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Abstract

Purpose – The purpose of this paper is to evaluate the effect of design awareness on consumers' purchase intention.

Design/methodology/approach – The experiment consisted of showing a new beer package design to 185 participants who evaluated it using a self-administered questionnaire.

Findings – Using an Item Response Theory approach, results show that there are two dimensions of consumer design awareness: basic design and differential design. These findings are, to some extent, consistent with the theoretical discussion within design literature. Moreover, a multiple regression model estimates the effect of both dimensions on consumers' purchase intention, and the paper concludes that both dimensions have a similar effect ($p < 0.05$). The sign of the effects are consistent with the theoretical discussion.

Practical implications – The design of new products must consider attributes associated to the basic and practical use of a product as well as those attributes that mark a comparative difference in the product category.

Originality/value – This paper conceptually and empirically combines two different areas of knowledge (design and consumer behavior) under the design awareness construct. This concept evaluates consumers' perceptions about new products, facilitating more accurate decisions in cases of innovation.

Keywords Packaging, Item response theory, Design attributes, Design awareness, Rasch model

Paper type Research paper

Introduction

Product design creates a competitive advantage when the product attributes are consistent with consumers' needs and expectations (Srivastava *et al.*, 2001). Thus, product design can add value for consumers, in the sense that it improves the quality of user experience (Bloch, 1995; Koukova *et al.*, 2012). It is unclear, however, to what extent consumers have the ability to identify, understand, and value product characteristics that are thought out during the product design phase. Consumers may not be interested in really new products because their little to no experience with such items means that they do not fully understand their function or how to incorporate them into their everyday lives (Noseworthy and Trudel, 2011).

The purpose of this study is to determine the effect of design attributes on a consumer's intention to purchase a product. In a practical sense, innovation as a way to create a competitive advantage, may predict a successful product if consumers are able to understand and value its design attributes.

The paper is organized as follows: first, the literature review explains the concept of consumer awareness. Second, the method section describes the measures and the data collection process. Third, findings are analyzed using Item Response Theory (IRT).

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Results show that the concept of design awareness is a two dimensional construct: basic design and differential design. Additionally, the use of a multiple regression model demonstrates that these dimensions explain consumers' purchase intention. Fourth, the discussion section presents some theoretical implications by analyzing the conceptual similarities and differences between the two dimensions presented in this study. Next, the discussion compares the basic and differential design with the functional and symbolic attributes defined in design theory. Finally, there is a review of the practical implications of the study.

Consumers' design awareness

Awareness is a cognitive process related to an individual's ability to recognize an object and understand what it is and what it is used for. This means that the consumer needs to have had contact with similar objects in the past, so that he or she is familiar with certain characteristics of the new product (Fiske and Taylor, 2008). This conceptual framework explains what it is to be aware of an object, defines design attributes, and lastly, combines both concepts to define the design awareness construct.

Awareness is defined as a subjective ability to recognize and pay attention to the presence of an object and its characteristics (Bower, 1990). The precise moment at which individuals become aware is when they express their opinion and will in relation to an object. Hence, being aware is a process which is apparently self-regulated, but it actually depends on individuals' previous experience (Dijksterhuis and Aarts, 2010) and, in turn, on the strength of advertising activity for a given product category (Barroso and Llobet, 2012). Awareness of an object does not occur suddenly or spontaneously. Being aware can be understood as a process that arises as the result of a sequence or flow of knowledge and learning (Fiske and Taylor, 2008). As individuals gain familiarity with an object in a certain category, they improve their ability to recognize more details associated to an object or to value new objects in a given category. In contrast, if individuals are not familiar with an object category and function, they will not be able to identify the object based on a general description or on analogies to objects of a similar use (Cohen and Basu, 1987).

Object design

Individuals' experience with an object creates awareness because the individual recognizes its particular external characteristics and functional attributes. When the characteristics of a product are thought out to make it stand out from other products in a category, it can be assumed that there is a differential value (Christensen and Bower, 1996; Srivastava *et al.*, 2001). Thus, design becomes a process of creating or recreating objects in order to a gain competitive advantage. Design experts create objects by thinking of attributes they consider to be central aspects of a successful design. In an important attempt to establish a guide of basic design attributes, Lidwell and others proposed a list of 125 design principles (Lidwell *et al.*, 2011). This long list of attributes reveals a lack of consensus in design theory, in terms of what the central and fundamental design attributes might be. This section provides a summary of some important design attributes gathered from within the design literature and attempts to reach a parsimonious conclusion.

The concept of a good design is an evolving concept. It has been modified as designers evaluate the object-user-environment relationship. What is consistent throughout the design literature is that it is essential for a design to serve a purpose by establishing a relationship between an object and a user. Bürdek (1994) classifies object functionality from a practical and symbolic point of view. Bürdek's conceptual definition of design attributes is used in this study as the reference definition from a designer perspective. According to Bürdek (1994), the practical (or instrumental) point of view of design stresses the usefulness of an object. From this practical point of view, design characteristics refer to an object itself. Thus, the practical perspective of an object is what is it made for, how it works, and what its basic function is.

In contrast, the symbolic perspective is more complex. A symbolic point of view refers to the relationship between an object and an individual or a context (Bürdek, 1994). The symbolic view of design is reflected in the idea that an object must be interpreted by an individual who recognizes it as aesthetic and has the ability to convey how it is used, what it is used for, and the quality of use (Bürdek, 1994). The symbolic point of view considers design as something meaningful to users who interpret it based on their social background. Thanks to the relationship between users and their environment, a symbolic perspective also considers environmental aspects as part of its principles. These aspects are associated with product durability, user safety, and environmental protection (Bürdek, 1994).

Thus, a good design is both; it has basic functional characteristics that are explicitly useful and is meaningful for the individual who uses it. The practical function of an object tends to be evident for a user, but the symbolic function, may not be; nevertheless, both perspectives are complementary. An individual, for example, can argue that a package is useful for containing a product, but may not be aware that the packaging represents a certain status or that he finds some degree of closeness to the product because he is familiar with the package.

Understanding the design principles makes it easier to recognize the reasons why an object has a given effect on people (Lidwell *et al.*, 2011). In practice, however, the use of these principles is almost exclusive for the individuals who design or decide about the product positioning. Consumers in general do not have any influence on the use of these basic principles, which may not always hold true when it comes to product development and testing. There are some schools of design that are now considering consumers in the design process of new products, suggesting co-design as an alternative to develop products that are more consistent with consumers' expectations (Cavallone and Cassia, 2012). Empirical studies show that consumers' involvement with the design process is associated with the innovative ability of a brand (Schreier *et al.*, 2012), and with consumers' perception of quality and emotional closeness to the brand (da Silveira, 2011). This co-design exercise leads to an understanding that consumers are not totally unaware of the practical and symbolic characteristics of a product. Hence, consumers, to some extent, could understand those attributes implicit in design theory. In the next section, we define the concept of design awareness by using design attributes, but from a consumer perspective.

Design awareness

From a design perspective, objects are understood based on their practical and symbolic function. Similarly, consumer behavior theory argues that consumers experience of an object allows them to understand and value them from an instrumental and symbolic standpoint (Prentice, 1987). Given the similarities between the two theories, this section re-examines the previously discussed definition of design principles, now using a consumer perspective. Our objective is to empirically create the consumers' design awareness construct. Design awareness is defined as an individual's ability to recognize attributes that have been created in an object with an instrumental and symbolic purpose.

For consumers, the instrumental (or practical) characteristics of an object determine to what extent it can be used for a specific purpose. Complementary to this, the symbolic characteristics of an object indicate whether it: has an aesthetic appearance that improves well-being through its use; is easy to use, conveys the way it should be used; and is durable and environmentally friendly (Bürdek, 1994). Symbolic characteristics are also associated with their capacity to represent a user's identity (Prentice, 1987; Rams, 1980).

Previous studies show that consumers have the ability to understand a product design (Karjalainen and Snelders, 2010) and make decisions about its design (da Silveira, 2011; Schreier *et al.*, 2012), meaning that consumers have the ability to appreciate design. Yet it is not clear how consumers use the attributes defined by the design theory, to what extent consumers use each of these attributes to evaluate an object, or to what extent awareness of these attributes could allow us to predict consumers' intention to purchase an object. This study aims to provide an empirical definition of the design awareness construct and evaluate its influence on consumers' purchase intention.

Relevance of the IRT and construct estimation

This section discusses a procedure for estimating the construct of consumers' design awareness and the reason for using IRT models in this particular case. IRT is an extensive area of the study of psychometrics employed by psychologists, sociologists, social scientists, and researchers in the fields of education, medicine and, in some cases, marketing (Sijtsma and Molenaar, 2002).

In general, IRT allows us to examine and analyze tests and questionnaires aimed at measuring characteristics (variables) that cannot be observed directly by using observable ordinal variables. Some examples of unobservable variables are intelligence, skills, accomplishments, personality features, and attitudes. In other words, IRT provides models that find the relation between directly observable variables (responses to items), either binomial (two options) or multinomial (multiple options) which are typically ordinal, and one or several latent variables (non-observable variables) which are expected to be continuous (Rizopoulos, 2006).

Additionally, traditional analysis of questions using Likert-type scales implicitly assumes that the same psychological distance separates all scale categories. This means that in using principal components or factorial analysis, it is assumed that there is the same psychological distance between categories such as "strongly disagree" and "disagree" or between "neutral" and "agree." If, for example, a respondent selects number 2 on a Likert scale, then conventional analysis assumes that the respondent's answer is exactly one unit greater than that of a respondent who chooses number 1 to answer the same question. Conventional analysis using continuous variables implies that results can be averaged. In the above example, the average would be 1.5. This assumption is strong and it does not necessarily hold in all cases. Furthermore, a priori in most of the cases, there is no reason to believe that the psychological distance is the same.

If we create a tool to measure the design awareness construct using a questionnaire with multiple items, where each item may be answered with a Likert-type scale, we will have a similar problem. For example, a response of 2 to rate product appearance does not mean that the respondent agrees with the appearance by one additional unit compared to a respondent who selects 1. It would also not be advisable to average these answers. To prevent this kind of bias, ordinal variables should be treated as categorical variables, not as continuous variables[1].

Wakita *et al.* (2012) demonstrated that the implied assumption (same psychological distance between scale categories) is incorrect in the context of the psychological tests that rates the big five personality traits (Wada, 1996). These authors found that, regardless of the number of categories in a scale, the best option was to use IRT models when working with a Likert scale. González-Betanzos *et al.* (2013) arrived at a similar finding in the case of a scale to rate "children's perception of stress." These findings support the need to use approaches like IRT to review the results of questionnaires using Likert-type scales. Thus, IRT models allow us to circumvent the assumption of equal psychological distance between categories and estimate latent and continuous variables underlying one or several sets of questions (items).

The Rasch model is perhaps the most popular family of IRT models with a latent variable. This model family has become an alternative to the common practice of finding a relationship between information gathered from questionnaires using Likert scales and a latent variable or a construct.

Nevertheless, this kind of model is not often used to determine consumer's perception of product design. Only recently, has the Rasch model been recognized as a useful tool for evaluating design pieces and a better alternative than conventional analysis. It is better because it makes it easy to process discrepancies in respondents' answers (Camargo and Henson, 2011, 2012). In a design evaluation, for example, an individual may not have a consistent opinion of an object, expressing a positive attitude toward a design aspect (rated 5) and a negative attitude (rated 1) toward a different aspect of the same piece. Because the construct measure uses an ordinal scale, the analysis could not process previous answers as symmetrically opposite scores in the way it is done when using conventional methodology. Thus, using IRT models seems to be the best option for building latent variables to study the effect of constructs associated with design attributes.

A formal model for estimating constructs

Muraki's (1992) Generalized Partial Credit Model (GPCM) is the most general IRT model. It is defined as follows:

$$P_{jik}(z_j) = \frac{e^{\sum_{c=0}^{k} \beta_i (z_j - \beta^*_{ic})}}{\sum_{r=0}^{m_i} e^{\sum_{c=0}^{r} \beta_i (z_j - \beta^*_{ic})}} \tag{1}$$

where $P_{jik}(z_j)$ equals the probability of obtaining a response in category k for item i for individual j, given the degree of latent skill (non-observable) of individual $j(z_j)$. This means that z_j represents the latent variable to be estimated. β^*_{ic} represent the parameters for each item (i) – category (c), β_i is a discrimination parameter of question (i), and m_i is the number of categories (options) for item i. Additionally, we have that:

$$\sum_{c=0}^{r} \beta_i (z_j - \beta^*_{ic}) \equiv 0$$

Masters (1982) demonstrated that GPCM is a more general version of the Rasch (1960, 1977) model for multinomial responses. In fact, if $\beta_i = 1$ $(\forall i)$ the GPCM will be the same as the Rasch (1960, 1977) model. If $\beta_i = \beta$ $(\forall i)$, then GPCM becomes the "rating scale" model, in which each question has the same degree of discrimination (or difficulty). The most general model, in which a different β_i is estimated for each item, is known as a "partial credit" model where there is a different degree of discrimination for each item.

Model (1) is commonly estimated using Marginal Maximum Likelihood Estimators (MMLE). Under this estimation method, it is assumed that the answers to each item represent a random sample of a population and that the skills follow a distribution determined by the function $F(z_j)$. The model parameters are estimated by maximizing the logarithm of the sample maximum likelihood function, which is derived from integrating with respect to the latent variable. In this case, the contribution of the mth observation is the following:

$$l_m(\theta) = \log p(x_m;\theta) = \log \int p(x_m|z_m;\theta)p(z_m)dz_m \tag{2}$$

where, $p(\bullet)$ is the function of density, x_m is the vector of answers to the items for the mth observation, z_m is the latent variable to be estimated for the mth individual which is assumed to follow a normal standard distribution, and θ equals the parameters to be determined. In our case, the Gauss-Hermite quadrature rule is used for computing an approximate solution to the integral in (2), and the BFGS algorithm is employed for the maximization process.

One of the advantages of using the GPCM model expressed in (1) using MMLE is that it allows the use of two different methods to determine the goodness of fit of the models:

(1) Pearson's χ^2 parametric test using simulated critical values (Bootstrap).

(2) A maximum likelihood ratio test for nested models.

Table I presents a summary of three specifications that can be checked using (1).

Pearson's χ^2 parametric test using simulated critical values (Bootstrap) implies the null hypothesis that the sample has been generated by the model under evaluation vs the alternative hypothesis that the model being reviewed is not the correct one. The resulting statistic is calculated as follows:

$$\sum_{r=1}^{2^p} \frac{[O(r)-E(r)]^2}{E(r)}$$

Name	Restriction	$P_{jik}(z_j) =$
Specification A (Rasch model)	$\beta_I = 1$ $(\forall i)$	$e^{\sum_{c=0}^{k}(z_j-\beta^*_{ic})} \Big/ \sum_{r=0}^{m_i} e^{\sum_{c=0}^{r}(z_j-\beta^*_{ic})}$
Specification B ("rating scale" model)	$\beta_I = \beta$ $(\forall i)$	$e^{\sum_{c=0}^{k}\beta(z_j-\beta^*_{ic})} \Big/ \sum_{r=0}^{m_i} e^{\sum_{c=0}^{r}\beta(z_j-\beta^*_{ic})}$
Specification C (GPCM model)	None	$e^{\sum_{c=0}^{k}\beta_i(z_j-\beta^*_{ic})} \Big/ \sum_{r=0}^{m_i} e^{\sum_{c=0}^{r}\beta_i(z_j-\beta^*_{ic})}$

Table I. Nested models of the GPCM family where, $O(r)$ and $E(r)$ represent the frequency of observed and expected answers, respectively, and p equals the number of items. In general, this statistic will not necessarily follow a χ^2 distribution if there are a relatively large number of items. It is advisable to simulate the distribution of the estimator in order to make a decision as to whether or not to reject the null hypothesis.

The maximum likelihood ratio test for nested models implies a null hypothesis that the restricted model is better than the unrestricted model vs the alternate hypothesis of no *H0*. The statistic is calculated as follows:

$$LR = -2(l_r - l_{sr})$$

where, l_r and l_{sr} are the maximum of the logarithms of the likelihood function of the restricted and unrestricted models, respectively. Asymptotically, the test's critical value will follow a χ^2 distribution. The degrees of freedom of χ^2 distribution are equal to the difference between the degrees of freedom of the restricted model and those of the non-restricted model. Another option is to simulate the critical values to decide whether to reject *H0* or not.

After selecting the best model that fits the sample, we can compute the characteristic curves for each item and obtain the information contributed by each item to explain the latent variable. Characteristic curves can be used for determining the difference between items to explain the construct (latent variable), while the information contributed by each item is used for estimating what percentage of the latent variable can be represented with each item. Thus, the characteristic curves and the information contributed by each item are useful for determining whether or not an item should be kept in a questionnaire estimating the construct. Lastly, after choosing the optimal model and the items that comprise the construct, the value of the latent variable (construct) can then be estimated for each individual. In this study, the latent variables that represent the consumer design awareness and purchase intention constructs are estimated using a model from the GPCM family as described in detail in the next section.

The estimates of these latent variables (design awareness and purchase intention) will be employed for estimating a multiple regression model. This regression model explains the purchase intention construct using control variables and constructs related to design awareness. The next section describes our study, the measures included in the instrument, and the sample characteristics.

Experiment, instrument, and sample

The sample consisted of 185 students studying different majors at a private university. All participants were adults with an average age of 22.7 years (SD: 5.23). In all, 44 percent of the students were males and 56 percent were females. In this laboratory experiment students were shown a new package for a relatively common product (a beer package). After observing the object, the participants were asked to complete a questionnaire rating each of the design attributes.

This was a 13-item questionnaire for evaluating design awareness. The items' wording took into account concepts that designers thought would lead respondents to think of an object with a good design (Bürdek, 1994; Lidwell *et al.*, 2011). These 13 attributes (items) are denoted as V1 to V13. Table II is a summary of those items. The questionnaire also included five items to evaluate purchase intention: "I would like to purchase the product in this package (this item is denoted by Y1)"; "If I had to choose

Concept	Questionnaire item	Final model
V1. Use	It meets a specific purpose	BD
V2. Communication	I understand how to use it	X
V3. Appearance	It is pretty	BD
V4. Identification	It is my style	X
V5. Quality	It does not break easily	BD
V6. Environmentally friendly	It has a positive impact on the environment	X
V7. Additional purposes	It offers something different from other products in the same category	DD
V8. Innovative	It is a creative object	DD
V9. Ergonomic	It is comfortable	DD
V10. Integrative	Anyone can use it	X
V11. Long-lasting	I hope to use the same object in the future	DD
V12. Surprise	It is perceived as something different from what was expected	
V13. Status	It provides me with status with respect to others	DD

Notes: X, item removed from the model; BD, basic design; DD, differential design

Table II. Design awareness attributes

a beer, I would look for it in this package (Y2)"; "I intend to get more information about this package (Y3)"; "I would recommend this package to anyone who is thinking about buying beer (Y4)"; and "I would rather buy the product in this package than in other package (Y5)."

For each of the design awareness and purchase intention items, we use an ordinal five-category Likert scale to record individuals' perceptions, where 1 represented "strongly disagree" and 5 "strongly agree." Because the design awareness and purchase intention constructs are measured with an ordinal scale, the best methodological option is to use an IRT approach.

Construction of the latent variables for the design awareness and purchase intention constructs

This section discusses the results of estimating the GPCM model described in a previous section and the estimation of the latent variables for the design awareness and purchase intention constructs. All estimations are determined using *R* (Team, 2010) and ltm (Rizopoulos, 2006) and eRm (Mair and Hatzinger, 2007) packages. We present a step-by-step analysis showing how the design attributes are not empirically organized according to the instrumental and symbolic dimensions (from the design theory), but rather to the innovative nature of a product. The following four-step procedure describes the item analysis for each construct:

(1) Estimate item intercorrelations;

(2) select optimal model for each construct;

(3) analyze the characteristic curves of the items and the information contributed by each item; and

(4) create latent variables associated with the constructs, which will be used for estimating the multiple regression model.

Next, we present the results for each of the constructs: design awareness and purchase intention.

Design awareness

The conceptual definition of the design awareness construct is embodied in the 13 items of the questionnaire administered. We explored these items to determine how reliably they measure the construct (latent variable). With this objective in mind, the first step was to conduct a Spearman and Kendall's correlation analysis for the items that evaluated design awareness. The correlation shows coherence between some of the items and the need to exclude other items (Table III). We can also observe that the items seem to be grouped into two subsets that coincide with the two dimensions of the construct discussed earlier: items 1 through 6 and items 7 through 13 (designated as V1-V6 and V7-V13 in Table II). The design attributes that comprise the first dimension are conceptually equivalent to basic or inherent aspects of any object and are not attributes that involve a major effort in terms of design. Having a clear use and being long lasting, for example, are basic typical aspects of any everyday object. Although these are not attributes that impart a differential character to an object, they are the ones that are more obviously valued by consumers. Thus, the first set of items reflects "basic" design concepts (V1-V16).

The second set of items, on the other hand, goes beyond practical aspects. Some of the attributes suggest that consumers perceive an object as different and unique. Additionally, other attributes included on this dimension emphasize emotions and individual experiences regarding that object. This second dimension contains attributes such as creativity, recognition, and surprise, which push a design from an instrumental value toward a symbolic value, essentially determined by product innovation. Hence, the second dimension observed in this analysis can be identified as a dimension in which an individual is aware that an object has a "differential" design (V7-V13).

After estimating the model expressed in (1), the same conclusion is reached. The design awareness construct can be explained based on two dimensions; one that contains basic design attributes and another that contains differential design attributes. These results are not reported because of space restraints. The following is a discussion of the estimation of each of the constructs that comprise design awareness.

Table III.
Correlation analysis of the 13 items (Kendall's τ and Spearman's ρ)

Item

Item	1	2	3	4	5	6	7	8	9	10	11	12	13
1				x				x	x	x	x		
2				x			x	x	x		x	x	
3										x			
4													
5											x		x
6										x		x	
7													x
8													
9													
10													
11													
12													
13													

Note: *** "X": represents a non-significant correlation with 95% confidence ($p > 0.05$)

Basic design

This section describes the creation of the latent variable for the basic design dimension. The first step was to estimate the model (1) and the corresponding nested (restricted) models, which are described in Table I. For each of the three specifications, a Pearson's goodness-of-fit test was carried out using critical simulated values (Bootstrap) to determine whether or not the observed data can be explained by the respective model. In this case, the three models exhibit a good fit (the results are not reported due to space restraints). To select among the three different specifications, we used the maximum-likelihood ratio test (see Table IV). Based on the test results, we can conclude that the best model for this dimension is the model that has no restrictions (model C in Table IV which is the equivalent of (1)). Item 4 (V4. Identification: "It is my style") in the above model is not significant; therefore, this variable is removed, and the model is estimated again (1).

Next, we analyzed the characteristics of the curves associated with each item of the first dimension and also how each item contributes to explain this first dimension. The analysis of the characteristics of the curves for all items in the basic design dimension shows that items 1 and 2 have identical curves, so they have the same effect on this dimension (V1: "It meets a specific purpose"; V2: "I understand how to use it"). Thus, we decided to remove item 2 (Figure 1). Additionally, an analysis of the contribution from each item to the basic design dimension shows that item 6 (V6: environmentally friendly) contributes with very little information (Table V). Item 6 was removed, and the model was estimated again excluding items 2 and 6 (item 4 was previously removed because it did not significantly contribute to the construct).

In the case in which only items 1, 3, and 5 were included, Pearson's parametric test results show that all three models exhibit a good fit. Meanwhile, based on the results of the maximum-likelihood test (Table VI), it can be concluded that the best specification of the GPCM family is that of model B in Table I ("rating scale" model). This model shows increased differentiation between items (Figure 2) and a greater contribution of information from each of the items in terms of a percentage (Table V). The internal consistency of items for the basic design dimension is 0.68. This means that this model will be used for generating the corresponding latent variable for this dimension using items V1, V3, and V5 (for a detailed description of each item, please see Table II).

Differential design

An analysis of the second dimension was conducted in a similar fashion to that of the first dimension. For all specifications, item 11 (V11. Long-lasting: "I hope I can use the same object in the future") is not significant. Therefore, the three models were estimated excluding this item. In this case, the three models exhibit a good fit (the results are not reported due to space restraints). Results for the maximum-likelihood

Restricted model	Unrestricted model	LR-statistic	Asymptotic *p*-value	Simulated *p*-value
A (Rasch)	B	33.1032746	8.74E-09***	0.00398406***
A (Rasch)	C	71.1198937	5.99E-14***	0.00404858***
B	C	38.0166191	1.11E-07***	0.00408163***

Note: ***Null hypothesis that the restricted model is better than the unrestricted is rejected with 99% confidence

Table IV. Maximum likelihood ratio rest for nested models including items 1, 2, 3, 4, 5, and 6. Basic design dimension

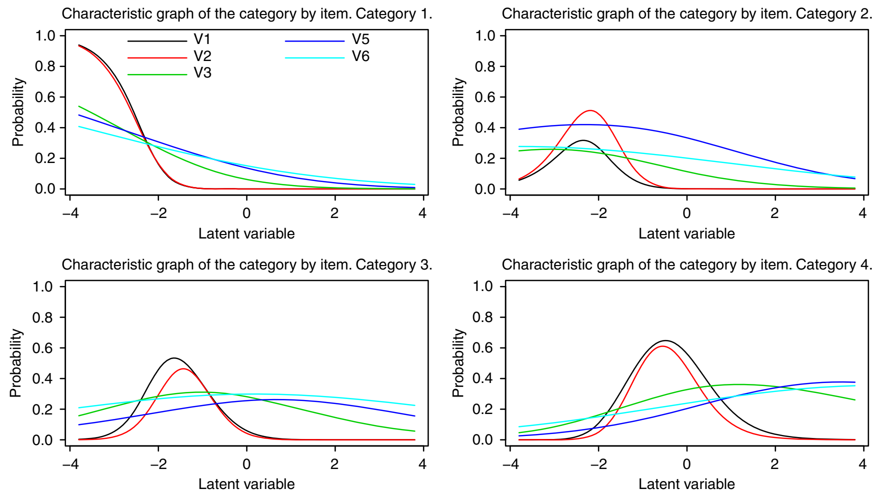

Figure 1.
Characteristics of items 1, 2, 3, 5, and 6. Basic design dimension

Table V.
Item analysis. Percentage contribution to total information from each item

Basic design (all items) Item	Info%	Basic design (corrected) Item	Info%	Differential design Item	Info %	Purchase intention Item	Info%
V1	39.21	V1	33.33	7	23.18	Y1	11.44
V2	44.37	V3	33.33	8	33.22	Y2	50.45
V3	7.51	V5	33.33	9	7.8	Y4	14.97
V5	5.77			12	6.23	Y5	23.14
V6	3.14			13	7.51		
α	0.55		0.68		0.95		0.90

Table VI.
Maximum likelihood ratio test for nested models including items 1, 3, and 5. Basic design dimension

Restricted model	Unrestricted model	LR-statistic	Asymptotic p-value	Simulated p-value
A (Rasch)	B	10.158256	1.44E-03***	0.00398406***
A (Rasch)	C	11.5525591	9.08E-03***	0.00398406***
B	C	1.39430302	4.98E-01	0.508

Note: ***Null hypothesis that the restricted model is better than the unrestricted is rejected with 99% confidence

ratio test reveal that the model that better fits this sample is the unrestricted model (GPCM model) (Table VII).

The items for the second dimension show high internal consistency with a Cronbach's α of 0.95. The column "Differential d." in Table V shows information contributed by each item to that dimension. This is complemented with Figure 3, which shows that each item has a different curve. This means that all items contribute with sufficient information and are not redundant. Thus, we will use the C model to create the latent variable for the second dimension of consumer design awareness using items V7, V8, V9, V10, V12, and V13 (for detailed information about each of these items, please see Table II).

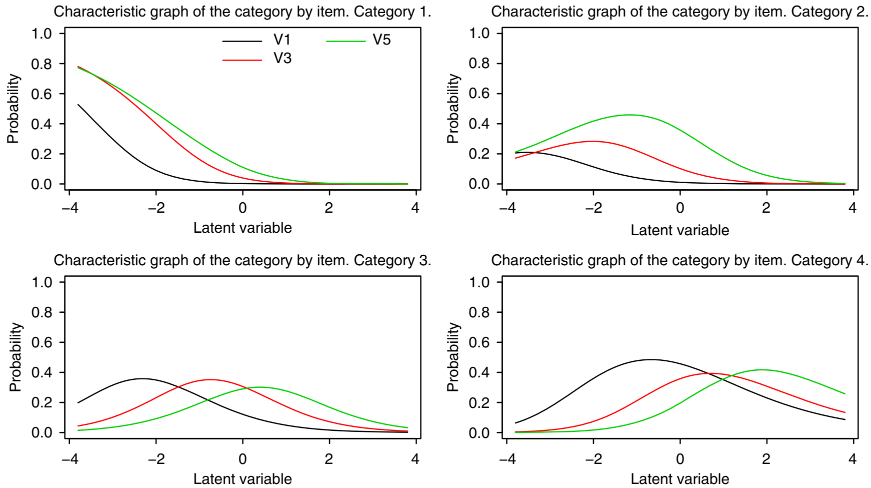

Figure 2. Characteristics of items 1, 3, and 5. Basic design dimension

Restricted model	Unrestricted model	LR-statistic	Asymptotic *p*-value	Simulated *p*-value
A (Rasch)	B	0.00796967	9.29E-01	0.91633466
A (Rasch)	C	65.3147185	3.72E-12***	0.00398406***
B	C	65.3067488	9.68E-13***	0.00398406***

Note: ***Null hypothesis that the restricted model is better than the unrestricted is rejected with 99% confidence

Table VII. Maximum likelihood ratio test for nested models including items 7, 8, 9, 10, 12, and 13

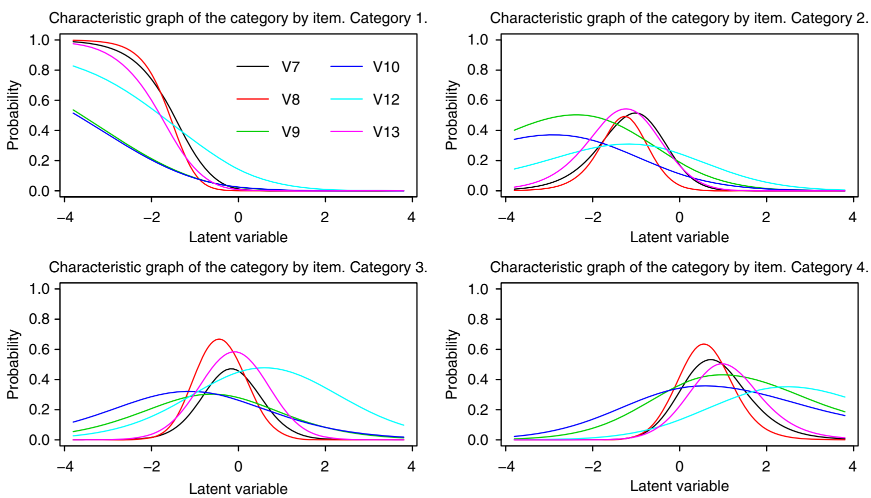

Figure 3. Characteristics of items 7, 8, 9, 10, 12, and 13. Differential design dimension

Purchase intention

We conducted the same kind of analysis for the construct that serves as the dependent variable in the multiple regression model: consumers' purchase intention. Because item Y3 (I intend to get more information about this package) is not significant in the three possible specifications, it is removed from the model's estimation process. In this case, similarly to the previous cases, the unrestricted model or model C (Table VIII) is selected based on the maximum likelihood ratio test. The items exhibit high internal consistency with a Cronbach's α of 0.90. Table V shows the percentage of information contributed by each item to the purchase intention; as can be observed, the four items supply a good percentage of information in the aggregate. The response curves reported in Figure 4 show the independence of each item in constructing the concept of purchase intention. Thus, we will use this model to construct the latent variable for the purchase intention construct using items Y1 ("I am interested in purchasing the product in this package"), Y2 ("If I had to choose a beer, I would look for it in this package"), Y4 ("I would recommend this package to anyone who is thinking of buying beer"), and Y5 ("I would rather buy the product in this package than in other package").

Relationship between purchase intention and design awareness

After constructing the latent variables for the purchase intention, basic design, and differential design, we can establish the effect of design attributes on the intention to purchase a product. Thus, the following model was estimated:

$$y_i = \beta_1 + \beta_2 age_i + \beta_3 sex_i + \beta_4 type_i + \alpha_1 z_{1,i} + \alpha_2 z_{2,i} + \varepsilon_i \tag{3}$$

Table VIII. Maximum likelihood ratio test for nested models including items related to purchase intention (Y1, Y2, Y4, and Y5)

Restricted model	Unrestricted model	LR-statistic	Asymptotic p-value	Simulated p-value
A (Rasch)	B	0.18737649	6.65E-01	0.68528296
A (Rasch)	C	20.1862028	4.59E-04***	0.00398406***
B	C	19.9988263	1.70E-04***	0.00398406***

Note: ***Null hypothesis that the restricted model is better than the unrestricted is rejected with 99% confidence

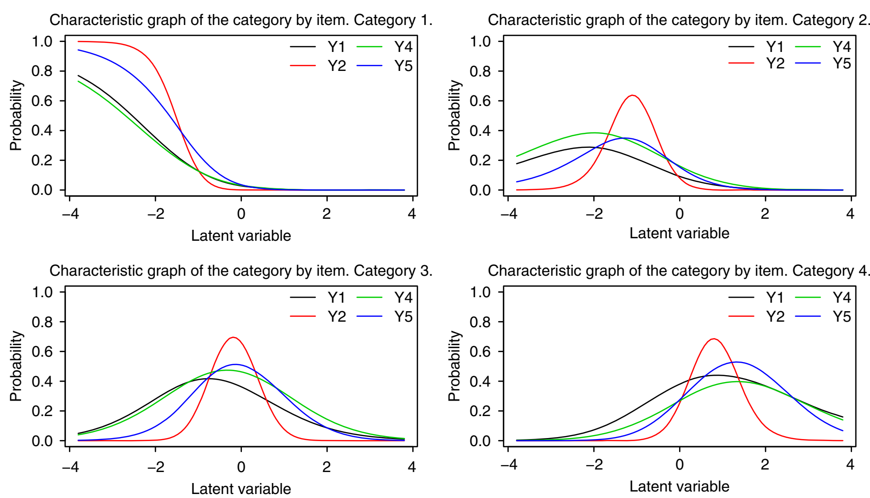

Figure 4. Characteristics of items associated with purchase intention (items Y1, Y2, Y4, and Y5)

where, y_i represents the latent variable constructed for the purchase intention of individual i. Meanwhile, age_i and sex_i represent the individual's age and gender, both of which were used as control variables. $type_i$ was used as a dummy variable that takes the value of 1 if the individual is a student in a design-related program and 0 otherwise. Finally, $z_{1,i}$ and $z_{2,i}$ denote the value of the latent variables of the basic design and differential design dimensions for individual i, respectively.

Estimating model (3), we found heteroscedasticity problems. To solve this, we used a generalized method of moments heteroscedasticity-consistent (HC) estimator for the variance-covariance matrix with small sample correction (Cribari-Neto, 2004). Using the relevant standard errors, we found that control variables did not have a significant impact on purchase intention (Table IX). Thus, we estimated a restricted model without these control variables (model (2) in Table IX).

Next, we ran a Wald's test (taking into account the HC variance matrix) to evaluate whether the restricted model was better than the unrestricted model; we obtained a Wald statistic with a p-value of 0.49. This result does not provide sufficient evidence to reject the null hypothesis that the restricted model is better than the unrestricted model.

By using the restricted model, we can conclude that there is a direct relation between purchase intention and both design dimensions. Given that the latent variables are created in such a way that they are standardized (particularly, with an average of zero and a variance of one), regression coefficients can be interpreted as standardized coefficients. This means that they are coefficients that allow us to determine what the most relevant variable is. Although specific estimators could

	Dependent variable and (HC standard error in parenthesis) [t is calculated in brackets]	
	Model (1)	Model (2)
(intercept)	−0.534607	−0.0085184**
	(0.367424)	(0.3674235)
	[−1.455]	[−0.0232]
z1	0.201631*	0.2262007***
	(0.110286)	(0.1102857)
	[1.8283]	[2.051]
z2	0.299196***	0.2948339
	(0.075293)	(0.752932)
	[3.9737]	[3.9158]
Age	0.022445	
	(0.16128)	
	[1.3917]	
Sex	−0.041971	
	(0.126042)	
	[−0.333]	
Type	0.110835	
	(0.131529)	
	[0.8427]	
R^2	0.1926	0.1768
Adjusted R^2	0.1701	0.1677

Notes: ***, **, *This means that the coefficient is individually significant with levels of confidence of 99%, 95%, and 90%, respectively

Table IX. Estimated models to explain purchase intention affirm that the differential design dimension is more important for explaining the purchase intention, when 95 percent confidence intervals are created for the slopes, it was found that these confidence intervals overlap each other. Hence, there is not sufficient evidence to reject the hypothesis that holds that these coefficients are statistically different. Therefore, we can conclude that both dimensions have the same impact on purchase intention ($p < 0.05$). Finally, both variables explain 17.7 percent of the variance in purchase intention.

Discussion

Findings show that there are two dimensions that comprise the design awareness construct: namely, a basic dimension and a differential dimension. The first encompasses the attributes of communication and use. Attributes in the latter dimension include ergonomics, additional functions, and surprise. These two dimensions have been named after considering the innovative nature of a design object and assuming that innovation contributes to a firm's competitiveness (Christensen and Bower, 1996; Schreier *et al.*, 2012; Utterback, 1987). Nevertheless, innovation *per se* does not guarantee a successful and strong purchase intention. Both dimensions contribute to the model in a positive manner and, to a similar extent, to explaining consumers' purchase intention. In other words, during the product development and launching phases, consideration should be given not only to basic design aspects to guarantee that an object is useful and attractive, but also to differential characteristics that signal the object as creative and meaningful to consumers.

It is worth noting that the basic design dimension is closely related to functional attributes, which are defined in design theory (Bürdek, 1994). Complementary to this, differential design, to some extent, represents the symbolic attributes described by design theory. However, design theory would not include differential or innovative attributes because these would be considered an implicit condition to the concept of design (Burry, 2013). The design awareness construct helps to understand that, in a consumer's mind, the symbolic function is closely related to the innovative nature of an object.

The symbolic nature of an object defines the meaning it has for the user. Therefore, the symbolic function of a design product may be associated with its capacity to create a particular social status for the user and to communicate the concept of uniqueness. This symbolic concept is better represented in a consumer's mind under the innovative nature of the design. Therefore, the concepts of basic and differential dimensions are different from those defined under functional and symbolic attributes of design. The basic and differential design constructs are relevant to explain how consumers understand and value a design. Based on the results of this study, we can conclude that consumers understand and value a design object on two equally important levels: its basic and innovative aspects.

Finally, there are some limitations and recommendations for future studies. With regard to the sample, the study was conducted with students and, although there was some variance in the age range, the use of students in the sample limits our results to a particular population. It is advisable to replicate this study in a less controlled environment. Additionally, the evaluated package is an incremental innovation design, not a radical innovation. This means that the evaluated object is actually a different package, which was not known on the market, but at that point in time there were other packages that led consumers to understand the one they were evaluating. Thus, it is important to differentiate the results of design awareness and compare radical innovations vs innovations that involve minor changes or improvements in a product category. For example, what would have happened if the Ipad, a really new product, had been evaluated before it was introduced on the market? It is also relevant to compare the design of mass consumer goods against that of exclusive goods or products that can be easily replaced. These conditions – how innovative the product is and the type of demand for it on the market – may moderate the relationship between design awareness and consumers' purchasing attitude.

Practical implications

Differentiating among basic and differential attributes of design may help organizations to understand the relevance of investing in the development of products with certain characteristics. We can assume that organizations that invest in unique, superior quality products that respond to functional and cognitive expectations of consumers should perform better on the market (Tatikonda and Montoya-Weiss, 2001). Consistently, when thinking of a new product, designers should consider different aspects; those related to the basic functionality of the product and those that impart a distinctive hallmark in the product category. It may occur that when an organization launches a new product emphasis is made on the innovative dimension, signaling the product as unique and providing a halo of exclusiveness to the consumer. Nevertheless, previous studies have come to the conclusion that, in the case of really new products which are unknown to consumers, greater emphasis should be placed on product functionality more than on hedonic aspects (Noseworthy and Trudel, 2011). This means that having an understanding of the usefulness of an object is as important as feeling emotionally represented by it.

Finally, thinking about implications for those who design, multiple attributes can be used as good design guidance (Lidwell *et al.*, 2011); however, these are not easily observed by a consumer's naked eye. The details of the design process are not evident to consumers who are able to or prefer to think of objects within a more general structure. In a very practical manner, consumers have the ability to recognize attributes that are basic and similar through the variety of products in a given category. Consumers also have the ability to value specific attributes that make a product unique within a category (Koukova *et al.*, 2012). Both basic and differential attributes contribute to product performance in a complementary manner in terms of consumers' purchase intentions.

Note

1. Note that conventional statistical methods, like multiple regression analysis, require all variables introduced to a model to be measured as continuous variables.

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