The benefits of design selection bias in the interplay between product modification and customer feedback

Abstract:
The way designers solve problems at the final stages of the product design process has received little attention in the extant literature. Existing work has mostly focused on the influence of designers' creativity, however, the role of non-creativity related mechanisms operating at these stages is still not well understood. We contribute to this work by analysing the influence of motivational factors in non-creative tasks at the later stages of a design process. Drawing on regulatory focus theory we examine how designers' motivations (promotion focus vs prevention focus) influence the effectiveness of late design decisions after the first commercialization of a product. We use a simulation model that represents design as a complex problem-solving task in which designers try to improve an existing product by making design modifications based on customers' feedback on product attributes. As postulated by regulatory focus theory, promotion-focused and prevention-focused designers use different strategies to search for solutions, and solve the design problem in different ways. We find that for complex design tasks, in which valenced customer feedback act as situational factors that bias designers' decisions, promotion-focused design strategies find better performing solutions than prevention-focused ones.

1. Introduction

Product design is a central aspect of innovation and new product development processes (Cooper, 1994; Perks et al, 2005; Roper et al, 2016). The design of a product can be conceived as a problem-solving task involving the mental processes and practices of designers (Brown, 2008; Liedtka, 2015; Ulrich, 2011). Most research using this conceptualisation of design has focused on understanding the mechanisms that influence the effectiveness of designers' decisions at the initial stages of the problem-solving process, specifically those that contribute to the early generation of creative ideas that lead to radically new designs (e.g. Dorst and Cross, 2001; Yilmaz et al.2010; Kroper et al, 2011).

In practice, however, many design decisions concern incremental product modifications that aim at meeting technological restrictions and consumers' needs uncovered at the final stages of the design process (Ecker et al, 2012; Snider et al, 2014). In fact, in many industries, product innovation is incremental (Abernathy and Clark, 1985), thus design becomes ongoing (Antioco et al, 2008; Eckert et al., 2004; Song and Montoya-Weiss, 1998) and focused on enhancements or the resolution of problems that emerge at the later stages of the new product development process (Snider et al, 2013). Evidence has shown that, in particular, ongoing design after the first commercialization of a product is crucial for product development since many newly developed products may still fail once they are in the market (Antioco et al, 2008; Carbonell et al, 2004; Cooper, 2001). For instance, the difficulties faced by Nokia in the smartphone market have often been attributed to the company's hardware-driven culture (Doz and Wilson, 2017), which has tended to relegate incremental improvements in their software design to a secondary concern. In comparison to early mobile phones, most smartphones on the market today are very similar in terms of hardware and it is the incremental enhancements of software design in combination with strong technological features that contribute to a phone commercial success (Menguc et al, 2014). In addition, later-stages design to transform a solution concept into a fully-fledged product can be complex (Eckert et al., 2012) and often requires significant amounts of time, effort, and financial resources (Snider et al, 2016; Antioco et al, 2008; Song and Montoya-Weiss, 1998).

Despite its importance, the way designers solve incremental problems at the final stages of a product design process has received little attention in the extant literature. Existing work has mostly analysed the influence of creativity (Eckert et al, 2012; Kroper et al, 2011; Snider et al, 2013; 2014; 2016). However, empirical work has shown that although creativity affects all stages of the design process (Dorst and Cross, 2001; Snider et al, 2013; 2016) its influence for design performance tends to decrease at the later stages (Kroper et al, 2011) where decisions made at previous stages place significant restrictions on what designers can do (Ecker et al, 2012). Particularly after the first commercialization of a product, in which designers often obtain customer feedback on product performance (Song and Montoya-Weiss, 1998), creativity may be less relevant for design effectiveness and designers' motivations and preferences may play a more significant role in ongoing design decisions. Indeed, internal motives intrinsic to individuals exert a significant influence on product design decisions (Spanjol, Tam, Qualls, & Bohlmann, 2011). As Noble and Kumar (2010: 652) note, "designers can enter a project with one or more dominant motivations that will knowingly or unknowingly guide their work". Moreover, motivations may differ between individuals. For instance, some designers might be motivated to avoid short term financial losses by removing certain atributes while others are motivated to increase long term adoption rates by improving other attributes (Spanjol et al., 2011; Noble & Kumar, 2010). In a related vein, some designers might be motivated to focus more on minimizing the utilitarian downsides of a product while others are motivated to improve its hedonic appeal (Chitturi, Raghunathan & Mahajn, 2008).

We maintain that one dominant motivation concerns designers' regulatory focus (Higgins, 1997), i.e., whether they regulate their feelings, thoughts and actions with a promotion focus or a prevention focus. According to Regulatory Focus Theory (RFT) (Higgins, 1997; 1998), when people make decisions towards achieving a goal, they adopt approach and avoidance strategies that derive from two distinct motivational systems: a promotion regulatory focus and a prevention regulatory focus. People with different regulatory focus behave differently in their attempts to achieve the same goal (Higgins, 1997; Crowe and Higgins, 1997): promotion-focused people are motivated by accomplishments, advancement, and growth and hence use 'eagerness' strategies that try to avoid the absence of positive outcomes. Prevention-focused individuals are motivated by the fulfilment of duty or responsibility, security, and safety and thus strive for their goal using 'vigilant' strategies that try to avoid the presence of negative outcomes.

Individuals' behaviour is also affected by the specific situations in which they are making a decision (Forster et al., 1998): i.e., they modify their behavior depending on the context to adjust it to situational factors, acting in a way that is aligned or unaligned with their regulatory orientation (Higgins and Scholer, 2009). The alignment of situationally-specific behaviors with regulatory focus is termed 'regulatory fit' (Higgins, 2000, 2006). Research has shown that regulatory fit may bias decisions (Yoon et al 2012; Wang and Lee, 2006; Cunningham et al., 2005) particularly in complex contexts characterised by high uncertainty and information load (Ahmadi et al., 2017). In these contexts, individuals tend to select situational information that is consistent with their regulatory focus orientation, since processing information that does not "fit" is more difficult and requires more cognitive resources (Wang and Lee, 2006). As a result, promotion-focused individuals thus tend to rely more on positive information when making decisions, while prevention focused oriented ones rely more on negative information (Yoon et al, 2012).

Building on RFT and regularity fit, we argue that designers solve ongoing design problems differently depending on their motivation or regulatory focus and that their decisions are biased due to situational factors. In particular, given the importance of customer feedback for later product design refinements (Song and Montoya-Weiss, 1998; Carbonell et al., 2004; Zahay et al., 2004) our analysis considers that the evaluations that customers make of a product's attributes (von Hippel, 1988; Franke et al, 2006; Fuchs and Schreier, 2010) act as situational factors that bias the decision of designers in a different way depending on their regulatory orientation. Promotion-focused designers attend more to positive customer evaluations, as this information is consistent with their regulatory focus, while prevention-focused designers attend more to negative ones. As a result, promotion focused designers tend to implement design refinements that enhance attributes that are more desirable, functional, or better liked by customers, while prevention focused designers tend to center on improving or fixing products attributes that customers think do not work or dislike.

To investigate how designers' regulatory focus affects their decisions and the ability to find improved design solutions we use a simulation model. Simulation modelling, and specifically the NK approach, has been recently suggested as an appropriate formal way to analyze the dynamics of design problem-solving processes (Kornish and Ulrich, 2011; Ulrich, 2011). Accordingly, we use an NK simulation model as a method for theory development (Davis et al., 2007) that represents ongoing design as a problem-solving task in which designers search for new design solutions by implementing incremental changes based on customer feedback on product attributes. In line with RFT, the model shows how designers with different motivations strive towards the same goal, i.e., achieving an improved new design solution, but through their different decisions and behavior – specifically, the search paths they follow over time – achieve very different final designs with different levels of performance. We compare the effectiveness of biased search processes of promotion and prevention focused designers (that we call 'hedonic search') with a 'standard search' that represents an ideal situation in which designers are able to make unbiased ongoing design decisions. We also analyse differences between the two types of regulatory focus/motivation. Our simulation results show that hedonic search performs better than standard search, and that for complex products, promotion motivated designers find better performing design solutions than those that are prevention focused.

2. Regulatory focus theory and Regulatory Fit

Regulatory focus theory (Higgins, 1997; 1998) postulates that humans are motivated to satisfy the two basic needs of approaching pleasure and avoiding pain (hedonic principle). When people make decisions towards achieving a goal, they adopt approach and avoidance strategies that derive from two distinct independent motivational systems: a promotion regulatory focus and a prevention regulatory focus. Regulatory focus operates across three levels of motivational abstraction: system, strategic, and tactical (Johnson et al, 2015; Scholer and Higgins, 2008). The system level relates to individuals' general goals and preferences, the strategic level to a general preference for means, and the tactical level to situationally specific means (Johnson et al, 2015).

At the system level, regulatory focus operates as an individual predisposition or chronic orientation that is generally consistent across different situations (Higgins, 1997, 2000). Individuals with a promotion-focused orientation tend to centre on hopes, ideals, and aspirations, and are motivated by accomplishments, advancement, growth and outcomes of gains (positive and desired) or nongains (negative and undesired). Promotion-focused people thus pursue their goals through self-growth, tend to disregard potential losses and move toward desired end states (and away from undesired) by ensuring that they do not commit errors of omission. Individuals with a prevention-focused orientation tend to centre on the fulfilment of duty or responsibility, and are concerned with security, safety, and responsibility, and are motivated by outcomes as nonloss (positive and desired) or loss (negative and undesired). They thus try to prevent mistakes, and move toward desired end states (and away from undesired) by ensuring they do not commit errors of commission (Higgins, 2000).

Regulatory focus at the strategic level concerns the general means that people use for goal striving (Higgins, 1997). Promotion focus people move toward desired outcomes using eagerness strategies that try to avoid the absence of positive outcomes, and prevention-focused ones do so by using with vigilant strategies that try to avoid negative outcomes (Crowe and Higgins, 1997). Strategies reflect the general means via which individuals pursue goals (eagerness versus vigilance), but do not reflect the specific tactical ways in which those means are enacted in a particular context (Higgins, 1997; Scholer and Higgins, 2008). The tactic level concerns the tactics that individuals use in specific situations (Scholer and Higgins, 2008). Tactics enact strategies as they are instantiation(s) of strategy in a given context (Johnson et al, 2015).

Since motivational orientation (the system level) is independent from the strategic ways in which goals are pursued (strategic and tactic levels), people can behave in ways that fit or do not fit their underlying orientation (Higgins and Scholer, 2009). More specifically, individuals modify their behavior to adjust it to contextual factors/cues concerning specific situations (Forster et al., 1998), and hence the way they act may be aligned or unaligned with their chronic regulatory orientation. For instance, while conservative tactics are usually associated with vigilant strategies, risky tactics can serve vigilance best when conditions are negative or threatening because it is then necessary do to whatever it takes to get back to safety and security (Higgings and Scholer, 2009; p. x). The alignment of situationally specific behaviors with chronic regulatory focus is termed “regulatory fit” (Higgins, 2000, 2006). Regulatory fit thus occurs when individuals use strategic means that fit their underlying motivational orientations.

Research has shown that regulatory fit influences the way people select and process information causing biases in their decision-making processes (Yoon et al 2012, Wang and Lee, 2006; Cunningham et al. 2005). Individuals tend to select and rely on situational information that is easier to process. This favours information that is consistent with their regulatory focus orientation, since processing information that does not “fit” is more difficult and requires more cognitive resources. Promotion-focused individuals thus tend to tend to and rely more on positive information while prevention-focused oriented ones rely more on negative information (Yoon et al, 2012). Wang and Lee (2006) have also suggested that regulatory focus affects the type of information that individuals rely on to make decisions, and that individuals direct attention to information that fits their regulatory orientation, placing more weight on features that fit their chronic regulatory focus. Pham and Higgins (2005) propose that when searching for information, promotion-focused individuals are more likely to focus on positive signals about the available options, and prevention-focused individuals are more likely to focus on negative signals. There is also neuroscientific evidence that suggests that regulatory focus is associated with relatively greater attention to positive stimuli under promotion focus and to negative stimuli under prevention focus (Cunningham et al. 2005).

Studies have shown that selective processing of consistent information occurs particularly when information load is high (Fischer et al, 2008; Kardes et al. 2004). For example, Fischer et al. (2008) showed that preference for consistent information gets stronger with an increasing amount of available information. According to these authors, when more than two pieces of information are available, individuals are motivated to reduce the complexity of decision making by relying only on a subset of the information that is consistent with their motivational orientation. They show that motivational orientation is more likely to guide their reliance under high information load (Fischer et al., 2008). When information load is low, individuals can process inconsistent information more easily (Malhotra 1982; Yzerbyt and Demoulin 2010) so they can process and rely on both on positive and negative signals (a bigger information set) to make decisions.

3. Regulatory focus in product design decisions

As indicated in the introduction, we build on these ideas and use a simulation model to investigate the role of motivational factors in late ongoing product design in which designers search for incremental design solutions to respond to customers' demands. Our analysis considers that designers with different motivations (promotion and prevention focus) implement different (eager and vigilance respectively) strategies, and that customers evaluations of product's attributes act as situational factors causing biases in their design decisions.

As a result of regulatory fit, promotion-oriented designers rely more on positive information to search and make decisions. For them it is easier to process positive customer feedback, i.e., the evaluations of those product attributes that customers find more desirable, liked and functional because these are consistent with their motivation for accomplishments, advancement, and outcomes of gains. As a consequence, promotion focused designers tend to focus on and overweight the contribution to design performance of positive attributes, and underestimate the effect on performance of negative ones. They try to achieve their goal of finding a better design by improving or further enhancing positive product features (they disregard the performance contribution of negative ones). In contrast, prevention focused designers rely more on negative information in their search and decision-making processes. For them it is easier to process negative informational cues (i.e. on attributes that customers dislike or think do not work) since these are consistent with their motivation for duty, responsibility and safety. They hence tend to focus on and overestimate the negative contribution to performance of these attributes and disregard that of positive ones. Prevention focused designer hence try to achieve the same goal of finding a better design in a totally different way: by 'fixing' or improving negative products attributes (they disregard the performance contribution of positive ones).

Our objective is to investigate if different motivation lead to difference in the effectiveness of the design tasks and hence of the performance of the final design. In other words, what strategy, or way of solving the design problem leads to design that are better preferred by customers? Is it better to improve what it works (eager strategies) or fix those things that do not work (vigilance strategies)? We also compare our hedonic-motivated search processes with an ideal 'standard search' in which designers are able to make unbiased ongoing design decisions. Designers performing standard search might be thought of as 'super' agents that are able to process information that is both consistent and inconsistent with their regulatory orientation, and hence able to pay equal attention to, and weigh equally both positive and negative customer informational cues.

4. The model

We adopted agent-based modelling as our simulation approach as it has been shown to have three key benefits for developing theory on human decision-making (e.g. Smith and Conrey, 2007; Healey et al., 2018). The first is specificity as agent-based models allow flexibility to formally represent any aspect of the decisions agents take, but also impose a level of control and accuracy in the operationalization of the variables of interest. The second benefit is plausibility, as they allow to incorporate assumptions about human decision-making and behaviour based on existing empirical evidence. This is particularly important in emerging theoretical fields where competing novel assumptions have yet to be tested. Third, agent-based models provide insights for theory improvement and internal validation by allowing the researcher to analyse how competing theories and assumptions may or not achieve empirically relevant results. From an empirical perspective, agent-based simulation modelling and laboratory experiments share many components in their methods. Simulations can be seen as complementing laboratory experiments, by providing tighter control of the experimental conditions and a facilitated monitoring of the variables of interest in inexpensively repeated experiments.

An agent-based model of ongoing design as a problem-solving task requires two main elements: a representation of the task, i.e. incremental design modifications, and a representation of the potential solutions to the task, i.e. alternative feasible product designs. To represent these two elements, we use an NK model (Kauffman 1993). The NK model has a widely recognized potential to adequately represent problem-solving tasks for the case of complex products and technologies (Kauffman and Macready, 1995; Ulrich, 2011) as it allows accounting for the effect of interdependencies between the technological or product attributes on their performance and value.[4] The NK model is particularly adequate to capture the effects of these interdependencies for the case of complex products and technologies in which the performance of a given attribute configuration can exhibit highly nonlinear or non-monotonic behaviour in response to changes in one or more of the attributes (Ethiraj and Levinthal, 2004, p. 161).

4 Several management and innovation scholars following the seminal work by Levinthal (1997) have used the NK-model to represent innovation related complex tasks, such as the solving of complex design problems (Baumann and Siggelkow, 2013; Frenken et al., 1999; Frenken et al., 1999; Querbes and Frenken, 2018), NPD processes (Mihm et al., 2003), technological evolution (Frenken, 2007; Querbes and Frenken, 2017), production techniques (Auerswald et al., 2000), and innovation projects (Sommer and Loch, 2004).

In an NK model in which the task is product design, N represents the number of components or attributes of the product, and the parameter K represents the number of interdependencies between these components. With $K = 0$ changes in one component do not affect any of the other components, while with $K = N - 1$, i.e., for a maximally complex product, each component depends on (and affects) every other. This view on interdependencies in product design can be traced back to Simon (1962) who studied design principles to solve complex problems resulting from complex architectural interactions, and to subsequent work on technological modularity (Baldwin and Clark, 2000; Ulrich and Eppinger, 1999) and invention as recombination (Schumpeter, 1939; Nelson and Winter, 1982).[5]

The multiple combinatorial possibilities achieved by the different variations of the N product attributes generate a landscape of potential product design solutions. The global performance of each design solution depends on the individual contributions to performance of N products attributes as assessed by customers. This means that not all alternative designs perform equally for customers (who are evaluating them), and so the landscape will include peaks (high performing solutions) and valleys (low performing solutions) and allow comparing the value of alternative design choices on a single scale. In the model we consider that design creates value for the customers both through the functions it enables, and the forms it creates (Baldwin and Clark 2000). Thus attributes can be related to functional, symbolic, or aesthetic product features. When assessing the design of a product, customers assign value to

5 Design Structure Matrices (DSM) (e.g., MacCormack et al., 2006) have also been used in the NK-model to represent the interdependencies between component technologies from an engineering perspective (Rivkin and Siggelkow, 2007; Querbes and Frenken, 2017).

functional attributes such as ‘easiness of use’, as well as to aesthetic, or symbolic (e.g. visual appealing) features (Norman, 2004; Rindova and Petrova, 2007; Burke, 2013).

Each attribute x_i can take a value of 0 or 1; hence the landscape contains 2^N alternative solutions. A design solution x is thus represented as $x \in \{0;1\}^N$. For instance, if the product is a mobile phone, attribute x_1 could be ‘device size’ with 0 representing smaller size and 1 representing bigger size, attribute x_2 could be ‘battery life’ with 0 representing shorter battery life and 1 longer battery life, attribute could be internet connection speed and so on. In the absence of interdependencies between the attributes ($K = 0$) the global performance F of a design solution is given by the average of the attributes’ individual contributions:

$$F(x) = \frac{1}{N}\sum_{i=1}^{N} f_i(x_i) \qquad (1)$$

where x_i is the variant (0 or 1) of the individual attribute, and $f_i(x_i)$ drawn from the random uniform distribution, is the contribution of this variant to the total performance of the design solution. $f_i(x_i) \in [-1,0]$ corresponds to ‘negative attributes’, i.e. attributes customers evaluate as contributing negatively to performance because they do not like them, they do not work properly, and/or they are not visually appealing. $f_i(x_i) \in (0,1]$ denotes the contribution of ‘positive attributes’, i.e. those that customers like, and think work well. In this setting, a product developer can easily find better designs by simply finding the highest-performing variant for each product attribute x_i which will ultimately lead to the design x with the best performance $F(x)$. For complex products $(K \neq 0)$, the contribution of each attribute to total performance $F(x)$ depends on the state of other K attributes. In this case, finding a better design is not such a simple task. For instance, making a product more appealing visually or easier to use may require a reduction in the performance contribution of other features. In complex product design, designers must make trade-offs focusing on a few attributes in preference to others. For example, Apple's decision to include product features (e.g., internal disk drive and large trackball mouse) to make its "PowerBook" easier to use meant the exclusion of other components to meet size and weight targets (March, 1994). In our example of a mobile phone, finding a better design that involves a longer battery life (change from 0 to 1 in attribute x_2) might entail a bigger device size (change from 0 to 1 in attribute x_1) and a reduction in its contribution to the performance of the design. Consequently, for complex products the total performance $F(x)$ of a design solution $x \in \{0;1\}^N$ is given by:

$$F(x) = \frac{1}{N}\sum_{i=1}^{N} f_i\left(x_i; x_{i_1}, \dots, x_{i_K}\right) \qquad (2)$$

where $x_{i_1}, \dots, x_{i_K}$ are the K components influencing the contribution of the component x_i and f_i now takes 2^{K+1} values drawn from the random uniform distribution in $[-1,1]$. [7]

An optimal strategy to solve a complex design task as defined above would require complete knowledge of the entire solutions landscape, including knowing the best performing design solution. However, knowing this exponentially high number of alternatives is at odds with human limitations in information gathering and processing. In our model, designers are bounded rational (Simon, 1976) and search the landscape following heuristics, i.e. using simple rules that guide the exploration of a subset of alternative design solutions (Gigerenzer et al., 1999). Our simple rule is hill-climbing, that is, a new solution is chosen if it involves an increase in the design performance, and since our task is ongoing design, our search is local, meaning that designers search in a subset of adjacent or close alternatives (Fleming, 2001). This means that they search by modifying one product attribute at a time, and then select the resultant alternative adjacent solution that offers the highest performance improvement. If no alternative solution provides an improvement, they stop searching. Search thus always ends on a design solution for which no close solution provides a design with better performance.

In the model, this cognitive process of refinement or incremental search occurs in a landscape of design solutions that is completely exogenous (Ganco, 2017). In other words, we are

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5 Complexity can be tuned via the ratio K/N with higher complexity making it more difficult to find higher performing design solutions or peaks. Complexity also makes it more difficult to maintain total performance in the local vicinity of potential alternative solutions which means that discarding design solutions with badly performing attributes becomes increasingly difficult (Frenken et al., 1999). Therefore, while a high number of attribute interdependencies increases the potential for synergies among them, and hence for increased solution performance, these synergies can be offset by conflicts or trade-offs in detriment of solution performance (Ulrich, 1995; Fleming and Sorenson, 2001).

assuming that customers' preferences and the mental schema they use to assign value remain stable over the simulation period. This is consistent with the idea that customers' assessments of products attributes contributions to performance are based on pre-existing and unchanging preferences (Ramirez, 1999). It is also consistent with studies that propose that customers evaluations are influenced by generic mental schema that can change when product design modifications are radical, but remain unchanged for incremental changes. For incremental design refinements customers tend to use the same generic schema to assign value (Rindova and Petkova, 2007). In our case, as ongoing design involves incremental changes, we can assume that generic schemas are stable over the simulation period.

The influence that biases have on decision making effectiveness in complex tasks has already been incorporated in previous formal models (e.g. Kauffman and Macready, 1995; Levitan and Kauffman, 1995; Macready et al., 1996) and in models of managerial bounded rational decision-making (e.g., Knudsen and Levinthal, 2007; Baumann and Martignoni, 2011). These models study how random biases in the way agents perceive and evaluate the global performance of solutions (e.g. new products, technologies) affect the effectiveness and the stability of search processes (e.g., Rivkin and Siggelkow, 2003). Our modelling approach differs from this previous work in two respects. First, our biases are not randomly created but driven by the agents/designers' motivational orientation and situational factors (valenced customer feedback). Second, in our model cognitive biases affect the effectiveness of the decisions by operating on the designers' perception and evaluation of information on individual solution components (feedback on product attributes) rather than on the perception of the global performance of a solution. Both contributions allow our model to provide a more nuanced and plausible account of how motivation and cognition affect the performance of a complex task.

As previously discussed, in our model prevention-focused product designers try to achieve better designs after receiving feedback from customers by performing what we call a ‘negative search’: they overweight the individual contribution of ‘negative’ product attributes (those that according to customers evaluations, contribute negatively to global design performance) and underweight those that contribute to performance in a positive way (‘positive attributes’). Promotion-focused designers perform a ‘positive search’: they overweight the contribution of positive attributes and underweight that of negative ones. The global performance of a design solution thus becomes a weighted average of the product attributes’ contributions as follows:

$$F_{\text{hedonic}} = \frac{1}{N}\left(\alpha \sum f_i^{+} + \beta \sum f_i^{-}\right) \qquad (3)$$

where f_i^{+} represents the contribution to performance of positive attributes ($f_i > 0$) and f_i^{-} represents the contribution of negative ones ($f_i < 0$).

The weights α and β allow us to represent how the magnitude of the biases influence the global performance of a given design solution by modifying (underweighting and overweighing) the values of f_i^{+} and f_i^{-}. With $\alpha = \beta = 1$, equation (3) becomes (2) which corresponds to a standard search in which designers process negative and positive customer evaluations in the same way (f_i^{+} and f_i^{-} values hence remain unaltered). In positive search, the values f_i^{+} are overestimated and f_i^{-} are discounted with magnitudes for $\alpha \in (1,2]$ and $\beta = 2 - \alpha$. The opposite holds for negative search in which $\beta \in (1,2]$ and $= 2 - \beta$. The magnitude of the biases depends on the values of α and β, which reflect the designer's focus when processing the valenced customer feedback.

At each time step designers receive customer feedback on the products attributes and proceed to look for refinements in the existing design solution based on this information. To compare hedonic ongoing design search with a standard search, we run simulations for standard search and for the full range of weights magnitude of α and β on an NK landscape of design solutions with $N = 20$ components and $K = 4$ (other values of N and K have been tested and produced the same results qualitatively). To control for the stochasticity of the landscapes, we repeated our simulations over 10000 landscapes, so all our results show the average of the values collected in these 10000 landscapes. To avoid unnecessary noise, all types of search always start from the same solution design of the landscape.

5. Results

The results of our simulation model are shown in Figure 1. Figure 1 shows the final design performance of standard and hedonic search for all the values of the parameters α and β.

Our first key result is that for complex products, prevention-focused designers performing negative search always performs worse than standard search in the long run. This is the case for any intensity of customer attributes preference, i.e., for any value of $\beta > 1$. In contrast, positive search performed by promotion-focused designers performs significantly better than both negative search *and* standard search, even for low values of α (with α as low as 1.05).

As the value of α increases, however, positive search loses its advantage (around $= 1.5$) and is outperformed by standard search.

The existence of this threshold is similar to a high level of dispositional optimism (tendency to expect positive outcomes even when such expectations are not rationally justified) which increases task performance, but only up to a point, beyond which a higher level actually decreases performance. For instance, in their study on optimism and entrepreneurship, Hmieleski and Baron (2009) find that while a moderate level of optimism encourages the performance of entrepreneurial tasks, for very high levels of optimism there is a negative relationship between entrepreneurs' optimism and new venture performance.

Figure 1 about here

Our simulation results also show that a similar intensity put on different valences of feedback (customer liking versus disliking product attributes) affects the final performance of the design task in a very different way. For instance (see Figure 1), the same intensity of 1.25 applied either to negative search ($\beta = 1.25$ on negative valence) or positive search ($\alpha = 1.25$ on positive valence) produces highly contrasted long-term results, with a final performance of 0.42 for negative search (significantly below unbiased standard search), and over 0.43 for positive search (significantly above unbiased standard search). This highlights that the valence of the feedback (i.e., positive versus negative) plays a more significant role in the performance of the task design than its intensity. This is consistent with evidence showing that motivation have asymmetric effects in information evaluation and decision-making performance (Spanjol et al., 2011; Noble and Kumar, 2010).

The differences in search paths are illustrated in Figure 2 which represents examples of standard search ($\alpha = \beta = 1$), negative search ($\alpha = 0.75;\ \beta = 1.25$) and positive search ($\alpha = 1.25;\ \beta = 0.75$). As the figure shows, almost from the start, different chronic motivations and regulatory fit lead designers to adopt different strategies and find improved solution designs that, even when they are similar in performance, involve a very different configuration of product attributes. The figure also illustrates that although incremental design modifications always lead to better performing solutions, standard search performs better at the beginning of the simulation, however, it is halfway through outperformed by positive search. Promotion focus thus make positive search more effective and allow designers to find better product designs than standard and negative search.

Figure 2 about here

Looking at the different paths followed by each type of search provides a better understanding of the origin of the performance advantage achieved by a promotion focused regulatory focus. Existing models (e.g., Knudsen and Levinthal, 2007; Baumann & Martignoni, 2011) of problem-solving tasks incorporating biased search have shown that biases provide an advantage over unbiased standard search by allowing agents to avoid getting locked-in or stuck with good solutions (but not the best ones) which gives them more stimulus to explore the search space (increasing the likelihood of them finding better more distant solutions). In our ongoing design task, this would be equivalent to say that in positive search designers search for longer than in standard search which allows them to find better design solutions. However, in our model, the advantage conferred by a promotion focus orientation is not due to a longer exploration path. As the bottom panel in Figure 1 shows, a promotion focus does not increase the duration of the search. In fact, designers achieve better performing designs after a relatively low number of incremental design refinements. In addition, despite the existence of a positive correlation between the ability to explore more design options and achieved final performance (in particular for negative search), the highest value for final performance ($\alpha \approx 1.25$) does not correspond with the highest number of design refinements, i.e., searching for longer does not necessarily lead to the best performing solution.

Figure 3 shows how changes in positive and negative product attributes in positive search affect increases in design global performance for the same values of α and β used in Figure 2. At the beginning of the search process, positive search follows a decisions path that diverges quite markedly from the path followed by standard search. As the figure shows, positive search initially favours design solutions in which the increase in performance is due to improvements in the contribution of positive attributes, at the cost of decreasing the performance contribution of negative ones. In positive search, increases in global performance resulting from fixing negative attributes occur towards the end of the search. Our results thus suggest that promotion-focused designers find and take a design path that neither unbiased nor prevention-focused designers are able to discover. At the beginning of this path, product design performance improvements (resulting from enhancements of positive elements) are more occasional than those executed by standard search, in which designers take more balanced (unbiased) design decisions that initially provide better gains (as seen in Figure 2). However, these design choices in the short run increases future availability of better designs that standard designers, already embarked in a currently more rewarding path will not be able to discover. Consequently, a promotion-focused orientation makes search more effective and increase the performance of late ongoing design tasks: the biases created by regulatory fit help designers to find a specific path that, although not very rewarding initially, leads them to better performing design solutions in the long run.

Figure 3 about here

5. Discussion and conclusion

Research has proposed that designers' motivation is an important determinant of effective design decisions (Noble and Kumar, 2010) and a critical antecedent to achieving high performing designs (Kroper et al, 2011). Despite the importance that incremental design decisions have for the commercialization of new products, the motivational factors that influence decision making and behaviour at these stages are still not well understood. Our work helps to fill this gap by showing how designers' motivations – specifically their regulatory focus and the cognitive biases it creates through regulatory fit – influence their behaviour and the performance of ongoing design decisions. Drawing on RFT, we have proposed that designers behave differently when undertaking ongoing design tasks depending on their motivational orientation and the way they process and perceive customers' evaluations of product attributes (acting as situational factors). We have considered that both the valence of the feedback and their magnitude (how much or less customers like a given attribute) will influence designers' behaviour. Promotion-focused designers use eager strategies and overestimate the performance contribution of positive attributes. Their search for design refinements is motivated by the prospect a successful new design that they see as an accomplishment. By contrast, prevention-focused designers use vigilance strategies and overestimate the 'damaging' contribution of negative attributes and are motivated by the prospect of a successful new design, but see this goal as a managerial responsibility to fulfil. The former, thus tend to make design refinements that achieve better global design performance by further improvements in positive attributes, the latter tend to favour incremental refinements that achieve better global design performance by 'fixing' negative aspects of the design.

According to our analysis, promotion-focused designers achieve better product designs than preventing focused ones. Their overestimation of attributes' positive performance makes them focus on improving those product attributes that are more valued by customers and disregard the potential damaging effect that this may have on the rest of attributes, and hence on overall design performance. Now why are eager search strategies more effective and allow designers to follow a more rewarding exploration path leading to better performing final design solutions? The answer to this question lies in the way that consumers value a newly designed product. Rindova and Petrova (2007) have proposed that customer assessments of the value of a new product are based on the specific configuration of the entire set of a product's attributes, and that the value of the product thus depends on if and how this set makes sense as a whole. Studies have also posited that this holistic evaluation depends on various trade-offs that consumers make among the different features or attributes of a product: consumers use the attributes of a product to determine its overall value, but they tend to place more value on certain attributes or features (Burke, 2013), and forego some features to obtain others (Fishbein and Azjen, 1975). For instance, research about the influence of specific design dimensions on product value have shown that consumers tend to value products that communicate ergonomic features such as ‘easiness of use’ (Creusen and Schoormans, 2005), and that they tend to have a preference for usability attributes over other functional features and price (Burke, 2013). Symbolic and aesthetics attributes have also been highlighted as having a significant role in the overall evaluation that consumers make of a product. For instance, the iMac introduced by Apple in 1998, incorporated relatively minor technological improvements, however its fruitlike colours and shapes made it to be acclaimed as "the coolest personal computer on the planet" (Needham, 2002, p. 10) and to become the best-selling computer in Apple's history (Yoffie and Kwak, 1999; Rindova and Petrova, 2007). Another example that illustrates how aesthetic attributes may predispose customers to evaluate products more positively overall is the design of the Mini Cooper. As the press appraised: "Whatever one may think of the Mini Cooper's dynamic attributes, which range from very good to marginal, it is fair to say that almost no new vehicle in recent memory has provoked more smiles" (Swan, 2002, p. 1). In this case, the Mini Cooper aesthetic properties may have overridden more objective assessments of its functional attributes, leading to an enhanced overall perception of its value, as illustrated by the high demand the vehicle generated (Rindova and Petrova, 2007). Finally, Norman (2002, 2004) has also proposed that people evaluate products in a holistic manner and that in certain situations, pleasurable design features (e.g., aesthetically better or visually more appealing features), may counteract or alleviate shortcomings in functional design features, and enhance the overall evaluation of the product.

These works hence suggest that when product design strategies are developed in response to consumer requests, focusing on salient features that customer value the most is a source of product differentiation and superior performance (Rindova and Petrova, 2007; Burke, 2013).

According to our analysis, this is precisely what a promotion-focused regulatory orientation does: their search strategy favours design refinements that further enhance these attributes and achieves design solutions that will be overall better valued by customers. In our analysis this overestimation is unintentional as it is driven by biases created by customers evaluations acting as situational factors (regulatory fit), it is the imperfect evaluation of customers information rather than a conscious strategic decision to satisfice them, that leads to better designs. In this sense, our work suggests that motivational factors may have strategic value for an organization, and that excitement and eagerness in ongoing design pay off.

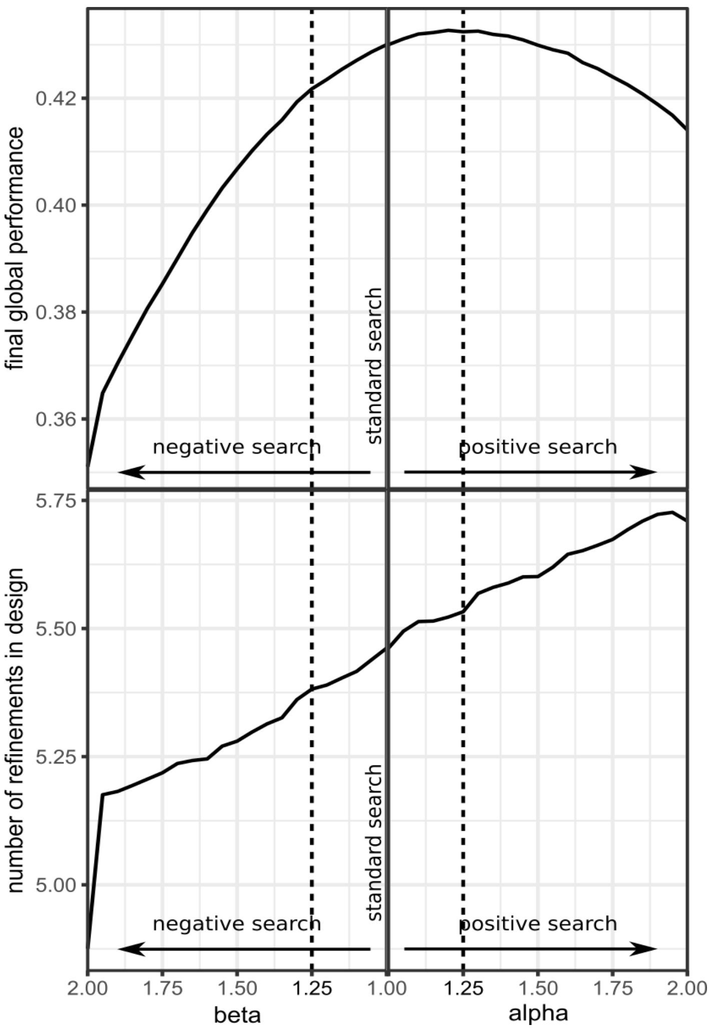

Figure 1 Search Performance and length
Top panel: search performance. Performance is measured for all weight values of α and β in the range [1,2] and using final global performance as defined in Equations 2 and 3, after search has stopped, i.e. when none of the adjacent solutions involve improvement in design. *Bottom panel:* Search path length

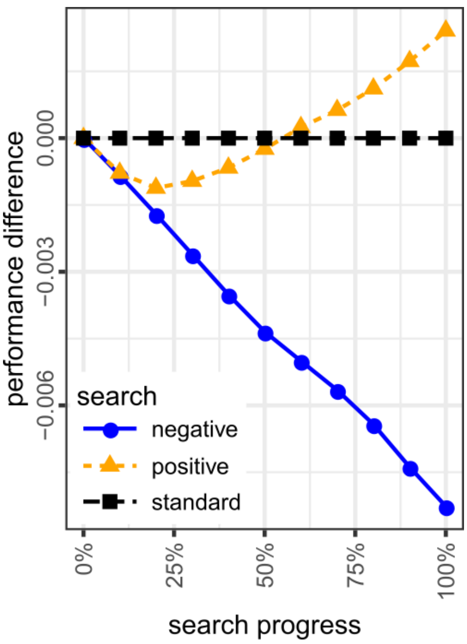

Figure 2: **Search path**. Search performance is measured at each time step after every design refinement. The graph reports the difference of performance between standard search ($\alpha = \beta = 1$) and one example of negative search ($\alpha = 0.75; \beta = 1.25$) and positive search ($\alpha = 1.25; \beta = 0.75$).

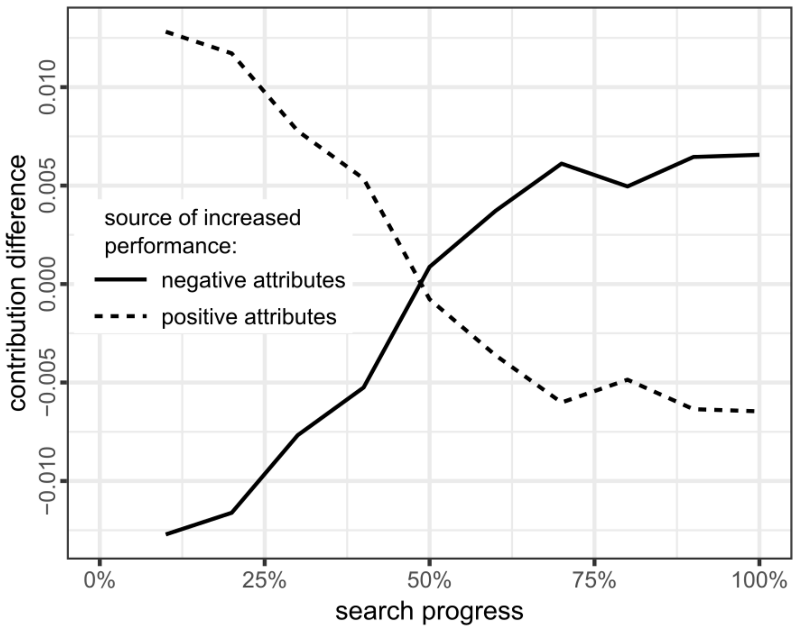

Figure 3: Source of changes in design solution performance in positive search. After every design refinement, we measure the changes in the contribution to performance of each product attribute. We constructed ratios to show the proportion of increase or decrease in global performance originating from positive and negative attributes.

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