Formulating Second-Hand Market Value as a Function of Product Specifications, Age, and Conditions

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Second-hand market value is important for manufacturers in that it affects the profitability of both new product sales and end-of-life recovery. To gain a better understanding of second-hand market value, this paper presents an empirical study of buy-back price using laptop computers and mobile phones as examples. A thousand items that were on the market in recent years were examined, and their current buy-back prices were estimated using the pricing engine of a real buy-back company. The statistical analysis provided a model that could assess the value of used products. The model links a product's specifications to its second-hand market value. It also incorporates the impacts of product age and cosmetic and hardware conditions. Based on the results of the analysis, the design implications for improving the value of used products were discussed.
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1 Introduction

1.1 Motivation. Rapid advances in technology have spurred rapid improvement of many consumer electronic products (e.g., personal computers, laptops, copiers, televisions, and cell phones). Although streams of new products have enhanced the quality of life in innumerable ways, they have also exacerbated an environmental problem, i.e., electronic waste. New products render formerly cutting-edge products quickly obsolete or outdated. Consequently, even though a product might be in good working order, it might be replaced by the consumer and regarded as waste. Evidence of this was apparent in a survey conducted by the Consumer Electronic Association in 2008 [1] in which only 38% of consumers reported that they had discarded a product because it no longer worked.

Fortunately, not all consumers desire brand new products or the latest technologies, which in turn creates demand for product reuse and/or remanufacturing [2]. These consumers seek lower cost, basic functions, and decreased environmental impact [3].

This paper focuses on the market value of used products and its design implications. Given the flourishing second-hand market, how consumers perceive the value of a used product has become more important to manufacturers in that it affects both new product sales and end-of-life management. Consumers in the new product market have begun to consider resale value when making purchases, just as they do when buying an automobile. To enhance competitiveness in the new product market, a manufacturer must also consider the second-hand market value early in the design stage, and, if necessary, identify ways to increase the second-hand market value of its own brand items. In this regard, the effects of design decisions on market value must be known at the design stage. An accurate estimation of second-hand market value is also essential in planning and optimizing end-of-life recovery. To maximize profit from recovery, a manufacturer needs an optimal recovery strategy, including which end-of-life products to take back and how to reprocess them (e.g., which parts to reuse or discard and which parts to upgrade). Such an optimal strategy is attainable only if the manufacturers know which products are more preferred in the second-hand market and how much profit can be achieved by reprocessing these products.

This paper presents an empirical study of second-hand market value using the examples of laptop computers and mobile phones (hereafter called cell phones). The goal of the study was to develop a value model for used products that can show how second-hand market value is determined and how product design (i.e., specifications) is involved in the valuation. The developed value models formulate a product's second-hand market value as a function of its characteristics, i.e., specifications, age (i.e., the time that has elapsed since the product was originally introduced to the market), and cosmetic and hardware conditions. The function gives a quantitative estimate on how each factor affects the second-hand market value. In addition, a comparative study of laptops and cell phones reveals the similarities and differences between different product types. More specifically, this study helps to answer the following research questions:

- What is the relationship between product specifications and the second-hand market value? Among various specifications, which one has the greatest influence on the value?
- To what extent do cosmetic and hardware conditions contribute to the market value?
- How does the age of a product affect the market value?
- Do different types of products have any significant differences in their value trends? If so, what are the differences?

The resulting value models can assist in making design decisions that benefit reuse and remanufacturing and facilitate recovery decision making. They can be used in applications to

- evaluate product design alternatives in terms of potential second-hand market value
- provide design guidelines for improving potential second-hand market value
- assess and optimize the potential profitability of recovery strategies

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- plan product take back, i.e., what to take back and when to take it back.

To construct the value model, this study used *buy-back price* (i.e., the price a buy-back company pays for used consumer electronics) as an indicator of second-hand market value. Buy-back companies purchase used electronics, test their functional status, and resell them through retail and wholesale outlets. In general, a higher buy-back price means a higher resale price in the second-hand market. Therefore, the buy-back price of a product is publicly available information that reflects the product's real second-hand market value.

The rest of the paper is organized as follows. Sections 2 and 3 describe the data collection conducted for product specifications and buy-back prices, respectively. Section 4 presents the regression analysis conducted for value model formulation and the resulting models. Concluding the study, Sec. 5 summarizes findings and discusses design and managerial implications.

1.2 Relevant Literature. An essential first step in planning and optimizing recovery decisions is to understand how consumers valuate a used product. Accordingly, various models have been developed to measure the values of used products and their depreciation over time. However, most such models have not measured the values in monetary terms. For example, Rachaniotis and Pappis [4] used performance value in evaluating and optimizing the design of a remanufactured product. The performance value of a product was formulated as the weighted sum of the performance values of its constituent parts. The part performance value was represented as a function of time, and fitted to the historical PC benchmark data using the least squares method. Pandey and Thurston [5] proposed a method for modeling the performance of a product that is made up of components with different ages. Effective age, in unit of time, was presented as a new measure for the performance value. Although these measures can identify products that are preferred in the market, they have a limitation. Since they are not based on monetary value, it is difficult to combine them with operational costs, which complicates recovery decision making.

The market values of products have been analyzed in several empirical studies. However, most of the studies have focused on the retail price of new products. For instance, Harris and Dave [6] quantified the relationship between the price of a laptop computer and its components. Based on the result, they identified the specifications that have the most significant influence on the price. Rutherford and Wilhelm [7] presented a model for forecasting the selling price of a laptop computer. The model was used to derive design and managerial implications relative to upgrading the product.

Even though it is very important to assess the value of a second-hand product, how to do so has not been examined in detail to date, especially in regards to, how product characteristics (i.e., specifications, age, and conditions) affect the value. In their discussion of the importance of responsiveness in managing the reverse network, Guide et al. [8] presented an exponential value decay function, i.e., $V(t) = V(0) \cdot e^{-at}$, to model the time-dependent market value of returned commercial products. The parameter a was used to represent the speed at which the technological advances. However, the impact of design specifications on the value received little attention in this model. Ferrer [9] proposed an estimation model for the market value of a remanufactured PC in his study of the economics of PC remanufacturing. The value of a PC was defined as a linear function of time and its components' market value. The value of each component was defined as a decreasing function of time, i.e., $V(t) = V(0) \cdot t^{-a}$, where a is the component-specific positive parameter obtained by a regression analysis of the retail prices of new components [4].

The current study differs from previous studies in two ways. Unlike previous studies, which have analyzed the retail prices of new products, this study analyzed real buy-back prices. Since the data incorporate information on cosmetic and hardware conditions and product age, the study quantified the link between second-hand market value and the conditions and age. In addition, the current study compared the value trends of two different product types, enabling a better understanding of second-hand market value by highlighting the differences between different product types.

Table 1 Specification data collected for laptop computers

Specification	Description
Brand	Original manufacturer of laptop
Published year	Year introduced by the magazine
Screen	Size of screen (inch)
Weight	Weight with battery and any drives (pound)
Battery life	Battery hours with continuous use
Processor (CPU)	Processor brand, model, and speed
Multicore	Whether the CPU has multiple cores or not
Hard drive (HD)	Size of hard drive in gigabyte
RAM	Size of memory in gigabyte
Optical drive	Type of optical drive
Networking ability (Wi-Fi)	Wireless networking capability
Operating system (OS)	Type of Windows system installed
Retail price	Approximate original retail price

2 Data Collection I: Product Specification

This section and Sec. 3 give an overview of the data collection for the analysis. Two different kinds of data, i.e., product specifications and buy-back prices, were gathered and then integrated into a master data set. This section explains the data collection related to product specifications. To cover a wide range of specifications with reasonable variety, a thousand items that were on the market in recent years were selected and examined.

2.1 Laptop Computers. To gather laptop specification data, *Consumer Reports*, published by Consumers Union, which performs product reviews, was used as the data source. One merit of using this source is that it deals with actual products that have been offered to the market, incorporating actual design trends from the past. The magazine reports laptop evaluations two or three times a year. Mainstream models across all product sectors (i.e., entry-, middle-, and premium-level laptops) were the major targets of the evaluation.

Among the laptops reviewed by the magazine from 1999 to 2009, a total of 367 laptops were sampled for the analysis. The data set included a wide spectrum of products, from low-end to high-end products. Only laptops with a Windows operating system were considered. Netbooks were excluded. Table 1 describes the product specifications collected.

Figure 1 illustrates how laptop specifications have advanced during the past decade. All laptops were classified into 11 groups, according to the year the review appeared in Consumer Reports (i.e., published year). With this grouping, the overall trend represents the continuing progress in the level of laptop specifications.

The biggest changes were observed in hard drives and RAM. The storage sizes of these two components have been increasing at a near exponential rate. Average hard drive storage has increased from less than 10 GB to 300 GB. Average memory has increased from 32 MB in 1999 to 6 GB today.

Processors showed an interesting pattern. After a considerable increase in speed, no significant advance was further observed. On the other hand, the processor type exhibited an important change. In 2006, multicore processors were first introduced and a rapid transition from single-core to multicore processors took place in only 1–2 years. Wireless networking, a feature that emerged in the early 2000s was also interesting. All laptops after 2006 were equipped with wireless networking capability. Shortly after the first appearance of this feature, it was incorporated by a majority

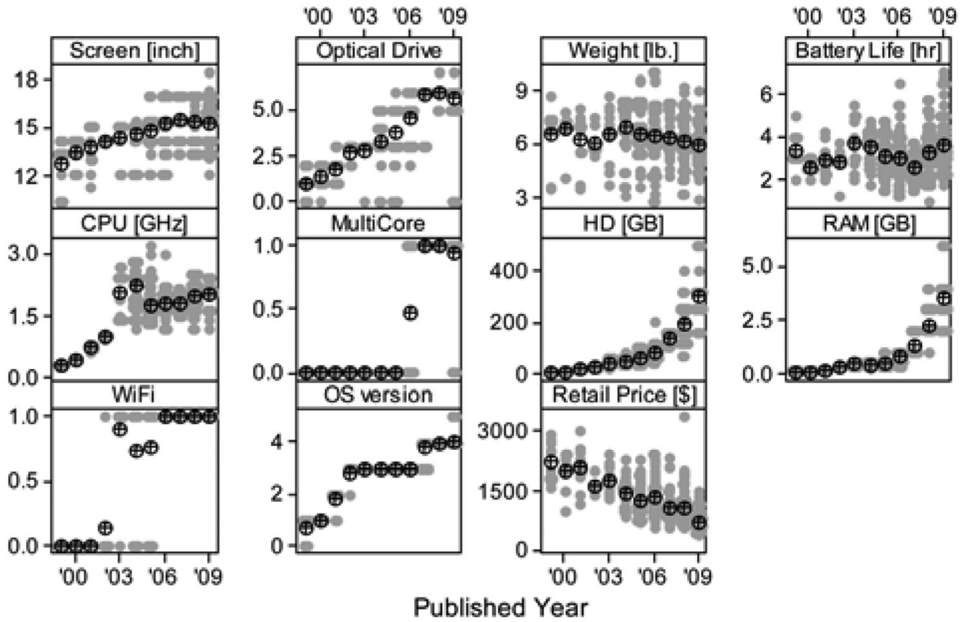


Fig. 1 Design trends in laptop specifications

of laptops, and only 4 years later, wireless networking became an essential feature in laptops.

Optical drives and operating systems, modeled as ordinal variables, exhibit continuous transitions from one technology to the next. Approximately in the middle of the time horizon (1999–2009), DVD burners replaced CD-ROMs, CD/DVDs, and CD-RW/DVD, and, now, Blu-ray players have begun to replace DVD burners. Similarly, Windows 95 in the late 1990s transitioned to Windows 98, which transitioned to XP in the early 2000s. XP, which dominated the mid 2000s transitioned to Windows Vista, and now Windows 7 has begun to replace Vista. Detailed definition of variable code is provided in the Appendix.

Screen size, weight, and battery life did not show significant trends in their mean values. However, the wide range of gray dots in a group implies increasing product variety in the market. A wide variety of products have continued to be offered to the market, from small-screen, light-weight, slim laptops for portable usage to large-screen, workhorse laptops for desktop replacement.

Finally, despite these dramatic improvements in technical specifications, the original retail price continues its decreasing trend. The average price dropped from $2230 in 1999 (i.e., $3000 in 2009 value with 3% annual interest) to $734 in 2009.

2.2 Cell Phones. To collect data for cell phone specifications, *phonearena.com*, a website dedicated to information on cell phones, was used as the data source. Among the cell phones introduced by the website from 2004 to 2009, 629 cell phones were sampled for the analysis. Table 2 describes the product specifications collected for each cell phone model.

Figure 2 shows the design trends in the cell phone market for the past 6 years. All cell phones were classified into six groups according to the introduced year. A binary indicator variable was used to model whether a key feature, such as Bluetooth, GPS, mp3, speakerphone, Wi-Fi, touch, and email, was available or not. Increasing trends in their mean values indicated that they are becoming more popular (or ubiquitous) in cell phone design. Among all of the features, the speakerphone has become a basic feature that was included on all phones introduced in 2009. Similarly, Bluetooth, mp3, GPS, and email will soon become basic requirements if current design trends continue.

There is also a trend associated with the handset design. Regarding the handset form factor, candybar and clamshell shapes are the most classical form factors. During the first 3 years, the candybar form lost its share as the clamshell became more popular. However, starting in 2006, the candybar shape has resurged in the market, which can be explained by the emergence of touch-screen phones. The type of keypad is another important design characteristic. The numeric keypad is the simplest, oldest type of keypad. Recently, only 30% of phones had numeric keys and even greater numbers of them are expected to be replaced by other keypad types, such as QWERTY and virtual keyboards, in the near future.

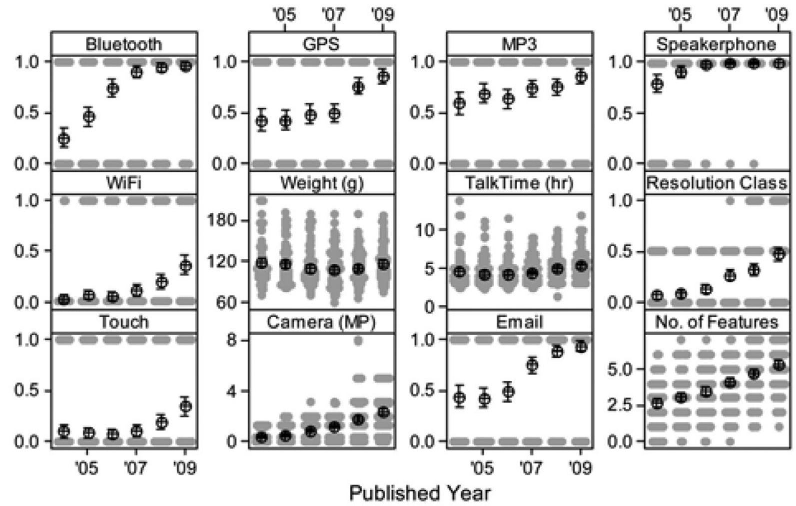
Finally, mobile technologies have shown a transition to third generation (3G) mobile cellular technologies, from CDMA to 3G CDMA, and from GSM to UMTS. Accordingly, about 78% of cell phones introduced in 2009 were equipped with 3G technologies, either 3G CDMA or UMTS.

At a glance, the overall trends of cell phones look similar to those of laptop computers. Two notable differences, however, exist between the two. First, the way in which technological

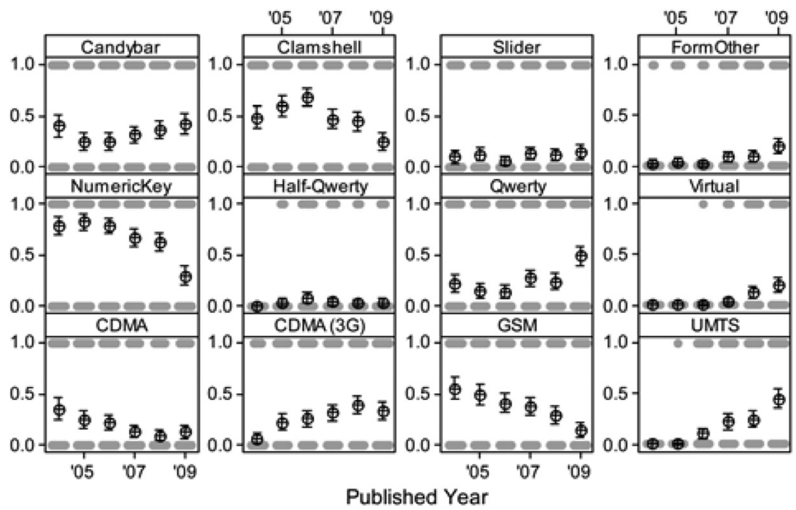
Table 2 Specification data collected for cell phones

Specification	Description
Brand	Original manufacturer of cell phone
Published year	Year introduced by the website
Status	Whether the phone is currently available or discontinued in the market
Technology	Mobile communication technology: GSM, CDMA, CDMA (3G), UMTS
Form factor	Form type of handset (e.g., candy bar, clamshell, slider, dual-slider)
Keypad type	Keypad type of handset: numeric key, half-QWERTY, QWERTY, touch
Key features	Whether the phone has the following functions: Bluetooth, GPS, mp3, speakerphone, Wi-Fi, email, and touch screen
Camera	Camera resolution in megapixels
Resolution	Resolution of main display defined in three levels (i.e., low, average, and high)
Talk time	Talk time in hours

Note: GSM, Global System for Mobile Communication; CDMA, Code Division Multiple Access; UMTS, Universal Mobile Telecommunications System.



(a) Key Feature



(b) Form Factor, Keypad Type, and Mobile Technology

Fig. 2 Design trends in cell phone specifications

transition occurs is different. Laptop computers advance by improving the level of each specification. The types and numbers of specifications are almost unchanged. However, as shown in Fig. 2(*a*), cell phones advance mainly by adding new features. The average number of features was 2.6 in 2004, but it had increased to 5.3 by 2009. Except for the display resolution, camera, and talk time, cell phones are characterized by whether they include a feature or not. The more advanced phones usually have a larger number of features.

Another difference is in the pace of technological transition. Compared to laptops, cell phones have shown slower and smoother transitions. As the design trends of the laptop computer depicted, if a new technology or feature entered the market, most laptops had included it within a couple of years. On the other hand, such rapid advances have not been observed in the cell phone market.

3 Data Collection II: Buy-Back Price

This section describes the data collection conducted for buy-back prices. *Gazelle.com* is one of the largest buy-back companies in the United States, and it was used as the source of buy-back price data. This for-profit company operates an online pricing engine, and it sets its buy-back price to reflect products' second-hand market values based on product specifications and conditions. This pricing engine was used in this study to estimate the second-hand market value of the laptop computers and cell phones described in Sec. 2.

For laptop computers and cell phones, the pricing engine requires four types of inputs, i.e., product specifications, functional status, cosmetic condition, and hardware condition. Among these factors, functional status is the factor that dominates all other inputs. A malfunctioning product is assigned a buy-back price of zero, regardless of its specifications and other conditions. Therefore, in this study, all products were assumed to be fully functional.

Cosmetic condition is an ordinal variable with four possible levels, i.e., poor, fair, good, and excellent. For laptop computers, hardware condition is a nominal variable with four classes, i.e., no failure, hard drive failure, optical drive failure, and battery failure. For cell phones, hardware condition is defined as a binary variable that indicates the presence of water damage, which is one of the most frequent accidental damages to cell phones [10]. The combination of cosmetic and hardware conditions generates a total of 16

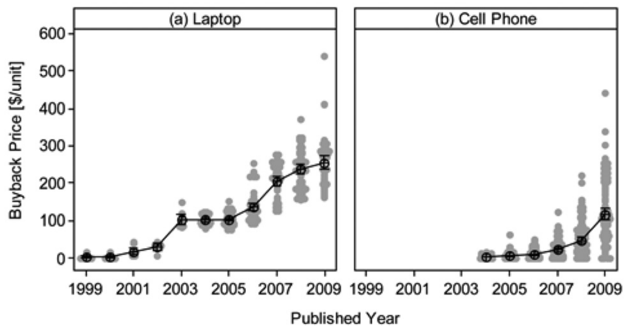


Fig. 3 Buy-back prices with excellent cosmetic condition and no hardware failure

different scenarios for each laptop computer and eight different scenarios for each cell phone. Thus, following all the scenarios, laptop computers were evaluated one by one 16 times, and cell phones were evaluated one by one eight times for identical product specs.

Figure 3 and Table 3 show the buy-back price trends for laptop computers and cell phones as a function of age when the cosmetic condition is excellent and no hardware failures have occurred. In general and as expected, newer products command higher buy-back prices.

As shown in Fig. 1, in general, laptop computers from more recent years have improved specifications. Accordingly, the mean buy-back price of a laptop made in 2009 is $249, but the mean buy-back price of laptops made in 2004 and 1999 are only $101 and $2, respectively. Two large decreases in buy-back prices were observed between 2006–2007 and 2002–2003 when there were significant advances in specifications, including the emergence of wireless networking and multicore processors. Conversely, during the relatively flat intervals that appeared in 1999–2002 and 2003–2005, only gradual technological transitions occurred, not much differentiated from the current point of view; for instance, the differences between 4-GB and 6.4-GB hard drives, or 32-MB RAM and 64-MB RAM are relatively insignificant at the present time.

Similar to the laptop computer example, a monotonically decreasing trend appears in the value of cell phones as their age increases. However, the pace of value depreciation is much more rapid than it is for laptop computers. Four to five years after market introduction, a phone has almost no market value. However, there are no sudden decreases, which indicate that the development of the technology has progressed smoothly. The greatest decrease in buy-back price for cell phones occurred between 2008 and 2009.

Table 3 Buy-back prices with excellent cosmetic condition and no hardware failure

	Laptop		Cell phone	
Published year	Mean	SD	Mean	SD
1999	1.80	4.47	—	—
2000	2.20	5.01	—	—
2001	16.64	12.73	—	—
2002	29.57	10.61	—	—
2003	101.27	19.46	—	—
2004	100.54	12.89	1.93	3.79
2005	101.04	16.22	4.28	8.66
2006	134.68	37.75	8.05	11.82
2007	203.83	44.98	20.73	22.08
2008	237.82	52.85	45.80	44.37
2009	249.11	54.13	115.36	80.41

One interesting point is that laptop buy-back prices have formed a funnel shape, while the cell phone buy-back price has formed a triangular area. Figure 3 shows a significant range in buy-back prices for a given year, especially for newer models. The range of buy-back prices is significantly smaller for older products, since the difference between low-end and high-end products is negligible from the current time point of view. However, none of the laptops has zero value unless it is 10 years old or older, whereas every age group of cell phones includes zero-value phones; even some of the phones released in 2009 and other phones that are still available for sale in the market have zero value in the second-hand market as of 2011. Generally, such phones are entry-level models that have limited features. A new phone with the same feature may still be available in the market for a reduced price. Thus, to be attractive as an alternative to a new phone, a used phone must have an even lower price. When considering the cost associated with recovering products for reuse (e.g., buy-back, testing, data destruction, and logistics), the used phone is very unlikely to maintain any profitability in reuse. Furthermore, unlike laptops, the market for component reuse is so immature that material recovery would be the only available option [11]. Unfortunately, material recovery from discarded cell phones is faced with serious limitations on the amount of profit that can be earned [12].

4 Value Model Development

This section explores the mathematical relationship between product characteristics (input variables, i.e., product specifications, age, and cosmetic and hardware conditions) and the buy-back price (output variable). The main issues here are how product characteristics determine the buy-back price and which characteristics are more influential than others. In this study, regression analyses were used to address these issues. The software package MINITAB 16 was used to perform the regression analysis done throughout the paper.

4.1 Background. One common idea about buy-back price is that it is inversely proportional to the age of product. The results of this study reinforced that idea. As Fig. 3 shows, in both laptop and cell phone cases, the value of a used product monotonically decreases as its age increases. However, Fig. 3 also implies that *age alone cannot sufficiently explain the buy-back price trend*, especially the price differences within the same age group. This indicates that more detailed value models are required. Table 4 also supports this requirement. Fitting the buy-back price to a function of age (t) alone results in significant error. The standard error S is in the same units as the response variable (buy-back price). Here, S is 40–56, which indicates that the observed buy-back prices fall a standard distance (roughly an average absolute distance) of $40–56 from the fitted buy-back prices.

One might hypothesize that the buy-back price of a product is proportional to its original price, so the original price can serve as a simple and viable indicator of buy-back price. For example, suppose that two people, X and Y, bought different laptops at the same time. If person X paid $2000 for a laptop while person Y paid $1000 for another, then person X would expect to receive a

Table 4 Buy-back price as a function of product age

Product	Function form	Fitted function	Standard error (S)
Laptop	$V(t) = V(0) - at$	$V(t) = 279 - 29.7t$	46.52
	$V(t) = V(0) \cdot e^{-at}$	$V(t) = 341.459 \cdot e^{-0.2182t}$	46.02
	$V(t) = V(0) \cdot t^{-a}$	$V(t) = 285.593 \cdot t^{-0.5414}$	55.69
Cell phone	$V(t) = V(0) - at$	$V(t) = 103 - 20.6t$	44.16
	$V(t) = V(0) \cdot e^{-at}$	$V(t) = 279.813 \cdot e^{-0.8891t}$	39.33
	$V(t) = V(0) \cdot t^{-a}$	$V(t) = 116.727 \cdot t^{-1.5881}$	39.57

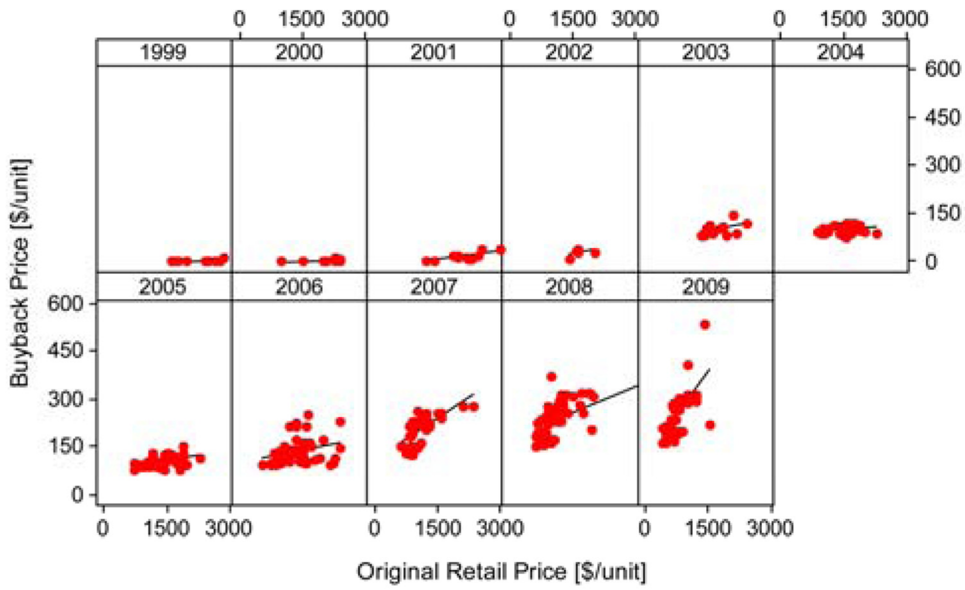


Fig. 4 Correlation between original price and buy-back price

Table 5 PLS regression results with different inputs (response: buy-back price)

Independent variable	Model R^2	Predicted R^2	Standard error (S)
Basic specifications	0.8592	0.8497	20.87
Basic specifications + processor brand	0.9497	0.9428	20.07
Basic specifications + processor brand + manufacturer brand	0.9553	0.9485	18.89
Basic specifications + processor brand + manufacturer brand + age	0.9575	0.9502	18.44

greater buy-back price than person Y. However, is it accurate to assume that the buy-back price will be proportionately greater because the original market price was greater? As shown in Fig. 4, this is not always the case, especially if products have old specifications.

The scatter plots in Fig. 4 depict the correlation between the original price of laptop computers and buy-back price (assuming that the computer is in excellent cosmetic and hardware conditions). The results of the detailed correlation analysis are provided in the Appendix. Figure 4 shows that the linear correlation is significant when the products were introduced in recent years. As the original price increases, the buy-back price also tends to increase. However, for older products, the buy-back price appears to have no clear relationship to the original purchase price. In addition, even though products have the same original retail prices, their buy-back prices can be significantly different. Thus, *the original price cannot be expected to have a significant correlation to the buy-back price or to provide a reliable measure of the buy-back price*, especially if buy-back occurs many years after the initial purchase. Again, this implies the need for an advanced value model.

Sections 4.2 and 4.3 explore the correlation between buy-back price and individual product specifications and age, to determine which attributes are most influential. Cosmetic and hardware conditions add variations to the buy-back price that is determined by product specifications and age. An analysis of the impacts of cosmetic and hardware conditions is presented in Sec. 4.4.

4.2 Regression: Buy-Back Price of a Used Laptop Computer. Using regression analysis, buy-back prices of laptop computers (with excellent cosmetic and hardware conditions) can be formulated as a function of product specifications and age. However, regression analysis that involves product specifications raises the issue of multicollinearity, which is a condition that occurs when two or more predictors are strongly correlated [13]. As shown in Figs. 1 and 2, product specifications are strongly correlated with each other. For instance, the relationship between hard drives and the amounts of RAM shows a definite linear pattern, since both features have increased markedly over the past few years.

One way to resolve the issue of multicollinearity is to perform a partial least squares (PLS) regression. PLS regression is particularly useful when the input variables are highly collinear; it reduces the number of predictors to a smaller set of uncorrelated components and conducts least squares regression on those components. However, PLS regression is not usually suitable for screening out predictors [14]. In this study, multiple regression analysis was performed alongside PLS regression to screen out insignificant factors, thereby complementing PLS.

Product specifications can be assigned to one of three different groups, i.e., basic specifications, processor brand (i.e., Processors A1–A3, Processor B1, and Processor B2), and manufacturing brand (e.g., Brand D). Basic specifications include screen size, type of optical drive, weight, processor speed, and type (whether it is multicore or not), hard drive size, RAM size, version of the operating system, wireless networking capability, and battery life.

Table 5 shows the results from different PLS regressions using different groups of input variables. Compared to the age-only model in Table 4, all PLS regressions better fit the buy-back price with smaller S values. Comparing the results gives an indication of the variables that can best approximate the buy-back price. Basic specifications are the best explanatory variables of buy-back price, having a predicted R-squared value of 85%. In addition, the processor brand provides additional significant explanation, thereby increasing the predicted R-squared value to 94.3%.

Table 6 Final PLS regression model (response: buy-back price)

Independent variable	Regression coefficient	
	Model 1 (unstandardized variable)	Model 2 (standardized variable)
(Constant)	21.53	33.80
Screen (inch)	1.42	11.38
Optical drive	3.13	22.15
Weight (lb)	–2.10	–15.29
Processor speed (GHz)	24.13	69.90
Multi core*processor speed (GHz)	14.14	48.48
Hard drive (GB)	0.11	54.67
RAM (GB)	8.78	51.80
Wi-Fi	13.69	13.85
Operating system	9.08	45.87
Processor A1	–12.20	–12.20
Processor A2	–12.86	–12.82
Processor A3	–10.94	–10.84
Processor A4	49.44	49.37
Processor B1	–37.13	–37.03
Processor B2	–38.36	–38.38
Brand D	–3.59	–3.56
Brand H	7.25	7.19
Brand T	–3.26	–3.32
Brand S	21.04	20.85
Brand G	–1.07	–1.08
Brand L	–1.00	–0.92
Age (year)	–3.89	–38.97
Model R^2	0.9567	0.9569
Predicted R^2	0.9503	0.9504
Standard error (S)	18.57	18.55
F statistics	1979.37	1985.14
p-value	0.00	0.00

Note: The p-value row shows the p-value from analysis of variance (ANOVA). The p-value indicates whether the regression model estimated is statistically significant; if the p-value is less than α (here, 0.05), the predictors (independent variables) in the model, as a set, are considered to be useful for estimating the value of response variable [14].

However, the effects of the manufacturer's brand and the product's age on the buy-back price seem to be smaller than the others. Only slight changes in the R-squared values were observed.

Table 6 shows the final PLS models with the highest predicted R-squared values. Two models were developed, i.e., model 1, which uses input variables without any scaling, and model 2, which uses standardized variables that are scaled first to lie within 0 and 1. Both models showed a predicted R-squared value of 95%. The p-values from ANOVA for buy-back price are 0.000, which are less than an alpha of 0.05, providing evidence that the models are statistically significant. A coefficient of model 1 indicates how much change in buy-back price is expected when the input variable increases by one unit. A coefficient of model 2 shows the sign and magnitude of the relationship between each input variable and buy-back price. Since all input variables are normalized first to lie within 0 and 1 in model 2, the resulting coefficients imply the relative influence of each specification in deciding buy-back price.

The results indicate that processors are the most influential design attribute in the model. Most processor-related specifications show strong correlation with buy-back price, for example, processor speed, processor brand and model, and multicore. Hard drive and RAM sizes are also identified as important specifications. Optical drive, operating system, wireless networking ability, and screen size are also significant variables, although their influences appear to be lower. Unlike other variables, the weight of the laptop is inversely proportional to buy-back price. Finally, battery life turns out to not be significantly correlated with buy-back price and thus was removed from the model.

An interesting result is that manufacturer brand can influence the buy-back price. A particular laptop manufacturer (Brand S) increased the buy-back price by \$21. This implies that the brand itself has a positive effect on the price, all else being equal. Another interesting result was observed from the product age. The coefficient of age in model 1 is -3.89, which means that the depreciation of value due exclusively to age was \$3.89 per year. Compared to product specifications, the impact of age seems very small. In other words, consumers in the second-hand market do not care much about how old the laptop is, but rather what specifications it has.

4.3 Regression: Buy-Back Price of a Used Cell Phone. In order to understand how product specifications and age affect buy-back price, regression analyses were conducted for the cell phone data. There are seven types of cell phone specifications, i.e., key features, keypad type, mobile technology, handset form factor, manufacturer brand, product age, and availability. The key features include Bluetooth, GPS, mp3, speakerphone, Wi-Fi, touch, and email. Product age denotes the time elapsed from the market release of the phone model, not the length of usage for a specific phone. Availability is a binary variable that indicates if the phone is still on sale or has been discontinued.

Table 7 compares how well different groups of variables explain the buy-back price. The lower standard error, *S*, values of all models implies that a model incorporating product specifications provides a better fit than the age-only model in Table 4. Among the groups of specifications, handset form factor seemed to have no correlation with buy-back price. Rather, including form factors in the model decrease the predicted R-squared value.

Table 7 also shows the interesting result that availability has a significant impact on buy-back price. Its impact seems to be even larger than the impact of product age. When its interaction with age (i.e., Availability*Age) is considered, the model provided a better approximation of buy-back price.

The final regression models in Table 8 give a clearer idea concerning how product specifications and age are correlated with buy-back price. Two models are presented, i.e., model 1 in which coefficients indicate the marginal change in buy-back price according to a unit of increase in the input variable and model 2 in which coefficients indicate the impact magnitude of each

Table 7 PLS regression results with different inputs (response: buy-back price)

Independent variable	Model R^2	Predicted R^2	Standard error (S)
Features	0.6572	0.6377	32.68
Features + keypad	0.6798	0.6522	31.76
Features + keypad + technology	0.6924	0.6612	31.08
Features + keypad + technology + form	0.6932	0.6589	31.06
Features + keypad + technology + form + brand	0.7009	0.6624	30.64
Features + keypad + technology + form + brand + availability	0.7503	0.7222	27.91
Features + keypad + technology + form + brand + age	0.7353	0.7003	28.86
Features + keypad + technology + form + brand + availability + age	0.7562	0.7282	27.59
Features + keypad + technology + form + brand + availability + age + availability*age	0.7935	0.7635	25.50

Table 8 Final PLS regression model (response: buy-back price)

Independent variable	Regression coefficient: Model 1 (unstandardized variable)	Model 2 (standardized variable)
(Constant)	–24.29	–20.52
GPS	8.79	8.79
Wi-Fi	24.94	24.94
Talk time (h)	2.84	35.93
Resolution	10.58	10.58
Touch	20.14	20.14
Camera (megapixel)	13.65	110.54
Virtual keypad	10.85	10.86
UMTS	9.48	9.48
Brand R	24.77	24.77
Availability	91.84	91.84
Availability*age	–34.13	–136.50
Model R^2	0.7841	0.7841
Predicted R^2	0.7663	0.7663
Standard error (S)	26.00	26.00
F statistics	375.85	375.85
P-value	0.00	0.00

specification in deciding buy-back price. By excluding insignificant factors, the final models improved their predicted R-squared values to approximately 77%. Among the phone features, Bluetooth, mp3, speakerphone, and email were excluded. Form factors were also removed, as expected from Table 7.

The results reveal an interesting point regarding the impact of the age of a phone. Surprisingly, age alone was not significantly correlated with buy-back price, and so was excluded from the model. Rather, availability and the interaction with age are the most influential attributes. Consumers in the second-hand market consider if the phone is currently on sale in the new product market first, rather than considering when the phone was released in the market. In other words, if a phone is discontinued, its age does not matter to consumers. The age becomes important only if the phone is currently available on the new product market. If the phone is still available, the older age depreciates the value of the phone by \$34.13 per year. Considering that the marginal decrease was \$3.89 per year in the laptop case, cell phones seem to be very sensitive to age. From this result, it can be inferred that design changes that are made too frequently and phase-out of a phone can have detrimental effect on the value of used products. In contrast, making a product that has a long market lifetime and maintaining a model's identity for longer periods seem to help increase the value of a used product.

The other specifications that have significant impacts on buy-back prices reflect market preferences toward better performance and cutting-edge features and technology. The market strongly prefers higher camera and screen resolutions and longer talk time (or battery life). It also highly appreciates the availability of recent phone features, such as Wi-Fi, touch, and virtual keyboards. A relatively old feature, GPS, also increases the buy-back price, but to a smaller extent. Advanced mobile technology is also important. If a phone supports UMTS, an increased buy-back price is expected. However, 3G CDMA does not show any significance. This implies that the second-hand market might prefer a GSM phone to a CDMA phone. Finally, similar to the example of laptop computers, a manufacturer brand (Brand R) has a significantly strong relationship with buy-back price. The impact of premium brands seems greater with cell phones, showing a stronger influence than some of the key features.

4.4 Impact of Cosmetic and Hardware Condition. Previous sections (4.2 and 4.3) established the mathematical model linking product specifications and age to buy-back price. Given excellent cosmetic and hardware conditions, this buy-back price varies if different conditions are applied. Denoting the buy-back price with excellent conditions as X, this section discusses the effects of cosmetic and hardware conditions on X.

Table 9 shows how cosmetic condition affects buy-back price when there is no hardware failure. Fundamentally, a degraded cosmetic condition decreases the buy-back price X. The worse the cosmetic condition is, the more the value of X is expected to decrease. However, if X is below a certain value (i.e., threshold X), the used product loses all its residual value, so the second-hand market value drops to zero. Using regression analysis, this study formulated the impact of a different condition as a function of X. For instance, consider a laptop computer, the value of which is \$300 when it has perfect cosmetic and hardware conditions (i.e., $X = 300$). If the cosmetic condition decreases to good, fair, and poor, the value becomes approximately \$267, \$169, and \$71, respectively. This corresponds to a *residual value ratio* (i.e., the ratio of the calculated buy-back price to Y) of approximately 89%, 56%, and 24%, respectively.

The resulting regression models are shown in Fig. 5. The x-axis represents buy-back price with excellent conditions X, while the y-axis represents the calculated buy-back price assuming a degraded cosmetic condition. Both laptop computers and cell phones show a similar trend. As X is higher, price differences (or, the vertical gaps between different lines in Fig. 5) increase for different cosmetic conditions. This indicates that a better cosmetic condition is more critical to a product with greater X. In other words, the benefit from better cosmetic condition increases as products have more advanced specifications and/or a younger age. In contrast, for the oldest and/or least-performing products, the cosmetic condition does not have much impact on the buy-back price.

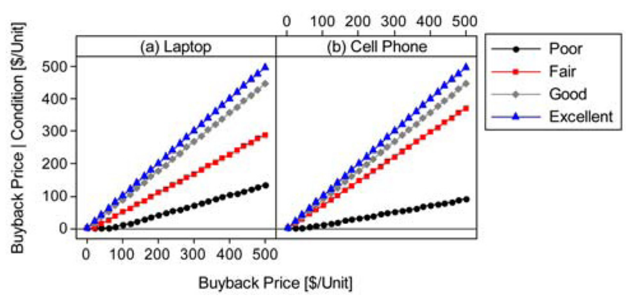


Fig. 5 Effect of cosmetic condition on buy-back price

Table 9 Effect of cosmetic condition on buy-back price (*X*: Buy-back price with excellent cosmetic and hardware conditions)

Type	Cosmetic condition	Regression model	Standard error (S)	Threshold X
Laptop	Poor	$\max[0, -22.7407 + 0.3126\,X]$	0.95	72.75
	Fair	$\max[0, -11.4804 + 0.6014\,X]$	0.49	19.09
	Good	$\max[0, -3.1241 + 0.9015\,X]$	0.46	3.47
Cell phone	Poor	$\max[0, -9.8936 + 0.1993\,X]$	0.13	49.64
	Fair	$\max[0, -3.0989 + 0.7501\,X]$	0.28	4.13
	Good	$\max[0, -1.2605 + 0.9001\,X]$	0.31	1.40

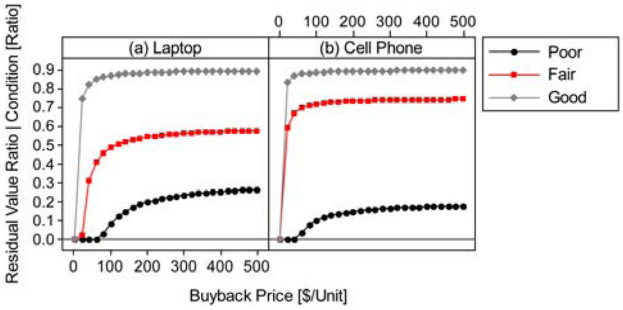


Fig. 6 Effect of cosmetic condition on residual value ratio

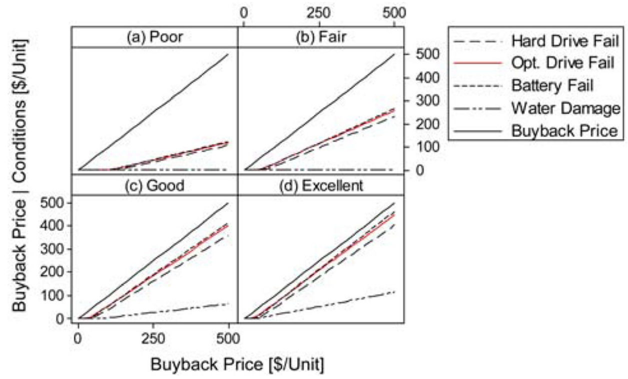


Fig. 7 Effect of cosmetic and hardware conditions on buy-back price

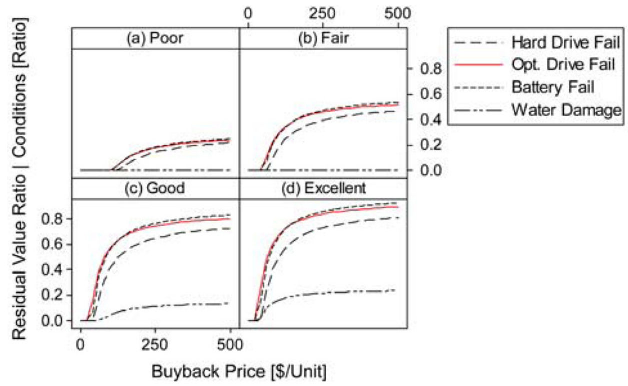


Fig. 8 Effect of cosmetic and hardware conditions on residual value ratio

Figure 5 gives another implication when comparing laptop computers and cell phones. The impact of cosmetic condition is different for different product types. Figure 6, which shows the residual value ratio, also confirms this. The differences between the two products stand out for fair and poor conditions. Fair condition seems more detrimental to laptop computers than to cell phones. For poor condition, however, the reverse is true, i.e., cell phones lose more of their value. For example, suppose a cell phone with the value of which is $X = 300$. Good, fair, and poor conditions change the cell phone value to approximately \$269 (90%), \$222 (74%), and \$50 (17%), respectively. Compared to the previous example of a laptop computer, the cell phone retains more value for fair condition, and less value for poor condition.

Combined with cosmetic condition, hardware conditions cause additional variations in the buy-back price. Table 10 shows the results of the regression analysis, which show the combined effects of cosmetic and hardware conditions. Figures 7 and 8 illustrate the resulting regression models and residual value ratio, respectively. Since Figs. 7(*d*) and 8(*d*) assume an excellent cosmetic condition, their results highlight the effect of hardware condition.

As expected, a hardware failure decreases the product value. Similar to cosmetic conditions, hardware conditions are more influential on buy-back price when the product has a higher X value. For laptop computers, failure of the hard drive had the most detrimental influence on buy-back price. Overall, however, the effect of hardware condition seemed relatively small, compared to that of cosmetic condition.

In the case of cell phones, hardware failure due to water damage is so detrimental that a cell phone loses most or all of its market value. Even current, available cell phones that have an excellent cosmetic condition can only maintain, at most, 23% of their X value. One outlier of this trend is the Apple *iPhone*. Even with water damage, an *iPhone* retains a value of \$30 to \$150, depending on the model. Considering that its X value ranges from \$122 to \$440, it maintains about 25% to 34% of the value in spite of the water damage. The fact that there is a demand for *iPhone*'s parts in the market helps understand why the damaged phone can have such exceptional value.

Going back to the difference between laptop computers and cell phones, the lower impact of hardware failure in the laptop computer example can be explained by similar reasoning. While laptop computers have a flourishing market for component recovery, cell phones do not have such a market at present. Facilitating component recovery seems essential to mining the value inside damaged products.

Table 10 Effect of cosmetic and hardware conditions

Hardware failure	Cosmetic condition	Regression equation	Standard error (S)	Threshold X
Hard drive (laptop)	Poor	$\max[0, -37.7465 + 0.2900\ X]$	2.15	130.16
	Fair	$\max[0, -35.8380 + 0.5370\ X]$	3.96	66.74
	Good	$\max[0, -38.2055 + 0.7993\ X]$	5.93	47.80
	Excellent	$\max[0, -39.3820 + 0.8884\ X]$	6.57	44.33
Optical drive (laptop)	Poor	$\max[0, -32.3110 + 0.3019\ X]$	2.62	107.03
	Fair	$\max[0, -28.1744 + 0.5720\ X]$	4.85	49.26
	Good	$\max[0, -28.2700 + 0.8579\ X]$	7.27	32.95
	Excellent	$\max[0, -28.4320 + 0.9539\ X]$	8.10	29.81
Battery (laptop)	Poor	$\max[0, -33.6691 + 0.3136\ X]$	1.77	107.36
	Fair	$\max[0, -31.6116 + 0.5976\ X]$	3.53	52.90
	Good	$\max[0, -33.4122 + 0.8967\ X]$	5.13	37.26
	Excellent	$\max[0, -34.0517 + 0.9963\ X]$	5.70	34.18
Water damage (cell phone)	Poor	0	0.00	—
	Fair	0	0.00	—
	Good	$\max[0, -10.5515 + 0.1496\ X]$	0.11	70.53
	Excellent	$\max[0, -9.3325 + 0.2501\ X]$	0.15	37.32

5 Discussion

Second-hand market value is important for manufacturers in order to increase profitability of both new and end-of-life recovery markets. This paper presented an empirical study of buy-back prices using the examples of laptop computers and cell phones in an effort to create a better understanding of the link between product design and second-hand market price.

One common idea about second-hand market value is that it is inversely proportional to the age of product. This study reinforced the idea. In both laptop and cell phone cases, the value of a used product monotonically decreased as its age increased. However, the study found that age alone does not sufficiently explain the buy-back price trend, especially the price difference among products of the same age and the value trend differences between product types. Therefore, this study focused on identifying the basic nature of buy-back price and its association with product design.

To clarify how product design relates to the buy-back price, this paper investigated three additional factors along with product age, i.e., product specifications, cosmetic condition, and hardware condition. Hundreds of laptops and cell phones from the past decade were examined and their buy-back prices at the present time were estimated using the pricing engine of a real buy-back company. The statistical analysis elucidated how the four factors influence the buy-back price, and their significant influences substantiate why product design is important and effective in increasing the values of used products.

The findings from this study suggest that design approaches should be tailored to a product by considering, for example, its pace and types of technological advances, lifetime, market positioning, maturity of second-hand component market, and average user behavior, etc. More specifically, three design implications for improving second-hand market value were obtained.

The first recommended design approach is *design for upgrading for laptop computers and design for component reuse for cell phones*. More advanced specifications are a necessary condition for higher second-hand market value. A product, however, cannot avoid technological obsolescence over its lifetime. With the current rapid pace of technological advances, it is difficult to retain high second-hand market value with the original specifications.

For laptop computers, upgrading can be a profitable solution for obsolescence. They evolve by improving the level of specifications, rather than adding a new type of specification. Moreover, laptops have a well-established modular structure that allows for easy replacement of parts and upgrading. By replacing obsolete parts with new parts and/or adding additional memory or hard drives, the profitability of laptop computers can be improved in the second-hand market. For example, Table 6 shows that the additional storage of hard drive can increase the second-hand market value by approximately \$0.12 per gigabyte. If the cost of upgrading a hard drive is less than \$0.12 per gigabytes, the profitability of laptop computers can be improved in the second-hand market. Given such a cost target, products can be designed so that they are easily expandable or upgradable. Some specifications are more effective than others in increasing product value. For example, processors, hard drives, and memory have a greater influence on the value of a laptop than other specifications. The magnitude of the impact of each specification (Tables 6 and 8) should be considered when design takes future upgrading into account.

Unlike laptop computers, cell phones might face significant challenges in upgrading their specifications. Cell phones advance mainly by adding new features. To increase their value in the second-hand market, they must be equipped with recent features. However, current cell phone design does not allow for easy disassembly and upgrading. Actually, considering their integrated, dense structure, it is doubtful if adding a new feature is technically feasible. Design for component reuse is an alternative design strategy that cell phones can employ to increase reuse. An important fact about e-waste recovery is that it requires that multiple generations and brands of products be processed at the same time. By increasing part compatibility with more advanced, next-generation models, it is possible to facilitate the reuse of components. Design for component reuse includes using standardized components and making a product easy to disassemble, inspect, and repair.

The second recommended design approach relates to the market positioning of product design, i.e., *design for reuse for high-end products* and *design for material recovery or design for repurposing for low-end products.* It will be difficult to achieve profit from reuse or remanufacturing of some products, irrespective of when they are returned or what their conditions are. For example, the cell phone study showed that some entry-level models with low-end specifications have zero value, even if they were produced recently and are still available for purchase in the new product market. If design for reuse can change this situation and ensure profitability in reuse, that should be the first priority. However, if this approach is not promising, such phones should be designed with different intentions from the beginning, e.g., material recovery and repurposing. The value models developed in this paper help evaluate the economic profitability of a design strategy. Thus, they can be used in choosing the best design strategy.

Design for material recovery helps low-end products to have increased profit from recycling. It includes, for example, reducing weight, using ecofriendly materials, improving the purity of the materials used in a product, reducing toxic materials, facilitating disassembly by material type, and using materials that are easy to refine. Design for repurposing creates demand for older products (more specifically, their parts) by designing another product that can utilize such parts. It is not essential that the repurposing item has the same identity as the original product. For instance, memory and processors from old equipment can be reused in making gaming machines or dolls.

Design for end-of-use conditions is another important design approach. Cosmetic and hardware conditions affect second-hand market value, which is determined by product specifications and age. This study quantified the importance of these conditions in retaining the value of a product. With this knowledge, a profitable investment can be made for better end-of-use conditions. For example, making products easy to recolor or retexture, adding protective film, and using more durable materials are ways to maintain good cosmetic condition. The use of engravings, stickers, and various ornaments is a recent trend in the electronic market, but it can be detrimental to the value of the product in the second-hand market. Thus, designing a product to allow reversible customization seems necessary.

Keeping the hardware in good condition is also important, especially if component recovery is not popular. As the cell phone example showed, an immature market for component recovery makes it difficult to mine the residual value of a damaged phone. If protecting/repairing hardware can be done with reasonable investment, it is better to include such features to appeal to consumers who want high resale value.

Both cosmetic and hardware condition are much more critical for products that have advanced specifications and/or that will be returned early. Thus, design for end-of-use condition would be more effective for products targeting business-purpose users and tech-savvy users.

In concluding this study, it should be noted that the buy-back prices used were from a single buy-back company and that assessments of buy-back prices would vary from company to company [15]. Future research can involve improving the fidelity of the value model by enlarging the amount and the coverage of input data. Conducting time-series analysis on the impact of product specifications could be another line of future research. Current value models are based on buy-back prices assessed in a single period of time. A specification of importance at the present time could change to unimportant in the future as new technologies become available. Time-series analyses based on buy-back prices collected over multiple time periods can help explore how the impact of each product specification changes over time.

Table 11 Data code

Code	Optical drive	Operating system
0	None	Windows 95
1	CD-ROM	Windows 98
2	CD/DVD	Windows ME
3	CDRW/DVD	Windows XP
4	DVD-R/RW	Windows Vista
5	DVD-SuperMulti	Windows 7
6	Dual Layer	
7	Blu-ray disc/super multi	

Table 12 Correlation between original price and buy-back price

Published year	Pearson correlation	P-value
1999	0.429	0.216
2000	0.348	0.325
2001	0.714	0.014
2002	0.393	0.384
2003	0.419	0.199
2004	0.287	0.095
2005	0.511	0.000
2006	0.278	0.033
2007	0.678	0.000
2008	0.461	0.000
2009	0.538	0.000

Rutherford and Wilhelm [7] and Tucker and Kim [16] would provide an excellent background along this line.

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Appendix

Table 11 shows the data code for optical drives and operating systems that were discussed in Sec. 2.1. Table 12 shows the results of correlation analysis between the original price and buy-back price of laptop computers (see Sec. 4.1).

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