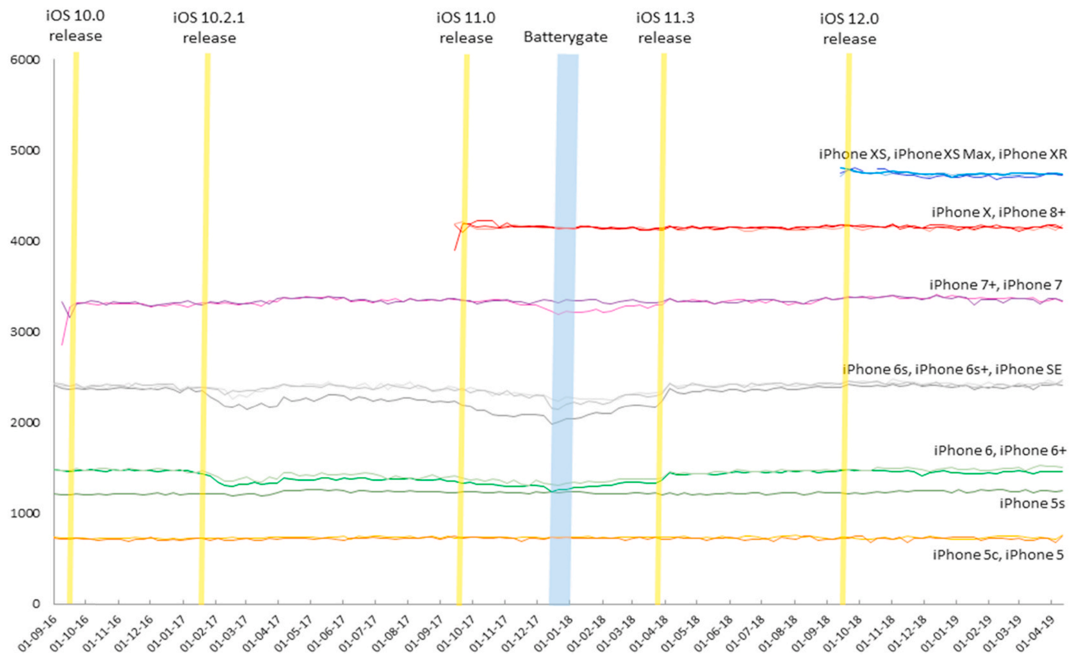

Fig. 2. Mean weekly testing score on Geekbench 4 by iPhone model over time.

analysis (beginning in September 2016) are at least three years old at the start of the dataset no evident deterioration in their performance is observed all the way up to 2019, at which point these devices were 6–8 years old. Furthermore, even the most meaningful performance reductions (observed across the iPhone 6 models, see more below), seem relatively marginal compared to the inherent differences between model groups (e.g. iPhone 6 models vs. iPhone 5 models; see Fig. 2). While our data did not allow us to track individual devices over time, these results suggest that it is unlikely that performance decay felt by consumers is driven by deterioration in the objective performance of the device's hardware.

A notable exception to the steady performance of iPhones is observed across the iPhone 6 models (i.e., iPhone 6, iPhone 6 Plus, iPhone 6s, iPhone 6s Plus, and iPhone SE) in the time period between January 2017 and April 2018. These results can be attributed to a series of software (i. e. iOS) updates which incorporated a performance management patch in response to incidences of devices' unexpected shutdowns. This "performance management" feature first introduced as part of the iOS 10.2.1 update released in January 2017, considered a combination of the device temperature, battery state of charge, and battery impedance, and slowed down the performance of devices with depleted batteries by automatically shifting them to a state similar to battery safe mode. While Apple claims that the performance management feature, which basically transitioned phones to a state similar to battery save mode) reduced unexpected shutdowns on iPhone 6 models by more than 70–80% (Panzarino, 2017) it failed to inform consumers how the issue with unexpected shutdowns had been handled and the potential impacts it might have on their phones. Some consumers took note of the fact that their devices suddenly became sluggish, triggering discussions on the website Reddit. Knowledge of the software fix and its negative effect on devices with weak batteries became public in December 2017 and was dubbed "batterygate". In 2020, The company agreed to pay $500 million USD to settle litigation related to this issue in the US with a string of fines in other countries as well (Stempel, 2020).

Apples public acknowledgment, that iOS updates had such impacts on phone performance tapped into the narrative of around planned obsolescence, and seemed to confirm what many consumers had already suspected-the company was using its software updates to intentionally degrade the performance of older devices in an attempt to drum up sales for its newest models.

To test whether Apple regularly used iOS updates to degrade the performance and shorten the service life of its older models (or those that had been used more intensely) we also examined differences between individual test scores and benchmarks by iOS version (see Fig. 3).

Results for the iPhone 6 models (Fig. 3b) clearly demonstrate that the inclusion of the performance management feature had a meaningful impact on the performance of some phones, resulting in a wider distribution observed from iOS 10.2.1 till the introduction of the iOS 11.3. For all other models however (Fig. 3a) there is little indication that software updates affected phone performance or its distribution. This is true not only for newer models, but also for older ones such as the iPhone 5 series. The fact that older models were not affected by the iOS updates seems to contrast with a planned obsolescence strategy. After all, if the company's strategy was to encourage replacement purchases by slowing down the iPhone 6 models, it would make sense for it to apply the same means to iPhone 5 models as well.

Furthermore, examining the percent difference between test scores and each model's benchmark score reveals that most phones tested (69%), scored more than 5% above their model's benchmark.

3.2. Perceived and absolute obsolescence

Fig. 4 presents daily usage volumes of the benchmarking app and the median daily difference between test and benchmark scores. In contrast to the relative stability of the device scores, people's curiosity about the performance of their device varies greatly. The low correlation (−0.09) between high testing frequency and low scores indicates that most phones are not tested when they objectively underperform. Rather, factors other than objective performance influence users' interest in testing how well their phones are functioning. For example, the high peak in testing frequency observed around December 2017, was most likely stimulated by Batterygate and the media coverage of Apple's response. Likewise, it is possible that updates to individual apps which assume the higher specs of newer devices could make these specific apps slower. Noticeably there was no spike in testing at the time that throttling commenced a year previously, with the introduction of iOS 10.2.1. As such, we posit that the usage trend of benchmarking tests for iPhones might be more informative than the actual results they produce which

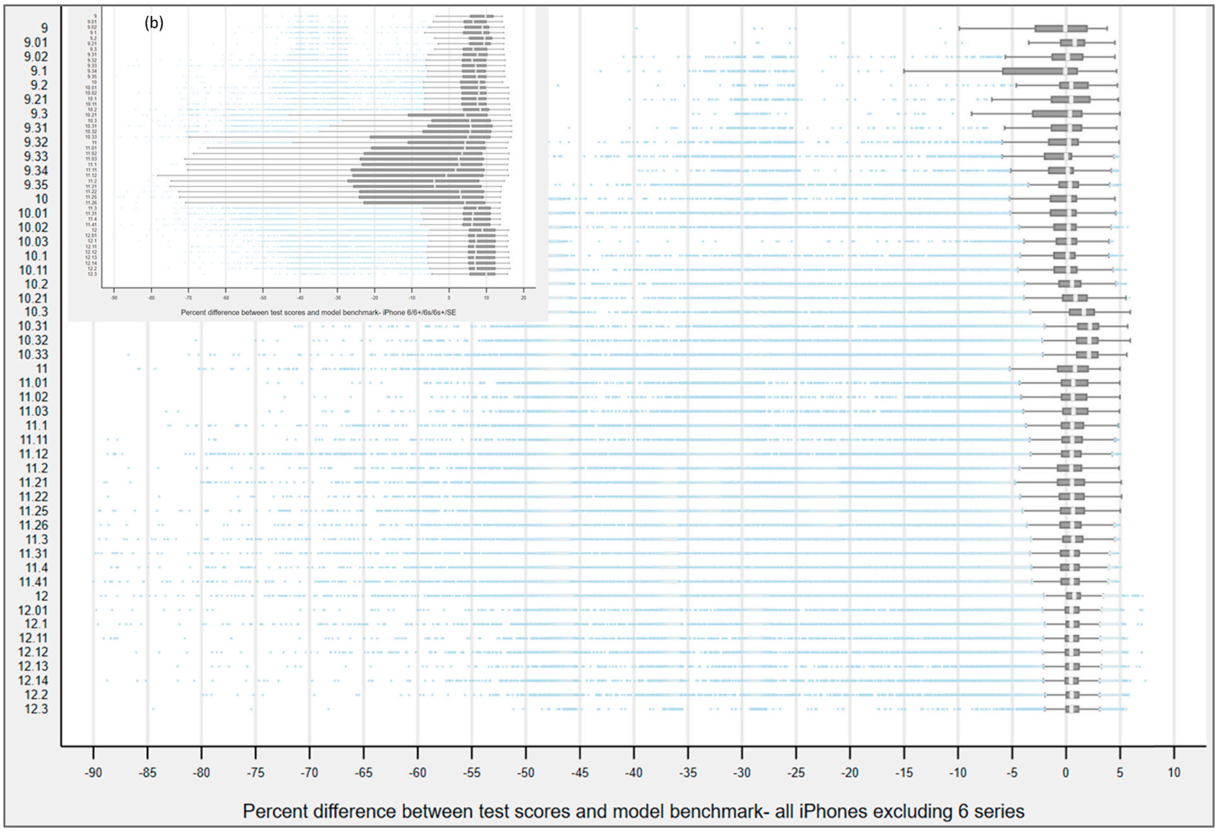

Fig. 3. Percent difference between test scores and model benckmark by iOS version.

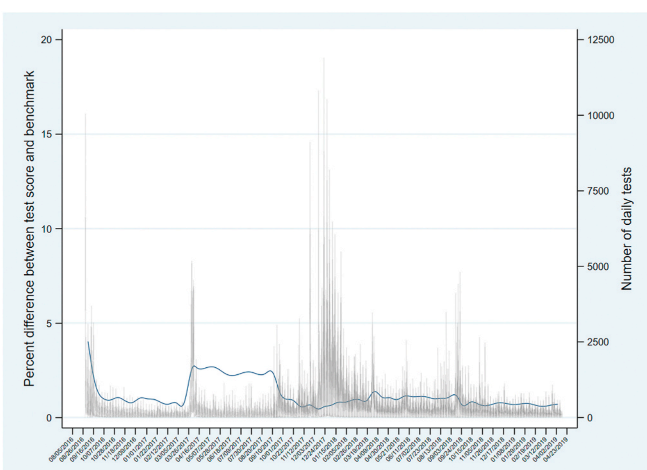

Fig. 4. *Daily testing frequency vs. performance median over time;* In dark blue- Median percent difference between test scores and model benchmark per day (primary Y axis); In light blue-overall number of tests performed daily (blue gray, secondary Y-axis).

show objective performance is highly stable in general.

While testing the causal relationship between media coverage and testing frequency is beyond the scope of this work, it is nonetheless interesting to note that annual spikes in testing seem to coincide with new model launches, typically scheduled for September–October. Since the launch of a new model does not directly affect the performance of older ones, we propose that testing is driven, to some extent, by mental depreciation and consumers' search for a "functional alibi". After all, the mere comparison between the score of older models and those of new one available via the benchmark app likely validates consumers suspicions that their incumbent devices are much slower than the new models available on the market. Indeed, the existence of a market for benchmark tools for iPhones, which are essentially fixed functionality devices, where users pay out of pocket and invest time and effort in testing how well their phones are functioning is suggestive of an ingrained belief that objective performance is degrading over time, or at least that it must be monitored.

3.3. Interest in repair and mental depreciation

Table 2 shows the parameters of interest in repair as well as the decay rate in visits as %age per month and the iFixit Repairability Score. This data can be examined to explore a number of relationships and test whether and how repair score and launch year affect smartphone lifespan. A regression analysis revels that, for the smartphone models examined, repairability is not a good predictor of lifespan (adj. $R^2 = 0.01$; See Fig. S1 in SM). While the sample used is not sufficiently large to support a robust analysis, these finding are well aligned with previous empirical work showing that repairability does not prolong the service life of smartphones (Makov et al., 2019). Consistent with market research, our analysis of repair interest also suggests that smartphone lifespans are getting longer, such that newer models seem to outlast older ones. For example, the iPhone 7 is expected to reach full mental depreciation in 104 months (8.6 years), while the Galaxy S7 is expected to do the same within 72 months (6 years). This analysis doesn't allow for causal determination of this suggested lengthening in the lifespan.

Comparing across brands however, our results indicate that the decay in repair interest tends to be faster for Samsung devices compared to Apple ones. Specifically, examining the relationship between visitor traffic trends for the iPhone 6, iPhone 5, Galaxy S4, and Galaxy S5 we find significant correlations within brands ($p < .00$ for Apple; $p < .00$ for

Samsung) and no significant correlations between brands (iPhone 5- Galaxy S5, $p = .76$; iPhone 5- Galaxy S4, $p = .28$; iPhone 6- Galaxy S5, $p = .12$; iPhone 6- Galaxy S4, $p = .074$). This is illustrated in Fig. 5a which shows the profile of the iPhone 6 and Galaxy S5, both released in 2014 where the repair interest in the Samsung devices peaks earlier and declines faster than its Apple counterpart. In line with previous work, our findings indicate that smartphone lifespans are not homogenies but vary across brands, with Apple outlasting Samsung (Makov et al., 2019).

Comparison of Repair Interest for Apple iPhone 6 (blue) & Samsung Galaxy S5 (orange) (30 day moving average as percent of peak visits per smartphone model). A value of 100 is the peak visits for the device. A value of 50 means a day with half as many visits as the peak.

4. Discussion & conclusions

The nature and quantity of data increasingly available in this new age can radically change our understanding of consumer perceptions, preference, and behavior. Here we analyze test scores and testing frequency on a leading benchmarking app, as well as visitor traffic to online repair manuals to gain insight into smartphone obsolescence and the potential mitigating impacts of repairability. Contrary to common perception, we find that the objective performance of a smartphone does not deteriorate substantially over time. Furthermore, we reveal that testing frequency is not as strongly correlated with objective performance which suggests that perceived obsolescence can affect consumers perceptions of a device's objective performance. In addition, we find that interest in smartphone repair declines as time goes by regardless of how easy or hard it is to repair a specific device. Collectively, our analyses suggest that mental depreciation plays a critical role in determining smartphone lifespan.

To date, efforts to prolong product lifespan and postpone obsolescence in smartphones have mostly focused on technical aspects, especially device repairability, the logic being that when the occasion arises, users will willingly repair devices themselves or have them repaired locally. The current work however, indicates that psychological (i.e. perceived) obsolescence and mental depreciation play a critical, yet seldom addressed role in shaping the point at which products are deemed obsolete and likely not worth the time and effort of repair. These findings are well aligned with previous work examining both the depreciation in market value of smartphones over time, as well as a steady decline in willingness to pay for repair (Makov et al., 2019; Sabbaghi and Behdad, 2018).

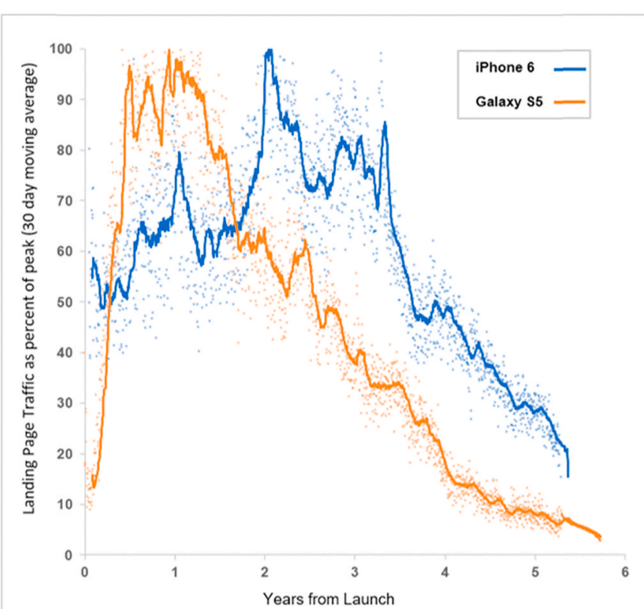

Fig. 5. Visitor traffic to iFixit pages over time. Lines represent trends, dots represent daily values.

For example, while the objective performance of an iPhone is highly stable over a long period (see Fig. 2), the use of benchmarking tools reveals a compulsion to check it which seems, on the surface, to be especially acute at key moments such as new product and operating system launches and updates (see Fig. 4). Why is there a baseline of about 7000 people per week testing the performance of their iPhone with significant spikes at and around times of major publicity for iPhones? Perhaps because they are being constantly communicated with messages that their phones are being deliberately degraded, e.g. (Harris, 2020; Chen, 2017).

Based on these findings, we argue that measures to improve the repairability of devices may not be enough in isolation to support lifetime extension and resource efficiency. While there is little doubt that companies such as Apple and Samsung have a vested interest in increasing product sales, it is also likely that, to some extent, consumers use the planned obsolescence narrative as a 'functional alibi' to justify purchases of new products they desire yet feel guilty buying. Moreover, public discourse around planned obsolescence is likely exacerbating the problem and hastening mental depreciation of older devices such that if they are damaged repair doesn't register as a real possibility for the user. Granted, other factors including repair cost, availability, and the time and effort required for repairing a phone likely play a role as well in deterring consumers from fixing their devices. Nonetheless, a more effective strategy to enhance repair might be to create a new narrative which highlights how good smartphones are performing over the long term and remind consumers of the amazing functional capabilities these devices nowadays poses. Indeed, we posit that repair advocates should work to inflate, or at least dampen the mental depreciation of older devices and employ what behavioral economists might call a "loss aversion framing" which emphasizes the lost utility of a broken screen or degraded battery. This is not to challenge the aim of devices being more repairable but more to highlight the importance of informed communication strategies that might assist in prolonging rather than shortening product lifespans.

Notably, our analysis has some important limitations. As it is based on real-world traffic to a commercial website and uses of commercial software, the underlying data is subject to questioning about the impact of advertising campaigns, search rankings, multiple visits to the site by the same user and web-crawling by bots (Google Analytics does take measures against this). While the large numbers and consistency in trends gives a degree of confidence in our analysis, we have at all times been moderate in the claims presented and advise that they should be considered in the context of the wider literature and evidence about this topic. In addition, it is important to note that we examined interest in repairability in absolute terms. Since consumers interested in repair are likely a subset of the overall active user population a major limitation in our repair analysis is that interest in repair is confounded by the fact that the installed base declines over time. As such, a cleaner indicator for interest in repair could be devised by examining iFixit visitor traffic in relation to each models' installed base over time. Unfortunately, reliable estimates regarding the number of smartphone devices still in use at the single model level are extremely hard to come by as both Apple and Samsung do not disclose such information on a regular basis. Yet while a systematic analysis along these lines was not possible, as a sanity check we used a few publicly available estimates regarding the overall number of iPhone 6 and 6 plus sold, and their remaining installed base in 2017 and 2018 (Dunn, 2017; Statista, 2020; Statista, 2018) to crudely compare the decline in the number of active devices with iFixit visitor traffic. Our results suggest that in April 2017, 89% of all iPhone 6 devices sold were still in use, and by May 2018 the installed base had dropped to 72% percent. In contrast, while iFixit traffic to the iPhone 6 repair manual page was 83% of peak in April 2017, it had dropped all the way to 52% of peak by May 2018. As this back of the envelop calculation demonstrates, traffic to iFixit depleted much faster than the number of units still in use which suggests that the interest in repair likely not a direct derivative of the installed base.

Ultimately, it is clear that there are limits to repair and that marketing of new devices will drive psychological obsolescence. New features will continue to provide functional alibis enabling the justification for replacement and lead to early/premature product replacements. To counter these forces, we propose that sustainability advocates focus more on the exceptional stability in performance of devices rather than narratives of planned obsolescence which might in fact convince consumers that repairing older devices is pointless. Similarly, service contracts, and warranty periods might also give consumers a faulty reference point, which then serves as an anchor for the time after which a device should be replaced.

The era of big-data offers many valuable opportunities to study product lifespans. Each day, a multitude of apps and related services now routinely gather information at the single user level for the purpose of consumer segmentation. Among other features (e.g. location, browsing history) such data often includes the specific make and model of the smartphone devices used to log in. Examining changes in device log-ins over time, would give a good indication of replacement intervals and could be used to assess actual use times across models and brands. Similarly, with the expansion of internet of things, real life data tracking of product lifespans, use intensity and much more can be collected. These would all greatly improve researcher's ability to generate data driven insights regarding product lifespan, actual use intensity, replacement drivers, and perhaps most importantly, differences within product categories (e.g. differences across brands).

Importantly, the strength of our novel approach to studying planned obsolescence and repair is not the size of our datasets but that they allow to examine expressions of consumer interest in smartphone performance and repair, which are not tainted by social desirability bias or people's aspirational, more sustainable selves. While we fully acknowledge that interest differs from action, we argue that by utilizing newly available forms of "big-data" offers the opportunity to push forward theory and policy making on issues such as repair, planned obsolescence, and circular economy more generally.

CRediT authorship contribution statement

Tamar Makov: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Colin Fitzpatrick:** Conceptualization, Methodology, Formal analysis, Writing – original draft, data collection & analysis, Writing – review & editing, Both authors contributed equally to the preparation of this manuscript.

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.

Acknowledgements

Authors report no competing interests. We would also like to thank Kyle Wiens, iFixit CEO for providing raw data for our analysis and Johnson Olayiwola and Bryan Tiernan for their support in preparing the datasets.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2021.127561.

References

Ackermann, L., Mugge, R., Schoormans, J., 2018. Consumers' perspective on product care: an exploratory study of motivators, ability factors, and triggers. J. Clean. Prod. 183, 380–391.
Adamson, G., 2003. Industrial Strength Design; How Brooks Stevens Shaped Your World. MIT Press.
Apple, 2019. Apple product environmental report iPhone 11 Pro. Available at: https://www.apple.com/environment/pdf/products/iphone/iPhone_11_Pro_PER_sept2019.pdf.
Bellezza, S., Ackerman, J.M., Gino, F., 2017. Be careless with that!" availability of product upgrades increases Cavalier Behavior toward Possessions. J. Market. Res. 54 (No 5), 768–784.
Benton, D., Coats, E., Hazell, J., 2015. A Circular Economy for Smart Devices; Opportunities in the US, UK and India. Green Alliance. green-alliance.org.uk/resources/A%20circular%20economy%20for%20smart%20devices.pdf.
Bocken, N., de Pauw, I., Bakker, C., van der Grinten, B., 2016. Product design and business model strategies for a circular economy. J. Ind. Product. Eng. 33 (5), 308–320.
Bolton, L, Alba W, J, 2012. When less is more: Consumer aversion to unused utility. J. Consum. Psychol. 22 (3), 369–383.
Chen, B.X., 15th Nov 2017. A New Phone Comes Out. Yours Slows Down. A Conspiracy? No. New York Times. Available at: https://www.nytimes.com/2017/11/15/technology/personaltech/new-iphones-slow-tech-myth.html.
Cooper, T., 2005. Slower consumption: reflections on product life spans and the "throwaway society. J. Ind. Ecol. 9 (1-2), 51–67.
Dunn, J., July 13, 2017. It looks like Apple will have plenty of iPhone owners that could use an upgrade this holiday season" Business Insider, Tech section. Available at: https://www.businessinsider.com/apple-iphone-most-popular-model-newzoo-chart-2017-7.
European Commission, 2019. Communication from the commission to the EUROPEAN parliament, the EUROPEAN council, the EUROPEAN economic and social committee and the committee of the regions. Euro Green Deal. Available at: https://ec.europa.eu/info/sites/info/files/european-green-deal-communication_en.pdf.
European Commission, 2018. Behavioural Study on Consumers' Engagement in the Circular Economy. Available at: http://trinomics.eu/wp-content/uploads/2018/10/CHAFEA2018-Behavioural-study-on-consumer-engagement-in-the-circular-economy.pdf.
European Commission, 2019. Special Eurobarometer 503: Attitudes towards the impact of digitalisation on daily lives. Directorate-General for Communication. Available at: https://data.europa.eu/data/datasets/s2228_92_4_503_eng?locale=en.
Glöser-Chahoud, S., Pfaff, M., Walz, R., Schultmann, F., 2019. Simulating the service lifetimes and storage phases of consumer electronics in Europe with a cascade stock and flow model. J. Clean. Prod. 213, 1313–1321.
Guiltinan, J., 2010. Consumer durables replacement decision-making: an overview and research agenda. Market. Lett. 21 (2), 163–174.
Harris, J., 2020. Planned Obsolescence: the Outrage of Our Electronic Waste Mountain. The Guardian, 15th April 2020 Available at: https://www.theguardian.com/technology/2020/apr/15/the-right-to-repair-planned-obsolescence-electronic-waste-mountain.
Heath, C., Fennema, M.G., 1996. Mental depreciation and marginal decision making. Organ. Behav. Hum. Decis. Process. 68 (2), 95–108.
Jacoby, J, Berning K, C, Dietvorst, T, 1977. What about disposition? J. Market. 41 (2), 22–28.
Kagan, D., Chesney, T., Fire, M., 2020. Using data science to understand the film industry's gender gap. Palgrave Commun. 6, 92.
Kakaes, K., June 2016. The all-American iPhone. MIT Technology Review available online at: https://www.technologyreview.com/2016/06/09/159456/the-all-american-iphone/.
Kantor World Panel, 2017. An Incredible Decade for the Smartphone: What's Next? Available at: https://www.kantarworldpanel.com/global/Reports.
Keinan, A., Kivetz, R., Netzer, O., 2016. The functional alibi. J. Assoc. Consumer Res. 1 (Issue 4), 479–496.
Makov, T., Newman, G.E., 2019. In: Nissen, N.F., Jaeger-Erben, M. (Eds.), Multifunctional Neglect leads to the purchase of redundant products. PLATE Product Lifetimes and the Environment 2019 – Conference Proceedings. TU Berlin University Press (in press), 978-3-7983-3124-2 (print), ISBN 978-3-7983-3125-9 (online).
Makov, T., Vivanco, D Font, 2019. Does the circular economy grow the pie? The case of rebound effects from smartphone reuse. Front. Energy Res. 6, 39.
Makov, T., Fishman, T., Chertow, M., Blass, V., 2019. What affects the secondhand value of Smartphones. Evidence eBay 23 (3), 549–559.
Makov, T., Shepon, A., Krones, J., Gupta, C., Chertow, M., 2020. Social and environmental analysis of food waste abatement via the Peer-to- Peer Sharing Economy. Nat. Commun.
Netzer, O., Lemaire, A., Herzenstein, 2019. When words sweat: identifying signals for loan default in the text of loan applications. J. Market. Res. 56 (6).
Okada, E.M., 2001. Trade-ins, mental accounting, and product replacement decisions. J. Consum. Res. 27 (No 4), 433–446.
Packard, V., 1960. The Waste Makers. Longmans.
Panzarino, M., 24th Feb 2017. Apple says iOS 10.2.1 has reduced unexpected iPhone 6s shutdown issues by 80%. Techcrunch. Available at: https://techcrunch.com/2017/02/23/apple-says-ios-10-2-1-has-reduced-unexpected-iphone-6s-shutdown-issues-by-80/?guccounter=1.
Park, M., 2010. Defying obsolescence. In: Cooper, T. (Ed.), Longer lasting products: Alternatives to the throwaway society. Farnham, Gower, pp. pp77–106.

Proske, M., Jaeger-Erben, M., 2019. Decreasing obsolescence with modular smartphones?–An interdisciplinary perspective on lifecycles. J. Clean. Prod. 223, 57–66.

Raz, G., Ovchinnikov, A., Blass, V., 2017. Economic, environmental, and social impact of remanufacturing in a competitive setting. IEEE Trans. Eng. Manag. 64 (Issue 4), 476–490.

Reck, B.K., Graedel, T.E., 2012. Challenges in metal recycling. Science 337 (6095), 690–695.

2021 Right to Repair, 27th Jan 2021. What we want, accessed at. https://repair.eu/what-we-want/.

Roster, C.A., Richins, M.L., 2009. Ambivalence and attitudes in consumer replacement decisions. J. Consum. Psychol. 19 (1), 48–61.

Sabbaghi, M., Behdad, S., 2018. Consumer decisions to repair mobile phones and manufacturer pricing policies: the concept of value leakage. Resour. Conserv. Recycl. 133, 101–111.

Shani, Y, Apple, G, Danzinger, S, Shahar, R, 2020. When and why consumers "accidentally" endanger their products. Manag. Sci. 66 (12), 5485–6064. https://doi.org/10.1287/mnsc.2019.3509.

Silver, L., 5th Feb 2019. Smartphone ownership is growing rapidly around the world, but not always equally. Pew Res. Centre. Available at: https://www.pewresearch.org/global/2019/02/05/smartphone-ownership-is-growing-rapidly-around-the-world-but-not-always-equally/.

Slade, G., 2006. Made to Break; Technology and Obsolescence in America. Harvard University Press.

Statista, 2018. iPhone device market share worldwide. Available at: https://www.statista.com/statistics/755593/iphone-model-device-market-share-worldwide/.

Statista, 2020. iPhone sales by model worldwide. Available at: https://www.statista.com/statistics/519699/iphone-sales-by-model-worldwide.

Stempel, J., 2nd March 2020. Apple to pay up to $500 million to settle U.S. lawsuit over slow iPhones" Reuters. Available at: https://uk.reuters.com/article/us-apple-iphones-settlement/apple-to-pay-up-to-500-million-to-settle-u-s-lawsuit-over-slow-iphones-idUKKBN20P2E7.

Stephens Davidowitz, S., 2018. Everybody lies; what the internet can tell us about who we really are. Bloomsbury.

Suckling, J., Lee, J., 2015. Redefining scope: the true environmental impact of smartphones. Int. J. Life Cycle Assess. 20, 1181–1196.

Troger, N., Wieser, H., Hubner, R., February 2017. Smartphones are replaced more frequently than T-shirts; Patterns of consumer use and reasons for replacing durable goods. AK Wien, Vienna. Available at: https://www.akeuropa.eu/smartphones-are-replaced-more-frequently-t-shirts.

van Nes, N., Cramer, J., 2005. Influencing product lifetime through product design. Bus. Strat. Environ. 14 (5), 286–299.

Wieser, H., Troger, N., 2018. Exploring the inner loops of the circular economy: replacement, repair, and reuse of mobile phones in Austria. J. Clean. Prod. 172, 3042–3055.

Wilhelm, W.B., 2012. Encouraging sustainable consumption through product lifetime extension: the case of mobile phones. Int. J. Bus. Soc. Sci. 3 (3).