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Knowledge management in high-tech products and customer satisfaction: The smartphone industry

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A R T I C L E I N F O

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A B S T R A C T

Knowledge management for high-tech products, based on innovative product architectures and components, is a critical issue for market satisfaction. Scientific research has widely investigated the competitive advantage that product knowledge owned by Original Equipment Manufacturers (OEMs) has on product innovation. Nonetheless, the linkage between OEMs' accumulated knowledge on single modules and customer satisfaction is less explored. The article aims at identifying what level of knowledge OEMs should have on both the single modules and the whole product architecture to achieve better customer satisfaction. The research method uses text mining techniques on patent documents to detect associations of modules and product knowledge with patented technologies. Regression analyses are thereafter performed to test the linkage of such a knowledge with customer satisfaction using SPSS. The explorative analysis of the smartphone industry demonstrates that an effect on the final market is found for specific modules, such as application processor, camera and touchscreen controller.

Introduction

In an era of globalization, featured by new digital technologies and extremely variable markets, products are becoming increasingly complex and customized (Cammarano et al., 2021; Cappa et al., 2021; Olsen and Tomlin, 2020). Effectively managing the complexity of high-tech products featured by modular architecture may require a specific level of knowledge. Knowledge management is an essential and strategic element for a company's competitive advantage (Gloet and Terziovski, 2004; Pereira et al., 2021; Yang, 2010). In particular, companies performance is highly dependent on the exploitation of internal knowledge resources to create greater value for the end product (Alavi and Leidner, 2001). From managerial literature, several theoretical developments, such as the 'Knowledge Based-View', affirm that the innovative abilities of companies strictly depend on intellectual capital and knowledge (Lam et al., 2021; Subramaniam and Youndt, 2005; Xie et al., 2018b). Moreover, it is well-known that, in order to gain cost and production flexibility, many high-tech companies employ modular product architectures as a competitive strategy to manage product complexity (Garud and Kumaraswamy, 1995; Grant, 2005). Specifically, a modular product architecture simplifies the complexity of product development by defining the design of the single modules which will be integrated into the end product through standard interfaces (Baldwin and Clark, 2002).

Among high-tech sectors, the smartphone industry is particularly interesting since it is based on modular and complex product architectures with a high variability in market demand (Tseng and Chiang, 2013). Within this market, OEMs are constantly pressured by consumers for continuous product innovations that allow them to keep a competitive advantage over other competitors (Dedrick and Kraemer, 2016; Muhammad et al., 2021; Varriale et al., 2022a). Research on OEMs knowledge and experience on product architecture is commonly recognized in high-tech industries (Lee and Veloso, 2008; Yoon et al., 2017); however it is not clear whether knowledge on single modules owned by the OEM has a potential impact on customer satisfaction. The research focused more on the effects that efficient knowledge management within end product has on product innovation and less on the different levels of knowledge, globally and on single modules, that an OEM should accumulate internally to achieve better customer satisfaction.

Hence, the aim of the article is to investigate what level of knowledge OEMs should have both on single modules and on product to gain competitive advantage. The article identifies different levels of knowledge that an OEM preserves internally to define capacity and focalization both on the product and on the single modules. The study

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segments OEM knowledge into product knowledge and a module knowledge. Additionally, module-level knowledge is segmented into: a) a general module knowledge, regardless of its application in a specific end product; b) a specific module knowledge related to its application for the smartphone. This study is one of the first explorations that associates the importance of knowledge on the modules of an end product to achieve better customer satisfaction. The originality of the work is to detect for which modules, the OEM should accumulate knowledge in order to improve customer satisfaction. In addition, the study suggests what level of knowledge (general or specific) the OEM should preserve on each module of a smartphone to achieve competitive advantage on the final market.

The suggested methodology uses an original classification of patent data based on content analysis that allows to filter and select subsets of patents that can be linked to a product, improving traditional filtering techniques based on International Patent Classification (Parraguez et al., 2020; Venugopalan and Rai, 2015). It is commonly recognized that the concept of knowledge is linked to patent data, which are known as a tool for measuring and analysing the knowledge of a company, in order to acquire significant quantitative data (Cammarano et al., 2022a, 2022b; Trajtenberg and Jaffe, 2002).

The following section presents a literature review on modular product architectures, knowledge management of products and modules and the topic of customer satisfaction. Next, the patent-based method for detecting raw technologies with specific modules is defined. Discussions on the theoretical and practical implications will be shown after a section that describes the results. Finally, conclusions close the article.

Literature review

Overview of modular product architectures features

In high-tech industries, characterized by complex products, companies are increasingly required to manage different modules and integrate them within an architecture (Zhou et al., 2019). When a product has a large number of components and requires in-depth knowledge of several modules from both a scientific and a technological perspective, it is classified as complex. (Prencipe, 2007). In recent years, research on modular product architectures has been an important topic in practical and theoretical research (Meissner et al., 2021; Sanchez and Shibata, 2021; Sorkun and Furlan, 2017). Modularity can be considered as a product design strategy aimed at specifying standard interfaces among the modules that make up a product, while the term “modularization” identifies the process that affects product design and the boundaries of business knowledge. Both concepts are deeply intertwined (Brusoni and Prencipe, 2001; MacDuffie, 2013). Conceptually, modularity reduces product complexity into distinctly separable modules, so that each of them can be developed separately without the required coordination with other ones (Langlois, 2002).

Most studies showed that modular product architectures positively impact on product innovation (Vickery et al., 2016; Vos et al., 2018), promoting competitive performance (Zhang et al., 2019) and increasing the launch speed of new products (Vickery et al., 2016). Ideally, the combination of separable modules and standardized interfaces allows for better interoperability, reduces coordination costs and improves autonomous innovation (MacDuffie, 2013). Moreover, modular product architectures allow a reduction in production costs for the OEM by outsourcing the production of modules to external suppliers (Garud and Kumaraswamy, 1995; Varriale et al., 2022b). Finally, the time-to-market is reduced because the different modules can be realized simultaneously and independently (Persson et al., 2016). In some cases, suppliers are directly involved in the new modules and products development in order to embrace open innovation practices (Colombo et al., 2011; Jin et al., 2022). Several studies on modularity have addressed the issue of joint development and collaboration in open innovation practices to gain a greater competitive advantage in the final market (Ozman, 2011). In particular, companies can benefit from shared innovation and acquire, design and evaluate innovative competitive strategies for modular systems (Colombo et al., 2020).

In this context, research has also highlighted the disadvantages of modular product architecture related to product innovation (Lau et al., 2011). Innovation of end product is often based on the innovation of single modules and the innovation of the entire architecture is limited (Shapiro and Varian, 1999). Additionally, modular product architecture reduces the sharing of valuable tacit knowledge among module team members. The team optimizes module performance but ignores overall product innovation (Ethiraj and Levinthal, 2004; Xie et al., 2018a). Finally, OEMs may need to select specific modules from external suppliers to reduce their production costs and, for this reason, they may lose part of their knowledge on modules to integrate into the whole product architecture (Garud and Kumaraswamy, 1995). However, knowledge incorporated in the outsourced module can be acquired from external suppliers. This could indirectly delineate open innovation practices (Moya et al., 2020; Scaringella, 2018). In the case of black-box approaches, the actors do not have to collaborate closely together, but rather the innovative technology of the module is acquired by the OEM and, indirectly, it can gain further specific knowledge (Karhade and Dong, 2021). Therefore, module innovation by suppliers generates several advantages for the OEM, influencing the overall quality of the final product architecture (Cammarano et al., 2022a, 2022b).

The scientific research did not investigate what knowledge the OEM should have on each module and this study aims at filling such a gap and contributing to the understanding of the phenomenon.

Knowledge management on products and modules

In the last decades, rapid changes in the performance and customization of high-tech products highlighted critical issues in knowledge management to improve market performance. As new fields of knowledge constantly increase, one of the main challenges is defining the boundaries of a company’s knowledge. Companies should define what knowledge they should retain internally. In fact, products developed by high-tech companies are increasingly “multi-technological”. Therefore, firms focus their technological knowledge in a wider range of technological fields in order to achieve competitive advantage in the market (Brusoni and Prencipe, 2001). In this scenario, it is crucial for the OEM to manage knowledge inflows and outflows following open innovation theories (Pustovrh et al., 2017; Tran et al., 2022; Zheng et al., 2022). According to the open innovation paradigm, external knowledge sources are acquired to improve revenues and innovation performance (Torres de Oliveira et al., 2022; Vrontis et al., 2022; Wu et al., 2021). In this case, knowledge flows may come indirectly from suppliers of highly innovative components through the exchange of specific modules (Cassiman and Valentini, 2016; Chiang and Hung, 2010; Czarnitzki and Thorwarth, 2012; S. Kim et al., 2016). In addition to expanding its knowledge and experience through collaboration with its suppliers, the OEM can increase its body of knowledge through the acquisition of innovative components (Erzurumlu, 2010; Lin et al., 2020).

In literature, two types of knowledge for complex products are distinguished: the knowledge on modules and the knowledge on the whole product architecture (Henderson and Clark, 1990; Tallman et al., 2004). Both affected OEM market performance results (Yoon et al., 2017). Module knowledge is about knowing each physical subsystem of a module and how it is designed. It consists of the accumulated knowledge within specific technologies related to identifiable physical parts inside a system (Schulze and Brojerdi, 2012; Tallman et al., 2004). Instead, product architecture knowledge is the knowledge on how modules are integrated and connected to each other in a coherent way and how it impacts on the overall system and on its single modules (Baldwin, 2018; Henderson and Clark, 1990; Zhou et al., 2019). It involves communication channels, problem-solving strategies that promote the coordination and integration of module knowledge into complex products (Henderson and Cockburn, 1994). In this case, product architecture knowledge may include information disseminated among OEMs' designers.

However, if the product architecture is complex, the OEM should accumulate high levels of knowledge even when the modules are technologically stable. Knowledge at the module level is the key element in being able to innovate complex products. In order to modify complex products by innovating modules, a higher level of knowledge is required (Galvin and Rice, 2008). Prencipe (2007) affirms that companies, in order to have a competitive advantage, should develop and retain knowledge to manage the integration of new modules. In addition, Brusoni et al. (2001) found that multi-technological companies based on high technological changes should invest in internal knowledge that is increasingly greater than what they need for production to reduce technological uncertainty at the end product level. The recent increase in complexity of high-tech products affected the way in which a module interacts with the others, increasing potential and unexpected problems for the integration of modules into the architecture (Brusoni and Prencipe, 2011). For instance, Galvin and Rice (2008) pointed out that product design and development require both module and product architecture knowledge integrated into an "information structure". Takeishi (2001) focused scientific attention on specific modules that OEMs should keep and know internally in order to properly integrate them into their product architecture. Brusoni et al. (2001) observed that a systems integrator can be essential for integrating modules and retain deeper knowledge in order to combine different technologies. Some authors suppose that maintaining both module and product architecture knowledge is important for designing innovations in new product development (Burton et al., 2020). OEMs should maintain not only product-level knowledge internally, but also module-level knowledge (Furlan et al., 2014).

The empirical evidence that OEMs can successfully retain product architecture knowledge while simultaneously maintaining high module knowledge is still unexplored. Hence, this study aims to understand how the OEM's knowledge on modules for a complex product is linked to a better customer satisfaction. The study investigates on which modules a company should retain knowledge in order to achieve competitive advantage in the market, i.e. the customer satisfaction. The contribution of this work suggests what level of knowledge (general or specific) the OEM should preserve on each module of a smartphone to achieve competitive advantage on the final market.

The linkage among customer satisfaction, modular products and knowledge management

Although definitions of customer satisfaction are varied and different in the literature, it is possible to frame this concept by considering three components: emotional response, particular focus and, particular time. Specifically, emotional response refers to affective evaluation during the purchase and use of a product or service (Edvardsson et al., 2000; Eshghi et al., 2007). The second component refers to the experience linked to the expectations and product consumption. Customers are satisfied if their expectations and purchasing experience are met, and they are enticed to buy the same product or service again (Parasuraman et al., 1994). The third component refers to the time of product use after its evaluation and selection based on accumulated experience (Giese et al., 2009). Therefore, customer satisfaction is the combination of emotional satisfaction, satisfaction of expectations and satisfaction of costumer needs (Lam et al., 2004). Customer satisfaction is one of the most commonly used metrics to investigate market performance in various sectors such as automotive (Gaspar et al., 2014), pharmaceuticals (Cobelli and Chiarini, 2020), electronics (Kuo and Nakhata, 2019), public sector (Agostino et al., 2021) and services (Venkatakrishnan et al., 2023). In the smartphone sector, this indicator has been widely used in several studies (Ling et al., 2006; Türkyilmaz and Özkan, 2007). For example, Ha and Park (2013) demonstrated through an online survey among smartphone users that hedonic advantage, utilitarian advantage, alternative attractiveness and non-monetary cost are indicators associated with customer satisfaction. Moreover, Kim et al. (2016), through a face-to-face survey method, demonstrated that device features (usability, functions and design) and company factors (brand image and customer service) significantly influence customer satisfaction. Several authors have measured customer satisfaction according to different attributes such as: design, applications, functions, usability and price (Kim et al., 2015; Xu et al., 2015). There are authors who have assessed customer satisfaction through the smartphone design; others who have analysed its ease of use and operating features (Oghuma et al., 2016; Tan and Sie, 2015). However, beyond surveys and face-to-face interviews, it is becoming increasingly important to measure customer satisfaction through online reviews and opinions (Gupta and Sebastian, 2018; Riva and Agostino, 2022; Trappey et al., 2018). Compared to traditional research methods, online data analysis allows researchers to collect data in less time, with lower costs and with higher sample size (Zhang and Zhou, 2018). By applying text mining techniques to user reviews and opinions, it is possible to detect attributes related to customer satisfaction to overcome the biases that an individual may assume during a face-to-face questionnaire (Kinne and Lenz, 2021).

Although customer satisfaction is closely related to issues of products and services for final customers, this concept is widely connected with the topics of modular products and knowledge management. For example, modular products can satisfy customers' needs for product customisation, increasing their final satisfaction (Ezzat et al., 2022; Ma et al., 2019). In particular, decisions on design strategies for modular products may involve various factors such as production costs, supplier reliability and customer satisfaction (Ali et al., 2022). Thus, modularity allows the management of high complexity and products customisation with the need to integrate customer needs (Gaspar et al., 2014). In addition, knowledge management theories are often linked to customer satisfaction (Žemaitis, 2014). Several authors have studied how process and product knowledge can support organisational performance such as operational, financial and customer satisfaction (Gupta and Chopra, 2018; Shah and Kant, 2020). Lin (2015) has shown that among the knowledge dimensions, knowledge absorption is crucial for improving customer satisfaction. Moreover, knowledge flows should be shifted between companies and external entities (e.g. customers and business partners) to increase customer satisfaction.

There are no studies in the literature that directly link the topics of modular products and knowledge management with customer satisfaction. The novelty of this research is to associate these three concepts and evaluate whether the OEM's knowledge of single modules and the smartphone architecture influences customer satisfaction.

Methodology

The aim of this work is to study the importance for OEMs of having specific knowledge on single modules of a whole product architecture. Furthermore, the article aims at clarifying which modules and what level of knowledge is necessary to increase the satisfaction of end product. This analysis is carried out by using a system that combines patent data with a performance indicator of customer satisfaction. The analysis is performed on a sample of 168 flagship smartphones launched from 2003 to 2017 by the following OEMs: Alphabet, Apple, AsusTek Computer, BBK Electronics, HTC, Huawei Technologies, Lenovo, LG Electronics, Motorola, Nokia, Research in Motion, Samsung, Sony, Sony Ericsson, Xiaomi, ZTE. Since the smartphone has several modules that are assembled within the whole product architecture, the analysis was performed on the top ten out of 24 modules in terms of economic value according to Nomura report (2012). Such modules are: application processor, battery, camera, DRAM (dynamic random access memory), image sensor, power amplifier, RF transceiver (radiofrequency transceiver), screen, sounds module, touchscreen controller. These modules were considered because they are always implemented in the smartphones of this sample. For instance, the fingerprint module is not present in this analysis as this technology was used in smartphones produced after 2017.

Conceptual framework

From a technological point of view, the smartphone industry is highly interrelated with other sectors, such as computers and tablets. Indeed, most of the modules included in a smartphone can also be found in different electronic devices. For this reason, the paper provides a methodology for distinguishing the OEMs' knowledge on modules into two different levels: the general knowledge, independently from the product/device in which the module is included, and the more specific knowledge related to the use of the module in a particular application, i.e. the smartphone. Moreover, given the wide range of different technological domains within the sector, not only the total amount of knowledge, but also the relative focalization on specific knowledge areas can be analysed, at both a general-purpose and specific-application level.

Therefore, the paper aims at understanding how and to what extent:

- OEMs' total knowledge on modules per se,
- OEM's total knowledge on modules for smartphone applications,
- OEM's knowledge focalization on modules per se,
- and OEM's knowledge focalization on modules for smartphone applications

is related to the customer satisfaction (Fig. 1).

In order to respond to such questions, a specific methodology for patent data classification was developed to define the four knowledge indicators.

Data collection and classification

Several authors have shown the importance of managing internal knowledge to improve market performance. In this context, patent data is widely recognised by various researchers as an indicator of the internal companies' knowledge and can support strategic technology planning (Asim and Sorooshian, 2019; Cammarano et al., 2019; Ernst, 1998; S. Lee et al., 2020). Furthermore, modular product architecture was also invoked at the knowledge level and many scholars analysed these concepts through patent analysis (Khurshid et al., 2019; Mawdsley and Somaya, 2018). However, most researchers used the International Patent Classification (IPC) to evaluate technological knowledge (Borgstedt et al., 2017; Wu and Mathews, 2012). Specifically, IPC codes classify patented technologies based on technical elements and application fields. The analysis of patent data based on these

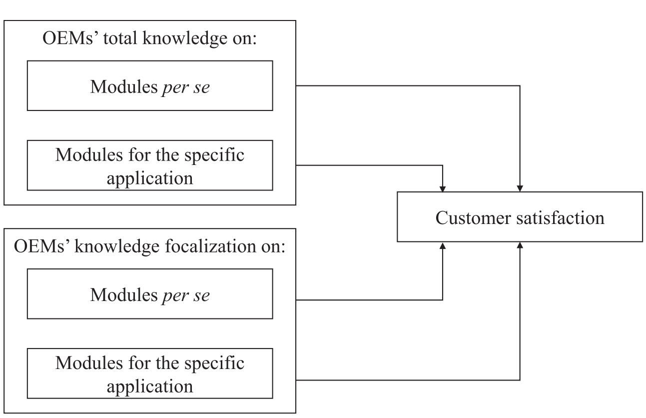

Fig. 1. Conceptual framework.

codes is not precise because it does not directly refer to the specific product or market (Parraguez et al., 2020; Venugopalan and Rai, 2015). In this study, the methodological approach is based on the content analysis of patent abstracts to overcome such limitations.

Data on the technological knowledge of each module were extracted from the PATSTAT database version October 2018. Patents filed with the European Patent Office (EPO), the United States Patent and Trademark Office (USPTO), or the World Intellectual Property Organisation (WIPO) were considered. Patent analysis was conducted only on the first patent application of each family for the protection of specific technological knowledge (Harhoff et al., 2003; Johnstone et al., 2012). In addition, the patent portfolio was reconstructed by searching the name of the parent company and its subsidiaries, avoiding disambiguation and typos, in order to precisely identify information about the "applicant". The manual activities were carried out by experts in database management and took about two months.

The statistical unit is the product-module couple of each smartphone produced by the OEM. The overall patent portfolio owned by the OEM is the stock of knowledge. It is the list of patent applications submitted before to the smartphone's launch date on which the module is assembled. Patents filed before five years from the launch date were excluded on the basis of technological obsolescence in the high-tech industry and theories of knowledge management and organisational learning (Harlow, 2019). This allows including within its patent portfolio only the knowledge useful and potentially available to the company at the launch date.

The methodology solves one of the limitations of patent data: the lack of direct correspondence between a marketed product and the technological knowledge of the company (Bessen and Hunt, 2007; Graham and Mowery, 2003; Hall and MacGarvie, 2010; Layne-Farrar, 2012). Other tools based, for example, on filtering through patent classification codes have already shown their limitations (Hunt et al., 2004; Valverde et al., 2017; Wang et al., 2019). On the contrary, scholars highlighted that text mining and content analysis techniques are a useful and statistically robust means of filtering patent information (Giordano et al., 2021; Jun and Park, 2013; Korkeamäki and Takalo, 2013; Puccetti et al., 2023; Valverde et al., 2017). Specifically, the level of false positives and false negatives obtained in this work is comparable to that of other published articles (Bessen and Hunt, 2007; Hall and MacGarvie, 2010; Layne-Farrar, 2012). Indeed, in literature, the ratio of false positives varies from 8% to 22% (Bessen and Hunt, 2007; Layne-Farrar, 2012), whereas the ratio of false negatives varies from 16% to 52% (Bessen and Hunt, 2007; Layne-Farrar, 2012). In this study, the results obtained are 4.92% for false positives and 24.15% for false negatives, for a total error ratio of 29.07%. While the methodology used within the aforementioned works is applied for other research purposes (i.e. study of computer software patents), the novelty of this framework concerns the identification of technological knowledge applied on technologically complex modules and not directly on end products.

As shown in Fig. 2, the patent classification allowed the partitioning of the stock of knowledge available to each analysed company. The stock of knowledge (*Stock*) - i.e. the amount of knowledge accumulated within a company - is filtered into two sets: the knowledge set related to the smartphone (*Product*), and a first level of OEM's module knowledge (*Modulelevel1*). The technological knowledge of the modules inside the *Modulelevel1* is general and independent of the specific use in a peculiar end product, e.g. a touchscreen that can be used both in a notebook and in a smartphone. A second level of knowledge derives from the intersection between *Product* and *Modulelevel1*. In this set there is the technological knowledge of the modules referred to the smartphone (*Modulelevel2*). Therefore, an OEM's stock of knowledge was doubly filtered to understand the accumulated knowledge and focalization of knowledge on each module.

Fig. 3 shows an example of patent classification using content analysis: a Samsung patent related to the camera module is analysed.

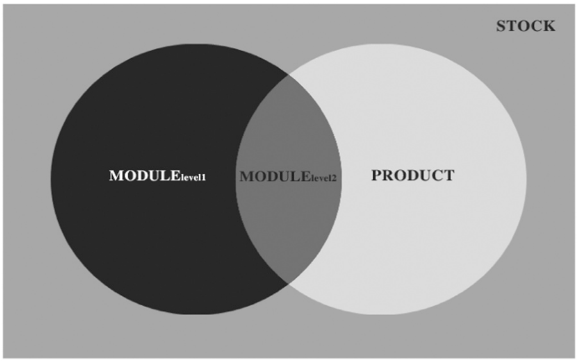

Fig. 2. Partitioning of an OEM's stock of knowledge.

Specifically, if there are no keywords linked to the smartphone or module within the abstract, the patent is excluded. If the patent has at least one keyword related to the module, it is classified as a patent associated to the focal module, which is a proxy of accumulated module knowledge (*Modulelevel1*). Furthermore, if the patent contains both the keyword related to both the module and the smartphone, then the patent identifies module knowledge for the smartphone that is a proxy of the specific accumulated knowledge of a module applied to a specific product (*Modulelevel2*). Finally, if the patent has at least one keyword linked to the smartphone and none related to the module, it is considered as a proxy of end product architecture knowledge (*Product*).

Regression analysis

In order to investigate whether OEM knowledge on single modules influences customer satisfaction, regression models were carried out. The following sections first describe the independent, dependent and control variables considered and then defines the regression models performed.

Independent variables

Four variables are considered to evaluate OEM module knowledge:

1. #Modulelevel1 is the count of the accumulated knowledge on the specific module and is a proxy of the accumulated knowledge that an OEM has on a module in general;
2. %Modulelevel1 is the ratio of #Modulelevel1 on the stock of knowledge (#Stock), emphasizing the focalization on the module, consequently indicating how important it is to accumulate knowledge for that module. This metric summarizes the knowledge strategy of focusing OEM's efforts on a few or more domains of technological knowledge;
3. #Modulelevel2 is the count of the knowledge accumulated on the module for the specific end product. It is a proxy of the specific accumulated knowledge that an OEM should have on the focal module for a specific end product;
4. %Modulelevel2 is the ratio of #Modulelevel2 on # Modulelevel1, emphasizing the focalization of module knowledge for a specific product. It is a proxy of the knowledge depth that an OEM should have about the module for a certain end product.

Dependent variable

A total score defined as *Alascore* was collected from the website *alaTest.com* to evaluate customer satisfaction (Alatest, 2022). Several other authors have used online reviews, expert ratings and user scores to measure customer satisfaction on single web portals (Gupta and Sebastian, 2018; Suh et al., 2017; Trappey et al., 2018).

alaTest.com is specialized in gathering reviews of high-tech devices. It uses a content analysis algorithm that collects various scores, ratings and product reviews from different reliable sources such as gsmarena.com, amazon.com and mobilechoiceuk.com. This database is continuously updated with new prices and reviews related to product specifications. Thereafter, a global, aggregated, standardised and unbiased score is calculated through a complex algorithm.

The total score ranges from 0 to 100. The evaluation of this score is based on four key factors. The first factor on which the algorithm operates is to avoid overstated evaluations of a product. AlaTest calculates the relevant score for each product and in each category (e.g. computers, smartphones, tablets and household appliances). Often, the number of positively rated product reviews is greater than the number

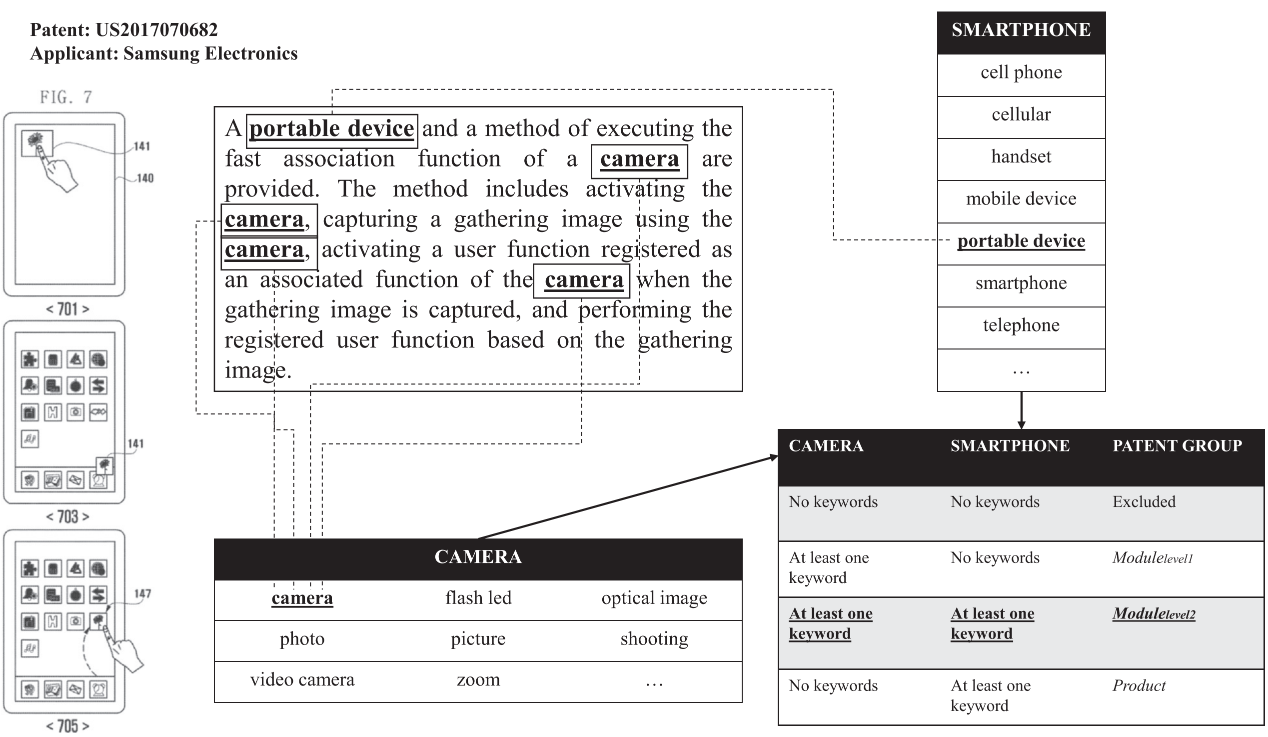

Fig. 3. An illustration of how to classify patents using text mining methods.

of negatively rated ones. The second factor is the amount of different reviews that a user has generated. The algorithm considers the user who has reviewed various products to be an expert in the field and consequently a higher weight will be assigned. The third factor considers the importance of the competence of professional experts. Finally, the algorithm considers a devaluation factor based on the age of the product. The presence of new products results in higher scores that will gradually decrease over time as technological innovation advances.

In this study, the number of reviews considered was 695,613, which can be assessed as the highest sample used to perform analyses in the smartphone industry. The work aims to have a significant dataset of more than a decade of smartphones that comprehensively assesses customer satisfaction over a long-time horizon.

Control variables

Control variables are added to consider the impact of the product architecture knowledge that the OEM has on customer satisfaction:

1. #Stock is the total patent portfolio held by the OEM from *t* to *t-5*. It is an indicator measuring the overall accumulated technological knowledge;
2. #Product is the number of smartphone-related patents owned by the OEM. It is an indicator that measures smartphone-related technological knowledge;
3. %Product is the ratio of #Product on #Stock, highlighting the accumulated knowledge carried out by the OEM in terms of concentrating R&D activities on improving their knowledge related to smartphones;
4. %OEM Market Share, is the worldwide market share achieved in the global smartphone market by the OEM in the quarter prior to the one relating to the smartphone's launch date, as a proxy of its brand reputation and market (Statista, 2021).

These parameters will control the role of the OEM in achieving the market results expressed through the customer satisfaction of the final market.

Regression models

Four sets of regression models will be presented (Figure 4):

1. #Modulelevel1 models, considering the ten OEM's accumulated knowledge of the modules in general as predictors;
2. #Modulelevel2 models, analysing the count of the OEM's accumulated knowledge of the specific modules related to smartphone;
3. %Modulelevel1 models, considering the focalization of module knowledge per se;
4. %Modulelevel2 models, investigating the focalization of modules knowledge for smartphone.

In all the set of models, control variables are added one at a time for each iteration and finally, in the last iteration, all the variables are present. In this way, six regression are presented for each model. The six iterations test the sensitivity and robustness of the models by varying the control variables and evaluate the effects on the independent variables. SPSS software is employed to implement the regression analysis.

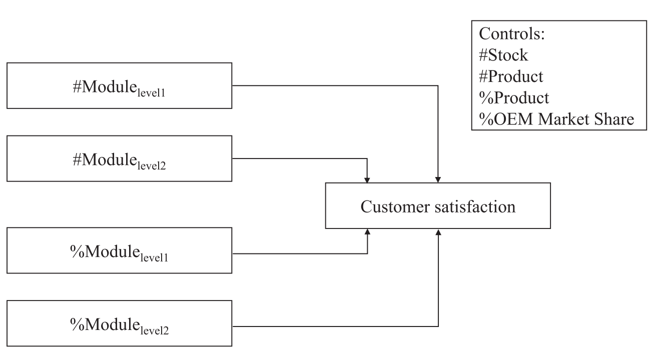

Fig. 4. Regression models.

Results

Descriptive statistics

Table 1 presents descriptive statistics related to the different levels of knowledge of each module under analysis, the total score and the control variables.

On average, OEMs have greater accumulated knowledge on the RF transceiver and power amplifier, as to both the modules per se and their use in smartphone applications. The lowest average knowledge of OEMs concerns batteries as to both the modules per se (#Modulelevel1, %Modulelevel1) and the amount of knowledge accumulated on batteries for smartphones (#Modulelevel2,), whereas the focalization of knowledge for such products (%Modulelevel2) is quite high (27%, being 31% the maximum value). It is interesting to note that, while the average value of %Modulelevel2 calculated on all the modules is around 10%, as to %Modulelevel2 the value is almost 30%: therefore, OEMs employ almost one third of their experience and knowledge about modules in the smartphone industry. Yet, the descriptive statistics show a significant variance in variables, especially in count ones, suggesting the existence of different behaviours among companies.

Regression Analysis

Since a smartphone is based on many technological modules that affect its overall quality, in this section regression analyses are performed using the total score as a dependent variable and the OEMs technological knowledge on the ten modules as independent variables for evaluating their association. Regression analysis allows evaluating the joint effect of the technological knowledge on more modules and highlights which modules specific knowledge is required in relation to customer satisfaction.

Table 2 shows the #Modulelevel1 models in which the module knowledge is accumulated regardless of end products they are designated to. Regarding DRAM and RF transceiver, it seems that OEMs who have significant accumulated knowledge on these modules are probably able to achieve a better result on end product, optimizing customer satisfaction. In this case, the result is obtained by accumulating general knowledge and not necessarily a more specific one. OEMs' general accumulated knowledge of the touchscreen controller has a positive association with customer satisfaction in the A1, A2, A5 and A6 models. However, this general accumulated knowledge is no longer significant when the variables #Product and %Product are introduced. Compared to the relationships of the previous modules with customer satisfaction, this link on the general accumulated OEM knowledge for the touchscreen controller is less robust. Considering this result, smartphone OEMs are often producers of other highly innovative electronic products. For example, Apple produces not only smartphones but also other electronic devices such as tablets and PCs. Therefore, the general accumulated knowledge on DRAM and RF transceiver allows Apple to integrate it within different product architectures. For some specific modules, there are negative associations between general accumulated knowledge and customer satisfaction. In particular, the OEM who does not accumulate general knowledge on the battery, the application processor and the sounds module has a positive influence on customer satisfaction. Moreover, in the A2 model, there is a negative relationship between the stock of OEM knowledge and customer satisfaction. This means that not all the company's technological knowledge is important to increase the customer satisfaction on the smartphone market. In the A4 model, the positive relationship between %Product and customer

Table 1
Sample description.

		N	Mean	SD	SD/Mean	Min	Max	Percentile	
Independent Variables								25	75
#Modulelevel1	Application Processor	168	234	355	1.52	0	2236	20	427
	Battery	146	32	34	1.05	0	176	4	45
	Camera Module	118	121	153	1.26	0	809	6	127
	DRAM	168	163	185	1.13	0	888	22	258
	Image Sensor	132	166	171	1.03	0	703	44	206
	Power Amplifier	141	328	488	1.49	0	3200	79	473
	RF Transceiver	120	480	818	1.71	0	5046	58	686
	Screen	126	144	176	1.23	0	711	35	178
	Sounds Module	147	117	136	1.17	0	665	17	165
	Touchscreen Controller	126	138	163	1.18	0	640	29	151
#Modulelevel2	Application Processor	168	48	64	1.34	0	333	3	77
	Battery	146	9	16	1.74	0	73	0	13
	Camera Module	118	24	32	1.33	0	161	1	34
	DRAM	168	31	46	1.51	0	247	1	45
	Image Sensor	132	39	47	1.20	0	190	6	62
	Power Amplifier	141	89	109	1.22	0	379	8	138
	RF Transceiver	120	118	142	1.20	0	514	15	193
	Screen	126	35	54	1.54	0	220	5	39
	Sounds Module	147	31	41	1.34	0	155	2	48
	Touchscreen Controller	126	46	64	1.38	0	255	3	67
%Modulelevel1	Application Processor	166	14%	9%	0.64	0%	58%	10%	18%
	Battery	166	3%	3%	1.00	0%	14%	0%	5%
	Camera Module	166	9%	8%	0.89	0%	29%	0%	17%
	DRAM	166	11%	6%	0.55	0%	29%	7%	15%
	Image Sensor	166	10%	8%	0.80	0%	26%	2%	18%
	Power Amplifier	166	18%	10%	0.56	0%	39%	15%	26%
	RF Transceiver	166	20%	15%	0.75	0%	55%	0%	30%
	Screen	166	9%	7%	0.78	0%	19%	0%	15%
	Sounds Module	166	7%	5%	0.71	0%	40%	5%	10%
	Touchscreen Controller	166	8%	7%	0.88	0%	28%	0%	13%
%Modulelevel2	Application Processor	158	26%	21%	0.81	0%	100%	10%	39%
	Battery	116	27%	24%	0.89	0%	100%	6%	41%
	Camera Module	105	20%	17%	0.85	0%	76%	9%	33%
	DRAM	157	21%	22%	1.05	0%	76%	5%	33%
	Image Sensor	128	27%	24%	0.89	0%	100%	9%	40%
	Power Amplifier	139	28%	18%	0.64	5%	67%	13%	42%
	RF Transceiver	119	31%	19%	0.61	7%	100%	16%	39%
	Screen	123	27%	19%	0.70	0%	70%	9%	48%
	Sounds Module	144	25%	19%	0.76	0%	72%	10%	34%
	Touchscreen Controller	122	30%	16%	0.53	0%	61%	19%	43%
Dependent Variable									
	Total Score	165	87.43	2.87	0.03	80.00	94.00	86.00	89.50
Control Variables									
	#Stock	168	1390	1754	1.26	0	10,840	295	2399
	#Product	168	359	460	1.28	0	2187	49	506
	%Product	166	28%	2%	0.06	5%	86%	13%	37%
	%OEM Market Share	150	11%	10%	0.91	1%	42%	4%	16%

satisfaction indicates the importance of focusing knowledge on the specific end product in order to achieve higher customer satisfaction.

The role of the application processor is instead emphasized by the # Modulelevel2 model, which shows a positive relationship between customer satisfaction and the accumulated knowledge on this module for smartphone applications (Table 3). Indeed, such a module is crucial for the interaction with the other modules of the product architecture. Therefore, OEMs are recommended to gain technological knowledge and experience on it in order to increase customer satisfaction. In all models, except for the A4, the OEM's specific accumulated knowledge of the image sensor also has a positive relationship with customer satisfaction. Indeed, this module is particularly relevant for the smartphone. In the A6 model, specific accumulated knowledge for battery module positively influences customer satisfaction. Nevertheless, this link is weaker than the previous ones as this result is only found in this model. In A5 and A6 models, there are negative relationships between OEM-specific accumulated knowledge on the camera module, DRAM, power amplifier, screen and customer satisfaction. This result indicates that low OEM-specific knowledge on these modules positively influences customer satisfaction. Moreover, in these models the variables #Stock, %Product and %OEM Market Share positively affect the final market. The usefulness of the control variables is confirmed since the success of the product depends on the market reputation of the company, but also on the overall size of the stock of knowledge (which is also a proxy of the size of the company). Finally, the success of the product depends on how much the OEM decides to invest in the smartphone instead of other products: the greater the focalization on the smartphone, the greater the success on customer satisfaction.

Table 4 shows the %Modulelevel1 models where there are conflicting situations. The OEM knowledge on the camera has a positive influence on customer satisfaction. For example, Sony and Samsung, besides being smartphone manufacturers, are known as camera manufacturers. Therefore, having general knowledge focused on this module allows it to be used on various end products. Furthermore, it is widely recognised that one of the main features demanded by users for today's smartphones is camera quality. In some models such as A1, A3 and A4 for the applications processor, A4, A5 and A6 for the DRAM, and A2, A3 and A4 for the screen, and finally A5 for the touchscreen controller, having a general focalization of OEM knowledge on these modules positively enhances customer satisfaction. A lower degree of

Table 2
#Modulelevel1 Regression Model.

	A1			A2			A3			A4			A5			A6		
Model summary	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.
	0.331	4.719	0.000	0.445	6.469	0.000	0.350	4.674	0.000	0.491	7.574	0.000	0.328	4.288	0.000	0.503	6.348	0.000
Independents	B	t	Sig.	B	t	Sig.	B	t	Sig.	B	t	Sig.	B	t	Sig.	B	t	Sig.
Application Processor	-3.541	-2.929	0.005	-2.071	-1.773	0.081	-1.701	-1.054	0.296	-2.513	-2.331	0.023	-3.930	-3.162	0.002	-2.304	-1.267	0.210
Battery	-0.993	-2.634	0.011	-1.027	-2.989	0.004	-0.911	-2.429	0.018	-0.353	-0.990	0.326	-1.026	-2.502	0.015	-0.874	-1.947	0.056
Camera Module	1.187	0.852	0.397	0.738	0.579	0.565	0.568	0.400	0.691	0.645	0.528	0.599	0.842	0.589	0.558	0.686	0.530	0.598
DRAM	1.704	2.539	0.014	2.759	4.106	0.000	1.559	2.338	0.023	1.831	3.123	0.003	1.931	2.776	0.007	2.598	3.845	0.000
Image Sensor	-0.034	-0.031	0.975	0.635	0.630	0.531	0.192	0.177	0.860	0.236	0.248	0.805	0.125	0.112	0.912	0.328	0.330	0.742
Power Amplifier	-3.593	-1.123	0.265	-5.103	-1.735	0.088	-6.841	-1.854	0.068	-8.814	-2.927	0.005	-3.864	-1.195	0.237	-7.352	-2.237	0.029
RF Transceiver	7.176	2.211	0.031	11.946	3.716	0.000	8.635	2.606	0.011	10.548	3.606	0.001	7.571	2.306	0.024	12.733	3.881	0.000
Screen	-0.180	-0.168	0.867	-0.046	-0.047	0.963	0.957	0.764	0.447	1.339	1.350	0.182	0.047	0.043	0.966	0.938	0.849	0.399
Sounds Module	-3.957	-4.663	0.000	-2.212	-2.457	0.017	-4.463	-5.024	0.000	-2.937	-3.801	0.000	-3.602	-3.959	0.000	-1.881	-1.983	0.052
Touchscreen Controller	3.090	3.639	0.001	3.155	4.078	0.000	1.954	1.822	0.073	1.218	1.442	0.154	2.785	3.028	0.004	2.403	2.274	0.027
#Stock				-7.464	-3.783	0.000										-5.624	-1.795	0.078
#Product							1.111	1.695	0.095							-0.325	-0.388	0.699
%Product										0.734	4.621	0.000				0.508	1.789	0.079
%OEM Market Share													-0.017	-0.129	0.898	0.211	1.522	0.133
Constant		186.128	0.000		195.866	0.000		188.781	0.000		79.149	0.000		173.456	0.000		44.191	0.000

Table 3
#Modulelevel2 Regression Model.

	A1			A2			A3			A4			A5			A6		
Model summary	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.
	0.258	3.604	0.001	0.253	3.313	0.001	0.251	3.286	0.001	0.252	3.300	0.001	0.248	3.221	0.002	0.350	3.841	0.000
Independents	B	t	Sig.	B	t	Sig.	B	t	Sig.	B	t	Sig.	B	t	Sig.	B	t	Sig.
Application Processor	2.030	3.438	0.001	1.941	3.220	0.002	2.251	3.292	0.002	2.016	3.401	0.001	2.551	3.694	0.000	2.167	2.900	0.005
Battery	0.475	0.761	0.449	0.571	0.896	0.374	0.733	0.988	0.327	0.637	0.958	0.342	0.725	1.110	0.271	3.132	3.284	0.002
Camera Module	-1.189	-1.727	0.089	-1.355	-1.876	0.065	-1.479	-1.796	0.077	-1.091	-1.550	0.126	-1.671	-2.153	0.035	-2.359	-2.816	0.007
DRAM	-0.529	-1.402	0.166	-0.546	-1.440	0.155	-0.822	-1.394	0.168	-0.505	-1.328	0.189	-0.957	-2.011	0.049	-1.188	-2.010	0.049
Image Sensor	2.232	2.080	0.041	2.499	2.214	0.030	2.482	2.168	0.034	2.123	1.951	0.055	3.343	2.555	0.013	5.117	3.865	0.000
Power Amplifier	-2.716	-1.577	0.120	-2.815	-1.626	0.109	-2.221	-1.175	0.245	-3.239	-1.729	0.089	-1.216	-0.598	0.552	-5.618	-2.372	0.021
RF Transceiver	0.230	0.204	0.839	0.105	0.092	0.927	-0.907	-0.435	0.665	0.478	0.405	0.687	-0.574	-0.447	0.657	0.258	0.129	0.898
Screen	-0.225	-0.266	0.791	-0.529	-0.567	0.573	-0.515	-0.537	0.593	-0.131	-0.153	0.879	-0.660	-0.721	0.473	-2.297	-2.227	0.030
Sounds Module	-0.344	-0.558	0.579	-0.265	-0.422	0.674	-0.566	-0.800	0.427	-0.332	-0.536	0.594	-0.632	-0.963	0.339	-0.154	-0.214	0.831
Touchscreen Controller	0.496	0.590	0.557	0.650	0.751	0.455	0.091	0.087	0.931	0.510	0.605	0.548	-0.529	-0.476	0.636	-0.138	-0.112	0.911
#Stock				0.251	0.785	0.435										1.820	3.093	0.003
#Product							1.355	0.649	0.518							-0.015	-0.007	0.994
%Product										0.094	0.724	0.472				0.862	3.558	0.001
%OEM Market Share													0.237	1.470	0.147	0.432	2.487	0.016
Constant		217.926	0.000		212.839	0.000		216.322	0.000		116.235	0.000		166.133	0.000		54.078	0.000

Table 4
%Modulelevel1 Regression Model.

	A1			A2			A3			A4			A5			A6		
Model summary	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.
	0.306	8.140	0.000	0.328	8.184	0.000	0.308	7.568	0.000	0.316	7.815	0.000	0.321	7.311	0.000	0.417	8.525	0.000
Independents	B	t	Sig.	B	t	Sig.	B	t	Sig.	B	t	Sig.	B	t	Sig.	B	t	Sig.
Application Processor	0.201	2.623	0.010	0.151	1.939	0.054	0.191	2.495	0.014	0.222	2.894	0.004	0.052	0.632	0.529	-0.030	-0.350	0.727
Battery	-0.294	-3.328	0.001	-0.241	-2.684	0.008	-0.287	-3.250	0.001	-0.325	-3.639	0.000	-0.363	-3.785	0.000	-0.323	-3.517	0.001
Camera Module	0.337	3.538	0.001	0.391	4.061	0.000	0.382	3.755	0.000	0.393	3.952	0.000	0.269	2.566	0.011	0.343	3.254	0.001
DRAM	0.124	1.418	0.158	0.053	0.589	0.557	0.113	1.293	0.198	0.232	2.207	0.029	0.257	2.534	0.012	0.465	4.029	0.000
Image Sensor	0.057	0.489	0.626	-0.006	-0.047	0.962	0.008	0.069	0.945	-0.015	-0.123	0.902	0.121	1.007	0.316	-0.016	-0.132	0.895
Power Amplifier	-0.085	-1.008	0.315	-0.081	-0.969	0.334	-0.083	-0.984	0.327	-0.075	-0.895	0.372	-0.026	-0.325	0.745	0.032	0.419	0.676
RF Transceiver	0.037	0.435	0.664	-0.047	-0.515	0.607	0.025	0.295	0.769	0.056	0.655	0.513	0.054	0.624	0.534	-0.067	-0.783	0.435
Screen	0.232	1.891	0.060	0.294	2.382	0.018	0.267	2.122	0.035	0.295	2.329	0.021	0.193	1.540	0.126	0.369	2.990	0.003
Sounds Module	-0.119	-1.528	0.129	-0.106	-1.378	0.170	-0.120	-1.549	0.123	-0.114	-1.473	0.143	-0.260	-2.711	0.008	-0.232	-2.499	0.014
Touchscreen Controller	0.208	1.901	0.059	0.213	1.970	0.051	0.205	1.872	0.063	0.136	1.176	0.241	0.285	2.389	0.018	0.123	0.989	0.324
#Stock				0.198	2.442	0.016										0.599	4.546	0.000
#Product							0.092	1.244	0.215							-0.428	-2.878	0.005
%Product										0.164	1.821	0.071				0.486	3.681	0.000
%OEM Market Share													-0.045	-0.592	0.555	-0.059	-0.761	0.448
Constant		119.992	0.000		121.959	0.000		117.442	0.000		80.885	0.000		93.544	0.000		60.990	0.000

Table 5
%Modulelevel2 Regression Model.

	A1			A2			A3			A4			A5			A6		
Model summary	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.	Adj.R^2	F	Sig.
	0.291	3.629	0.001	0.278	3.238	0.002	0.297	3.456	0.001	0.279	3.251	0.002	0.286	3.300	0.002	0.312	3.038	0.002
Independents	B	t	Sig.	B	t	Sig.	B	t	Sig.	B	t	Sig.	B	t	Sig.	B	t	Sig.
Application Processor	0.512	1.588	0.118	0.511	1.549	0.127	0.390	1.157	0.253	0.475	1.359	0.180	0.512	1.604	0.115	0.151	0.420	0.676
Battery	0.229	0.987	0.328	0.229	0.969	0.337	0.262	1.128	0.265	0.224	0.956	0.343	0.254	1.088	0.282	0.206	0.878	0.384
Camera Module	0.146	0.394	0.695	0.146	0.390	0.698	0.060	0.160	0.874	0.120	0.314	0.755	0.178	0.468	0.642	-0.389	-0.856	0.396
DRAM	-0.743	-2.663	0.010	-0.743	-2.609	0.012	-0.814	-2.865	0.006	-0.772	-2.586	0.013	-0.834	-2.991	0.004	-0.943	-3.116	0.003
Image Sensor	-1.260	-2.143	0.037	-1.262	-2.075	0.043	-1.338	-2.271	0.027	-1.289	-2.144	0.037	-1.438	-2.301	0.025	-1.054	-1.551	0.127
Power Amplifier	0.175	0.272	0.786	0.177	0.268	0.790	0.409	0.611	0.544	0.180	0.278	0.782	0.110	0.174	0.863	0.545	0.802	0.426
RF Transceiver	-0.210	-0.469	0.641	-0.211	-0.458	0.649	-0.283	-0.629	0.532	-0.289	-0.550	0.585	-0.204	-0.466	0.644	-0.275	-0.531	0.598
Screen	0.150	0.356	0.723	0.151	0.348	0.729	0.236	0.555	0.581	0.101	0.222	0.825	0.207	0.490	0.626	0.037	0.077	0.939
Sounds Module	-0.320	-1.110	0.272	-0.321	-1.060	0.294	-0.363	-1.253	0.216	-0.374	-1.088	0.281	-0.347	-1.191	0.239	-0.236	-0.629	0.532
Touchscreen Controller	1.482	4.938	0.000	1.484	4.551	0.000	1.646	5.007	0.000	1.444	4.375	0.000	1.605	4.956	0.000	1.509	4.027	0.000
#Stock				-0.002	-0.013	0.990										0.565	1.940	0.058
#Product							-0.181	-1.198	0.236							-0.736	-1.982	0.053
%Product										0.310	0.293	0.771				0.755	0.630	0.532
%OEM Market Share													-0.171	-1.239	0.221	-0.044	-0.267	0.790
Constant		102.646	0.000		98.502	0.000		103.061	0.000		100.311	0.000		88.020	0.000		68.883	0.000

OEM knowledge on the battery led to a greater customer satisfaction. The results show that accumulating knowledge on the battery is not strategic and those who have adopted this strategy have obtained a lower result on customer satisfaction. Similarly, the OEM that does not focus its general knowledge on the sounds module has a better impact on customer satisfaction (A5 and A6 models). Moreover, in these models, %Product and #Stock have a positive relationship on customer satisfaction. This is reasonable since the greater the global knowledge of the OEM and the concentration on smartphones, the greater customer satisfaction.

In %Modulelevel2 models shown in Table 5, OEMs who concentrate most of their knowledge and experience in the touchscreen controller have a positive association in terms of customer satisfaction. Indeed, the touchscreen controller is the main way in which the user interacts with the device. Therefore, the specific knowledge and experience accumulated in this module becomes essential in order to ensure the correct functioning of the end product. In addition, the focus of specific knowledge on the image sensor has a negative relationship with customer satisfaction. Regarding the image sensor, it is important to accumulate specific knowledge (Table 3) but not to focus and concentrate on the specific knowledge to achieve higher customer satisfaction (Table 5). OEMs that focused primarily on the DRAM did not perform well on customer satisfaction. Comparing results in Tables 2 and 5, it seems that it is appropriate for OEMs to focus on DRAM but not for the specific smartphone applications.

Discussions

The study aims to investigate the importance of technological knowledge for the OEM on the single modules of a product architecture. Specifically, it aims to clarify on which modules specific technological knowledge is needed to influence customer satisfaction. The study combined knowledge management and modular product issues considering patent data with customer satisfaction. A first exploration through descriptive statistics shows that the OEM possesses different levels of knowledge, i.e. general and specific on the smartphone modules. More detail is provided through regression analyses that highlight different outcomes and linkage on specific modules knowledge and customer satisfaction.

The literature has already widely recognised the value of product architecture knowledge on customer satisfaction. Several studies, applying different methodologies such as surveys and case studies, have reached this result (Baldwin and Clark, 2002; Takeishi, 2002). As already stated by Squire et al. (2009) in their study for the UK manufacturing industries, this study on the smartphone sector highlights how OEMs need to retain different levels of knowledge on product architecture. Similar to the automotive and aerospace literature (Brusoni, 2001; Zirpoli and Becker, 2011), this research states that in the highly competitive and rapidly developing smartphone industry, it is necessary to preserve high levels of knowledge not only on the end product but also on specific modules. In this context, the study was in line with previous literature on the value of product architecture knowledge for customer satisfaction. In Table 4, in model 6, the variable %Product has a positive relationship with customer satisfaction. This means that focusing knowledge on the smartphone is important for improving customer satisfaction. However, this research investigated beyond the importance of knowledge of product architecture and delved deeper into the analysis of the knowledge required on single modules to achieve greater customer satisfaction. This work adds and suggests further insights to previous research. In fact, the analysis of module knowledge related to customer satisfaction is less discussed in the literature. Obviously, not all knowledge on each module has a positive association with customer satisfaction. The study revealed the key modules for which an OEM should have a specific level of knowledge to be successful in the smartphone market. This study analyses module knowledge in depth on two levels, a general one, independent of the product for which it is used, and a more specific one, related to the end product. Regression models show that, to be successful in the smartphone market, OEMs should consider two levels of accumulated technological knowledge and two levels of knowledge focalization. Since they are crucial for the smartphone, it is important for the OEM to preserve this knowledge even if it is general (Table 2). This result is reinforced by the negative linkage between DRAM knowledge focalization and customer satisfaction (Table 6).

From the perspective of general module knowledge, it is important for the OEM to preserve and accumulate general knowledge about the DRAM, the RF transceiver and the touchscreen controller to increase customer satisfaction. Effectively, these modules can be applied in other electronic devices and thus the OEM can gain more knowledge and increased customer satisfaction. This highlights the fact that the OEM should possess general knowledge on this module; a higher knowledge focalization does not increase customer satisfaction. Therefore, having general knowledge on these modules increases the OEM's competitive advantage because it ensures greater knowledge of the technology, yet it does not need to delve deeper and specialise on these technologies that it could acquire in outsourcing from external suppliers. For modules such as the battery and sounds module, not accumulating general OEM knowledge has a positive influence on customer satisfaction. They are important for the proper functioning of the smartphone, however possessing technological knowledge on these modules for the OEM is not necessary to achieve greater customer satisfaction. Compared to the other modules analysed, the accumulated knowledge concerning their integration may not be high as their interfaces are more standardised. For instance, in spite of modules such as the applications processor, touchscreen controller and DRAM, where their integration within the smartphone is complex, their development can be carried out by external suppliers who can specialise and have accumulated knowledge.

An interesting result relates to the application processor, which is the module with the highest economic value. Specifically, the general and specific accumulated knowledge on this module allows for higher customer satisfaction. It is one of the main modules of a smartphone that guarantees better performance of the entire product architecture. Its features are fundamental to the proper functioning of this product. Therefore, specific accumulated knowledge to this module is crucial as it is highly integrated into the product architecture. Considering the specific accumulated knowledge, another module for which the OEM should possess technological knowledge is the image sensor. This module in modern smartphones has become important for smartphone applications. A specific accumulated knowledge of the OEM allows for greater customer satisfaction (Table 3). Although it is a module of which specific accumulated knowledge is necessary, its focus on specific knowledge by the OEM is not positively associated with customer satisfaction. Several specialised external suppliers develop and produce this module, such as Omnivision and Aptina, which are not smartphone manufacturers (Nomura, 2012).

Another important insight is the general knowledge focalization on the camera module. This module has assumed considerable importance in modern smartphones and is considered relevant for customer satisfaction. The spread of social media has increased the relevance of OEMs retaining technological knowledge on this module. Nevertheless, the technological knowledge that the OEM should retain for it is general. The OEM who retains this knowledge is able to apply it to other electronic devices. In some regression models in Table 4, other modules are positively associated with customer satisfaction. The most relevant is the screen. It is of considerable importance because it improves product usability and provides a greater customer experience. The OEM needs to have a general knowledge focalization on this module to exploit it for other electronic devices. Finally, the touchscreen controller is a key module for smartphones because it enables all the functionalities of the electronic device. It is important for the OEM to have a specific knowledge focalization on it because otherwise it risks not achieving higher customer satisfaction (Table 6). Being a highly integrated module in the smartphone, it is necessary for the OEM to have focused specific knowledge to achieve better customer satisfaction. The regression models presented are unique in the current literature as scholars have not investigated knowledge on specific modules and linked them to customer satisfaction. The identification of general and specific knowledge by the OEM, using patent data, is one of the ground-breaking researches in the smartphone industry. The links between knowledge on certain modules such as the applications processor, touchscreen controller, battery, sounds module and image sensors and customer satisfaction can be considered unique and pioneering. In addition, other variables that have a positive impact on customer satisfaction concern the increased knowledge of the product architecture and the OEM's reputation in the final market. The significance of these variables is in line with other studies already in the literature (Lee and Veloso, 2008; Yoon et al., 2017). This framework suggests that companies adopt strategies of accumulating or focusing knowledge on specific modules depending on the association with customer satisfaction.

The applied methodology provides a new approach to analysing the dynamics of the smartphone industry by considering the topics of knowledge management, modular products and customer satisfaction. Text mining techniques applied to patent data demonstrate the value of research that overcomes the limitations of traditional methodologies to perform analyses on marketed products. The double filter on modules related to the particular application allows for a better investigation of the knowledge management strategies that the OEM should possess on modular products. This approach could be considered for other products or for further research purposes. From managerial implications, the study investigates knowledge management strategies in modular products. It identifies the key smartphone modules for which it is important to possess knowledge in order to achieve greater customer satisfaction, and which ones are not crucial. Furthermore, the double level of knowledge clarifies when it is appropriate to focus specific knowledge and when it is sufficient to accumulate general module knowledge on the smartphone to achieve higher customer satisfaction.

Conclusions

The study investigates the relationship between knowledge management, modular products and customer satisfaction in the smartphone industry. Patent data provides an indication of the technological knowledge possessed by the company, while customer satisfaction was measured through a total score based on online reviews and opinions. The use of text mining techniques supported the decomposition of a complex product into several modules. Specifically, the patent content analysis defined different levels of knowledge on the product and smartphone modules. Using this approach, it was possible to analyse the association between knowledge on single modules and customer satisfaction. The results provide a range of insights, indicating on which modules knowledge needs to be preserved for the OEM in order to increase customer satisfaction.

The use of patent data to identify the stock of knowledge a corporation possesses is one of this study's drawbacks. In fact, not all inventions are filed for patents and, aspects of tacit knowledge are not considered. Future research will aim to analyse other sectors with modular products such as automotive. A further direction of future research might involve analysis on a bigger and more recent sample of smartphones, also considering other modules besides the ten studied in this article.

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