BULLETIN
OF
ECONOMIC THEORY AND ANALYSIS

Journal homepage: https://dergipark.org.tr/tr/pub/beta

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To cite this article: Kargı, B., M. & Coccia, M. (2024). The Developmental Routes Followed by Smartphone Technology Over Time (2008-2018 Period). *Bulletin of Economic Theory and Analysis*, *9*(2), 369-395.

Received: 04 Dec 2023

Accepted: 05 Mar 2024

Published online: 30 jun 2024

Bulletin of Economic Theory and Analysis

Volume 9, Issue 2, pp. 369-395, 2024

https://dergipark.org.tr/tr/pub/beta

Original Article / Araştırma Makalesi

Received / Alınma: 04.12.2023 Accepted / Kabul: 05.03.2024

The Developmental Routes Followed by Smartphone Technology Over Time (2008-2018 Period)

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ABSTRACT

This paper's aim is to identify and examine the key technical attributes that propel product innovation, facilitating the prediction of swiftly evolving technological trajectories. The present study introduces the hedonic pricing method and various other approaches, which have been employed in the context of smartphone technology, comprising a sample of 738 models spanning from 2008 to 2018. The findings indicate that the progression of smartphone technology is primarily steered by technical features related to the perceptual experience of users, including the resolution in total pixels, the first and second camera in megapixels (Mpx), and storage capacity (RAM and memory in gigabytes, Gb). Implications for innovation product management are also deliberated upon.

Anahtar Kelimeler
Evolution of Technology, Management of Technology, Economics of Technical Change, Smartphone Technology, Economic change

JEL Kodu
O30, O32, O34, O38

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Akıllı Telefon Teknolojisinin Zaman İçinde İzlediği Gelişim Rotaları (2008-2018 Dönemi)

ÖZ

Bu makalenin amacı, ürün yeniliğini teşvik eden ve hızla gelişen teknolojik yörüngelerin tahminini kolaylaştıran temel teknik özellikleri belirlemek ve incelemektir. Bu çalışma, 2008'den 2018'e kadar uzanan 738 modellik bir örneklemi kapsayan, akıllı telefon teknolojisi bağlamında kullanılan hedonik fiyatlandırma yöntemini ve diğer çeşitli yaklaşımları tanıtmaktadır. Bulgular, akıllı telefon teknolojisindeki ilerlemenin öncelikle teknik faktörler tarafından yönlendirildiğini göstermektedir. Toplam piksel cinsinden çözünürlük, megapiksel (Mpx) cinsinden birinci ve ikinci kamera ve depolama kapasitesi (gigabayt cinsinden RAM ve bellek, Gb) dahil olmak üzere kullanıcıların algısal deneyimiyle ilgili özellikler. İnovasyon ürün yönetimine yönelik çıkarımlar da tartışılmaktadır.

Keywords
Teknolojinin Evrimi, Teknoloji Yönetimi, Teknik Değişim Ekonomisi, Akıllı Telefonlar, Ekonomik Değişim.

JEL Classification
O30, O32, O34, O38.

1. Introduction

In the field of research on technical change and technology management, the examination of technological advancements holds a central and long-standing position as a research theme focused on understanding how technology and technological progress evolve in society (Coccia, 2005, 2005a, 2018; Saviotti, 1985). More specifically, the exploration of the nature and development of innovation represents a vital area of research for predicting the developmental paths and features of emerging technologies (cf., Arthur, 2009; Arthur & Polak, 2006; Hall & Jaffe, 2018; Linstone, 2004; Coccia, 2017, 2017a). Scholars in these fields strive to gauge technological progress, the level of technological advancement, and shifts in technology to foresee emerging directions (Coccia, 2005; Coccia & Wang, 2015, 2016; Daim et al., 2018; Faust, 1990; Farrell, 1993; Magee, 2012; Sahal, 1981; Tran & Daim, 2008; Wang et al., 2016). However, the methods for identifying essential technical characteristics that underlie the evolution of specific technologies remain somewhat elusive. This study seeks to present a method for analyzing the most crucial technical attributes that facilitate the enhanced development of new technology (cf., Lee & Lim, 2014; Coccia, 2017b).

For this purpose, we have selected smartphone technology as a case study. Smartphone technology is one of the most pivotal Information and Communication Technologies (ICTs) employed globally. It serves as a testbed for the approaches presented here and helps illuminate the general attributes of the evolutionary paths of new technology. Specifically, in this study, smartphone technology is simplified into a linear hedonic pricing function, which aids in identifying the technical characteristics that have the most significant impact on technological evolution. This approach can be extended to analyze and clarify the evolutionary trajectories of various technologies across different domains. Furthermore, the findings can offer guidance for best practices in technology management, directing Research and Development (R&D) funding towards critical technologies and technical characteristics of emerging products with the potential for rapid evolution in society. Before we delve into the proposed methodology, the following section introduces the theoretical framework.

2. Theoretical Framework

Within the field of technology research, the idea of technometrics acts as a theoretical structure for quantifying technological progress and shifts in technology with policy implications (Sahal, 1985, 1981). The assessment of technological advancement has been addressed through different techniques in engineering, scientometrics, technometrics, economics, and related fields (Coccia, 2005, 2005a, p.948ff).

As Daim et al. (2018) show in the context of robotics technologies, modern methods of technological evaluation use the technology development envelope to pinpoint several avenues for technological evolution and create strategic roadmaps. For information and energy technology, Koh & Magee (2006, 2008) support a functional approach to assessing technological advancement that focuses on three functional operations: storage, conveyance, and transformation. Their findings generally point to constant advancement within each functional category, regardless of the particular underlying technological artifacts that are dominant at any one moment. But there are differences between information technology and energy. According to Magee et al. (2016), experience curves might be more applicable when examining a single design in a single instance, but Moore's law offers a more realistic depiction of long-term technological development when performance data include multiple designs.

Particularly, Magee et al. (2016, "Moore’s exponential law appears to be more fundamental than Wright’s power law for these 28 domains (where performance data are record breakers from numerous designs and different factories)." Farmer & Lafond (2016, p. 647) construct Moore's law as a correlated geometric random walk with drift in relation to the predictability of technological advancement, and then apply it to historical data on 53 technologies. With a thorough grasp of the prediction quality, their method makes forecasts possible for any given technology. Generally speaking, a number of models—including functional forms by Moore, Wright, Goddard, Sinclair-Klepper-Cohen, Nordhaus, and others—have been put out to forecast technological advancement (Nagy et al., 2013). Wright's model, for instance, characterizes cost decreases of technology as a power law of cumulative production, while generalized Moore's law posits that technologies improve exponentially over time. Nagy et al. (2013) utilize a database covering the cost and production of 62 different technologies to rank the performance of these postulated laws. They argue that "Wright's law produces the best forecasts, but Moore's law is not far behind. ... a previously unobserved regularity that production tends to increase exponentially... results show that technological progress is forecastable, with the square root of the logarithmic error growing linearly with the forecasting horizon at a typical rate of 2.5% per year.

The results of this study have implications for ideas concerning technology evolution as well as for assessing prospective technologies and climate change mitigation strategies. One of the most important Information and Communication Technologies (ICTs) used worldwide in modern society is smartphone technology, which is the subject of certain research in the economics of technical change (cf., Watanabe et al., 2012; Woods, 2018). Notably, growth rates for smartphones and mobile phones have surpassed those for fixed phones, as indicated by the number of subscribers (Watanabe et al., 2012). Lee & Lim (2014, pp.808-809) describe the key characteristics of mobile phones, including mass, physical dimensions (length, width, and thickness), dominant vibration frequency, peak acceleration, and peak inertia force, among others.

The evolution of smartphone technology is closely linked to incremental functionality development, which involves "the ability to significantly enhance the performance of production processes, goods, and services through innovation" (Watanabe et al., 2009, p.738). Functionality development stimulates customer demand, resulting in a rapid increase in the number of subscribers, leading to a significant decline in handset prices due to learning and economies of scale (Watanabe et al., 2009, p.738). The balance between price increases due to functionality development and price decreases attributable to learning effects and economies of scale has driven the growth of mobile phones (cf., Lacohée et al., 2003).

Researchers have also looked at other technologies, including digital cameras, in the fields of innovation economics and industrial organization by examining the relationship between sales and camera attributes (Carranza, 2010). While the average optical zoom of cameras sold somewhat reduced throughout the same period, Carranza (2010, p. 605) adds that growing resolution is a necessary part of the functionality development of camera quality. This trade-off results from improved resolution making digital zoom a more affordable option than optical zoom, especially in lower-end cameras. According to Watanabe et al. (2012), learning effects in ICTs can promote self-propagating technological advancement, making it possible to adopt new features from the digital sector. Building upon these studies, a fundamental question in the economics of innovation pertains to identifying the technological characteristics that have the most significant impact on the evolutionary paths of new technology, facilitating the prediction of successful technological trajectories (Coccia, 2005, 2005a, 2017a, 2017b). The literature on suitable methods for addressing this technological challenge remains somewhat limited. This study addresses this question by establishing a theoretical framework based on technology as a complex system, complemented by the application of the hedonic pricing method. These approaches are utilized to analyze smartphone technology with the goal of pinpointing the most critical technical characteristics that drive evolutionary pathways over time.

To begin, it is crucial to clarify the concept of a complex system, which forms the basis of the theoretical framework presented here. Simon (1962, p.468) defines a complex system as "one made up of a large number of parts that interact in a nonsimple way... complexity frequently takes the form of hierarchy, and... a hierarchic system... is composed of interrelated subsystems, each of which is hierarchic in structure until we reach some lowest level of elementary subsystem." McNerney et al. (2011, p.9008) expand on this concept, asserting that "The technology can be decomposed into n components, each of which interacts with a cluster of d − 1 other components" (cf., Gherardi & Rotondo, 2016). In this context, technology is defined as a complex system comprising multiple components and relationships between each component and at least one other element within the system. Sahal (1981) also emphasizes that systems innovations result from the integration of two or more symbiotic technologies.

Additionally, various methods have been employed to analyze technological advancements (Coccia, 2005, 2005a, p.948ff; Sahal, 1985). One method employed in technology analysis is the hedonic approach. The hedonic method takes into account both economic and technical factors

(Saviotti, 1985). While in economics, this approach is driven by economic goals, such as identifying sources of firms' competitive advantage, in engineering, it is particularly valuable for pinpointing specific technical changes designed to enhance the performance of new products (Triplett, 1985, 2006). The fundamental premise of this approach is that there is a positive correlation between the market price of a product and its quality. Specifically, a product can be described by a set of characteristics, each associated with a specific value. The product's quality, represented as Qj, is considered a function of these defining characteristics:

$$Q_j = f(a_1,...,a_i,...,a_n, X_{1j},..., X_{2j},..., X_{hj})$$

Where Qj represents the quality of the product, and X1, X2, ..., Xn denote the various defining characteristics.

a_i = relative importance of the *i*-th characteristics (*i*=1, …, n)

X_{ij} =the qualitative level of the same characteristics in product *j*

The technological progress or evolution of product J is quantified as the change in its quality over a specific time period:

$$TC_j = TP_j = \frac{\Delta Q_j}{\Delta t}$$

Specifically, price fluctuations can be broken down into two main factors: the "pure price effect" and the "quality/technological change" effect (Coccia, 2005a, pp.948-949; Saviotti, 1985, p.309ff). It is emphasized by Saviotti (1985, p. 315, original emphasis) that the hedonic price method has mainly been used with products. In order to apply this strategy to process technology, it is necessary to obtain cost/price data for each individual element as well as to characterize the process as a whole and its separate elements as sets of attributes. In addition, a sufficient quantity of "process models" ought to be accessible in order to produce results that are statistically significant.

The hedonic pricing method involves specific steps for assessing technological evolution. Firstly, to analyze the technological evolution of a product, it's essential to identify the product characteristics (Xij) and their relative importance (ai). These product characteristics can typically be found in technical literature, describing the internal aspects of technology. Engineers manipulate these technical characteristics to improve innovative devices over time. For instance, Saviotti (1985, p.310) mentions characteristics like the bore, stroke, and number of revolutions per minute (RPM) of a motor car engine, which engineers manipulate to achieve the desired engine power and fuel consumption. Carranza (2010) demonstrated, using a hedonic price model, that camera prices decreased over time while controlling for quality improvements, measured by technical characteristics like resolution and digital zoom. This approach is crucial in markets because technology adopters are interested in the technical features a product provides to meet their needs. Secondly, the hedonic pricing method entails the selection of a set of variables that represent the technical characteristics of a product. Thirdly, to analyze the evolution of technology after identifying the technical characteristics of a given product, a functional form is used based on the relationship between quality and product characteristics. This functional form should show that positive increases in the levels of technical characteristics lead to an enhancement in quality. The simplest representation of this relationship is a linear combination. However, the connection between the price and technical characteristics of a product may not be linear and can take the form of functions such as semilog or log-log functions (Triplett, 1985). The choice of the functional form for the hedonic pricing relationship largely depends on empirical considerations (Saviotti, 1985). In a log-log model of hedonic pricing, product prices are regressed with respect to technical characteristics, as represented in the following equation:

$$logP_j = \alpha_0 + \alpha_1 logX_{1t} + \cdots + \alpha_i logX_{it} + \cdots + \alpha_n logX_{nt}$$

where

P_j= price of a product over time. It represents the value that firm has given to a specific product

X_i= explanatory variables are given by technical characteristics of product over time, such as weight, efficiency, velocity, etc.

a_0= constant

a_i= coefficient of regression ($i=1, \ldots, n$)

This approach provides an effective means to elucidate the dynamic development of technology functionality, enabling the detection of technological pathways aimed at satisfying the needs of adopters and maintaining the competitive edge of firms in rapidly changing markets. The following section outlines the methods and materials employed in this study to analyze the evolution of smartphone technology.

3. Material and Methods

Specifically, price fluctuations can be broken down into two main factors: the "pure price effect" and the "quality/technological change" effect (Coccia, 2005a, pp.948-949; Saviotti, 1985, p.309ff). It is emphasized by Saviotti (1985, p. 315, original emphasis) that the hedonic price method has mainly been used with products. In order to apply this strategy to process technology, it is necessary to obtain cost/price data for each individual element as well as to characterize the process as a whole and its separate elements as sets of attributes. In addition, a sufficient quantity of "process models" ought to be accessible in order to produce results that are statistically significant. The process of technological development results in the emergence of a complex system (Sahal, 1981, p.33). Sahal (1981) contends that "evolution... relates to the very structure and function of the object (p.64)... involves a process of equilibrium governed by the internal dynamics of the object system (p.69)." Furthermore, short-term technological evolution results from changes within the system, while long-term evolution occurs through the formation of an integrated system, leading to increasingly comprehensive systems (Sahal, 1981, pp.73-74). In general, "the evolution of a technology often proceeds along more than one pathway so as to meet the requirements of its task environment" (Sahal, 1981, p.116). In conclusion, technical evolution is a complicated process that is influenced by a range of socioeconomic and technical variables, leading to a slow shift in technology from simplicity to complexity. Here, a hedonic pricing model is used to illustrate the suggested method of technological analysis and pinpoint the essential technical features determining the future directions of smartphone technology. Other simple methods are used in addition, the hedonic pricing method to evaluate the consistency of the findings on the technical paths of the new technology under study.

3.1. Data and Sources

According to Watanabe et al. (2012), smartphones are among the most important Information and Communication Technologies (ICTs) used worldwide. An oligopolistic structure results from brand concentration in the smartphone market, where a small number of companies control a disproportionately large market share (Lee & Lim, 2014). The trade publications tailored to the Italian market are the source of the data used in this analysis (Punto-Cellulare, 2018). More specifically, the study examines a sample of N = 738 smartphone models that were offered for sale in Italy from 2008 to 2018. The years 2012 through 2018 are the main focus of the data collecting. Table 1 provides a detailed breakdown of the sample composition by smartphone brands examined in this study.

Tablo 1

Sample of This Study

Brand of smartphone	N. models (2008-2018)
APPLE	16
ASUS	46
HTC	81
Huawei	121
LG	64
MOTOROLA	61
NOOKIA	112
SAMSUNG	105
SONY	80
ZTE	52
Total cases (sample)	738

3.2. Measures

In this approach, we consider the monetary value of smartphones, which is quantified using the practical unit of price in the market:

Price (P): This represents the prices of smartphones in Euros, reflecting their value in the Italian market during the period from 2012 to 2018. It's worth noting that some models may have been introduced in previous years. This measure of price is consistent with the relatively stable inflation prevailing in Europe during the study period.

The evolution of smartphone technology is assessed using Functional Measures of Technological characteristics (FMT) covering the years from 2008 to 2018. These FMTs encompass both major and minor innovations (cf., Sahal, 1981, pp.27-29) and include the following characteristics of smartphones: Display (in inches); Display resolution (in total pixels): Calculated as the product of the display size in rows and columns; Main Camera (megapixels, Mpx); Second Camera (megapixels, Mpx); Processor (GHz, GigaHertz); Memory (Gb, Gigabyte); RAM (Gb); Battery (milliampere hour, mAh).

3.3. Models and Data Analysis Procedure

The technical characteristics of smartphones have exhibited accelerated development since 2006, aligning with trends in the ICT market (cf., Lee & Lim, 2014). To identify the technological trajectories in the evolution of smartphones, we conduct an initial analysis involving the arithmetic, geometric, and exponential growth rates for each essential characteristic (i) under consideration (i = 1, ..., n).

Let:

FMTi, 2018 represent the level of technical characteristic i in 2018.

FMTi, 2008 represent the level of technical characteristic i in 2008.

This calculation involves taking the difference in the level of the technical characteristic between 2018 and 2008, divided by 10 years to obtain the annual arithmetic growth rate.

$$FMT_{i,2018} = FMT_{i,2008} + FMT_{i,2008}(r_{art} \cdot t)$$

$$FMT_{i,2018} - FMT_{i,2008} = FMT_{i,2008}(r_{art} \cdot t)$$

$$r_{art} = \frac{FMT_{i,2018} - FMT_{i,2008}}{FMT_{i,2008} \cdot t}$$

If the development of technical characteristic i (i=1, …, n) in smartphone technology is assumed to be of geometric type, the rate of growth is given by:

$$FMT_{i,2018} = FMT_{i,2008} \cdot \left(1 + r_{geom}\right)^{t}$$

$$Log\left(\frac{FMT_{i,2018}}{FMT_{i,2008}}\right) = t \cdot Log \cdot \left(1 + r_{geom}\right)$$

$$Log\,\frac{\left(\frac{FMT_{i,2018}}{FMT_{i,2008}}\right)}{t} = Log \cdot \left(1 + r_{geom}\right)$$

$$r_{geom} = \frac{\left(\frac{FMT_{i,2018}}{FMT_{i,2008}}\right)}{t} - 1$$

If the development of technical characteristic i (i=1, …, n) in smartphone technology is of exponential type, the exponential rate of growth is given by:

$$FMT_{i,2018} = FMT_{i,2008}e^{rexp_i t}$$

$$\frac{FMT_{i,2018}}{FMT_{i,2008}} = e^{rexp_i t}$$

$$log\left(\frac{FMT_{i,2018}}{FMT_{i,2008}}\right) = r_{exp_i} t$$

$r_{exp_i} = \frac{log\left(\frac{FMT_{i,2018}}{FMT_{i,2008}}\right)}{t}$ = rate of exponential growth of technological characteristic *i*

The primary technology analysis employed here to understand the evolution of technology is based on the hedonic price method. To operationalize this approach, we utilize a log-log model of hedonic pricing, wherein smartphone prices are regressed with respect to technological characteristics.

ln(P) represents the natural logarithm of the smartphone price.

α is the intercept of the regression model.

β 1, β2, β3, β4, β5, β6, β7, β8 are the coefficients associated with the respective natural logarithms of the technological characteristics.

ε represents the error term.

This log-log model allows us to assess the relationships between smartphone prices and the logarithms of various technological characteristics.

$$log\ P_{smartphone} = \alpha_0 + \alpha_1 log\ Display\ in\ inch + \cdots + \alpha_i log\ Camera\ (megapixel) + \cdots + \alpha_n logRAM\ Gb \quad (1)$$

a_0= constant

a_i= coefficient of regression (*i=1, ..., n*)

A t-test is performed for each coefficient in the hedonic price equation. The standardized values of these coefficients, denoted as ai, provide insights into the most crucial technological trajectories that drive the technological progress of a given product over time. Additionally, this study employs multiple regression analysis with model [1] using the stepwise method (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).

Hierarchical regression is also used in the study to validate the findings and evaluate their generalizability. In order to ascertain whether extra variables of interest explain a statistically meaningful amount of variance in the dependent variable (price of smartphone) after accounting for all other variables, this strategy uses a linear model akin to Eq. [1]. This technique assesses whether the additional variables significantly increase R2, which is the percentage of the dependent variable's variance that the model can explain.

The hierarchical regression models are structured as follows:

Model 1: Explanatory variables include technical characteristics of smartphones that interact with the visual perception of adopters, such as display resolution in pixels and camera resolution in megapixels.

Model 2: In addition to Model 1, this model includes a variable measuring the technical characteristic of storage and functionality of smartphones, specifically RAM in Gb.

Model 3: In addition to Model 2, this model includes a variable related to the long battery life in mAh, which allows for extended smartphone usage to meet adopters' needs.

Hierarchical regression calculates $\Delta R2$ and ΔF to determine if Model 2 and Model 3 perform better than Model 1. These regression equations are estimated using the Ordinary Least Squares method, and the statistical analyses are conducted using IBM SPSS Statistics version 21.

4. Results

4.1. Preliminary Analyses

Table 1A in the Appendix presents descriptive statistics using a natural logarithmic scale. Typically, variables transformed into natural logarithms tend to exhibit a normal distribution. However, in this case, certain technical characteristics like Display in inches, 1st Camera Mpx, Processor, and Memory do not follow a normal distribution when left untransformed. Therefore, if these variables do exhibit a normal distribution in their original form, they are included in the statistical analyses. Otherwise, variables that do not display a normal distribution are excluded from the statistical analyses. Ensuring the normality of the distribution of FMT (a variable of interest) is crucial for accurate parametric analyses, as it helps reduce distortions and prevents misleading results.

Table 2A in the Appendix presents bivariate correlations between variables with a normal distribution. Notably, the most significant bivariate correlations among the studied variables are as follows: log price and log resolution display in pixels (r=0.66, p-value=0.01), log price and processor GHz (r=0.61, p-value=0.01), log price and log RAM Gb (r=0.58, p-value=0.01), log price and display in inches (r=0.56, p-value=0.01). The correlation coefficient is slightly lower between log price and log battery mAh (r=0.51, p-value=0.01), as well as log price and log 2nd Camera Mpx (r=0.41, p-value=0.01).

In the main text, Table 2 presents the rates of growth in technical characteristics of smartphone technology, considering arithmetic, geometric, and exponential measures. While these growth rates may differ in magnitude, the ranking of crucial technical characteristics with the highest evolution remains consistent, with the highest to lowest value maintained across these different equations. Table 2 highlights that the technical characteristics in smartphone technology with the most significant exponential growth (rexp) from 2008 to 2018, in descending order, are Gb of memory (rexp=1.02), Gb of RAM (rexp=0.67), resolution display in pixels (rexp=0.62), Mpx of the main camera (rexp=0.54), and Mpx of the second camera (rexp=0.45). In contrast, the slowest growth rates are observed for mAh of the battery (rexp=0.19) and inches of display (rexp=0.16).

Based on these growth rates in Table 2, the first technical characteristic to experience significant growth is memory Gb and RAM. This can be attributed to the increasing need for smartphones to have ample memory and RAM to support continuous software application updates and enhanced web surfing and functionality. The accelerated improvement of other technical characteristics, such as higher display resolution and camera resolution, is associated with improved displays, images, and videos, ultimately enhancing the visual perception and satisfaction of users (cf., Bhalla & Proffitt, 1999; Iriki et al., 1996; Leutgeb et al., 2005).

Table 2

Rates of Exponential, Geometric and Arithmetic Growth in Technical Characteristics of Smartphone Technology from 2008 to 2018

Rates of growth	Memory Gb	RAM Gb	Resolution Display Pixels	1st Camera	2nd Camera	Processor GHz	Battery mAh	Display in inches

				Megapixels	Megapixels			
r exponential	1.015	0.668	0.623	0.542	0.454	0.331	0.190	0.155
r geometric	1.759	0.951	0.864	0.720	0.574	0.393	0.209	0.167
r arithmetic	2559.900	79.900	50.525	22.567	9.233	2.645	0.567	0.369

4.2. Main Analyses

Table 3 presents findings regarding the evolutionary pathways of smartphone technology. On average, these pathways are primarily driven by two key factors: the resolution of the display in pixels and the performance of RAM in Gb, as indicated by the standardized coefficients of regression. The Ordinary Least Squares (OLS) estimation of the model in Table 3 reveals specific insights into how changes in these factors affect smartphone prices:

Display Resolution: A 1% increase in the level of quality in Display resolution (measured in pixels) is associated with an approximately 0.44% increase in the expected price of smartphones. This relationship is statistically significant, with a p-value of less than 0.001. In practical terms, higher display resolution contributes positively to smartphone prices, reflecting the importance of visual quality to consumers.

RAM Performance: A 1% increase in the level of RAM in Gb (Giga bytes) is linked to approximately a 0.27% increase in the expected price of smartphones. This relationship is also statistically significant, with a p-value of less than 0.001. This suggests that smartphones with greater RAM capacity tend to command higher prices in the market.

These findings emphasize the critical role that display resolution and RAM performance play in shaping the technological evolution of smartphones and, consequently, their pricing dynamics. It underscores the significance of these technical characteristics in influencing consumers' purchasing decisions and the competitive landscape within the smartphone industry.

Table 3

Estimated Relationship for the Evolution of Smartphone Technology (Log-Log Model)

Dependent variable: *log* Price			
Smartphone	*Unstandardized Coefficient*	*Standardized Coefficient*	*t-test*
Constant. α (St. Err.)	1.41 (0.80)		1.77
Coefficient *log* Resolution Display in pixels (St. Err.)	0.44*** (0.04)	0.58	11.62

Coefficient *log* 2nd Camera megapixel (St. Err.)	−0.05* (0.03)	−0.1	−2.06
Coefficient *log* RAM Gb (St. Err.)	0.27*** (0.05)	0.30	2.50
Coefficient *log* Battery mAh (St. Err.)	−0.32*** (0.1)	−0.15	−3.23
R^2 *adj. adj.* *(St. Err. of the Estimate)*	0.44 (0.43)		
F *(sign.)*	124.16 (0.001)		

Note. Dependent variable: *log* Price; *** = *p-value*< .001; ** = *p-value*< .010; * = *p-value*< .050

Table 4

Model Summary with Stepwise Method

Model	*Adjusted R Square (std. error of the estimate)*	*F*	*Sign.*
1 a.	0.415 (0.438)	436.27	0.001
2 b.	0.427 (0.433)	230.86	0.001
3 c.	0.441 (0.428)	163.27	0.001
4 d.	0.444 (0.427)	124.16	0.001

Note. These are different regression models with varying sets of predictor variables, and the dependent variable in each case is the log price in euros. Here's a breakdown of each model: a) Model with one predictor: Dependent Variable: log price in euros. Predictors: (Constant), log resolution display in pixels (px). b) Model with two predictors: Dependent Variable: log price in euros. Predictors: (Constant), log resolution display in pixels (px), log RAM in Gb. c) Model with three predictors: Dependent Variable: log price in euros. Predictors: (Constant), log resolution display in pixels (px), log RAM in Gb, log Battery in mAh. d) Model with four predictors: Dependent Variable: log price in euros. Predictors: (Constant), log resolution display in pixels (px), log RAM in Gb, log Battery in mAh, log second camera in Mpx.

These models are used to analyze the relationship between the log price of a smartphone in euros and the specified predictor variables, which include log resolution display, log RAM, log battery capacity, and log second camera resolution. Depending on the model, different combinations of these predictor variables are used to predict the log price of the smartphone.

The results of the multiple regression analysis with a stepwise method provide valuable insights into the factors influencing smartphone prices. Here are the key findings from the analysis:

Initial Model (Table 3): The initial model suggests that approximately 42% of the variation in smartphone prices can be linearly attributed to the resolution of the display in pixels. This finding indicates the strong influence of display quality on smartphone pricing, with higher-resolution displays commanding higher prices.

Adding Other Variables (Table 4): When additional variables are introduced into the model, such as RAM capacity and camera specifications, the goodness of fit improves by about 2%. This suggests that these variables contribute to explaining variations in smartphone prices. Model 4d, which includes these additional variables, achieves a goodness of fit similar to the estimated relationship in Table 3. This implies that these technical characteristics also play a role in determining smartphone prices, albeit to a slightly lesser extent than display resolution.

Table 5: Hierarchical Regression: Approximately 41% of the difference in smartphone costs can be explained by Model 1, which incorporates technical features linked to visual perception (resolution display in pixels and second camera in Mpx). This demonstrates how crucial these technical aspects connected to appearance are in affecting pricing choices.

In conclusion, the results demonstrate how much display resolution affects smartphone costs, indicating that users are prepared to pay more for gadgets with better screens. Apart from display quality, additional technological factors that affect price are RAM size and camera specs. However, their impact is marginally smaller than that of display quality.

Table 5

Hierarchical Regression Analysis of Predictors of Smartphone Prices

	Model 1	*Model 2*	*Model 3*
Constant λ_0	–1.94***	–0.61	1.41
(St. Err.)	(0.43)	(0.50)	(0.80)
log (Resolution Display in Pixels)			
Coefficient λ_1	0.52***	0.41***	0.44***
(St. Err.)	(0.03)	(0.04)	(0.04)
log 2nd camera in Megapixels			
Coefficient λ_2	–0.02	–0.08***	–0.05*
(St. Err.)	(0.02)	(0.03)	(0.03)
log RAM Gb			
Coefficient λ_3		0.24***	0.27***
(St. Err.)		(0.05)	(0.05)
log Battery mAh			
Coefficient λ_4			–0.32***
(St. Err.)			(0.10
F	218.56	159.61	124.16
Sig.	0.001	0.001	0.001

R^2 adj.	0.41	0.436	0.444
(St. Err. of the Estimate)	(0.44)	(0.43)	(0.43)
ΔR^2	0.41	0.023	0.009
ΔF	218.56***	24.78***	10.43***

Note. Dependent variable: log Price; *** = p-value< .001; ** = p-value< .010; * = p-value< .050

The hierarchical regression analysis provides further insights into the factors influencing smartphone prices, including the contribution of different technical characteristics:

Model 2: The introduction of the technical characteristic related to storage and functionality of smartphones, represented by RAM capacity in Gb, explains an additional 2.3% of the variance in smartphone prices over and above the variables associated with visual perception. This is a significant contribution (p-value < 0.001) and underscores the importance of RAM capacity in pricing.

Model 3: When the variable representing the long battery life in mAh is added to the model, it explains an additional 1% of the variance in smartphone prices, again with a significant contribution (p-value < 0.001). This suggests that a longer-lasting battery is associated with higher smartphone prices.

Table 6 furnishes descriptive statistics pertaining to the evolutionary advancements in technical attributes of smartphone technology between 2008 and 2018. The maximum values highlighted in the table signify the peak levels attained by these characteristics in 2018. This tabulated data serves as a concise overview of the progression of diverse technical facets within smartphones over the specified research duration, providing valuable insights into the transformation of these features.

Table 6

Descriptive Statistics of the Evolutionary Stepwise Improvements of Technical Characteristics in Smartphone Technology from 2008 to 2018

Technical characteristics	N	Minimum	Maximum	Mean	Std. Deviation
Display in inches	55	1.45	6.80	4.44	1.49
Resolution Display total pixels	33	16384.00	8294400.00	1411271.03	1845077.45
1st Camera megapixels	38	0.30	68.00	18.50	13.72
2nd Camera megapixels	25	0.30	28.00	7.85	8.25
Processor GHz	29	0.10	2.80	1.45	0.81
Memory Gb	30	0.01	256.00	17.25	52.02
RAM Gb	15	0.04	32.00	4.96	8.39
Battery MAh	123	750.00	5000.00	2411.87	931.22

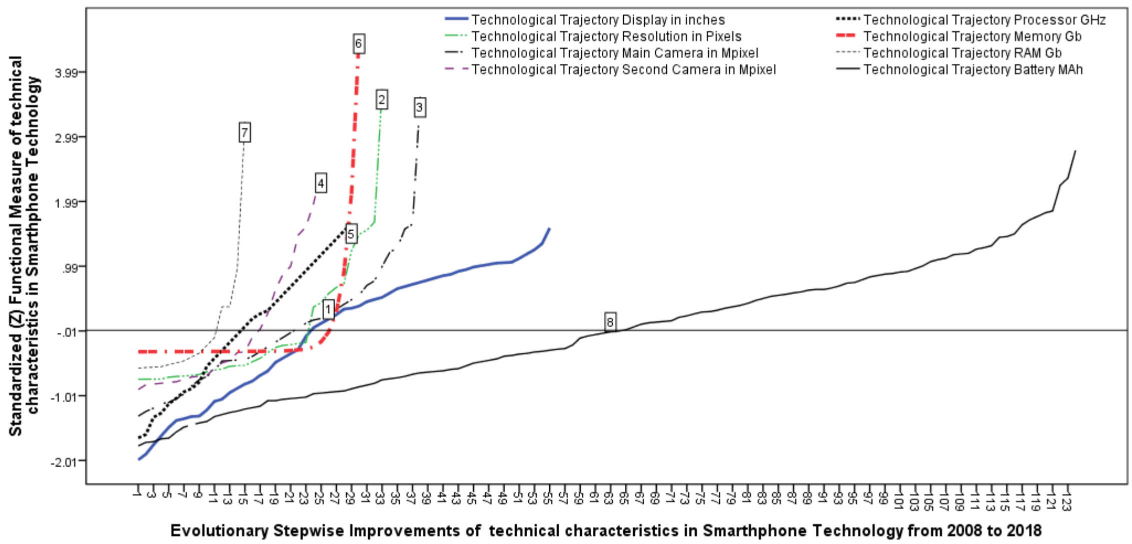

Figure 1. Technological Trajectories of the Evolution of Smartphone Technology from 2008 to 2018

Figure 1 visually conveys the trajectories of technological development, illustrating the evolutionary enhancements in various technical attributes of smartphone technology from 2008 to 2018. The figure emphasizes two distinct patterns in the technological progression of these characteristics:

Arithmetic Growth Trajectories: These are noticeable for the technological advancements in battery capacity (mAh) and display size (inches), denoted by trends labeled as "1" and "8" in Figure 1.

Exponential Growth Trajectories: These trajectories are apparent for the technological advancement of several crucial characteristics, including RAM in Gb, 1st and 2nd camera resolution in Mpx, memory in Gb, display resolution in total pixels, and processor speed in GHz. These exponential growth patterns are represented by trends labeled as "2" through "7" in Figure 1.

Figure 1's representation of technological trajectories suggests that technical characteristics that improve user experience visually (high definition displays and better quality cameras), increase storage capacity (measured in Gb by memory and RAM), and improve functionality (processor speed in GHz) are the main drivers of smartphone technology evolution.

Table 7 further supports these findings by revealing a very high coefficient of correlation between the technical characteristics of smartphone technology and processor speed (GHz), which serves as a proxy for the overall performance of smartphone technology. The strong correlations (with coefficients greater than 0.81 and a p-value of 0.001) imply that the evolution of smartphone technology is a coevolutionary process, where different subsystems of technology within the complex smartphone system interact and contribute to its development.

Table 7

Correlation between Evolution of Technical Characteristics within Smartphone Technology

		log Display inches	*log* Resolution Pixels	*log* Main Camera Mpx	*log* Second Camera Mpx	*log* Processor GHz	*log* Memory Gb	*log* RAM Gb	*Log* battery MAh
log Processor GHz	Pearson Correlation	.966**	.955**	.985**	.923**	1	.817**	.944**	.263
	Sig. (2-tailed)	.001	.001	.001	.001		.001	.001	.168
	N	29	29	29	25	29	29	15	29

Note. **. Correlation is significant at the 0.01 level (2-tailed).

5. Discussion and concluding observations

Using a hedonic price method and other techniques, this article provides an informative examination of the evolution of smartphone technology, focusing on the key technical features that propel technological advancement. The results offer important insights into the dynamics of technical growth in the smartphone market and throw light on the elements influencing the evolutionary routes of smartphones.

Among the study's main conclusions are: The report identified the key drivers of technological growth in smartphones as display resolution in pixels and RAM performance in gigabytes. These technological features are crucial for meeting customer needs and maintaining competitive advantage because they have a big influence on smartphone prices.

Visual Perception and Functionality: As smartphone technology has advanced, factors like camera quality and display resolution that are directly tied to visual perception have become increasingly important. According to this research, RAM, camera resolution, memory, and display resolution have all grown exponentially. This highlights how crucial it is to satisfy users' expectations for excellent visual experiences.

Coevolution of Technologies: The study highlights the coevolution of technologies within the smartphone ecosystem. Smartphone technology advances are closely linked to innovations in associated technologies, such as digital cameras, display technologies (e.g., HD, 4K), and other subsystems. Learning effects and cumulative knowledge contribute to the assimilation of new technologies into smartphones, fostering innovation and diversification.

Implications for Technology Policy: Management techniques and technology policy can both benefit from the knowledge gathered from this study. Policymakers and technology managers can more effectively allocate resources and support research and development efforts in areas expected to undergo fast evolution by understanding the forces driving technological advancement and evolutionary pathways.

However, the article also acknowledges certain limitations and challenges in applying the hedonic price method and other techniques for technological analysis. These include the need for improvements in the theoretical framework and empirical evidence, the requirement for a homogeneous market, and the necessity for accurate knowledge of the technology under study.

In conclusion, this study advances our knowledge of how smartphone technology changes over time and emphasizes the importance of particular technological traits in promoting this change. It draws attention to how interrelated technologies are inside complex systems and how market needs and consumer expectations influence the direction of technical advancement. To continue advancing the analysis of technological growth and evolution, more investigation and improvement of the hedonic price approach are recommended. Sahal (1985, p.9) about limitations of the hedonic technique argues that:

> “First, the technique works best in cases of a distinct product technology with clearly defined characteristics (e.g., computers, automobiles, and farm tractors). It cannot easily be applied to cases of a process technology (e.g., the oxygen-steel process, the catalytic cracking process of petroleum refining, and nuclear power generation). Second, the technique is evidently inapplicable to technological changes in areas not governed by the free play of supply and demand (e.g., military or aerospace items, scientific instruments, and genetic engineering products). Third, the Hedonic approach is unsuitable for international comparisons because of significant differences in factor prices among different countries. Fourth, the application of the technique, in practice, is beset by a number

of difficulties. One main reason for this is that the data are most often available in the form of list prices which do not accurately represent the quality of the product."

In summary, the methodology used in this study is still relevant and useful for elucidating the particular technological traits that propel the development of modern technology such as cellphones. In the end, it helps in the prediction of rapidly evolving technological trajectories for competitive advantages in new product development. It is a significant first step in applying the hedonic pricing method to analyze crucial technological characteristics that support technological evolution.

Beyond its particular results, the study is important because it could lay the groundwork for the creation of more sophisticated theoretical frameworks for technical forecasting and analysis. Future studies can use the hedonic pricing technique to identify and predict technological trajectories that change quickly in volatile and dynamic marketplaces. It's crucial to understand that finding a thorough approach to identifying crucial technological evolution pathways—particularly those impacted by the actions of other technologies—remains a difficult undertaking. Technology's dynamic and complex nature presents a number of characteristics that are not constant in space, time, or across different technology domains. Therefore, in order to improve and broaden our understanding of the evolution and invention of technology, continual study activities are required. In conclusion, the methodology used in this study has the potential to make a substantial contribution to the field of technology analysis and forecasting, while also acknowledging that continued research and methodological flexibility are necessary due to the dynamic and complex nature of technology. In this context, Wright (1997, p.1562) properly claims that: "In the world of technological change, bounded rationality is the rule."

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APPENDIX

Table 1A

Descriptive Statistics of Technical Characteristics of Smartphone

		log Price in Euros	*log* Display in inches	*log* Resolution display pixels	*log* 1st Camera megapixel	*log* 2nd Camera megapixel	*log* Processor GHz	*log* Memory Gb	*log* RAM Gb	*log* Battery mAh
N	Valid	735	733	733	724	624	673	716	656	727
	Missing	0	2	2	11	111	62	19	79	8
Mean		5.206	1.551	13.735	2.303	1.416	0.414	2.710	0.717	7.792
Std. Deviation		0.647	0.260	1.157	0.786	1.073	0.438	1.443	0.742	0.381
Skewness		-.034	-2.018	-1.094	-1.528	-1.111	-2.597	-1.669	-.750	-.783
Std. Error of Skewness		.090	.090	.090	.091	.098	.094	.091	.095	.091
Kurtosis		.379	4.125	1.174	4.507	.780	12.780	4.083	2.346	.092
Std. Error of Kurtosis		.180	.180	.180	.181	.195	.188	.182	.191	.181
Minimum		3.07	.372	9.704	-1.204	-1.204	-2.283	-5.298	-3.219	6.620
Maximum		7.44	1.917	15.931	4.220	3.332	1.030	5.545	3.466	8.517

Table 2A

Correlations

		log Price Euro	*log* Resolution display pixels	*log* 2nd Camera megapixel	*log* RAM Gb	*log* Battery mAh	Display in inches	Processor in GHz
log Price Euro	Pearson Correlation	1						
	Sig. (2-tailed)							
	N	735						
log Resolution Display pixels	Pearson Correlation	.655**	1					
	Sig. (2-tailed)	.001						
	N	733	733					
log 2nd Camera megapixels	Pearson Correlation	.408**	.673**	1				
	Sig. (2-tailed)	.001	.001					
	N	624	624	624				
log RAM Gb	Pearson Correlation	.575**	.714**	.736**	1			
	Sig. (2-tailed)	.001	.001	.001				
	N	656	656	617	656			
log Battery MAh	Pearson Correlation	.509**	.849**	.689**	.683**	1		
	Sig. (2-tailed)	.001	.001	.001	.001			
	N	727	727	624	654	727		
Display in inches	Pearson Correlation	.564**	.905**	.697**	.643**	.914**	1	
	Sig. (2-tailed)	.001	.001	.001	.001	.001		
	N	733	733	624	656	727	733	
Processor GHz	Pearson Correlation	.609**	.838**	.562**	.781**	.669**	.711**	1
	Sig. (2-tailed)	.001	.001	.001	.001	.001	.001	
	N	673	673	609	638	670	673	673

Note. ** Correlation is significant at the 0.01 level (2-tailed).