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Association rule mining and cognitive pairwise rating based portfolio analysis for product family design

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Abstract Changing customer needs coupled with rapid technology advances has boosted stronger requirements for a greater variety of consumer electronics. This trend has forced global companies to reconsider their product-positioning strategies. To reduce design cost and shorten the time to market, portfolio analysis for product family design is usually adopted to acquire diverse but related market applications. This study presents a novel framework to implement product differentiation and product configuration. Initially, association rule mining is used to capture user perceptions to identify the significant portfolios of hedonic attributes. Secondly, cognitive pairwise rating is conducted to elicit user preferences for utilitarian attributes (UAs). Finally, the Technique for Order Preference by Similarity to Ideal Solution is used to prioritize the optimal portfolios of UAs. Experiment results show that "keyboard interface", "body material", and "screen size" are the most concerned HAs for differentiating the product family while "CPU performance" is the most important UA for configuring padbooks, ultrabooks and notebooks. In summary, this research allows companies to effectively and efficiently incorporate user perceptions or preferences into the entire decision-making process.

Keywords Portfolio analysis · Product family design · Association rule mining · Cognitive pairwise rating · TOPSIS ranking

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Introduction

Portfolio analysis and management (PAM) is fundamental to operationalize product family design and development. A product family is a collection of designed alternatives that share the common platform or technology to acquire different but related market applications. In practice, four common goals must be accomplished for PAM: (1) maximize the aggregated value of product portfolios, (2) balance the determined product portfolios, (3) align product portfolios with a firm's corporate strategy and (4) choose the right projects and assign sufficient resources to them (Ulrich and Eppinger 2008). In the area of consumer electronics, padbooks, ultrabooks and notebooks are typical to characterize a product family (http://www.ultrabookreview.com/). A padbook means a tablet that is combined with a keyboard. The similarities between these three alternatives are referred to an industrial report. According to the IDC's survey (https://www.idc.com/), the conventional notebook is continually declining while the shipments of smartphones or tablets have been increasing since 2012 (Wang 2013; Wang and Shih 2013; Wang and Hsueh 2013). This trend induces innovative product design, such as phablets (phone + tablet) and 2-in-1 tablets (ultrabook + tablet).

Recently, the rising wave of virtual reality (VR) and augmented reality (AR) has boosted the gaming industries. In Fig. 1, the top 2 votes for users' favorite gaming platforms are PCs (desktop or laptop) and mobile handsets (smartphones or tablets). This trend implies that there is a stronger demand for gaming notebooks and discrete graphics cards. To satisfy diverse customer needs, companies design a great variety of cross-boundary products, such as Asus's PadFone/Transformer series, Acer's Switch/Swift series, and Sony's VAIO Duo/Pro series. The product lifecycle that is defined in Fig. 2 explains the rise and the fall of a product (Ulrich and Eppinger 2008). It begins with stage 0—idea generation, followed by stage 1—"introduction", stage 2 is "growth", stage 3 is "maturity" and the last stage is "decline". It is observed that the maximal sale occurs at stage 3 (maturity) but the maximal profit occurs before the stage of maturity. The rapid decline in profitability is due to the fact that increasing competitors enter the market in the stage of growth. As defined by the Boston Consulting Group (Kotler and Keller 2011), a new product usually starts with a question mark, becomes a star, then a cash cow and eventually degenerates to become a dog.

To ensure a successful product lifecycle/portfolio management, companies need to rethink product strategies and allocate sufficient resources to accommodate rapidly changing market dynamics (Askin and Dawson 2000; Liu et al. 2011). To assist product planners and designers in acquiring the market niches, product positioning is concerned not just what you do to a product but it is what you want to do to the prospect of customers (Xu et al. 2007; Zhang et al. 2009; Wang 2013). In practice, product differentiation and product configuration are two common schemes in implementing the concept of product positioning. Specifically, "differentiation" means creating tangible or intangible characteristics that ensure these characteristics can occupy a unique position in the minds of users (Luo et al. 2012). In contrast, "configuration" prioritizes and optimizes a series of portfolios to ensure that these portfolios can satisfy diverse customer needs or so-called mass customization (Jiao and Tseng 1999; Pakkanen et al. 2016; Wang 2016).

In reviewing the past studies, quantitative schemes have been proposed to tackle different domain problems, including multi-criteria decision making (MCDM), mathematical programming and data-mining algorithms (Agard and Kusiak 2004; Ayağ 2005; Song and Kusiak 2009; Bae and Kim 2011; Liu et al. 2011; Otten et al. 2015). Although numerous studies have been presented, few of them incorporate user perceptions of hedonic attributes (HAs) or user preferences for utilitarian attributes (UAs) into the decision-making process of product family design. To survive in a globally customized economy, affective HAs and functional UAs must be designed and linked to consumers' emotional feelings (Dhar and Wertenbroch 2000). Undoubtedly, the front-end aspects not only influence product sales, but also impact on a company's brand image or product impression (Luo et al. 2012; Guo et al. 2014).

To the best of our knowledge, most of the past studies rarely consider both affective HAs and functional UAs and incorporate them into the decision-making process of portfolio analysis and product family design. Inspired by the concept of Kansei engineering (Nagamachi 1995), several critical issues are highlighted as follows:

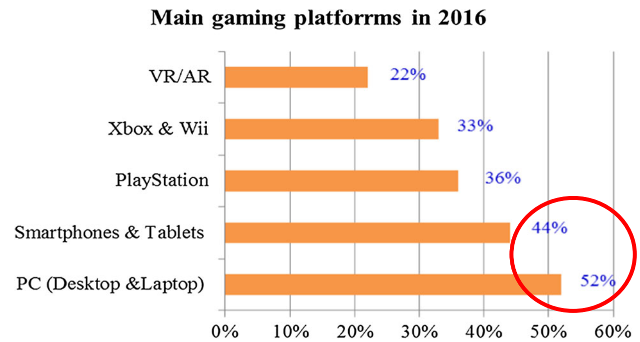

Fig. 1 Gamer's votes for popular gaming platforms in 2016 (http://graphs.net/majority-of-gamers-vote-for-vrar-gaming-platform-in-2016.html)

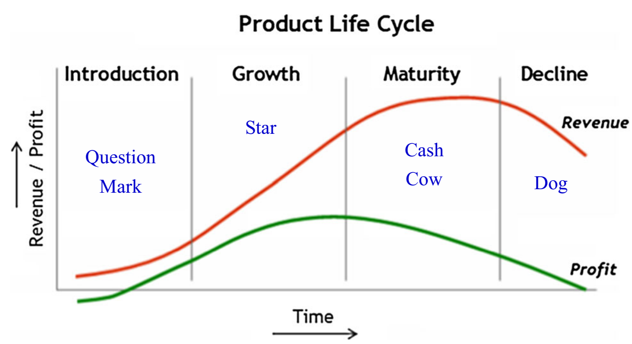

Fig. 2 Temporal stages defined in product lifecycle management (https://tackk.com/krc38t)

- How to capture user perceptions of HAs and incorporate these into the process of product differentiation?
- How to elicit user preferences for UAs and incorporate these into the process of product configuration?
- How to identify the significant portfolios of HAs/UAs to conduct a user-driven portfolio analysis and achieve a better design of a product family?

The remainder of this paper is organized as follows. "User-driven portfolio analysis and product family design" section. "The proposed framework" section. A case study for the design of a series of padbooks, ultrabooks and notebooks is illustrated in "An example for illustrating user-driven product family design" section. "Discussion and research limitation" section are listed. Finally, conclusions and future work are detailed in "Conclusion" section.

User-driven portfolio analysis and product family design

Product portfolio analysis is a systematic approach to assess a company's product mix in order to determine the optimal allocation of limited resources (Wang and Chen 2012; Otten et al. 2015). As shown in the BCG matrix or the GE model

(Kotler and Keller 2011), two measures frequently used in a portfolio analysis include market growth (market attractiveness) and market share (business strength). Figure 2 shows the different stages that are defined in product lifecycle management. Product-family platforms are used for designing related but different alternatives. In the past, a platform means a set of physical elements, such as components, modules, or parts from which a stream of derivative products can be quickly developed. Nowadays, not only physical elements but also intangible assets, such as user-experience, feedback or product knowledge are included together. Using product platforms, companies can provide sufficient variety (mass customization) while maintain necessary economies of scale (mass production).

In terms of mass production, a platform based product family design can reduce development time and system complexity and diminish development and production costs, so there is superior learning across related products (Simpson et al. 2006; Kumar et al. 2009). In terms of mass customization, a product platform can also increase companies' flexibility and responsiveness to develop more differentiated products, improve the ability to upgrade the existing alternatives, and enable a variety of products to be quickly launched into the marketplace so as to satisfy a variety of market niches (Jiao and Tseng 1999; Jiao et al. 2007). In practice, product family design is a powerful method to give a nuanced view of company's growth prospects, profit margin drivers, revenue contributions, market or technology leadership and overall operational risk.

To balance the trade-offs between promoting product varieties and controlling manufacturing complexities, a user-driven portfolio analysis plays a key role in product family design (Nayak et al. 2002; Wang and Chen 2012). A *platform based product family* is defined as (Jiao and Zhang 2005; Jose and Tollenaere 2005; Gershenson et al. 2007): (1) a set of common components or modules from which a stream of derivative products can be efficiently developed, (2) a collection of the common elements, especially the underlying core technology, manufacturing knowledge, that is implemented across a range of products, and (3) a bunch of tangible or intangible assets like key components, production processes, design knowledge, people and patents that are shared by a set of products.

Despite numerous schemes have been proposed to tackle product family design (Liu et al. 2011; Smith and Smith 2012; Guo et al. 2014), most of them rely on experts' subjective assessments (Ayağ 2005; Zhai et al. 2009). To incorporate user involvement into the decision-making process, several techniques have been suggested, such as conjoint analysis, analytical hierarchy process, Kano model, and Kansei engineering (Luce and Turkey 1964; Saaty 1980; Kano 1984; Nagamachi 1995). Among them, Kansei engineering (KE) has been widely used to process affective features (i.e. color, interface, size, form, body material, etc.) and convert affective words into product design, such as transforming human perceptions, emotional feelings and mental images into design of tangible product features (Jiao et al. 2006; Zhai et al. 2009).

Using a sematic differential scale, the conventional KE measures users' psychological perceptions in terms of pairwise terminologies, such as "modern versus classical", "warm versus cold", or "masculine versus feminine". Various data-analytics schemes, such as artificial neural network (ANN), support vector machine (SVM), rough set theory (RST), and association rule mining (ARM), have been presented (Yang and Shieh 2010; Yang 2011; Shi et al. 2012; Guo et al. 2014). In practice, causality tracking and dependence identification are critically important to accomplish successful product portfolio management (Ulrich and Eppinger 2008). To identify the significant portfolios of HAs (dependence identification), ARM is used for product differentiation. Then, cognitive pairwise rating is used for product configuration. For convenience, a brief comparison between this research and other published studies is given in Table 1. Rather than limiting to either HAs or UAs, this study considers both affective and functional components and incorporates these into the decision-making process of user-driven portfolio analysis and product family design.

The proposed framework

Figure 3 demonstrates the operational procedures to accomplish the goal of user-driven portfolio analysis and product family design. The details are described below:

(1) Affective HAs and functional UAs are used to characterize padbooks, ultrabooks and notebooks that comprise the whole product family,
(2) Association rule mining is applied to user perceptions to determine the significant portfolios of HAs,
(3) CPR is applied to elicit user preferences and TOPSIS ranking is used to prioritize the optimal portfolios of UAs,
(4) Managerial insights are generated to guide product family design and development.

Conducting association rule mining to capture user perceptions of HAs

Association rule mining (ARM), which originated from affinity analysis, is also called market basket analysis to examine the issue of "what goes with what". A typical example comes from using bar-code scanners in supermarkets to automatically look for associations between purchased items, particularly in an implicit form of $A \Rightarrow B$. In brief, the

Table 1 A brief comparison between this study and other published papers

References	Affective HAs	Functional UAs	Market segmentation	Product positioning
This study	*	*	Product family	ARM + CPR + MCDM
Askin and Dawson (2000)		*		MP
Jiao and Zhang (2005)		*		CJA + GA
Jiao et al. (2006)	*			KE + CJA + ARM
Kumar et al. (2009)		*	Product family	Nested logit
Zhang et al. (2009)		*	Product family	CJA + fuzzy clustering
Zhai et al. (2009)	*			RST
Yang and Shieh (2010)	*			KE + SVR/BPN
Bae and Kim (2011)	*	*		ARM + DT
Yang (2011)	*			KE + SVR + GA
Luo et al. (2012)	*	*	User preference	Multinomial logit
Nayak et al. (2002)		*		MP
Shi et al. (2012)	*			RST + ARM
Oküdan et al. (2013)	*	*	Demographics	MAUT
Guo et al. (2014)	*			KE + GA
Pakkanen et al. (2016)	*			Brownfield process
Wang and Chen (2012)		*	Affordable price	MP
Wang (2013)		*	Affordable price	KM + MCDM
Wang and Hsueh (2013)		*	Expert defined	KM + MCDM
Wang and Shih (2013)		*	Expert defined	CJA + MCDM
Wang (2016)		*	Expert defined	CPA + MCDM

% *ARM* association rule mining, *BPN* back propagation network, *DT* decision tree, *MCDM* multi-criteria decision making, *MAUT* multi-attribute utility theory, *CJA* conjoint analysis, *CPA* correspondence analysis, *GA* genetic algorithm, *KE* Kansei engineering, *KM* Kano model, *MP* mathematical programming, *RST* rough set theory, *SVR* support vector regression

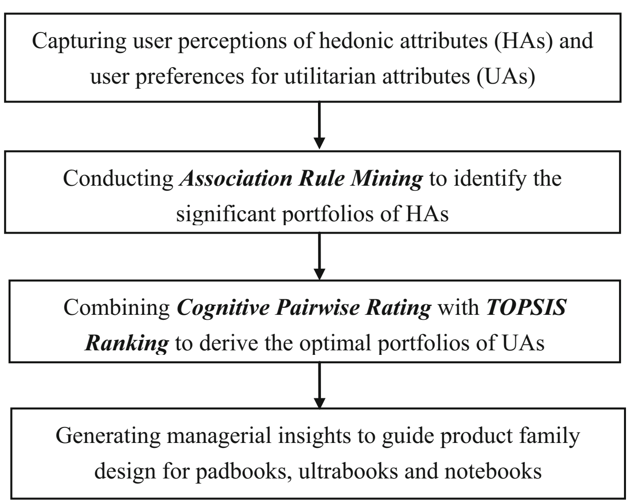

Fig. 3 The proposed research framework

idea behind association rule is to examine all possible rules among items in terms of an "*if-then*" format, like the following question: *If item A (antecedent) has been purchased, what is the possibility for item B (consequent) to be purchased later*? A brief comparison between three rule-based schemers is shown in Table 2 to reveal ARM's elegant properties, such as simplicity, capability to identify significant portfolios of input features and low computational complexity. Hence, ARM is particularly used in the area of cross selling.

Although several algorithms have been proposed for generating frequent item sets, the most famous and classic algorithm is the Apriori algorithm presented by Agrawal et al. (1993). Basically, the key idea of this algorithm is using $(k-1)$ frequent item sets to generate k candidate item sets (the step of joining) and then dropping inappropriate sets (the step of pruning) after checking their critical measures. Note that the subsets of large itemset(s) are also frequent in reality and three common metrics (i.e., support, confidence and lift) are respectively defined for measuring association between the antecedent and the consequent (Tan et al. 2010):

$$Support = \frac{\#\{antecedent \cup consequent\}}{\#\{all \quad records\}}, \tag{1}$$

$$Confidence = \frac{Support\{antecedent \cup consequent\}}{Support\{antecedent\}}, \tag{2}$$

$$Lift = \frac{Support\{antecedent \cup consequent\}}{Support\{antecedent\} \times Support\{Consequent\}} \tag{3}$$

Table 2 A brief comparison among rule-based schemes

	Association rule mining (ARM)	Rough set theory (RST)	Decision tee (DT)
Input features	Discrete	Discrete	Numeric/discrete
Output features	Discrete	Discrete	Numeric/discrete
Main purpose	Association	Classification	Classification/regression
Extracting important predictors	Not applicable	Core and reduct	Information entropy and Gini index
Identifying significant portfolios of features	Support, confidence and lift	Not applicable	Not applicable
Computational complexity	Low	High	Medium

Table 3 A comparison among the three common schemes

	AHP	CA	CPR
Basic principle	Pairwise comparison	Design of experiment	Pairwise comparison
Handling more than 7 criteria at a time	Decomposing into hierarchies	Difficult	Decomposing into hierarchies
Mathematical principle	Eigen-decomposition	Orthogonal factor design	Multiple attribute utility theory
Effort for alternative ranking	Medium	Tedious	Fast
Computational complexity	High	Medium	Low

Table 4 A numerical rating scale used in CPR

Positive measure		Negative measure	
0	Equally preferred	0	Equally dispreferred
2	Moderately preferred	−2	Moderately dispreferred
4	Highly preferred	−4	Highly dispreferred
6	Significantly preferred	−6	Significantly dispreferred
8	Absolutely preferred	−8	Absolutely dispreferred
1, 3, 5, 7	Intermediate scale: slightly, fairly, strongly, extremely		

Apparently, the support is used to measure how significant the rule is. And the confidence is equivalent to the conditional probability that measures the probability of including all items given the antecedent(s) has been captured in advance. In contrast, the lift is the ratio of the observed support (intersect) to that expected if "antecedent" and "consequent" were assumed to be independent. Simply speaking, the lift which value is more (less) than unity means the antecedent and the consequent are positively (negatively) correlated.

Employing cognitive pairwise rating to elicit user preferences for UAs

User preferences are unusually subjective, diverse and vague to be captured. However, user preferences are critical to influencing user satisfaction with product design and user purchase intention on designed alternatives. To the best of our knowledge, there are several common ways to elicit user preferences (Oküdan et al. 2013), such as conjoint analysis (CA), analytical hierarchy process (AHP) and cognitive pairwise rating (CPR). Basically, all of them originate from a main stream called multi-attributed utility theory. For convenience, an overall comparison is listed in Table 3. A numerical and symmetrical rating scale for the CPR is described in Table 4. Although both AHP (Saaty 1980) and CPR (Yuen 2012, 2014) adopt pairwise comparisons to assess two criteria or alternatives, CPR's rating scale is symmetric (0∼+8/−8 for preference or dispreference). In contrast, AHP's assessment is seriously criticized because of its asymmetric scales (1∼9 for preference but 1∼1/9 for dispreference). With consideration of the ease-of-survey and computational complexity, CPR is selected in this study because of its simplicity, efficiency and effectiveness. Here, CPR is applied to extract user preferences for FAs.

The details of the CPR are described as follows: Initially, asking decision makers to make pairwise comparisons to formulate preference matrix B with elements of b_{ij}. Specifically, the rating scales are linguistically described as *equally*, *moderately*, highly, *and absolutely* preferred or dispreferred among two alternatives [see Eq. (4)].

$$B = b_{ij} = \begin{bmatrix} v_1 - v_1 & v_1 - v_2 & \cdots & v_1 - v_n \\ v_2 - v_1 & 0 & \cdots & v_2 - v_n \\ \vdots & \vdots & 0 & \vdots \\ v_n - v_1 & v_n - v_2 & \cdots & v_n - v_n \end{bmatrix} = \begin{bmatrix} 0_1 & b_{12} & \cdots & b_{1n} \\ b_{21} & 0 & \cdots & b_{2n} \\ \vdots & \vdots & 0 & \vdots \\ b_{n1} & b_{n2} & \cdots & 0 \end{bmatrix}, \tag{4}$$

where v_i/v_j represents the priority value of object i (row index) and j (column index), b_{ij} stands for the preference degree of attribute (alternative) i over attribute (alternative) j. For example, $b_{ij} = 2$ means a user thinks object 1 is moderately preferred to object 2.

Suppose there are S evaluators and n criteria (features), the priorities of objects can be derived by using row average plus the normalized utility (RAPNU):

$$\text{RAPNU} = v_i : v_j = \frac{1}{n}\sum_{j=1}^{n} b_{ij} + k, \quad \forall i \in \{1, \cdots n\}, \tag{5}$$

where $k = 8$ is the levels of rating scales to describe positive preference or negative rejection. Finally, the importance weights of objects can be derived below:

$$w_i = \frac{v_i}{nk}, \quad \forall i \in \{1, \cdots n\}, \quad \sum_{i=1}^{n} v_i = nk, \tag{6}$$

To assess the reliability of the evaluation process, accordance index (AI) shown below is used. In practice, if *AI=0*, then matrix B is perfectly consistent. If $0 < AI \leq 0.1$, matrix B is satisfactory. On the contrary, if $AI > 0.1$, matrix B is unsatisfactory and the corresponding survey needs to be reassigned and reassessed again.

$$\text{AI} = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\sqrt{\frac{1}{n}\sum_{p=1}^{n}\left(\frac{b_{ip} + b_{pj} - b_{ij}}{k}\right)^2}. \tag{7}$$

Use of TOPSIS to determine the optimal portfolios of EFs

TOPSIS (*Technique for Order Preference by Similarity to Ideal Solution*) was originally proposed by Hwang and Yoon (1981). It was originally devised to search for an optimal solution that is closest to the "*PIS*" (positive ideal solution) and farthest from the "*NIS*" (negative ideal solution). If there are m alternatives and n features (attributes), the TOPSIS is operated as follows (Wang 2013):

- Generating a decision matrix. A $m \times n$ decision matrix (i.e. m represents the number of alternatives and n denotes the number of attributes) in which X comprises the elements of x_{ij} represents alternative i's performance rating in attribute j.
- Construing a normalized decision matrix. To reduce the scale effect among multiple dimensions, the normalized matrix Y is:

$$y_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \quad i = 1, \cdots m;\ j = 1 \cdots n, \tag{8}$$

- Searching for the elements of "*PIS*" (S^+) and "*NIS*" (S^-) by using:

$$S_j^+ = \left\{\underset{i}{Max} \quad y_{ij} | j = 1, 2, \ldots n\right\}, \tag{9}$$

$$S_j^- = \left\{\underset{i}{Min} \quad y_{ij} | j = 1, 2, \ldots n\right\}, \tag{10}$$

where S_j^+/S_j^- denote the jth element of S^+/S^-, respectively. The "benefit" attributes have the property of "the-larger-the-better" while the "cost" attributes have the characteristic of "the-smaller-the-better".
- Measuring a weighted distance from alternative i to the "*PIS*" and the "*NIS*":

$$dis_i^+ = \sqrt{\sum_{j=1}^{n}\left(y_{ij} - S_j^+\right)^2}, \quad i = 1, 2, \ldots m \tag{11}$$

$$dis_i^- = \sqrt{\sum_{j=1}^{n}\left(y_{ij} - S_j^-\right)^2}, \quad i = 1, 2, \ldots m, \tag{12}$$

- Constructing a priority index (*PI*) for competing design alternatives:

$$PI_i = \frac{dis_i^-}{dis_i^+ + dis_i^-}, \quad i = 1, 2, \ldots m. \tag{13}$$

An example for illustrating user-driven product family design

The boundary between padbooks, ultraboks and notebooks is becoming much more blurred because firms need to satisfy consumers' diverse as well as conflicting requirements, such as portability, durability, performance and affordability.

Since 2012, worldwide shipments of the conventional desktops and notebooks are declining because of the popularity of smartphones or tablets. The growth in the popularity of AR/VR has boosted sales of gaming notebooks. In terms of affective HAs and functional UAs (Dhar and Wertenbroch 2000), this research presents a novel framework that allow companies to rethink product positioning strategies and make better decisions.

Specifically, respondents' perceptions of HAs form the basis of product differentiation and respondents' preferences for UAs form the basis of product configuration. In this study, more than 500 questionnaires were sent (55% were online samples) to consult user attitude towards padbooks, ultrabooks, and notebooks. After removing samples containing missing values, the remaining number of samples is 468. In brief, the surveyed respondents consist of graduate students (33%), business users (45%) and PC retailers (22%). The entire process has two steps: (1) eliciting user perceptions of HAs and (2) capturing user preferences for UAs.

Conducting association rule mining to identify the significant portfolios of HAs

To elicit user perceptions of HAs (see Table 5; Fig. 4), the participants were required to answer the following question: *With respect to padbooks, ultrabooks, or notebooks, please mark the necessity (dichotomous scale) for detailed levels of a specific hedonic attribute*. Table 6 demonstrates the support of 1-item set for HAs. For a padbook, the priority is H3 $\succ H1 \succ H5$ (keyboard interface > screen type > body color). For an ultrabook, the priority is H4 $\succ H1 \succ H3$ (body material > screen type > keyboard interface) while it is H2 $\succ H4 \succ H1$ for a notebook (screen size > body material > screen type). The support for body color (H5) is more than 50% for an ultrabook and a notebook but it is ranked #4 among the five HAs. According to the priorities of different HAs, product differentiation can be accomplished w.r.t. the three alternatives.

Furthermore, using three measures (support, confidence and lift), 8 significant rules (in terms of 3-item sets) are displayed in Table 7. The thresholds for the support and the confidence are 0.2 and 0.6, respectively. Intuitively, a lower threshold results in superfluous rules while a higher threshold leads to insufficient rules for making decisions. After setting the consequent (the right-hand side), three itemsets are systematically derived as the antecedents (the left-hand side). Table 7 shows that padbook users prefer a touch screen with a pen (H12), a small-sized screen (H21), a slider keyboard (H32) and silver body color (H53), and a separable keyboard (H31) and white body color (H52). Commercial products, such as Acer's switch series, Asus's transformer series, and Microsoft's Surface series can be found in the marketplace. A stylus pen is not commonly included in most tablets but the results show that it should be embedded in a padbook.

In contrast, the biggest group for an ultrabook (see rule 6) prefers a medium-sized screen (H22) and the joint design-carbon-fiber body material (H41) with black body color (H51) because users are concerned about the balance between system performance and portability. This high-level product can fit the requirement of the business segment. Interestingly, individual ultrabook users prefer a touch screen with a pen (H12) with a slider keyboard (H32) in rule 4 and a touch screen without a pen (H13) with a 360° rotatable keyboard interface (H33) in rule 5. Commercial products, such as Sony's VAIO Pro series, Gigabyte's X11 series, and Lenovo's

Table 5 Hedonic attributes (HAs) and utilitarian attributes (UAs)

	Detailed levels	Descriptions
Hedonic attributes (multi-levels)	H1 screen type (3)	Non-touch (H11), touch with a pen (H12), touch without a pen (H13)
	H2 screen size (3)	10–12.1 inch (H21), 12.2–14.1 inch (H22), 14.2–17 inch (H23)
	H3 keyboard interface (3)	Separable (H31), slider (H32), 360° rotatable (H33)
	H4 body material (3)	Carbon fiber (H41), Mg/Al alloy (H42), plastics (H43)
	H5 body color (3)	Black (H51), white (H52), silver (H53)
Utilitarian attributes (multi-levels)	U1 CPU performance (3)	Low (U11)/medium (U12)/high (U13) performance
	U2 graphics card (3)	Integrated (U21), 3GB discrete or less (U22), 4GB discrete or more (U23)
	U3 RAM capacity (2)	6GB or less (U31), 8GB or more (UF32)
	U4 storage type (3)	Flash ROM (U41), SSD (U42), SATA (U43)
	U5 screen resolution (2)	Full HD or worse (U51), above full HD (U52)
	U6 battery capacity (2)	3 cell or less (U61), 4 cell or more (U62)

Fig. 4 Visualizing various types of keyboard-interface design

Table 6 The support of HAs for 1-item set

Utilitarian attributes	Padbook (%)	Ultrabook (%)	Notebook (%)
H1 screen type	68	65	54
H2 screen size	55	45	72
H3 keyboard interface	81	58	34
H4 body material	32	75	66
H5 body color	61	51	52

ThinkPad X1 series are found in the marketplace. Finally, association rules for designing a notebook are relatively simple and consistent. Users prefer a big-sized non-touch screen (H11 + H23) with Mg/Al-alloy body material (H42) or a medium-sized touch screen (H13 + H22) with carbon-fiber body material (H41). Obviously, body color is not significant for designing a notebook. And notebook users in rule 8 are partially overlapped with ultrabook users in rule 6.

Employing cognitive pairwise rating to derive the optimal portfolios of UAs

In this step, user preferences for utilitarian attributes are extracted and aggregated to derive the optimal portfolios of UAs. Table 4 shows that an invited respondent needs to complete pairwise comparisons: *Please give a positive/negative rating scale to express your preference/dislike between attribute i and attribute j*. In this case, a respondent needs to conduct 7 pairwise comparisons (one is between six UAs and the others are among UAs' detailed levels). After gathering the surveys of all respondents, the importance weights with regard to the three products are derived in Table 8 [see Eqs. (5)–(6)]. For clarity, the top three UAs for configuring padbooks, ultrabooks, and notebooks are respectively marked in different colors.

For a padbook, the priority is U1 $\succ$ U5 $\succ$ U3 (CPU performance $>$ screen resolution $>$ RAM capacity) and battery capacity is almost as equally important as RAM capacity. For an ultrabook, the priority becomes U1 $\succ$ U6 $\succ$ U4 (CPU performance $>$ battery capacity $>$ storage type). Storage type is a little more important than RAM capacity because the trade-off between system performance and durability/portability needs to be addressed for configuring an ultrabook. For a notebook, the priority is U1 $\succ$ U2 $\succ$ U3 (CPU performance $>$ graphics card $>$ RAM capacity) because a notebook needs to be operated in a gaming entertainment. Therefore, powerful graphics cards are necessary for an environment of 3D visualization or AR/VR applications.

Table 7 Conducting association rule mining to seek the significant portfolios of HAs

Rule	Antecedent	Consequent	Support (%)	Confidence (%)	Lift
#1	(Screen type = H12) and (screen size = H21) and (keyboard interface = H31)	Padbook	37	81.9	3.44
#2	(Screen type = H12) and (keyboard interface = H32) and (body color = H53)	Padbook	23.6	64.3	2.75
#3	(Screen size = H21) and (keyboard interface = H31) and (body color = H52)	Padbook	23.8	70.5	1.75
#4	(Screen type = H12) and (screen size = H22) and (keyboard interface = H32)	Ultrabook	22.1	65.7	2.18
#5	(Screen type = H13) and (keyboard interface = H33) and (body material = H42)	Ultrabook	27.7	71	3.68
#6	(Screen size = H22) and (body material = H41) and (body color = H51)	Ultrabook	31.3	76	4.13
#7	(Screen type = H11) and (screen size = H23) and (body material = H42)	Notebook	24.7	74.8	4.28
#8	(Screen type = H13) and (screen size = H22) and (body material = H41)	Notebook	21.8	68.5	2.84

% The respective thresholds of support and confidence are 0.2 and 0.6 for 3-item portfolios

Furthermore, user preferences for UAs' detailed levels are derived and shown in Table 9. As an alternative, the sum of UAs' preference scores definitely equals to unity. The TOPSIS ranking gives the top three varieties, as shown in Table 10. The most recommended alternative is quite similar for the three products: (U13, U23, U32, U41, U52, U62) for configuring a padbook and (U13, U23, U32, U42, U52, U62) for configuring an ultrabook and a notebook. The only difference between them is the storage type (U4). However, with consideration of users' affordable prices (proportional to manufacturing costs), the optimal portfolios of UAs are expected to differ substantially.

Table 8 Derived importance weights of UAs

Utilitarian attributes	Padbook	Ultrabook	Notebook
U1 CPU performance	0.240	0.205	0.243
U2 graphics card	0.122	0.104	0.205
U3 RAM capacity	0.198	0.170	0.170
U4 storage type	0.045	0.177	0.124
U5 screen resolution	0.205	0.163	0.168
U6 battery capacity	0.191	0.181	0.090

Discussion and research limitation

This study combines association rule mining with cognitive pairwise rating to respectively derive the significant/optimal portfolios of HAs/UAs. In Table 6, the most significant HAs which have the maximal support are "keyboard interface" for a padbook, "body material" for an ultrabook and "screen size" for a notebook. These distinct results provide a good basis for achieving product differentiation. In Table 8, although "CPU performance" is the most critical for the three alternatives, "screen resolution" is the second important attribute for a padbook, "battery capacity" is for an ultrabook and "graphics card" is for a notebook. These findings explain why more high-resolution (2K or 4K) tablets are being launched into the marketplace. Longer usage and sufficient computational capability must be balanced for designing an ultrabook. Finally, entertainment requirements for gaming notebooks that arise from the rising demand for AR/VR have boosted the popularity of high-performance graphics cards. Most gaming notebooks must control power dissipation and so an innovative alloy design for body materials is necessary. The aforementioned information provides a good way to configure functional UAs in a more systematic manner.

This paper cannot be without limitations although ARM and CPR are combined to accomplish product differentiation and product configuration, respectively. First, determining the thresholds of ARM's measures, such as support and confidence, is subjective and an open issue in practice. To the best of our knowledge, no systematic rules are suggested to guide product planners. Second, CPR is limited to handling at most 7 evaluation criteria at a time. Based on the so-called "pairwise" comparisons, it's infeasible to ask the respondents to assess more than 7 attributes. Third, the issue of market segmentation is not addressed (Zhang et al. 2009). User demographics (i.e. age, gender, education level), psychographics (i.e. preferences, perceptions, lifestyle, satisfaction), and monetary factors (i.e. taxable income, affordable prices) are commonly adopted to seek

Table 9 The derived user preferences for UAs

UAs	Levels	Padbook	Ultrabook	Notebook
U1 CPU performance	U11-low	0.07	0.04	0.051
	U12-medium	0.08	0.074	0.078
	U13-high	0.09	0.091	0.114
U2 graphics card	U21-integrated	0.032	0.027	0.034
	U22-3GB or less	0.041	0.036	0.074
	U23-4GB or more	0.049	0.041	0.097
U3 RAM capacity	U31-4GB or less	0.093	0.074	0.064
	U32-6GB or more	0.104	0.096	0.106
U4 storage type	U41-flash	0.022	0.049	0.029
	U42-SSD	0.014	0.076	0.055
	U43-SATA	0.009	0.052	0.045
U5 screen resolution	U51-full HD or worse	0.077	0.066	0.061
	U52-above full HD	0.128	0.097	0.102
U6 battery capacity	U61-3 cell or less	0.072	0.079	0.042
	U62-4 cell or more	0.119	0.102	0.048

Table 10 The top three portfolios of UAs with respect to the three alternatives

	Padbook			Ultrabook			Notebook		
	#1	#2	#3	#1	#2	#3	#1	#2	#3
U11									
U12						*			
U13	*	*	*	*	*		*	*	*
U21									
U22			*		*				
U23	*	*		*		*	*	*	*
U31									
U32	*	*	*	*	*	*	*	*	*
U41	*		*						
U42		*		*	*	*	*	*	
U43									*
U51									
U52	*	*	*	*	*	*	*	*	*
U61								*	
U62	*	*	*	*	*	*	*		*

market niches. Quantitative schemes, such as multiple correspondence analysis, multi-dimensional scaling or nested logit (Kumar et al. 2009; Luo et al. 2012; Wang 2016) can be used to visualize the joint effects of user demographics and psychographics on product selection (user decision). Finally, user profile and product characteristics (i.e. complexity, compatibility, usefulness, ease of use) can be treated as a priori for forecasting purchase intention, which allows firms to reduce the gaps between designed alternatives and user requirements (Jahng and Jain 2006; Wang and Chen 2012).

Conclusion

Changing customer needs and rapid technology advances induce a new trend (low volume but high variety) in consumer electronics. Thus, global companies need to reconsider product-positioning strategies in a more effective and efficient way, such as product differentiation and product configuration (Pirmoradi et al. 2013). On the one hand, plenty of alternative options allow firms to improve customer satisfaction and gain more market share. On the other hand, the increased variety represents more complexity, higher design and production costs, and longer lead time. Therefore, there is a need to consider the trade-off between satisfying customer needs and controlling product complexities (Wang and Chen 2012). In reality, a company's market share or profitability is affected by its product portfolios since each alternative contributes to an overall profit margin as a whole. As a result, a user-driven portfolio analysis and management plays a key role to solve the aforementioned issues.

In this study, product positioning in product family design is achieved by conducting product differentiation (using affective HAs) and product configuration (using functional UAs). The experimental results show that hedonic attributes, compared to utilitarian attributes, have a greater impact on product positioning because the priorities of the HAs are very different among padbook, ultrabook and notebook. To help firms better understand how these related but different alternatives are perceived by end customers, a novel framework is presented to accomplish the following goals:

- Association rule mining is used to tackle user perceptions of HAs and identify the significant portfolios (a basis of product differentiation),

- Cognitive pairwise rating is used to capture user preferences for UAs (a basis of product configuration),
- TOPSIS ranking is used to prioritize the top three varieties to guide industrial practitioners for developing the next-generation product families.

In the future, other schemes including text mining or social media mining could be applied to gather user feedback to build a customized recommender system. Furthermore, the causality between product portfolio selection and a company's profitability/market share could also be financially justified.

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