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Memory-based models for predicting inferences about product quality

Iveta Simonyan

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DECLARATION

I certify that the thesis I have presented for examination for the PhD degree of the London Business School is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

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ABSTRACT

How are consumers' inferences about product quality related to brand information in memory? Prior literature suggests that, in vast majority of cases, consumers tend to assign higher quality to the products they have seen or heard of before than to those they do not recognize (Allison and Uhl 1964; Hoyer and Brown 1990). People's tendency to assign higher value to the objects they recognize has been documented in many areas outside consumer product domain as well (Gigerenzer and Goldstein 2011; Pachur and Hertwig 2006; Serwe and Frings 2006; Pachur and Biele 2007; Hertwig and Herzog 2011; Frosch, Beaman, and McCloy 2007; Richter and Späth 2006). However, people sometimes deviate from this tendency (Newell and Shanks 2004; Oppenheimer 2003; Pohl 2006; Richter and Späth 2006). While some reasons behind these deviation have been explored (Bröder and Eichler 2006; Gigerenzer and Goldstein 2011), others call for further investigation. For example, it still has not been explained why people assign higher criterion value to recognized objects less often when comparing unrecognized objects with "merely recognized" ones (Marewski et al. 2010), or why people report different levels of confidence for different pairs including a recognized and an unrecognized brand (Goldstein 1994).

This work investigates the reasons behind these deviations and suggests a psychological model that builds on the idea that perceived product quality should be viewed not as a point estimate, but as a distribution of beliefs about quality. By modelling inferences, as well as confidence in inferences, via belief distributions, this thesis aims at explaining some unsolved phenomena regarding the relationship between quality perceptions, on one side, and recognition and other memory information, on the other. First, it tries to find out whether the belief distributions reflect the relationship

between brand quality perceptions and recognition (as well as other memory cues), documented in the marketing literature. Second, it explores whether people infer that recognized brands associated with mediocre reputation are of higher quality than unrecognized brands. Third, using belief distributions, it attempts at explaining why people sometimes infer that an unrecognized brand is of higher quality than a recognized brand. Forth, it investigates whether the belief distributions predict inference and confidence in inferences better than existing models.

In an attempt to answer these questions, I conducted two lab studies comprising over 35,000 individual inferences and collected field data concerning brands' frequency of mentions on the Internet. When predicting consumers' inferences about brand quality based on memory information, this thesis uses the following memory cues: recognition (whether or not consumers have seen or heard of a particular product brand), perceived frequency of encountering (how many times they think they have seen or heard of that brand), knowledge volume (how much they think they know about that product's quality) and knowledge valence (what proportion of that information suggests that the quality is high). In pursuit of externally valid and robust findings, I investigated these links for actual brands in five domains: refrigerators, vacuum cleaners, walking shoes, headphones and business schools.

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1. INTRODUCTION

Which of the following vacuum cleaners is ranked higher according to a published quality ranking: Black&Decker or Kalorik? How might a consumer answer this question?

Marketing science has developed models of how brand attributes affect choice and inference, however, decision makers often cannot process all available attribute information for alternatives due to time, cognitive and other constraints (Simon 1955; Bass and Talarzyk 1972). In such settings, information in people's memory influences the way the product information is processed or, if no product information is obtainable, serves as a sole input for consumers' decisions (Bettman and Park 1980; Lynch and Srull 1982; Fazio, Powell, and Williams 1989). Yet, decision making research says little about how information in human memory is integrated to form brand perceptions (Alba, Hutchinson, and Lynch, 1991).

How do consumers make inferences about product quality in paired comparisons based on the information they have about brands in memory? If they recognize both brands, cues like the country of origin, company size, or prior experience could be used. If only one brand is recognized, recognition could be used as a cue. But what do people infer about the quality of brands they recognize and the quality of the brands they do not?

Prior literature suggests that the majority of people infer that recognized brands are of higher quality most of the time, but there are many unanswered questions in recognition-based decision making (Gigerenzer and Goldstein 2002; Newell and Shanks 2004; Oppenheimer 2003; Pohl 2006; Richter and Späth 2006; Marewski et al. 2010; Goldstein 1994). For example, why are recognized objects not always chosen? Consider a simple model, in which each object is placed in a ranking of objects. Depending on whether consumers recognize a brand and what they know about it, they can assign different probabilities for each rank a brand can take. In other words, consumers can have a distribution of beliefs about quality for each brand. When making inferences about two brands, for example, Black&Decker and Kalorik, people may compare their belief distributions for those brands instead of comparing only the most probable rank a brand could have. As a result, people may not assign higher quality to a recognized brand, if its belief distribution "overlaps" that of an unrecognized brand.

This thesis suggests such a "belief distribution" model and explores how well it answers the following questions. What do consumers believe about the brands they recognize and the brand they have never seen or heard of before? When do consumers infer that unrecognized brands are of higher quality than the recognized brands? In an attempt to understand how memory information is related to consumers' brand quality perceptions, this work investigates the brand information structure of the environment and models inferences about brand quality as a function of information in memory. Using formal mathematical models, it tests whether psychological models, such as the proposed "belief distribution" model, can explain how consumers make brand quality inferences and whether these mental models are accurate relative to other models. The current thesis does not provide evidence for the use of belief distributions by consumers in their inference decision making and cannot affirm the "belief distribution" model as a descriptive process model. Instead, it tests the ability of belief distributions to predict outcome, but not necessarily the process, of inference making and posits the "belief distribution" model as a tool that can explain such psychological mechanisms better than the existing alternatives.

In summary, the goal of the present work is to contribute to the existing research on the role of memory in consumer decision making by developing a model of how information in memory combines in the minds of consumers to generate brand quality inferences.

The proposed model makes several *theoretical* contributions by shedding light on some unexplained phenomena in psychology and marketing. It helps understanding why people tend to infer that recognized brands are of higher quality than unrecognized ones and why they sometimes deviate from such tendency (Newell and Shanks 2004; Oppenheimer 2003; Pohl 2006; Richter and Späth 2006; Marewski et al. 2010; Goldstein 1994). Building on the idea of cue substitution, it also explores to what extent awareness predicts consumers' beliefs about brand quality and to what degree more elaborate cues, such as knowledge about the product, matter. The model suggested in this thesis attempts at predicting not only inferences about brand quality, but also confidence in those inferences along with its covariate, inference response latency. While contributing to the existing knowledge in psychology and marketing, this thesis also attempts at verifying the applicability of findings in psychology for the domain of consumer decision making and explores the effect of environmental factors on consumers' tendency to attribute higher quality to recognized brands.

One of the main aims of this work is to look at what people believe about the quality of the brands they recognize and that of the brands they have never seen or heard of before by analysing both means and variance of quality. By doing so, this thesis makes several *methodological* contributions. Proposing a model that considers not only a point estimate of quality, but also the distribution of beliefs about quality, it captures the uncertainty in quality levels of recognized and unrecognized brands more directly than existing approaches that elicit the level of uncertainty through ratings of perceived risk associated with a product (Roberts and Urban 1988; Erdem and Swait1998; Erdem and Swait2004; Laroche, Kim, and Zhou 1996). Next, this work suggests a framework, according to which memory cues are integrated to form a distribution of beliefs about brand quality. In contrast to the existing models, which predict inferences for paired comparisons based on the cues directly, the suggested model makes predictions based on the belief distributions that are, in turn, predicted based on memory cues. Such an approach enables using all the available memory information for predicting inferences in paired comparisons, whereas the rival models can only use the memory cues that are available for both objects, which limits the ability of the latter models to explore the effect of knowledge valence on the inferences for pairs of recognized and unrecognized brands.

Answers to these questions will contribute to the further understanding of the role of branding. In their paper, highlighting some of the most influential work in the branding area, Keller and Lehmann (2006) state that though academic research has covered a number of different areas of branding in recent years, not all topics have received equal attention. Whereas some effort has been made to explore how and under what conditions information in memory can affect consumer choices among alternative brands or products (Bettman and Park 1980; Hoyer and Brown 1990; Jacoby, Syzabillo and Busato-Schach 1977; Park and Lessig 1981; Petty and Cacioppo 1986; Roselius 1971), the majority of research in consumer decision making has typically provided participants with all necessary information about the choice alternatives during the experiment (Wyer 2008). This is a so-called “choice from givens” paradigm. Consequently, although consumer decision research has devoted much attention to task and context factors affecting the decision rules used to combine information about alternatives in order to arrive at a final choice (Einhorn 1971; Johnson, Payne, and

Bettman 1988; Klein and Bither 1987; Wright 1975; Wright and Weitz 1977), memory has been assigned a secondary role. Some 20 years after a gulf in the literature was first recognized (Alba, Hutchinson, and Lynch, 1991), there is still little overlap of the consumer behaviour literature with mainstream memory research in judgment and decision making. Aiming at closing that gap, this thesis restricts itself to settings in which information in memory plays a key part.

Why study the role of memory information in consumer decision making? First, very few decisions in the real world are made in purely stimulus-based situations, when all relevant brand and attribute information is physically present at the time of choice (Lynch and Srull 1982). In most choice settings, some or all relevant information is not present directly, in which case consumers may fully (pure memory choice) or partially (mixed choice) rely on information about the brands from their memory. Choices made solely on the basis of information in memory are influenced by the characteristics of memory: information may be incomplete, inferences may be made about missing information, and the information that can be recalled may be a function of incidental factors that influence retrieval from memory.

Second, even in stimulus-intense environments (for example, when a consumer looks at brands of packaged goods on a grocery store display, which supplies names of all alternatives along with their package information), people may not use all available information due to the lack of time and motivation. Consumers are known to fail to scan all brands displayed in a given product category (Park, Iyer, and Smith 1989) or to avoid inspection of particular alternatives when they feel sufficiently knowledgeable about them (Bettman and Park 1980; Johnson and Russo 1984). Consequently, according to observational studies of shopping for frequently purchased packaged goods

(Dickson and Sawyer 1990; Hoyer 1984), consumers exhibit extremely low levels of external search.

Third, people may not attend to all available information because of differential accessibility in memory. The marketing literature has well documented the influence of long-term memory on information utilization in such settings and identified the factors that influence the ease with which specific brands attract attention and enter into a consideration set (the handful of brands that receive serious consideration for purchase), even if a decision maker looks at the display without preconceptions (Alba, Hutchinson, and Lynch 1991; Biehal and Chakravarti 1983; Feldman and Lynch 1988). Consumers may not consider an alternative for purchase because they do not recognize it as a potential alternative or because they do not recognize it quickly enough (Fazio, Powell, and Williams 1989; Baker et al. 1986). When faced with multiple alternatives from which to choose, most people use a consider-then-choose decision rule (Hauser and Wernerfelt 1990), making the consideration set an important concept for understanding decision making (Howard and Sheth 1969; Narayana and Markin 1975; Roberts and Lattin 1991; Silk and Urban 1978). In fact, Hauser (1978) reported an analysis of brand choice in which 78% of the explainable variation across consumers was attributable to whether the brand was included in the consumer's consideration set. In the domains of durable goods, such as automobiles, computers, and appliances, simple memory-based decision rules may be less common than in non-durable product categories. Nonetheless, even among durables, consumers may use memory cues for forming a consideration set by screening available alternatives before seriously evaluating only those brands that are not screened out (Hauser 2011).

Finally, information in memory can distort people's evaluations of product attributes when they are examined directly (Allison and Uhl 1964; Hoyer and Brown

1990). For example, Allison and Uhl demonstrated that even though consumers could not identify the brands they most frequently consumed in a blind taste test, they consistently rated “their” brands higher than other brands, if the products were labelled.

Thus, information in memory influences many decisions by shaping the way the information about products is processed or by providing an input for decision making. This work focuses on psychological models that can be used for making inferences about brands in memory-based environments. In particular, drawing on the rich psychological literature on memory-based decision making, it demonstrates how brand awareness and other memory cues can be used in predicting inferences about brands’ quality, which constitutes one of the most important measures of brand equity (Aaker 1996; Agarwal and Rao 1996; Keller 1993; Keller 2003).

Companies value awareness as a critical factor, some investing heavily in uniformative advertising that conveys no product information (Kihlstrom and Riordan 1984; Toscani 1997). This research may suggest ways in which managers responsible for less-recognized brands (which, of course, are most brand managers) can hope to compete with incumbent, recognized brands - a topic of growing importance during this time of globalization in which brand exports are common.

Given the nature of the issues under investigation, the present work belongs to a research paradigm that differentiates itself from the existing literature in memory-based decision making in the following ways.

This thesis uses objects from *natural environments* as it traces how information about objects in the environment is related to information in memory and, ultimately, to the people’s inferences about these objects. This makes the current research different from those works in psychology that investigate decisions involving artificial objects, experimentally-induced recognition, or information provided by the experimenter (Bröder and Eichler 2006; Newell and Shanks 2004; Oppenheimer 2003; Richter and Späth 2006; Bettman, Johnson and Payne 1991).

Furthermore, of the two awareness constructs measured in marketing and used in managerial decision making, i.e., *recall* and *recognition* (Baker et al. 1986; Keller 1993) only the latter will receive attention in this work. Recall, or unaided awareness, is used when consumers must retrieve decision alternatives from memory, for example, when writing a shopping list or deciding where to eat lunch. In the domain of this work, when consumers are presented with alternatives, recall, however, is not necessary. Instead, aided awareness (recognition), plays a central role. By focusing on recognition, the present work differentiates itself from the literature on unaided recall (availability) and its effect on decision making (Tversky and Kahneman 1973) and, more specifically, on consideration set formation (Baker et al 1986; Nedungadi 1990).

Another distinction that sets the present work apart is its focus on *inferences* as opposed to *preferences*, which have been thoroughly studied (e.g., Bettman and Park 1980; Hoyer and Brown 1990). Even though inferences are one of the potential predictors of preferences, these two constructs have distinct influences: consumers can infer that Brand A is of higher quality than Brand B, but show preference for the lower-quality brand because of other brand characteristics, for example, higher affordability of Brand B.

Alternatively, consumers' choice may be affected by the overall *attitude* towards a brand rather than its perceived quality. Research on attitudes, an important aspect of brand knowledge, explores "summary judgments and overall evaluations to any brand-related information" (Keller 2003), including non-product-related attributes and symbolic benefits. This thesis, however, focuses on specific aspects of product quality, eliminating the effect of non-product related associations, along with connected constructs such as liking (Ahluwalia, Burnkrant, and Unnava 2000; Zajonc 1968; Zajonc and Rajecki 1969). In sum, the third specific aspect of this research is its focus on *perceived quality* rather than *overall attitude* towards brands. That is, I investigate what people think about the quality of brands based on what they know, as opposed to what consumers prefer or how they like brands.

This work is organized the following way. First, I will review the past literature to identify existing findings and gaps. Next, I will describe the methods for the lab studies and field data which were used to answer all questions posed in this work. These general sections will be followed by four chapters, each covering the following research topics, by reviewing relevant literature, stating hypotheses, summarising related findings from this thesis and discussing their implications.

The main query "*What psychological model can explain how consumers make inferences about brand quality based on the memory information?"* will be addressed by positing a new model based on the distribution of beliefs about brand quality as a predictor of individual-level inferences concerning brand quality for pairs of brands, as well as confidence and response latency for these inferences.

<u>Research topic 1. Do subjective belief distributions reflect the relationship between memory information and brand quality perceptions?</u> To validate the "belief distribution" model as a psychological mechanism explaining how consumers make brand quality inferences based on memory information, this thesis first tests whether belief distributions reflect the relationship between memory information and quality perceptions, documented in the marketing literature. That is, do subjective belief distributions reflect the effect of brand recognition, frequency of encountering the

brand, and brand knowledge on brand quality perceptions? For example, do belief distributions reflect the fact that recognized brands are believed to be of higher quality than unrecognized ones, or the fact that unrecognized brands are characterized with higher uncertainty about quality than recognized brands?

Research topic 2. Do people infer that recognized brands associated with mediocre reputation are of higher quality than unrecognized brands? This thesis explores the role of knowledge valence as additional information in predicting inferences about brand quality. What do people believe about brands associated with mostly negative information? Do they infer that they are of lower quality than unrecognized brands? Can knowledge valence predict brand quality inferences more accurately than brand awareness? While answering this question, the current thesis tries to explain the findings by studying the environmental relationship between quality and information available for brands.

Research topic 3. Can belief distributions explain why people sometimes infer that an unrecognized brand is of higher quality than a recognized brand? In an attempt to shed light on some unexplained phenomena in psychology, this work explores the situations in which people deviate from their tendency to assign higher quality to recognized brands than to unrecognized ones. When do people infer that unrecognized brands are of higher quality than recognized brands? Two candidate explanations are pursued: i) some recognized brands are thought to be of low quality ii) some recognized brands are infrequently mentioned and, thus, are somehow “less recognized”. This thesis hypothesizes that, when an unrecognized brand is compared with a relatively unfamiliar recognized brand, the quality perceptions for these compared brands are fairly similar and are characterized with high uncertainty, which leads to an “overlap” of belief distributions for the compared brands and, hence, to higher chances for unrecognized brands to be perceived as of higher quality than recognized brands.

Research topic 4. Can belief distributions predict inference and confidence in inferences better than existing models? Finally, this thesis tests the ability of belief distributions to predict brand quality inferences along with inference confidence and response time. If belief distributions are a function of memory cues, can we predict brand quality inferences using the belief distributions predicted based on memory cues?

2. LITERATURE REVIEW

When choosing from a large number of alternatives in a product category, consumers often face difficulty processing product information available from various sources, for example, word-of-mouth, past experience, or advertisements (Bettman et. al. 1991), delivered through press, radio, television, mobile devices, or the Internet. Two prominent views have been suggested about how consumers handle such difficulties. Favoured by economists, one approach to consumer decision making assumes that consumers are exquisitely rational beings, who act as if they obtain complete information on the alternatives, compute utilities for every alternative, make trade-offs, and select the alternative that maximizes utility. A proponent of an alternative view, Simon argues that decision makers cannot be perfectly rational in the sense described above due to limits of memory, time, knowledge, and the ability to process information (Simon 1955, 1956, 1978). Research in decision making has identified a host of decision rules (Hastie and Dawes 2001), which can enable decision makers to cope with such bounds of rationality (Payne, Bettman, Johnson, 1993; Gigerenzer, Todd, and the ABC Research Group, 1999). Ecologically rational to the degree that they are adapted to the structure of the environment, heuristic decision strategies "can enable both living organisms and artificial systems to make smart choices quickly and with a minimum of information" (Todd and Gigerenzer 2000, 727).

How do such heuristics work? In natural situations, pieces of information present in the environment may be related and, hence, redundant. So, cue substitution, that is, trying cues one at a time instead of all at once, can compete with cue integration (Gigerenzer and Goldstein 1996). In the domain of this work, if the cues that predict product quality are highly correlated, a subset of cues can be exploited without a considerable decrease in inferential accuracy (Steenkamp 1990). Such information structure is especially beneficial in decision making settings characterized by limited information input, for example, memory-based judgements (Lynch and Srull 1982). Whereas consumers working from given information have at their disposal a wealth of information about product features, consumers working from memory may know far less about a product. According to the hierarchy-of-effects model (Lavinge and Steiner 1961, Keller 1993, 2003), or purchasing funnel, which is common to marketing textbooks, the most minimal level of product knowledge is recognition. In later stages of the funnel, more informed consumers may have knowledge concerning a brand's quality, varying in valence and amount. How much impact this additional knowledge has on people's perception about product quality is largely an unanswered question.

In his recent article, Hauser argues that recognition-based heuristic and its analogues are "excellent descriptions of the decision rules that consumers use to consider and to choose brands" (Hauser 2011, 406) and stresses the need for additional insight into such fast and frugal heuristics. Discussing the benefits of such research for the design and marketing of products, he suggests why consumers can rely on simple heuristics. According to one of such theories, signalling theory (Erdem and Swait 1998; Milgrom and Roberts 1986; Kirmani and Rao 2000; Nelson 1974), the firm will choose to advertise only if it can recover its advertising expenditures through repeat purchases due to product's high quality. Consumers, who learn through experience that heavily advertised brands are of high quality, infer brand quality from advertising. And since advertising causes brand awareness, they can infer high quality from recognition as well. The link between recognition and quality can be reinforced by observational learning, that is, consumers might infer that a product is of high quality, if they observe other consumers using it. Such observation increases awareness, causing association between recognition and quality.

Thus, recognition information in the environment shaped by advertising and other sources, serves as a proxy to infer the product quality (Goldstein and Gigerenzer 2002). According to Goldstein and Gigerenzer (2002), the strength of association between the criterion and recognition memory can be described by recognition validity, which can be viewed as an example of ecological validity from Brunswik's lens model (Brunswik 1955, Dudycha and Naylor 1966, Steenkamp 1990). Recognition validity plays a critical role as it affects the degree to which people rely on the recognition heuristic when making inferences about objects with respect to the judged criterion (Gigerenzer and Goldstein 2011): while in some domains, such as fashion, recognition may not be as predictive, in other domains recognition is highly correlated with the criterion, for example, academic quality of business schools.

Building strong brands is a marketing priority for many firms as brands are argued to confer multiple advantages (Hoeffler and Keller 2003). This assumption is supported by a number of findings, for example, people's tendency to assign higher quality ratings to products they recognize and their tendency to choose familiar products over unfamiliar ones. In one of the earliest studies, when nonsense syllables were differentially exposed to subjects and subsequently identified with boxes containing nylon stockings, the generated familiarity significantly influenced brand preference and brand choice (Becknell, Wilson, and Baird 1963). In another study, Allison and Uhl observed how beer drinkers would assign superior ratings to the brands they were familiar with if the bottles were labelled, but did not rate the taste of that brand beer superior over all of the other beers in the blind test (Allison and Uhl 1964). Other research found that, when posters of fictitious candidates were placed around a university campus in varying frequency, students who had seen the posters frequently were most likely to vote for the most publicized candidates, though no information other than the candidate names and the contested elected position was communicated (Stang 1974). The effect of recognition seems to extend to situations, in which people try the products: Hoyer and Brown gave people a taste test offering three jars of peanut butter (Hoyer and Brown 1990). While all jars contained the exact same product, one was labelled as a recognized national brand, and the other two as unrecognized store brands. In 75% of cases people chose the jar labelled as a recognized brand, even though they have never tasted peanut butter of any of these brands before.

Such decisions in selecting a peanut butter brand or a poster candidate may be caused not only by people's tendency to infer higher quality for recognized brands, but also by affective response generated by the prior exposure to the objects under consideration. The latter effect is explored in "mere exposure effect" literature, which confirms a positive "repetition – affect" relationship arising merely as a result of repeated stimulus exposure both in humans and animals without cognitive mediation (Hill 1978; Wilson 1979; Zajonc 1968; Zajonc et al. 1974; Zajonc 1980; Zajonc and Markus 1982; Zajonc, Markus and Wilson 1974; Zajonc and Rajecki 1969). The affective evaluations of a brand should be differentiated from the evaluations of quality, which is the focus of the current dissertation. For example, when choosing a vacuum cleaner, a consumer may like Kalorik more than Black&Decker due to his/her more favourable attitude towards Kalorik's non-product-related attributes and/or symbolic benefits (i.e., the country of origin). On the other hand, he/she may assign higher quality to Black&Decker due to prior knowledge about the brands. As a result, the consumer may prefer Kalorik over Black&Decker, if the brand's country of origin is a more important aspect in his/her choice that the brand's quality. While the "mere exposure" research has produced numerous evidence for the relationship between the affective response (that is, what people like) and stimulus exposure (Zajonc 2001), it did not explore the link between the object's perceived quality and its exposure, or, more specifically, people's tendency to attribute a recognized brand with higher quality.

Such tendency can be predicted by the recognition heuristic, formulated the following way: If one of two objects is recognized and the other is not, then infer that the recognized object has the higher value with respect to the criterion (Goldstein and Gigerenzer 2002). Goldstein and Gigerenzer showed that the recognition heuristic predicts inferences even in the presence of conflicting information. For example, when American students were tested on their ability to infer which of two German cities was the larger one, they inferred that the recognized city was larger in the vast majority of cases. They did so even when they were told that the recognized city did not have a football team, a cue that it was not particularly large.

The recognition heuristic has been shown to make accurate predictions in a variety of domains, including the incidence rate of infectious diseases (Pachur and Hertwig 2006), the outcome of tennis or football matches (Serwe and Frings, 2006; Pachur and Biele, 2007; Hertwig and Herzog 2011); the wealth of people (Frosch, Beaman, and McCloy 2007), the population of animals, and the safety of airlines (Richter and Späth 2006). It is useful when there is a strong correlation between recognition and a criterion, for example, product quality. The recognition heuristic is also useful when knowledge is limited – it even requires a certain amount of missing information. That is, only some, but not all objects can be recognized for the recognition heuristic to be applied. Another factor that increases the applicability of the recognition heuristic is forgetting, as it increases the chances that only one object is recognized (Schooler and Hertwig 2005). More recent findings in the field demonstrate that the recognition heuristic is domain specific: the higher the correlation between the recognition and the criterion, the more often the recognition heuristic predicts behaviour (Gigerenzer and Goldstein 2011). Another moderator of the recognition heuristic use seems to be additional time: people adhere to the recognition heuristic more often under time pressure (Pachur and Hertwig 2006; Hilbig, Erdfelder and Pohl 2012). Furthermore, it has been found that the recognition heuristic adherence is higher when judgments are made deliberatively, rather than intuitively (Hilbig, Scholl and Pohl 2010), though, interestingly, analytic thought seems to decrease the use of the recognition heuristic (Halberstadt and Catty 2008). Finally, another boundary condition may be whether additional cue knowledge has been learned outside or within the experimental setting (Pachur, Bröder, and Marewski 2008).

The use of recognition as a sole cue in making inferences may be affected not only by endogenous, but also exogenous factors. For example, adherence to the recognition heuristic varies with individual differences (Hilbig and Pohl 2008). In particular, the use of recognition as a primary cue was found to positively correlate with neuroticism (Hilbig 2008).

Though the recognition heuristic makes accurate predictions in many cases, people do not always adhere to it (Newell and Shanks 2004; Oppenheimer 2003; Pohl 2006; Richter and Späth 2006). For example, Newell and Shanks extended the test of the recognition heuristic to a situation in which participants learned to "recognize" fictional company names, which were presented repeatedly to them during an experiment (Newell and Shanks 2004). In addition, the validity of the induced recognition was manipulated. When the recognition was the most valid cue, the choice was consistent with the recognition heuristic and recognition was frequently the only cue used. On the other hand, when it was the cue with the lowest validity, most participants enquired additional information and picked the company they did not recognize. Oppenheimer (2003) presented subjects with pairs of fictitious and well-known cities, which were carefully selected so that participants either knew that the city they recognized was relatively small or they knew that their ability to recognize a city was due to factors other than its size (for example, Chernobyl is known for being a disaster site). Oppenheimer found that recognition information was overruled, however, suspending the recognition heuristic when one explicitly knows that a city is very small does not conflict with the model of the heuristic: it is plausible to assume that the mind attempts a direct solution by retrieving definitive knowledge about the criterion (that is, no one lives in a radioactive disaster site). Furthermore, Pohl found that the choice of a recognized object depends, sometimes to a great extent, on whether this choice proves to be correct or incorrect (Pohl 2006). This contingency would arise if direct (valid) criterion knowledge was available. For example, the recognized town was chosen as larger much less often when it was only known as a ski resort. Other research demonstrated that people's tendency to assign higher criterion value to recognized objects diminished for those pairs of objects, in which the recognized object was "merely recognized" (Marewski et al. 2010).

Despite being criticized for its inability to explain these phenomena (Dougherty, Franco-Watkins, and Thomas 2008; Newell and Shanks 2004; Oppenheimer 2003; Richter and Späth 2006), the recognition heuristic has not been replaced by a more accurate alternative model (Gigerenzer and Goldstein 2011). Aiming to find that alternative, this work builds on memory-based heuristic research while testing a model that integrates recognition, as well as other memory cues, to make inferences about brand quality.

The model is built on the concept used in measuring a consumer's past information about brand attributes introduced by Woodruff (1972). Woodruff's measurement instrument is based on a multi-point scale, a popular marketing assessment tool. But in contrast to the marketing techniques requiring respondents to indicate one point on the scale, Woodruff's instrument elicits probability distribution over all the scale gradations. According to Woodruff, the former tools encourage the respondents to state the most likely evaluation of an attribute, given their prior information. That is, a respondent "may be implicitly forming a probability distribution he considers possibly applicable and then using the modal (or mean) gradation" as his/her response. Instead, Woodruff suggests requesting not just the modal (or mean) value, but the entire distribution on each rating scales.

Using a measurement concept suggested by Woodruff (1972), this research attempts at developing a framework, according to which the mind integrates memory cues and arrives at a probability distribution of beliefs about brand quality, assigning some likelihood for each level of quality a brand might have. Such a representation allows for capturing consumers' perceptions of quality not only in terms of valence, ranging from unfavorable to favorable, but also in terms of certainty, the degree to which an individual is confident in the perceived level of quality.

The latter concept attracted substantial scholarly attention in marketing and psychology, generating evidence that consumers are sensitive not only to the average quality of a product, but also to the dispersion around the mean quality (Meyer 1981; Pras and Summers 1978; Roberts and Urban 1988; Rust et al. 1997; Thurstone 1927). Erdem and Keane suggest that consumers are risk-averse with respect to variation in brand attributes, which discourages them from buying unfamiliar brands (Erdem and Keane 1996). When uncertainty about the quality is high, consumers tend to rely on one or a few cues (with brand name among the most important) to make inferences about a wide variety of consumer durables and nondurables (Derbaix, 1985; Roselius, 1971). Emphasising the importance of brand awareness and brands as signals of mean and variance of quality, Keller and Lehmann (2006) call for further attention to this topic and pose a question: “To what extent is increased confidence in decision making a key or even critical factor of brands and brand equity; i.e., are standard deviations more important than means?” Picking up on this idea and noticing that there have been few studies measuring the exact relationship between information in memory about brands and consumer's perceptions of brand quality, this thesis also attempts at exploring the difference in the variance of perceived quality for recognized and unrecognized brands and at modelling confidence in inferences about pairs of brands as a function of both the mean and variance of quality.

3. METHODS

Before addressing research questions one at a time in individual chapters, I describe here how all data were collected across all studies. This is done because each study data answer multiple questions.

Two lab studies were conducted to collect the data reported in this thesis. In addition, brand-specific field data on environmental frequency and expert-judged quality were collected using Web-search engines and published rankings. Finally, a New York based company, General Sentiment, specialising in sentiment data analysis, provided environmental frequency data for different media sources.

The domains under investigation are business schools and consumer goods, such as refrigerators, washing machines, walking shoes, and headphones. The reason business schools are chosen as the domain for the current work is that choices and beliefs about business schools should be highly influenced by recognition. After all, consumers are buying the product "sold" by a particular business school not only because of its quality, but also because of the perception of their alma matter in the eyes of other people, such as future employers: "I am choosing this brand not only because I recognize it, but because others recognize it". This way of reasoning may lead to a higher sensitivity towards recognition than in some other domains, because consumers search for brand names much more frequently when evaluating prestige than when evaluating any other quality dimension (Brucks, Zeithaml, and Naylor 2000). In other domains where advertising is more prevalent and in which brand recognition is less clearly related to quality, it may be the case that people attend more to brand reputation. To test for generalization of the results obtained for the business school domain in study 1, I attempted at replicating the results for four traditional consumer products in study 2.

The choice of domains where memory cues, for example, recognition, have an impact on inferences is crucial for this work. For a recognition-based heuristic to be ecologically rational, the information in the environment should be such that consumers can exploit recognition to make better decisions (Goldstein and Gigerenzer 2002, Hauser 2011). In other words, recognition should be correlated with the brand quality. If it is not ecologically rational to use the recognition heuristic, people will need to use other kinds of decision strategies to make accurate inferences.

To investigate how sensitive consumers are to the domain-specific relationships between information about brands in memory and their quality, this work tests the hypothesized framework on four domains of consumer goods with different recognition validity. Whereas in two domains of consumer durables, refrigerators and vacuum cleaners, familiarity and quality are positively correlated (for the chosen set of brands), in other two domains, walking shoes and headphones, that correlation for the brands used in the studies is negative or does not appear to exist (see Appendices B, D and N for the recognition validity data in the domains tested in the study1, study 2, and pilot studies, correspondingly).

Study 1

Respondents. One hundred and sixteen participants from the London Business School Behavioural Lab panel took part in the study. To ensure that there were no major differences in the exposure to the stimuli (US universities) through media and other sources, this work only drew upon participants who did not spend more than 6 months in the United States. UK residents served as participants to increase the likelihood that the typical participant would recognize only some of the (US-based) stimuli. All participants were paid 12 British pounds ($19USD) for participating.

Material. The domain under investigation was a set of global business schools, taken from the US News and World Report rankings. Recognition should correlate with university quality: business schools ranked as top quality are frequently mentioned in media. To be included in the study, business school names could not include: a US state name (i.e. University of Pennsylvania); a large US city name (i.e. New York University); or contain the word “state” (St. Cloud State University). Universities that had a state or large city name included in their names were omitted because the respondents might recognize the state or the city, but not the university, and mistakenly respond that they recognized the business school (Aribarg, Pieters, and Wedel, 2010). Alternatively, the name of the state or the city might influence the perception of the quality of the school. Universities that had the word “state” included in their names were eliminated because people might perceive the quality of non-state (University of X) and state universities (X State University) differently. These assumptions are based on the findings that people evaluate unrecognized brand names differently depending on the words in the name (Wänke, Herrmann, and Schaffner 2007). Applied to the domain under investigation, the results of that study suggest that the name "Baylor University", for example, may not really tell anything other than it is unrecognized. However, the "Baylor Community College of Jackson, Mississippi", even if unrecognized, may convey some information about its quality: people may think that community colleges are of different quality than universities, or that Mississippi schools are of different quality than schools outside the state. The final list included the top twenty schools (according to the published ranking) that fit these criteria (see appendix A).

Procedure. Each participant answered three randomly ordered sets of questions (henceforth, Question Sets 1, 2 and 3). The participants were instructed on how to answer each question and tested for comprehension before they could start the actual tasks[1]. Participants were advised that the questions in the study concerned US business schools only.

Question set 1: Memory information self-report. The goal of the Question Set 1 was to gauge respondents' memory for the stimuli. Participants were asked several questions about each business school: whether or not they had seen or heard of the brand before the study (recognition), how frequently they had seen or heard about it (perceived environmental frequency), how much they knew about its quality (perceived knowledge volume), and what proportion of that knowledge suggested that the quality was high (perceived knowledge valence).

During the recognition task, participants indicated whether or not they had seen or heard of each of the 20 US business schools. Each school was presented on a new page. The respondents were asked to answer as quickly and accurately as possible by pressing the "Y" and "N" keys on a computer keyboard. They were told to keep their fingers over these keys during the experiment, instructed on how the questions were asked, and given several training questions about US cities, before proceeding to the actual recognition task on US business schools. The stimuli were presented in the following manner. The question "Do you recognize the following US business school?" was presented for 3000 ms, followed by a fixation point (a cross in the centre of the screen) that stayed on the screen for 1000 ms. After the cross disappeared, the screen

[1] If participants answered any of the questions incorrectly, they were redirected to the instructions and answered the quiz questions again. After three unsuccessful attempts to answer the questions, the study was paused and the participants had to call a research assistant to continue. In that case, the research assistant clarified the task and ensured the participant understood it.

stayed blank for 1000 ms, after which a school name appeared on the place where the fixation point was. The school name remained on the screen until a response was given. The time that elapsed between the point the school appeared on the screen and the point the participant pressed the keys was recorded. To avoid differential response to the first item presented, participants first answered a question about a US business school that was not included in the analysis, and then about the 20 US business schools from the aforementioned list. The order in which the 20 schools were presented was randomized.

Subsequently, participants indicated how familiar they were with each school. They were asked to think how frequently they have seen or heard of each of the 20 schools when answering this question. To answer the question, they used a slider with “Not familiar at all” and “Very familiar” on its ends, which was coded on a scale of 1 to 50, though these values were not shown to the participants. The slider was programmed to avoid anchoring the respondents to the starting point of the slider handle. Each time a new slider appeared on the screen, it lacked a handle. The handle only appeared once the participant moved the mouse pointer over the slider bar. The order in which the 20 schools were presented was randomized for each participant.

During the last two tasks of Question Set 1, participants used the same type of sliders to answer questions about their knowledge regarding each of the 20 schools. The first question was “How much do you know about the academic quality of the following US business school?”, and the responses were measured using 1 to 50 scale, corresponding to ”I know little about it” and “I know a lot about it”, respectively. The second question, presented on a new page, was “Of what you know about the academic quality of the following US business school, how much suggests that it is good or bad?” This was coded on a -25 to 25 scale, corresponding to “0% good, 100% bad” and “100% good, 0% bad”, respectively. Again, in case of both questions, the corresponding values remained invisible to the participants. The questions were presented separately, one per screen for each of the 20 schools, and presented in a random order for each participant. To prevent confusion, the slider for the knowledge amount question was vertical, and the one for proportions of bad and good knowledge was horizontal. The participants could indicate that they knew nothing about the school by clicking on a separate "I know nothing about it" button for both questions.

Question set 2: Inferring product quality for individual brands. The aim of the Question Set 2 was to measure respondents' quality rank estimates. During this task, belief distributions were elicited while participants guessed the most probable, highest possible and lowest possible ranks a school could have according to a published quality ranking. Participants were told that the ranking they were trying to infer was taken from publications that evaluate business schools. Before beginning the estimation task, the participants were presented with the list of all 20 schools, which were presented in alphabetic order on one screen, and asked to estimate the rank of each US business school according to its academic quality. When performing the actual task, they saw one business school at a time. Each time a new school appeared on the screen, respondents were asked "Where would you guess this school might rank?", "What is the highest rank you think it might have?", "What is the lowest rank you think it might have?" and were reminded that "1" was the highest rank a brand could have, and "20" was the lowest.

Question set 3: Inferring product quality for pairs of brands. Question Set 3 consisted of paired comparisons. During this task, the participants made inferences about relative academic quality for 100 pairs of business schools randomly drawn from a list of all possible pairs of 20 business schools. The order in which the 100 pairs of schools appeared in the inference task was determined at random for each participant. Just as before, participants were told that they were trying to infer which school was ranked higher according to published rankings. For each question, which was worded “Which of the following two US business schools is ranked higher according to its academic quality?”, the respondents were asked to indicate their answer by clicking on one of two buttons, corresponding to each school, on the computer screen. The time elapsed between the moment a pair of schools appeared on the screen and the moment the participant responded was measured, but the participants were not informed that their response times were being recorded. For the second question (presented on a new page) “How confident were you in your decision on whether [school A] or [school B] was ranked higher according to its academic quality?” the participant had to use a vertical slider similar to the one from the first set of questions. The response was measured using a 1 - “Not confident at all - I was guessing” to 50 - “Very confident - I was absolutely sure” scale. Once again, the corresponding values remained invisible to the participants.

On average, participants took 37 minutes to complete the experiment.

Study 2

Participants. Two hundred and fifty six people from the panel of regular study participants of the London Business School Behavioural Lab participated in the study. All participants were paid 10 British pounds ($16USD) for participating. One group of randomly selected participants answered questions about vacuum cleaners and refrigerators, and the other answered questions about headphones and walking shoes.

Materials. The domains investigated in this study were four categories of consumer goods: refrigerators, vacuum cleaners, headphones, and walking shoes. The brands of consumer goods were taken from Consumer Reports magazine. These domains were selected from a list of 27 product categories after a pilot study was conducted to determine the environmental validity of recognition and other memory cues for the brands included in the rankings (see appendix L part a). While refrigerators and vacuum cleaners were chosen as brands with high recognition validity (that is, brand recognition was positively correlated with the quality of the ranked brands), headphones represent a category, where recognition is not correlated with quality. In case of walking shoes, brand recognition is inversely correlated with its quality.

The final list of consumer brands included 12 brands of refrigerators, 10 brands of vacuum cleaners, 12 brands of headphones, and 10 brands of walking shoes. In pursuit of representative design (Brunswik 1956) and to avoid a biased selection of items, the brands were chosen from the refined list by a computerized randomizing procedure. Appendix C lists the brands in each domain.

Procedure. Each participant performed three randomly ordered sets of tasks. The first set was used to familiarize the respondents with the questions they were going to be asked throughout the study. Just like in Study 1, the participants were instructed on how to answer each question and tested for comprehension before they could start the actual tasks. A set of printer brands was used for the training tasks. For the last two sets of tasks, participants answered questions about two categories of consumer brands. For each product category, they were asked three sets of questions, which were similar to Question Sets 1, 2, and 3 in Study 1. Procedures for question sets in Study 2 were identical to those in Study 1 with one exception: when participants were asked to indicate how frequently they had seen or heard of each brand in Question Set 1, they used a slider with “Very rarely” and “Very often” on its ends, corresponding to 1 and 50, respectively. If they had not seen or heard of the brand before the study, they could indicate that by clicking on a special box instead of using the slider. In Question Set 3, for the refrigerator and headphone domains, participants were asked to make inferences for 66 pairs of brands, and for the vacuum cleaner and walking shoe domains, they were asked to make inferences for 45 pairs of brands.

On average, the respondents took 48 minutes to complete a session.

Field data collection

To explore the relationship between the volume of the information in the environment and the quality of the brands, this thesis used the frequency of citations of business schools on the Web, which were collected by a company specializing in sentiment data collection, and quality ratings from Consumer Reports or U.S. News and World Report. Volume of information in the environment was captured by the number of times the brand was mentioned in news media, which was transformed using logarithmic transformation[2]. In addition, environmental frequency was measured by the number of search results generated by Google, Bing, and New York Times web search engines for the combination of the university name and “business school” or “school of business” word groupings, for example, “harvard” and “business school” or “school of business”. A natural logarithmic transformation was used to transform the numbers of

[2] Box-Cox transformation results imply that different power transformation functions should be used for different domains. However, for the purpose of simplicity and uniformity, logarithmic transformation was used in all domains.

search results generated by these three sources, that is, search engines, before the results were normalized within each source. Then, mean values of the normalized results collected from each search engine, were calculated for each school.

Business school quality ranks were determined by averaging the schools' scores published by US News and World Report in 2008 and 2009. For the consumer good brands, both overall and attribute scores published by Consumer Reports were available. However, since these scores were correlated (see appendix C), the overall scores were used in the further analysis for the sake of simplicity.

4. ARE BELIEF DISTRIBUTIONS COMPELLING MENTAL REPRESENTATIONS OF BRAND QUALITY PERCEPTIONS?

The purpose of this chapter is to introduce the “belief distribution” model as a psychological mechanism explaining how people make brand quality inferences based on memory information and to validate it as a model reflecting the relationship between memory information and quality inferences, documented in the marketing literature. For example, do belief distributions reflect the fact that recognized brands are believed to be of higher quality than unrecognized ones, or the fact that unrecognized brands are characterized with higher uncertainty about quality than recognized brands? Do they reflect the relationship between the frequency of encountering the brand or brand knowledge, on one side, and brand quality perceptions and certainty about them, on the other?

4.1. Introduction

Since the recognition heuristic was defined a decade ago, the decision making literature has accumulated rich evidence for people’s tendency to attribute recognized objects with higher values with respect to some criterion (Gigerenzer and Goldstein 2011; Pachur and Hertwig 2006; Serwe and Frings 2006; Pachur and Biele 2007; Hertwig and Herzog 2011; Frosch, Beaman, and McCloy 2007; Richter and Späth 2006). At the same time, it has been shown that people sometimes deviate from that tendency (Newell and Shanks 2004; Oppenheimer 2003; Pohl 2006; Richter and Späth 2006). Some of these deviation can be explained by the fact that the recognition validity varies across domains (Newell and Shanks 2004; Gigerenzer and Goldstein 2011).

Moreover, people follow the recognition heuristic less often when object recognition is induced artificially rather than developed through natural settings (Bröder and Eichler 2006). Yet, other deviations have not been explained and require further attention. The recognition heuristic has been criticized for its inability to explain the following anomalies; however, no other psychological model has been suggested as an alternative. For example, people assign higher criterion value to recognized objects less often when they compare unrecognized brands with "merely recognized" objects (Marewski et al. 2010). Adherence to the recognition heuristic also diminishes when people are provided with conflicting information about recognized brands (Richter and Späth 2006). Finally, people report different levels of confidence for different pairs including a recognized and an unrecognized brand, which is reflected in varying inference response times for such paired comparisons (Goldstein 1994).

This work has attempted at testing whether these findings are applicable to inferences about brand quality. For the purpose of this analysis, inferences for paired comparisons involving a recognized and an unrecognized brand were grouped based on whether or not the inference was made in line with the recognition heuristic: those in line with the recognition heuristic were classified as *confirming*, and those not in line with it were classified as *violating*. Analysis of inferences in all five domains explored in this thesis demonstrated that, on average, respondents made confirming inferences (that is, they inferred that a recognized brand was of higher quality than an unrecognized brand) in 88-95% of cases (table 1).

Table 1. Mean individual proportion of inferences when in paired comparisons a recognized brand is inferred to be of higher quality than an unrecognized brand (recognition heuristic adherence)

Domain	N of respondents	Mean individual proportion of relevant pairs	Mean recognition heuristic adherence
Business schools	107	.43	.89
Vacuum cleaners	202	.52	.91
Refrigerators	203	.49	.88
Walking shoes	48	.48	.92
Headphones	47	.53	.95

The results of this analysis also revealed that, in line with the existing research, when pairs of brands were grouped based on whether or not they were made consistent with the recognition heuristic, average confidence in inferences was higher and average response latency was lower for those pairs, in which the recognized brand was inferred to be of higher quality (table 2).

Table 2. Confidence for paired comparisons including a recognized and an unrecognized brand

		Confirming pairs			Violating pairs		
Domain	N of respondents	N of pairs	Mean	SE	N of pairs	Mean	SE
Business schools	107	4144	.86	.00	479	.71	.01
Vacuum cleaners	202	4300	.81	.00	385	.64	.01
Refrigerators	203	5822	.78	.00	752	.64	.01
Walking shoes	48	955	.84	.00	78	.69	.02
Headphones	47	1558	.85	.00	76	.65	.02

The output of a mixed-effect linear model testing the relationship between the stated confidence and the type of inference (that is, whether the recognized brand was inferred to be of *higher* or *lower* quality) confirms these findings (business schools: β = 13.71, SE = .67, t = 20.52; vacuum cleaners: β = 11.75, SE = .66, t = 17.83;

refrigerators: $\beta = 9.07$, SE = .50, t = 18.13; walking shoes: $\beta = 15.31$, SE = 1.32, t = 11.63; headphones: $\beta = 10.85$, SE = 1.33, t = 8.17)[3].

Analogous analysis for the response time spent on making inferences revealed that average response time was lower for those inferences that were made in line with recognition heuristic in all domains under consideration except vacuum cleaner (table 3), where the relationship was not statistically significant (business schools: $\beta = 240.17$, SE = 47.54, t = 5.05; vacuum cleaners: $\beta = 27.61$, SE = 48.62, t = .57; refrigerators: $\beta = 343.06$, SE = 52.25, t = 6.57; walking shoes: $\beta = 316.3$, SE = 125.1, t = 2.53; headphones: $\beta = 326.5$, SE = 138.0, t = 2.37).

Table 3. Response time for paired comparisons including a recognized and an unrecognized brand (ms)

		Confirming pairs			Violating pairs		
Domain	N of respondents	N of pairs	Mean	SE	N of pairs	Mean	SE
Business schools	107	4144	1947	16	479	2113	59
Vacuum cleaners	202	4300	1675	14	385	1593	45
Refrigerators	203	5822	2037	18	752	2313	57
Walking shoes	48	955	1761	32	78	2075	166
Headphones	47	1558	1882	28	76	2270	150

These results, along with the afore-mentioned unexplained phenomena, suggest that their solution may be related to the notion of certainty about brand quality: merely

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[3] The following describes the model used to test this relationship for the fixed effect variable, the type of inference, and the random effect variable, respondent.

$$CITPC_{ij} = \beta_0 + \beta_1 * ITPC_{ij} + b_{ij} * z_i + \varepsilon_{ij},$$

where CITPC represents confidence in an inference made by respondent i about paired comparison j, β_0 is the intercept, β_1 is the slope estimated for all respondents and comparisons, b is the vector of coefficients specific for respondent i, ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, ITPC is the dummy variable for the type of inference made by respondent i for paired comparison j, and z is the random effect for observations for respondent i.

recognized objects, which by definition are not associated with any knowledge about them, must by characterized by lower level of certainty about brand quality than other, more familiar ones. On the other hand, the objects associated with conflicting information, for example, brands attributed with mixed information about their quality, should be characterized by high variance in perceived quality. Consequently, people may have lower confidence in inferences for pairs including an unrecognized brand and a recognized brand attributed with high uncertainty (for example, a "merely" recognized brand or a brand attributed with mixed quality information) than for pairs including an unrecognized brand and a well-known high quality brand, characterized by high certainty. If uncertainty about the rank estimates is high and the distance between the rank estimates of compared brands is small enough for the belief distributions of two compared brands to overlap, during a paired comparison task, a brand with a lower rank estimate can be inferred to be of higher quality due to mere chance.

Thus, this thesis suggest a psychological model that considers not only quality point estimates, but also quality belief distributions in an attempt to explain why people sometimes do not adhere to the recognition heuristic. "Belief distribution" models have been used in other contexts (Woodruff 1972; Rust et al. 1997), but they have never been tested as accurate mental representations of people's quality perceptions as a function of memory cues, or as mechanisms explaining how people make quality inferences in paired comparisons, in general. Can these mental models describe how people make inferences about brand quality based on the information in their memory? Can they explain why people sometimes infer that an unrecognized brand is of higher quality than a recognized brand?

Before addressing these questions in chapters 6 and 7, this thesis will attempt at validating belief distributions as compelling mental representations of quality perceptions by testing whether or not the belief distributions reflect the current findings about the relationship between memory information and quality perceptions.

Prior literature suggests that consumers opt for recognized objects, that recognized objects are perceived to be of higher quality, and that perceived quality increases with object familiarity (Goldstein and Gigerenzer 2002, 2011; Hoyer and Brown 1990; Roberts and Urban 1988; Rust et al. 1997; Thurstone 1927). If belief distributions are accurate representations of how memory information is related to perceived quality of brands, that quality, measured as a point estimate, should be higher for recognized brands than for unrecognized ones, and the perception of quality about recognized brands should increase with the frequency of encountering the brand and the proportion of information suggesting that the brand is of high quality. Thus, this thesis suggests the following hypothesis:

H1: Perceived quality of brands, captured via belief distributions, is higher for recognized brands than for unrecognized brands and is positively correlated with the frequency of encountering the brand and knowledge valence.

On the other hand, according to findings in marketing, certainty about the quality of unrecognized brands is lower than that about recognized brands (Roberts and Urban 1988; Erdem and Swait1998; Erdem and Swait 2004; Laroche, Kim, and Zhou 1996). So, if belief distributions are able to reflect this relationship, belief distributions of unrecognized brands should be wider than those of recognized ones:

H2a: Variance in the perceived quality of brands, captured via belief distributions, is lower for recognized brands than for unrecognized brands and is inversely correlated with the frequency of encountering.

Variance in the perceived quality should be related to knowledge valence as well: brands associated with mostly positive or mostly negative quality should be attributed with lower variance than those associated with mixed quality information. Note that even though theoretically it is possible for a brand to be associated with only negative brand quality information, in practice, such brands would not survive in the long run. Hence, it is reasonable to assume that the brands with the lowest proportion of information suggesting that the brand is of high quality are attributed with both positive and negative information and are associated with lower certainty than the brands with only positive information.

H2b: Variance in the perceived quality of brands, captured via belief distributions, is inversely correlated with knowledge valence.

4.2. Methods

These hypotheses were tested by analysing the relationships between brand quality belief distributions elicited through participants' quality estimates and memory information reported by them. Perceived quality of recognized brands was captured by the most probable quality estimate assigned by participants, and the variance in the perceived quality (or certainty) was measured by the difference between the highest and lowest possible quality estimates. The general Methods section (chapter 3) describes how the relevant data were collected in three randomly ordered tasks performed by each participant during the lab studies. In one of the tasks, participants were asked about the information in memory for each brand: whether or not they had seen or heard of the brand (recognition), how frequently they had seen or heard about it (perceived environmental frequency), how much they knew about its quality (perceived knowledge volume), and what proportion of that knowledge suggested that the quality was good or bad (perceived knowledge valence). In the second task, quality belief distributions were elicited for each brand: participants guessed the most probable, highest possible and lowest possible ranks a brand could have according to a published quality ranking, such as Consumer Reports or U.S. News and World Report. Finally, they made inferences about quality for pairs of brands in a two-alternative forced choice task.

4.3. Results

Recall that Hypothesis 1 predicted that the perceived quality of brands would be higher for recognized brands than for unrecognized brands. To test this hypothesis, the average estimates of the most probable quality ranks for all recognized business schools and all unrecognized business schools were calculated.

The results show that, in line with past research (Allison and Uhl 1964; Hoyer and Brown 1990; Jacoby, Olson, and Haddock 1971; Goldstein and Gigerenzer 2002), the perceived quality of recognized brands was higher than that of unrecognized ones. For example, means of estimated ranks of business schools, grouped based on whether they were recognized or not, were 5.90 (out of 20) and 13.19, respectively. Table 4 shows the results of these analyses in each of the five domains.

Table 4. Most probable rank estimates for recognized and unrecognized brands

Domain	N of respondents	Recognized brands			Unrecognized brands		
		N	Mean	SE	N	Mean	SE
Business schools	107	872	5.90 (out of 20)	.15	1268	12.69 (out of 20)	.12
Vacuum cleaners	202	887	3.15 (out of 10)	.06	1133	6.77 (out of 10)	.06
Refrigerators	203	1062	3.88 (out of 12)	.07	1374	7.44 (out of 12)	.07
Walking shoes	48	197	3.52 (out of 10)	.15	283	7.07 (out of 10)	.12
Headphones	47	264	3.45 (out of 12)	.14	300	8.28 (out of 12)	.15

The output of a mixed-effect linear model testing the relationship between the estimated ranks and recognition (with recognition as a fixed effect dummy variable and respondent as a random effect variable) confirms that estimated ranks for the recognized brands are higher than those for unrecognized ones (business schools: $\beta = 7.5$, SE = .19, t = 40.29; vacuum cleaners: $\beta = 3.67$, SE = .08, t = 44.80; refrigerators: $\beta = 3.68$, SE = .10, t = 38.04; walking shoes: $\beta = 3.77$, SE = .18, t = 20.83; headphones: $\beta = 4.95$, SE = .18, t = 27.10)[4].

Furthermore, results of the Spearman and Kendall correlation analyses testing the relationship between the perceived quality of recognized brands and the frequency of encountering them, show positive correlation between these two constructs. That is,

[4] The following describes the model used to test this relationship for the fixed effect dummy variable, brand recognition, and the random effect variable, respondent.

$$QRE_{ij} = \beta_0 + \beta_1 * R_{ij} + b_{ij} * z_i + \varepsilon_{ij},$$

where QRE represents quality rank estimate of respondent i about brand j, β_0 is the intercept, β_1 is the slope estimated for all respondents and brands, b is the vector of coefficients specific for respondent i, ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, R is the dummy variable for brand recognition for respondent i and brand j, and z is the random effect for observations for respondent i.

as hypothesis 1 would predict, the more often the respondents had seen or heard of a brand, the higher was the brand's quality estimate (table 5).

Table 5. Relationship between estimated (most probable) quality ranks and perceived environmental frequency

Domain	N of observations	Spearman r_s	Kendall τ
Business schools	872	.60*	.45*
Vacuum cleaners	869	.46*	.36*
Refrigerators	1026	.41*	.31*
Walking shoes	193	.53*	.42*
Headphones	264	.32*	.25*

* $p < .01$

Likewise, the perceived quality of recognized brands was positively correlated with the respondents' perceived knowledge valence: the higher the perceived proportion on the information suggesting that a brand was of higher quality, the higher the brand's estimated (most probable) quality rank (table 6). Thus, the results of correlation analyses support hypothesis 1.

Table 6. Relationship between the estimated (most probable) quality ranks and perceived knowledge valence

Domain	N of observations	Spearman r_s	Kendall τ
Business schools	712	.59*	.46*
Vacuum cleaners	822	.55*	.43*
Refrigerators	928	.56*	.43*
Walking shoes	179	.59*	.47*
Headphones	251	.57*	.44*

* $p < .01$

Are belief distributions successful in capturing certainty as a function of memory cues? Analysis of variance in quality captured by average differences between the highest and lowest quality rank estimates for all recognized and all unrecognized business schools suggest that quality belief distributions for unrecognized brands are more dispersed than those for recognized brands: the average differences between the highest and lowest estimates are higher for unrecognized brands than for recognized brands in all but one domain, walking shoes (table 7).

Table 7. Variance of estimated ranks, captured as a difference between the highest and lowest possible rank estimates, for recognized and unrecognized brands

		Recognized brands			Unrecognized brands		
Domain	N of respondents	N	Mean	SE	N	Mean	SE
Business schools	107	872	5.63	.13	1268	6.84	.11
Vacuum cleaners	202	887	3.23	.07	1133	3.68	.07
Refrigerators	203	1062	4.05	.08	1374	4.45	.08
Walking shoes	48	197	2.97	.14	283	3.05	.14
Headphones	47	264	3.16	.13	300	3.88	.17

The output of a mixed-effect linear model testing the relationship between the estimated rank intervals and recognition (with recognition as a fixed effect dummy variable and respondent as a random effect variable) confirms that there is a statistically significant relationship between the rank estimate interval and recognition in the other four domains (business schools: $\beta = 1.58$, SE = .12, t = 13.14; vacuum cleaners: $\beta = .50$, SE = .05, t = 9.08; refrigerators: $\beta = .59$, SE = .07, t = 9.10; walking shoes: $\beta = .13$, SE = .12, t = 1.10; headphones: $\beta = .59$, SE = .13, t = 4.48)[5]. Thus, hypothesis 2a, which

[5] The following describes the model used to test this relationship for the fixed effect dummy variable, brand recognition, and the random effect variable, respondent.

$$QREI_{ij} = \beta_0 + \beta_1 * R_{ij} + b_{ij} * z_i + \varepsilon_{ij},$$

where QREI represents the difference between the highest and lowest possible quality rank estimate of respondent i about brand j, β_0 is the intercept, β_1 is the slope estimated for all respondents and brands, b is the vector of coefficients specific for respondent i, ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, R is the dummy variable for brand recognition for respondent i and brand j, and z is the random effect for observations for respondent i.

predicts that variance in the perceived quality of brands is lower for recognized brands than for unrecognized brands, is partially supported.

Finally, the results of Spearman correlation analyses provide support for hypotheses 2a and 2b, which predict that brand perceived quality variance is inversely correlated with the respondents' perceived frequency of encountering the brand and the perceived proportion of information suggesting that the brand is of high quality. Table 8 summarizes the results of correlation analysis between the "belief distribution" width, that is, the difference between the highest and lowest possible rank estimates, on one side, and perceived environmental frequency or perceived knowledge valence, on the other.

Table 8. Relationship between the variance of estimated ranks, captured as a difference between the highest and lowest possible rank estimates, and perceived environmental frequency or knowledge valence

	Perceived environmental frequency		Perceived knowledge valence	
Domain	N of observations	Spearman r_s	N of observations	Spearman r_s
Business schools	872	-.39*	712	-.38*
Vacuum cleaners	869	-.24*	822	-.33*
Refrigerators	1026	-.16*	928	-.28*
Walking shoes	193	-.34*	179	-.35*
Headphones	264	-.19*	251	-.12*

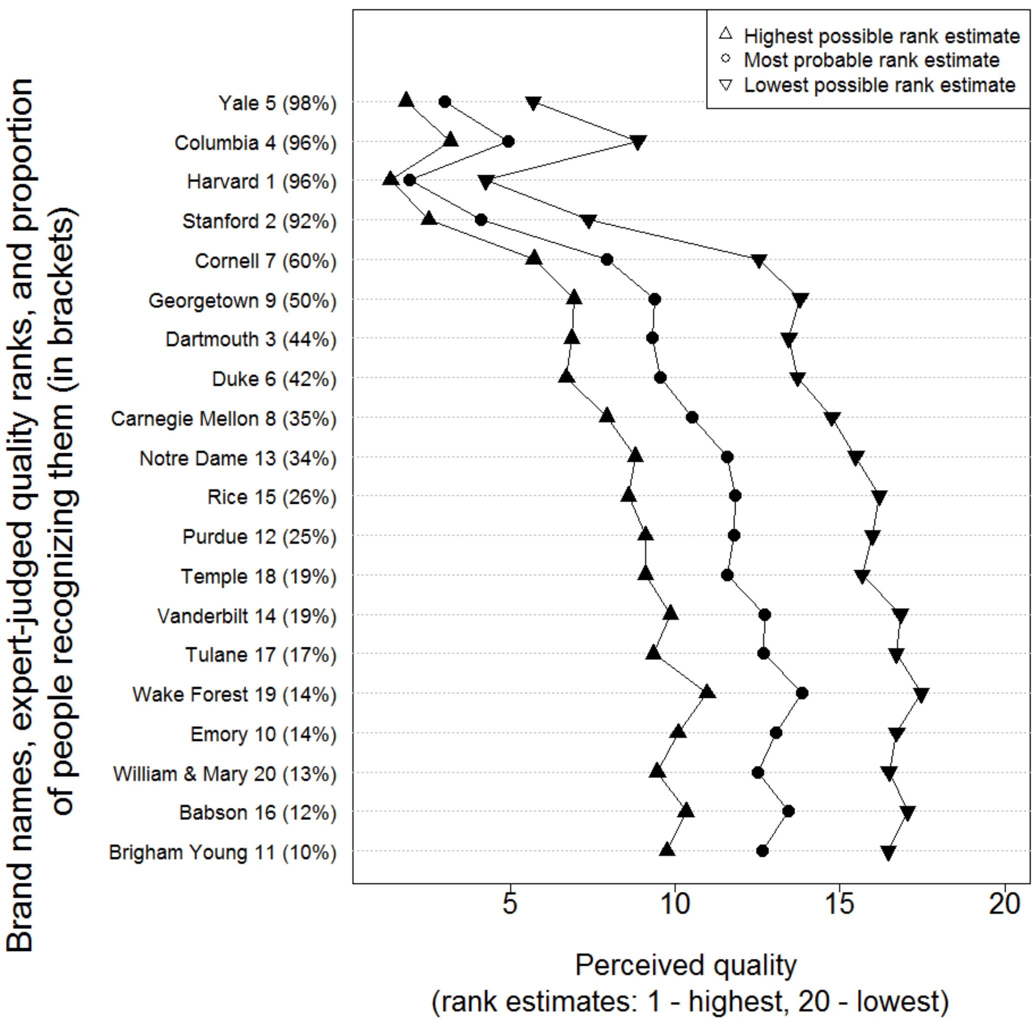
* $p < .01$

Figures 1A-E show how the brands recognized by most respondents are perceived differently from mostly unrecognized ones in terms of the quality rank. These graphs show the relationship between the proportion of people recognizing the brand and belief distributions for individual brands used in the studies. The brands are sorted according to the proportion of people recognizing them: top half of the brands are those recognized by at least a third of the participants, and the rest are mostly unrecognized brands.

As we can see on figure 1A, top recognized business schools are the ones that are assigned high perceived quality. The less recognized the brand is, the lower its perceived quality. While belief distributions for the top 10 business schools, which are relatively more recognized, vary across the brands, those for the relatively unknown bottom 10 look fairly similar. These patterns demonstrate once more the effect of memory information on beliefs about brand quality.

Figures 1 A-E. Relationship between the proportion of people recognizing the brand and quality ranking estimates

A. Business schools



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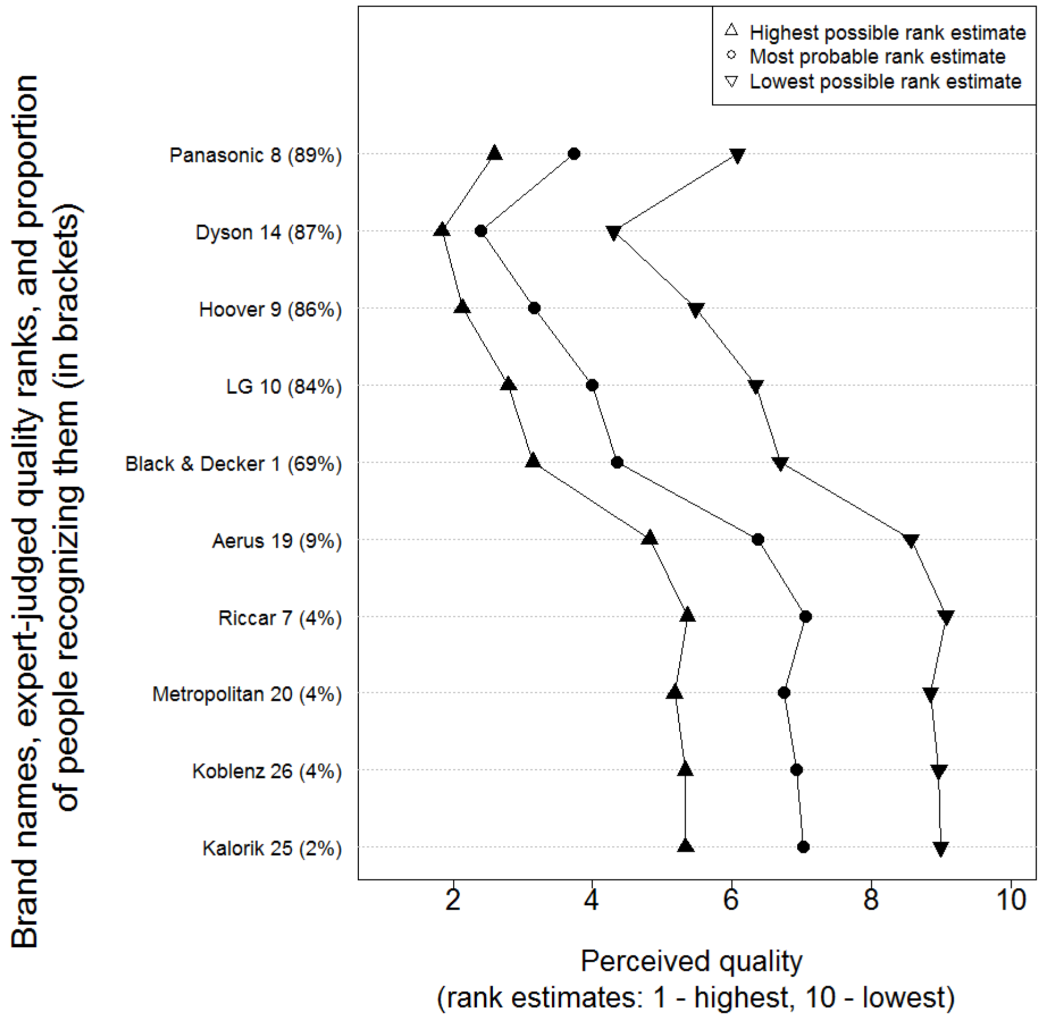
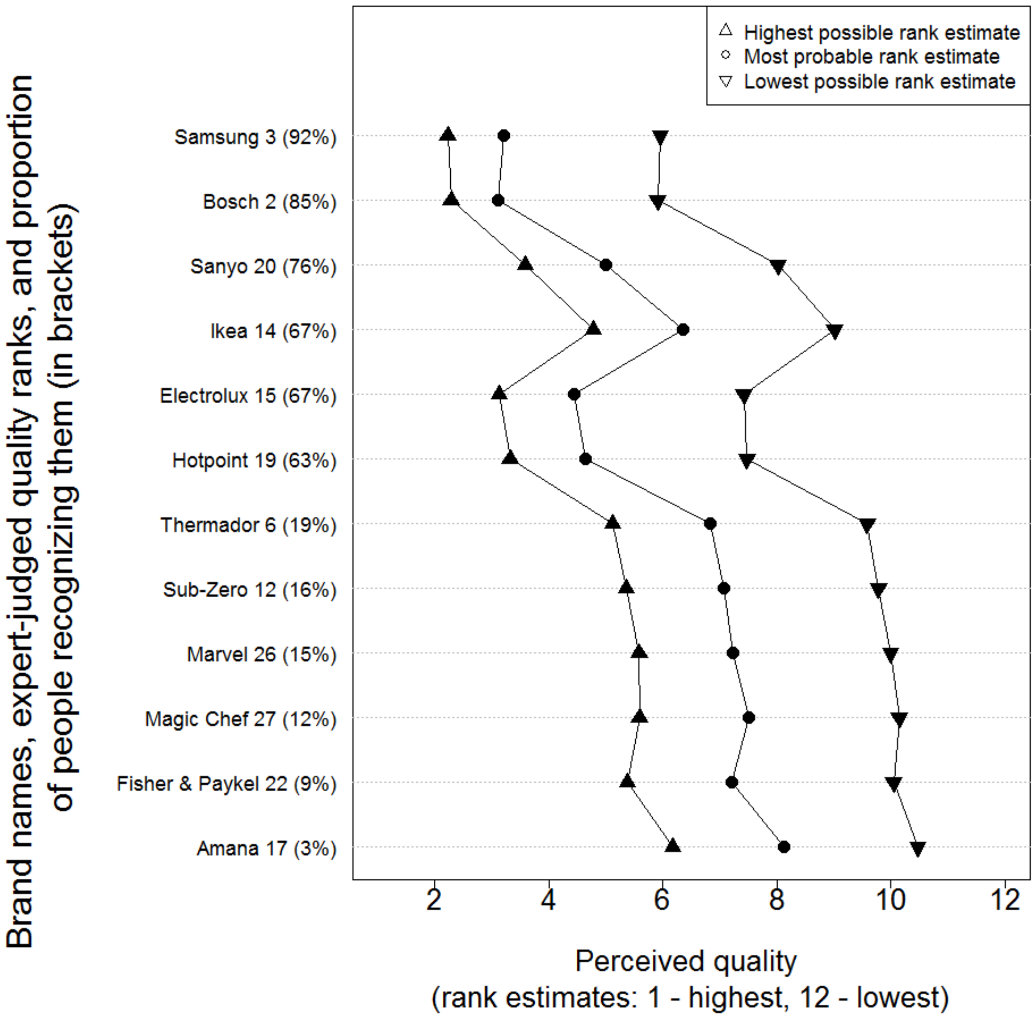
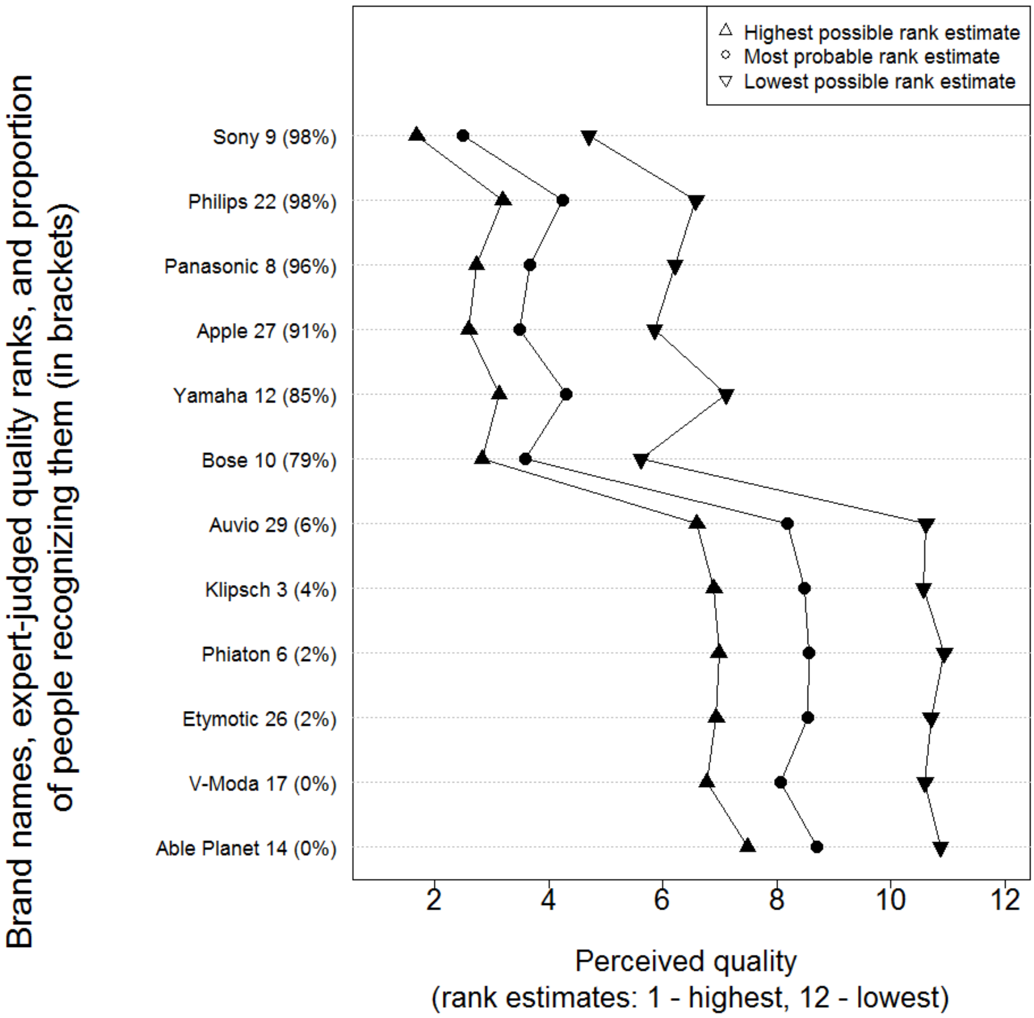
B. Vacuum cleaners



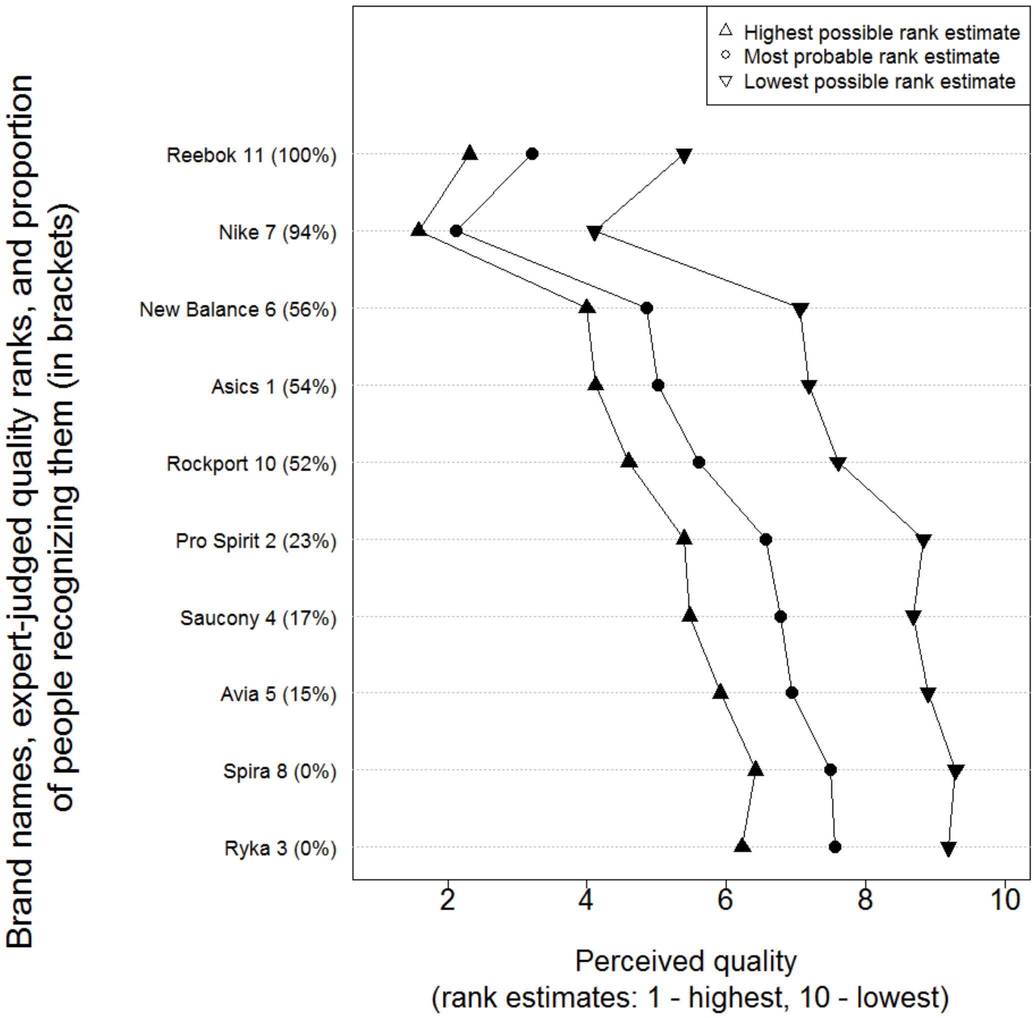
C. Refrigerators



D. Headphones



E. Walking shoes



4.4. Discussion

The findings demonstrated in this chapter suggest that quality belief distributions are capable of reflecting the effect of memory information both on mean and variance of quality. Consistent with the findings in marketing (Roberts and Urban 1988; Erdem and Swait1998; Erdem and Swait 2004; Laroche, Kim, and Zhou 1996), which suggest that recognized brands are characterized with higher certainty about quality levels than unrecognized brands, belief distributions for recognized brands were narrower than those for unrecognized brands. The results also replicated those findings in psychology and marketing that demonstrated the effect of recognition on quality perceptions (Allison and Uhl 1964; Hoyer and Brown 1990; Jacoby, Olson, and Haddock 1971; Goldstein and Gigerenzer 2002): recognized brands were attributed with higher quality rankings than unrecognized ones.

These results suggest that, when people compare typically recognized top business schools with unfamiliar ones, their quality estimates for the compared schools are significantly different both in terms of mean and variance of quality. On the other hand, when people compare an unrecognized brand with a brand they recognize, but are not very familiar with, people's brand quality estimates for the compared brands are characterised by lower means and high variances. This may lead to an "overlap" of belief distributions and a lower perceived probability of the recognized brand being of higher quality, which can explain why sometimes people deviate from the recognition heuristic. Thus, the demonstrated results support the rationale behind suggesting the "belief distribution" model as a compelling representation of how people make brand quality inferences, which will be tested further in chapters 6 and 7.

Before that, chapter 5 will continue the investigation of the power of recognition as an inferential cue. Does people's tendency to attribute recognized brands with higher quality than unrecognized brands extend to those brands that are associated with negative information? The next chapter looks at the brand quality perceptions of recognized brands with different brand knowledge valence and explores whether it is better for a brand to be attributed with mixed quality information or to be unknown.

5. IS THE DEVIL YOU KNOW BETTER THAN THE DEVIL YOU DON'T?

Could brands associated with mostly negative information–those with poor reputations–be perceived as superior to unrecognized brands? A reasonable consumer should value reputation; however, it is also sensible to put a heavy weight on brand recognition. To investigate this question, consumers' inferences about brand quality for recognized products associated with predominantly negative information about quality and unrecognized products in five domains were analysed. Results suggest that consumers infer that brands associated with predominantly negative information are indeed perceived as of higher quality than unrecognized brands. In addition, when modelling consumer inferences, the frequency of encountering a brand dominates what people profess to know about it. This chapter explores the ecological rationality of this strategy by studying the environmental relationship between expert-judged quality and consumer knowledge.

5.1. Introduction

Does the old saying "Better the devil you know than the devil you don't" apply to brands? The marketing literature has demonstrated an adverse effect of negative publicity on product and brand evaluation, arguing against the lay belief that "all publicity is good publicity." For example, Tybout, Calder, and Sternthal (1981) showed that evaluations of McDonald's restaurants were less positive when study participants were exposed to negative rumours about the brand. As would be expected, econometric analyses show that critical reviews have negative effects on box office revenue or book sales (Basuroy, Chatterjee, and Ravid 2003; Chevalier and Mayzlin 2006). However, recent findings introduce the possibility that negative publicity may have different effects on known and unknown brands. Berger and colleagues showed that negative publicity about a product may increase purchase likelihood and sales of unknown products by increasing their awareness, perhaps because consumers remember they heard something about these products, but forget the valence of the information (Berger, Sorensen, and Rasmussen 2010; Skurnik et al. 2005).

But what if people remember that the publicity was bad–could negative brand knowledge still be beneficial?

The current thesis addresses this question by looking at consumer inferences about the quality of brands. A few aspects of this research distinguish it from previous studies on the effect of information valence. While prior research looks at the links between critical reviews and product sales (Basuroy et al. 2003; Berger et al. 2010; Chevalier and Mayzlin 2006; Duan, Gu, and Whinston 2008; Liu 2006) or stock prices (Luo 2007), the current work focuses on the relationship between information in people's memory and their inferences about brand quality, which are important consumer-based measures of brand equity (Agarwal and Rao 1996; Keller 1993; Keller and Lehmann 2006).

The difference can be illustrated with the following example. Suppose a consumer, Joanne, is in a small seaside town for a day. After a long day on a beach, she is heading back home with her family, but before they leave the town, she wants to buy a quick meal. Joanne sees a number of fast-food restaurants on both sides of the streets. Some of them, such as Burger King and McDonald's, are familiar to her, but she does not recognize any of the local family businesses, because she has never been to this town before. Which restaurant offers higher quality food? On the one hand, Joanne has heard numerous negative remarks about the quality of famous fast-food chains. On the other hand, she knows nothing about the local options. Which brands do consumers infer to be of higher quality: the brands associated with mostly negative quality information, or ones they have never seen or heard of before?

As it will be explained, one can predict that brands associated with mostly negative information will tend to be perceived as superior to unrecognized brands. This hypothesis was tested for inferences about individual brands as well as for inferences about brands in paired comparisons.

H1a: Ranking: When making quality inferences about individual brands, consumers infer that recognized brands associated with mostly negative information are of higher quality than unrecognized brands.

H1b: Paired comparison: When making quality inferences about pairs of brands, in which one brand is recognized and the other is not, consumers infer that the recognized brands associated with mostly negative information are of higher quality than the unrecognized brands.

These hypotheses are based on the idea that simple cues can substitute for more complex pieces of information without a considerable decrease in inferential accuracy, because brand information in the environment and inferential cues are often strongly correlated in natural settings (Goldstein and Gigerenzer 2002; Steenkamp 1990). For example, if higher-quality vacuum cleaner brands are associated with a fair number of both positive and negative facts about brand quality, then consumers may learn that the valence of their knowledge is often not informative for inferring quality. At the same time, if they observe that more commonly mentioned brands tend to be of higher quality, they may learn that perceived environmental frequency, which is a pre-requisite for the more complex memory information represented by knowledge valence, may be a robust single predictor of brand quality.

H2: When memory cues are used to predict quality inferences, models including knowledge valence in addition to other cues are not more accurate than models including only simpler cues, such as recognition and perceived environmental frequency.

These hypotheses were tested using the data collected in the lab studies, field data and formal mathematical models.

5.2. Methods

As it was described in the general Methods section (chapter 3), three randomly ordered tasks were performed by each participant during the lab studies. In one of the tasks, participants were asked about the information in memory for each brand: whether or not they had seen or heard of the brand (recognition), how frequently they had seen or heard about it (perceived environmental frequency), how much they knew about its quality (perceived knowledge volume), and what proportion of that knowledge suggested that the quality was good or bad (perceived knowledge valence). In the second task, perceived brand quality was elicited: participants guessed the most probable rank a brand could have according to a published quality ranking, such as Consumer Reports or U.S. News and World Report. Finally, they made inferences about quality for pairs of brands in a two-alternative forced choice task.

For comparison of the predictive accuracy of models using different memory cues, quality inferences were modelled as a function of one or more measures, such as recognition, perceived environmental frequency, knowledge volume and valence, and response latency.

To explore the relationship between the volume of the information in the environment and the quality of the object, the frequency of citations on various Internet sources for the brands and quality ratings from Consumer Reports or U.S. News and World Report were used.

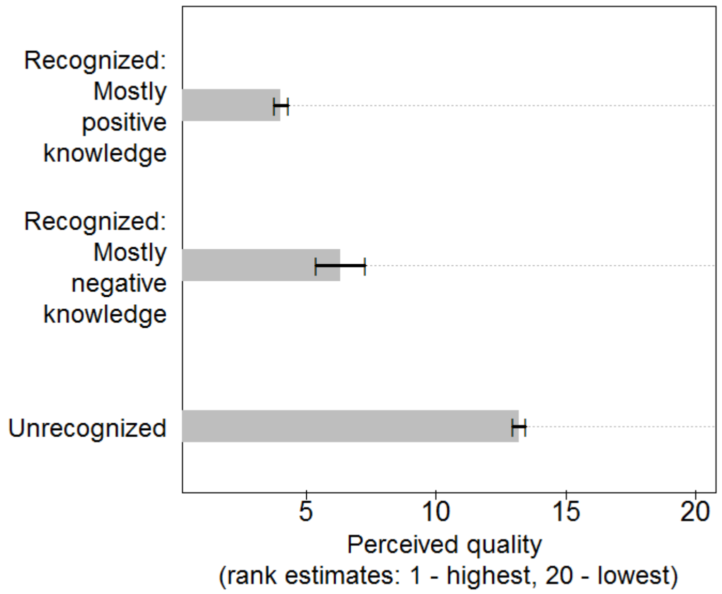
5.3. Results

Individual estimates of brand quality ranking. Recall that Hypothesis 1a predicted that consumers would rank recognized brands associated with mostly negative information as being of higher quality than unrecognized brands. To test this hypothesis, average quality rank estimates were calculated for all unrecognized business schools and all recognized business schools, which individual participants rated as having mostly negative quality in Question Set 1 (the responses to the question, capturing perceived knowledge valence were grouped into three categories: *predominantly negative* –"0% good, 100% bad"–"39% good, 61% bad", *predominantly positive* – "61% good, 39% bad"–"100% good, 0% bad", and *neutral* – "40% good, 60% bad"–"60% good, 40% bad"). Any observation with inconsistent responses (for example, a respondent indicated that he/she had knowledge about a particular business school, but his/her other responses indicated that he/she had never seen or heard of that school before) were eliminated from the data set before any analysis were conducted.

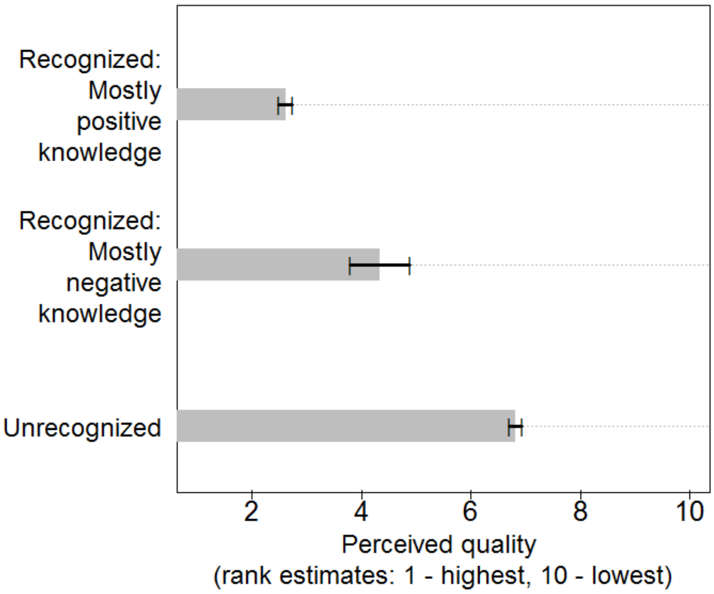
Analysis of rank estimates grouped by recognition valence demonstrate that the effect of recognition was so strong that even the brands with predominantly poor quality reputation were rated higher than unrecognized brands (figures 2A-E).

Figures 2A-E. Perceived quality for unrecognized business schools and for recognized business schools with different levels of knowledge valence

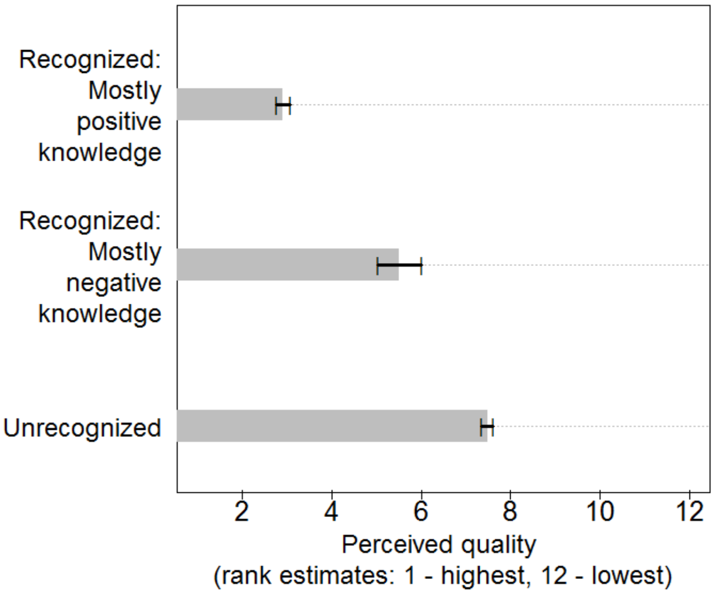
A. Business schools



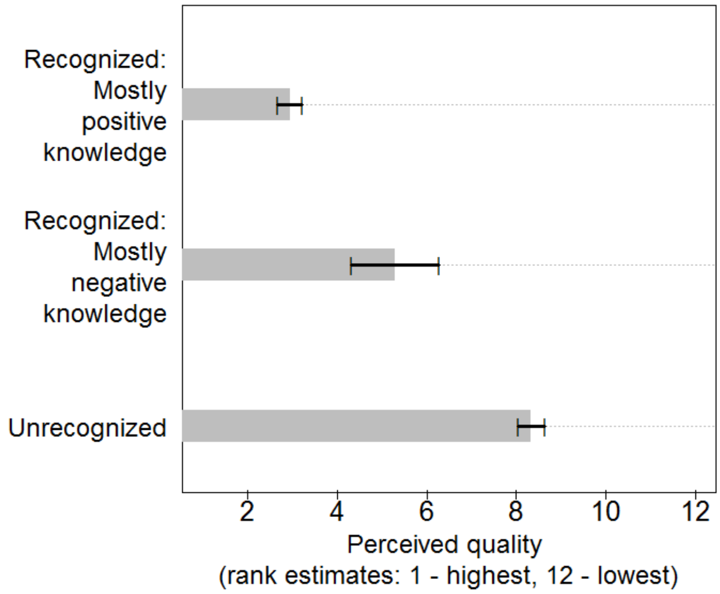
B. Vacuum cleaners



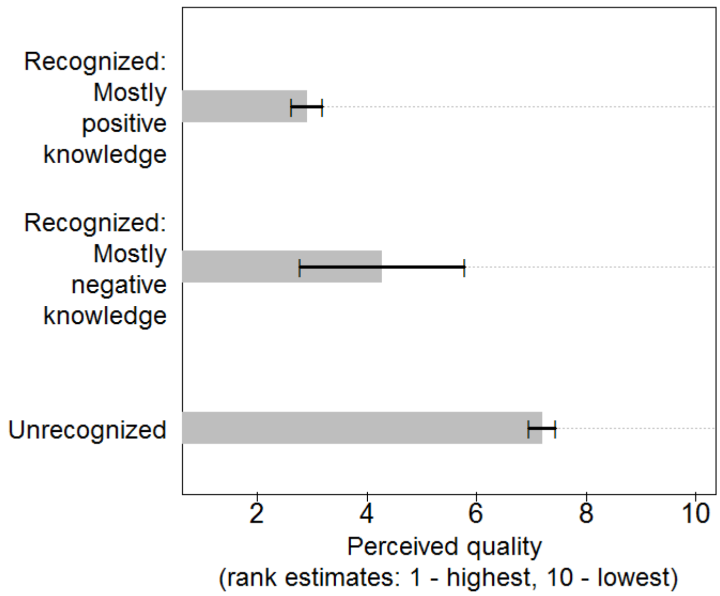
C. Refrigerators



C. Headphones



D. Walking shoes



For example, the typical recognized vacuum cleaner or walking shoe brands associated with poor quality ranked about 4th out of 10 on average, while unrecognized schools ranked about 7th out of 10. The corresponding means in these domains were 4.34 versus 6.83 (SE_{RKn-} = .28, SE_U = .06) for the vacuum cleaner brands, and 4.29 versus 7.22 (SE_{RKn-} = .77, SE_U = .12) for the walking shoe brands. For refrigerator and headphone brands, which could be ranked between 1 and 12, the corresponding average ranks were 5.52 versus 7.51 (SE_{RKn-} = .25, SE_U = .07) and 5.30 versus 8.36 (SE_{RKn-} = .50, SE_U = .15). Similarly, for business schools, the means were 6.33 vs. 13.24 out of maximum 20 (SE_{RKn-} = .48, SE_U = .13). The output of a mixed-effect linear model testing the relationship between the estimated ranks and recognition (with recognition as a fixed effect dummy variable and respondent as a random effect variable, as described on page 47) confirms that estimated ranks for the recognized brands attributed with mostly negative quality information are higher than those for unrecognized ones: business schools (1113 responses from 105 respondents), β = 7.16, SE = .50, t = 14.35; vacuum cleaners (1098 responses from 198 respondents), β = 2.78, SE = .24, t = 11.74; refrigerators (1305 responses from 199 respondents), β = 2.11, SE = .24, t = 8.78; walking shoes (263 responses from 48 respondents), β = 3.11, SE = .49, t = 6.39; headphones (304 responses from 46 respondents), β = 2.99, SE = .41, t = 7.28). These results support hypothesis 1a. As would be expected, recognized brands with predominantly positive information were rated higher than the ones with mostly negative information, which is confirmed by the correlational analysis reported in table 6 of chapter 4.

Brand quality inferences in paired comparisons. Recall that hypothesis 1b predicts that, when given a pair of brands, in which one brand is recognized and attributed with predominantly poor quality information and the other is not recognized, consumers infer that the recognized brand is of higher quality. To test this hypothesis, the proportion of times a recognized brand associated with mostly negative information was inferred to be of higher quality than an unrecognized one was calculated.

The results demonstrate that participants inferred that the recognized brand was of higher quality in the vast majority of cases. For example, participants made such inferences for 89% of applicable pairs of business schools, indicating a strong tendency of people to infer that recognized brands are of higher quality, even when they were attributed with mediocre quality information. This result is significantly greater than chance ($\chi^2(1, N = 275) = 99.32$, $p < .01$).

The results of this analysis across the four consumer domains replicated those in the business school domain: in most cases, participants inferred that the recognized brand associated with predominantly poor quality information was of higher quality than the unrecognized brand, and proportions of such inferences were significantly greater than chance: 85% of such pairs for vacuum cleaners ($\chi^2(1, N = 270) = 55.93$, $p < .01$), 78% of such pairs for refrigerators ($\chi^2(1, N = 582) = 42.28$, $p < .01$), 79% of such pairs for walking shoes ($\chi^2(1, N = 73) = 13.79$, $p < .01$), and 89% of such pairs for headphones ($\chi^2(1, N = 196) = 69.37$, $p < .01$). Even though these rates were lower than the ones calculated for all pairs in which one brand was recognized and the other was not (see table 1 in chapter 4), they still indicated a strong tendency of people to infer that recognized brands were of higher quality, even when they were attributed with predominantly poor quality information.

These results suggest that consumers might not use knowledge valence information in making inferences about brand quality when comparing recognized brands attributed with mostly negative information with an unrecognized brand, and these inferences can be predicted without knowledge valence information. To test this idea, that is, hypothesis 2, consumers' brand quality estimates were predicted based on models that did or did not use knowledge information as predictors.

Predictive accuracy of models. To compare accuracy of different memory cues in predicting quality inferences in paired comparisons, that is, to test hypothesis 2, quality rank estimates were modelled as a function of one or more measures. As the findings from chapter 4 suggest, brand quality inferences can be predicted by brand recognition, perceived environmental frequency and knowledge valence, which is in line with the prior literature (Goldstein and Gigerenzer 2002, 2011; Hoyer and Brown 1990; Roberts and Urban 1988; Rust et al. 1997; Thurstone 1927; Pachur and Hertwig 2006; Serwe and Frings 2006; Pachur and Biele 2007; Hertwig and Herzog 2011; Frosch, Beaman, and McCloy 2007; Richter and Späth 2006). Variance in brand quality estimates can also be explained by the covariates of the perceived environmental frequency - recognition response latency and perceived knowledge amount (Keller 2003; Hertwig et.al. 2008): the higher the perceived environmental frequency the higher the perceived knowledge volume and shorter recognition response latency. Therefore, models not including knowledge measures, used recognition, recognition response latency, and perceived environmental frequency as predictors. More complex models, which included knowledge information for predicting inference, used knowledge volume and valence in addition to the three predictors from the afore-mentioned more parsimonious models.

First, quality rank estimates stated by the participants were predicted based on simple (not including knowledge information) or complex (including knowledge information) models. Section a in appendix F provides more detailed description of the models (models for predicting the quality estimates for merely recognized and unrecognized brands were similar in both sets). Then, the outputs of these models, that is, quality rank estimate predictions for recognized and unrecognized brands, were used to predict inferences in paired comparisons. Next, the inference decisions predicted by the models were compared with inferences stated by the respondents, and the percentage of times a model made an accurate prediction of the stated decision was calculated for each model. Finally, two sets of models were compared based on their ability to make accurate predictions of people's inferences in paired comparisons.

Analysis of the ability of models to make accurate predictions of inferences in paired comparisons in all five domains revealed that, as predicted by hypothesis 2, the simpler models, not including brand knowledge data as one of the predictors of rank estimates, were as accurate as the complex ones, which included brand knowledge data (table 9).

Table 9. Predictive accuracy of models for inferences in paired comparisons including an unrecognized brand and a recognized brand attributed with quality information (when predictions are made based on rank estimates modelled as a function of memory cues)

		Percentage of accurate predictions		
Domain	N of observations	Models *not including* knowledge valence	Models *including* knowledge valence	Fisher's exact test p-value
Business schools	3173	94.30	92.50	.00
Vacuum cleaners	3904	92.98	92.98	1.00
Refrigerators	4756	89.70	89.23	.48
Walking shoes	796	94.10	92.34	.19
Headphones	1342	95.31	95.23	1.00

Potential criticism of this method can be the overall complexity of the modelling approach through several afore-mentioned steps, each based on cross-validated outputs, which can lower the accuracy of the more complex models. To overcome this drawback, the accuracy of models was also compared by modelling inferences in paired comparison based on memory cue data directly. First, inferences in paired comparison were modelled as a function of response latency, perceived environmental frequency, and, were applicable, as a function of knowledge volume and knowledge valence, for the recognized brand. That is, for models not including knowledge data, the probability that a recognized brand is inferred to be of higher quality can be expressed as follows.

(1) $$P_{ij} = \beta_0 + \beta_1 * RL_{ij} + \beta_2 * PEF_{ij} + \varepsilon_{ij},$$

where P represents the probability that respondent i judges the recognized brand j to be of higher quality, β_0 is the intercept, β_1, β_2 are the slopes estimated for all respondents and brands, and ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, RL is response latency, and PEF is perceived environmental frequency.

Alternatively, using knowledge data in addition to simpler cues, that probability can be modelled the following way.

(2) $$P_{ij} = \beta_0 + \beta_1 * RL_{ij} + \beta_2 * PEF_{ij} + \beta_3 * KVOL_{ij} + \beta_4 * KVAL_{ij} + \varepsilon_{ij},$$

P represents the probability that respondent i judges the recognized brand j to be of higher quality, β_0 is the intercept, β_1, β_2, β_3, β_4 are the slopes estimated for all respondents and brands, ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, RL is response latency, PEF is perceived environmental frequency, and KVOL and KVAL are knowledge volume and valence.

Then, the outcome of the models, that is, the probability of a recognized brand being inferred of higher quality, was rounded off to predict the inference in each pair. The proportion of times the model predicted the inference stated by the respondents correctly was used as a measure of predictive accuracy for the compared models shown in table 10.

Table 10. Predictive accuracy of models for inferences in paired comparisons including an unrecognized brand and a recognized brand attributed with quality information (when predictions are made based on memory cues directly)

		Percentage of accurate predictions		
Domain	N of observations	Models *not including* knowledge valence	Models *including* knowledge valence	Fisher's exact test p-value
Business schools	3173	95.43	95.43	1.00
Vacuum cleaners	3969	93.58	93.57	1.00
Refrigerators	4781	91.04	90.68	.59
Walking shoes	837	94.74	94.45	.91
Headphones	1348	96.14	96.14	1.00

These results suggest that, as hypothesis 2 would predict, perceived environmental frequency can be a single robust predictor of consumers' inferences about brand quality. To investigate the reasons for such results further, I analysed how the quality of brands is related to the number of times the brands are mentioned in the environment. Can the findings in this chapter be explained by that relationship? If correlated with the number of mentions, brand quality can be accurately inferred without the use of other cues.

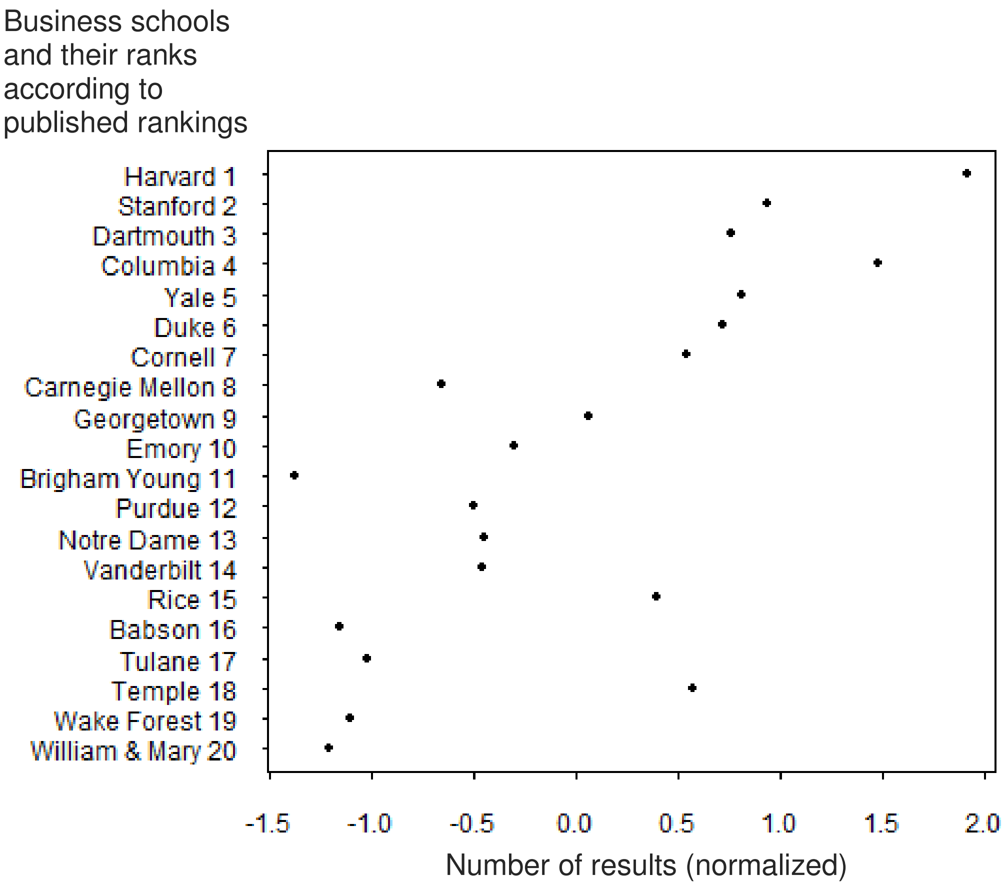
Field data analysis. To explore the relationship between the volume of the information in the environment and the quality of the brands, this work used the business school quality ratings from published rankings and the frequency of citations of business schools on the Web, which were collected by a company specializing in sentiment data collection, *General Sentiment*.

In addition, environmental frequency was measured by the number of search results generated by *Google*, *Bing*, and *New York Times* web search engines for the combination of the university name and “business school” or “school of business” word groupings, for example, “harvard” and “business school” or “school of business”. Natural logarithmic transformation was used to transform the numbers of search results generated by these three sources, that is, search engines, before the results were standardized within each source. Then, mean values of these standardized scores were calculated for each school.

Business school quality ranks were determined by averaging the schools’ ranks published by U.S. News and World Report in 2008 and 2009. When quality scores were needed, the scores published by U.S. News and World Report in 2008 were used.

The analysis of the relationship between brand quality and information volume in the environment in the business school domain revealed that knowledge valence may not be necessary for making inferences about brand quality. As Figure 3 shows, the more frequently business schools were cited on the Web, the higher they were ranked according to the published ratings. Expert-judged brand quality was positively correlated with the average number of Web search results ($r(18) = .83$, $p < .01$) and with the numbers of mentions in news and social media on the Internet ($r(18) = .70$, $p < .01$ for news media and $r(18) = .71$, $p < .01$ for social media).

Figure 3. Relationship between expert-judged quality and environmental frequency



These findings suggest that, if consumers observe such relationships, they can make inferences following a simple logic: “I have seen brand A and I have not seen brand B, brand A must be of higher quality than brand B, even if I know brand A for its mainly poor quality reputation.” What is interesting to know, whether the brands associated with mostly negative quality information are of higher quality than unrecognized brands according to experts’ opinion.

To answer this question, average expert-judged quality ranks were calculated for all unrecognized business schools and all recognized business schools, which individual participants rated as having mostly negative quality. The findings showed that the expert-judged quality of recognized brands was indeed higher than that of unrecognized ones: means for estimated ranks of business schools grouped based on whether they were recognized or not were 7.25 (out of 20) and 13.27 (SE_{RKn-} = .66 , SE_U = .14). A linear regression model testing the relationship between expert-judged quality ranks and recognition stated by 105 respondents for 1113 brands confirms that the ranks for the recognized brands associated with mostly negative knowledge valence are significantly higher than those for unrecognized ones (β = 6.02, SE = .60, t = 9.97, $p < .001$, $R^2 = .08$, $p < .001$)[6]. It seems that, in this domain, it is ecologically rational to use environmental frequency as a cue for quality inferences.

But what about the other domains, for example, consumer goods, in which the relationship between quality and environmental frequency can be more distorted by the ability of companies to increase environmental frequency via advertising, regardless of the brand quality? This distortion may also be caused by the fact that some high-end brands, such as Klipsch headphones, or brands serving niche markets, such as Ryka walking shoes, are not promoted via mass advertising while being top-quality brands and, hence, are not familiar to most consumers.

The afore-mentioned linear regression model confirms that expert-judged ranks of vacuum cleaner and refrigerator brands associated with mostly negative information are significantly higher than ranks of unrecognized brands in these domains (vacuum cleaners: 1098 responses from 198 respondents, β = 2.19, SE = .38, t = 5.83, $p < .001$, $R^2 = .03$, $p < .001$; refrigerators: 1305 responses from 199 respondents, β = 1.80, SE = .31, t = 5.74, $p < .001$, $R^2 = .02$, $p < .001$). Mean expert-judged quality ranks of

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[6] The following describes the model used to test the relationship between expert-judged quality and brand recognition.

$$EJQR_j = \beta_0 + \beta_1 * R_{ij} + \varepsilon_{ij},$$

where EJQR represents the expert-judged quality rank for brand j, β_0 is the intercept, β_1 is the slope estimated for all respondents and brands, ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, R is the dummy variable for brand recognition for respondent i and brand j.

recognized objects with mostly negative quality associations were 4.48 and 6.67, correspondingly, for the vacuum cleaner brands (SE_{RKn-} = .27, SE_U = .09) and 5.75 and 7.55, correspondingly, for the refrigerator brands (SE_{RKn-} = .27, SE_U = .1). That is, we see the same pattern as in the business school domain. However, average expert-judged quality of headphone brands attributed with mostly negative information is not higher than that of unrecognized brands (M_{RKn-} = 7.61, SE_{RKn-} = .55, M_U = 6.57, SE_U = .24): the results of the linear regression model suggest no significant difference between the average quality rating for those brands (304 responses from 46 respondents, β = 1.03, SE = .70, t = 1.47, p = .14, R^2 = .01, p = .14). Furthermore, in the walking shoe domain, expert-judged quality of brands associated with mostly negative information is on average lower than these ranks of unrecognized brands (M_{RKn-} = 8.29, SE_{RKn-} = .45, M_U = 4.74, SE_U = .16). Even though it may seem that, in this domain, knowledge valence is a more informative cue than perceived environmental frequency, it is not the case: expert-judged quality of brands associated with mostly positive information is also lower than that of unrecognized brands (M_{RKn+} = 6.67, SE_{RKn+} = .26), suggesting negative correlation between quality and environmental frequency for the set of walking shoe brands used in the study. The outcomes of the linear regression model reveal a significant difference between the quality ranks for the recognized brands associated with mostly negative information and unrecognized brands (263 responses 48 from respondents, β = 3.55, SE = .66, t = 5.34, p < .001, R^2 = .10, p < .001) and between the quality ranks for the recognized brands associated with mostly positive information and unrecognized brands (38 responses from 48 respondents, β = 1.93, SE = .28, t = 6.80, p < .001, R^2 = .10, p < .001).

Interestingly, respondents' quality rank estimates in this domain did not seem to be affected by the inverse relationship between expert-judged quality and environmental frequency. This suggests that they may assume a direct relationship between environmental frequency and quality for all domains. Alternatively, respondents may realize that some brands are not frequently mentioned or seen in the environment due to the fact that they are targeted not to a mass market, but to a niche consumer segments. However, when asked about a brand they do not recognize, they may find it safer to attribute lack of awareness about the brand to its low quality rather than to selective marketing. In both cases, the findings suggest that there may be benefits to uninformative advertising that only generates recognition.

5.4. Discussion

In line with past research, this work showed that the perceived quality of recognized brands was higher than that of unrecognized ones, and the perception of quality increased with the perceived environmental frequency. As a compelling extension of this result, this thesis found that in all five domains studied, while proportion of negative information about quality was inversely correlated with quality perception of known brands, the effect of recognition was so strong that even the brands with predominantly poor quality reputation were rated as better than unrecognized ones. When a familiar brand was compared with an unfamiliar one, mere awareness and perceived environmental frequency could predict inferences as accurately as the other self-stated knowledge participants had. This finding is consistent with firms' tendency to invest heavily in advertisements that provide no product information, and even attract negative attention to a brand, like in case of Benetton's controversial ad campaigns. In the 1990s, it used shocking images to grab people's attention: unlike most ads which centred around companies' products or image, Benetton's advertising showed a newborn baby still attached to its umbilical cord, a dying AIDS patient surrounded by his family, or a bloody corpse left by the Mafia. In spite of the criticism and, perhaps, in part due to it, Benetton became one of the most recognized in the world, entering top five, bypassing Chanel and approaching Coca Cola (Toscani 1997).

This pattern mirrors the structure of information in the environment: expert evaluations of quality published by U.S. News and World Report were positively correlated with the number of mentions on the Internet, which, naturally, involves both negative and positive remarks. This suggests that consumers may realize that environmental frequency can serve as a single robust inferential cue for brand quality, in line with the demonstrated results regarding participants' inferences.

If recognized brands are inferred to be of higher quality even when they are attributed with mostly negative information, why do people sometimes deviate from the recognition heuristic? The next chapter explores the properties of brands involved in inferences that are not in line with the recognition heuristic and uses the "belief distribution" model in an attempt to explain such deviations.

6. WHEN DO CONSUMERS INFER THAT AN UNRECOGNIZED BRAND IS OF HIGHER QUALITY THAN A RECOGNIZED BRAND?

The marketing and psychology literature has suggested that, though consumers tend to choose the brands they recognize over the ones they do not (Allison and Uhl 1964; Hoyer and Brown 1990; Jacoby, Olson and Haddock 1971, Goldstein and Gigerenzer 2002; Hauser 2011), it is often the case that people do not follow the recognition heuristic (Newell and Shanks 2004; Oppenheimer 2003; Pohl 2006; Richter and Späth 2006). In an attempt to shed light on some unexplained phenomena in psychology, this thesis explores the situations, in which people deviate from their tendency to assign higher quality to recognized brands than to unrecognized ones. Can belief distributions explain why people sometimes infer that an unrecognized brand is of higher quality than a recognized brand?

6.1. Introduction

When do people infer that unrecognized brands are of higher quality than recognized brands? Prior literature suggests that, in natural settings, people deviate from the recognition heuristic more often when they compare unrecognized brands with "merely" recognized objects, that is, relatively unfamiliar objects not associated with any knowledge (Marewski et al. 2010). Such deviations also happen more often, when a recognized object is known for having a low value with respect to criterion judged or is attributed with conflicting information (Oppenheimer 2003; Pohl 2006; Richter and Späth 2006).

This thesis tested whether such findings could be extended to brands. In particular, inferences for paired comparisons involving a recognized and an unrecognized brand were grouped based on whether or not an inference was made in line with the recognition heuristic: those in line with the recognition heuristic were classified as *confirming*, and those not in line with it were classified as *violating*. Then, recognized brands involved in confirming and violating pairs were compared based on perceived frequency of encountering and knowledge valence. The analysis confirms that perceived frequency of the recognized brands was lower in violating pairs than in confirming pairs (table 11).

Table 11. Perceived environmental frequency for recognized brands involved in paired comparisons

		Confirming pairs			Violating pairs		
Domain	N of respondents	N of pairs	Mean	SE	N of pairs	Mean	SE
Business schools	107	4144	38.25	.22	479	26.99	.73
Vacuum cleaners	202	4300	38.86	.20	385	29.62	.83
Refrigerators	203	5822	37.02	.19	752	27.52	.62
Walking shoes	48	955	40.40	.47	78	35.12	2.00
Headphones	47	1558	43.13	.28	76	36.67	1.85

The output of a mixed-effect linear model testing the relationship between the perceived environmental frequency and the pair type (with the pair type as a fixed effect dummy variable and respondent as a random effect variable) confirms these findings (business schools: $\beta = 9.91$, SE = .63, t = 15.82; vacuum cleaners: $\beta = 6.49$, SE = .66, t = 9.81; refrigerators: $\beta = 6.67$, SE = .52, t = 12.83; walking shoes: $\beta = 5.41$, SE = 1.50, t = 3.61; headphones: $\beta = 5.32$, SE = 1.03, t = 5.17).

Analogous analysis testing the relationship between perceived knowledge valence and pair type reveal that the perceived knowledge valence for the recognized brands is less positive in violating pairs than in confirming pairs (table 12), which is confirmed by the output of a mixed-effect linear model testing this link (with the pair type as a fixed effect dummy variable and respondent as a random effect variable)[7]: business schools, β = 4.72, SE = .59, t = 8.02; vacuum cleaners, β = 3.16, SE = .53, t = 5.95; refrigerators, β = 8.81, SE = .45, t = 19.66; walking shoes, β = 8.50, SE = 1.09, t = 7.77; headphones, β = 13.88, SE = 1.27, t = 10.94.

Table 12. Knowledge valence for recognized brands involved in paired comparisons

		Confirming pairs			Violating pairs		
Domain	N of respondents	N of pairs	Mean	SE	N of pairs	Mean	SE
Business schools	107	4144	13.92	.20	479	5.62	.71
Vacuum cleaners	202	4300	13.17	.18	385	6.48	.66
Refrigerators	203	5822	11.02	.17	752	.78	.51
Walking shoes	48	955	13.93	.39	78	3.08	1.93
Headphones	47	1558	12.49	.34	76	-1.32	1.81

[7] The following describes the models used to test these relationships for the fixed effect dummy variable, inference type, and the random effect variable, respondent.

$$PEF_{ij} = \beta_0 + \beta_1 * ITPC_{ij} + b_{ij} * z_i + \varepsilon_{ij}$$

$$KVAL_{ij} = \beta_0 + \beta_1 * ITPC_{ij} + b_{ij} * z_i + \varepsilon_{ij},$$

,

where PEF and KVAL represent perceived environmental frequency and knowledge valence, correspondingly, for respondent i and paired comparison j, β_0 is the intercept, β_1 is the slope estimated for all respondents and comparisons, b is the vector of coefficients specific for respondent i, ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, ITPC is the dummy variable for the type of inference made by respondent I for paired comparison j, and z is the random effect for observations for respondent i.

Recall that findings from chapters 4 and 5 suggest that recognized brands are perceived to be of higher quality than unrecognized brands (even if the recognized brands are associated with mostly negative information), and that quality perceptions are positively correlated with the frequency of encountering a brand and knowledge valence. In addition, analysis from these chapters revealed that recognized brands are associated with higher certainty about quality levels, that is, narrower belief distributions, than unrecognized brands, and that the distribution width decreases (that is, certainty increases) with the frequency of encountering a brand and knowledge valence.

Given these findings and the afore-mentioned results from this chapter, confirming that recognized brands in violating pairs are relatively unfamiliar or are attributed with less positive knowledge valence than the recognized brands in confirming pairs, this thesis makes the following assumptions. Recognized brands involved in violating pairs are inferred to be of lower quality than the recognized brands in confirming pairs. Since such recognized brands in violating pairs are characterized with higher uncertainty, they can be perceived as fairly similar to unrecognized brands even if the recognized brands are inferred to be of somewhat higher quality than unrecognized ones.

If these assumptions hold, then in situations when an unrecognized brand is compared with a relatively unfamiliar recognized brand (or a recognized brand attributed with mixed knowledge valence), the perceptions of the quality of these compared brands are relatively close and are characterized with high uncertainty, which leads to an "overlap" of belief distributions for the compared brands. The higher the degree of the distribution overlap, the lower the probability of a recognized brand being of higher quality. Once that probability reaches some threshold, an unrecognized brand can be attributed with higher quality due to mere chance. This is in line with results reported in table 2 of chapter 4 showing that confidence in violating inferences is lower than that in confirming inferences. If belief distributions can explain how people make brand quality inferences, the probability of the recognized brand to be of higher quality than an unrecognized brand derived from the degree of distribution overlap should follow the same pattern.

H1: The probability of a recognized brand being of higher quality than an unrecognized brand should be higher in confirming pairs than in violating pairs.

6.2. Methods

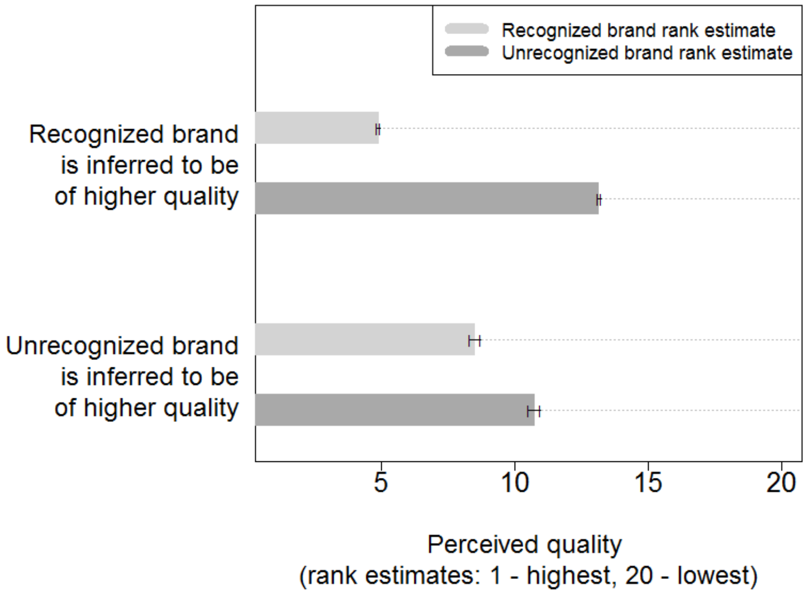
Analyses testing this hypothesis were based on the data from the three randomly ordered tasks performed by each participant during the lab studies, which are described in the general Methods section (chapter 3). In one of the tasks, participants were asked about the information in memory for each brand: whether or not they had seen or heard of the brand (recognition), how frequently they had seen or heard about it (perceived environmental frequency), how much they knew about its quality (perceived knowledge volume), and what proportion of that knowledge suggested that the quality was good or bad (perceived knowledge valence). In the second task, perceived brand quality was elicited: participants indicated the most probable, highest possible and lowest possible ranks a brand could have according to a published quality ranking, such as Consumer Reports or U.S. News and World Report. Finally, they made inferences about quality for pairs of brands in a two-alternative forced choice task.

6.3. Results

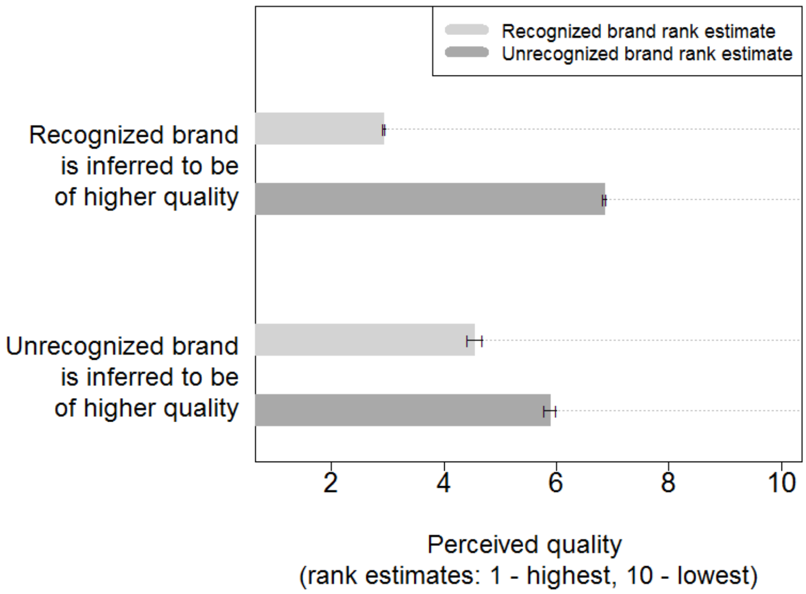
Recall that hypothesis 1 is based on the assumption that recognized brands are inferred to be of higher quality when inferences are in line with the recognition heuristic than when they are not. As figures 4A-E demonstrate, this assumption was supported in all five domains under investigation. The output of a mixed-effect linear model testing the relationship between the rank estimates and pair type (with pair type as a fixed effect dummy variable and respondent as a random effect variable) shows that the recognized brands are believed to be of higher quality in confirming pairs than in violating pairs: business schools, 4623 responses from 107 respondents, $\beta = 2.59$, $SE = .18$, $t = 14.34$; vacuum cleaners, 4685 observations from 202 respondents, $\beta = 1.09$, $SE = .09$, $t = 11.46$; refrigerators, 6574 responses from 203 respondents, $\beta = 1.99$, $SE = .08$, $t = 24.02$; walking shoes, 1033 observations from 48 respondents, $\beta = 2.11$, $SE = .22$, $t = 9.46$; headphones, 1634 observations from 47 respondents, $\beta = 2.78$, $SE = .25$, $t = 11.28$).

Figures 4A-E. Perceived quality for recognized brands and unrecognized brands involved in paired comparisons

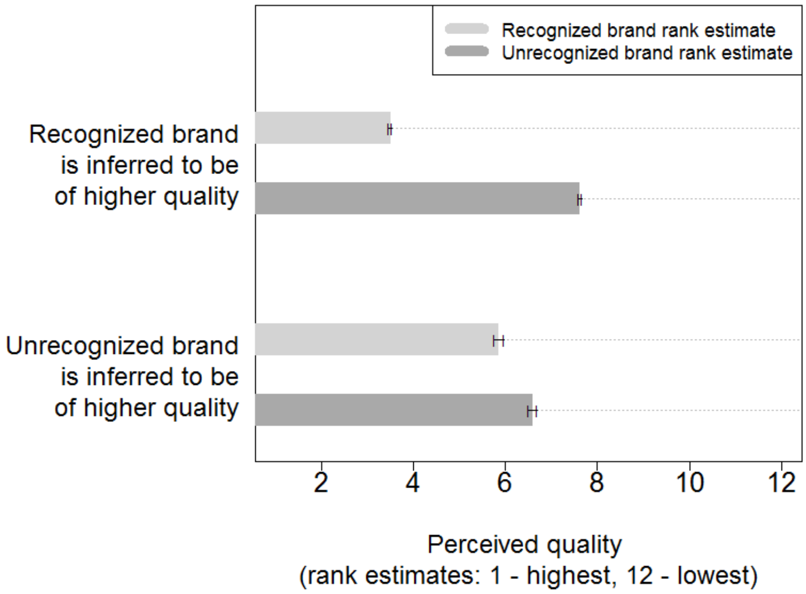
A. Business schools



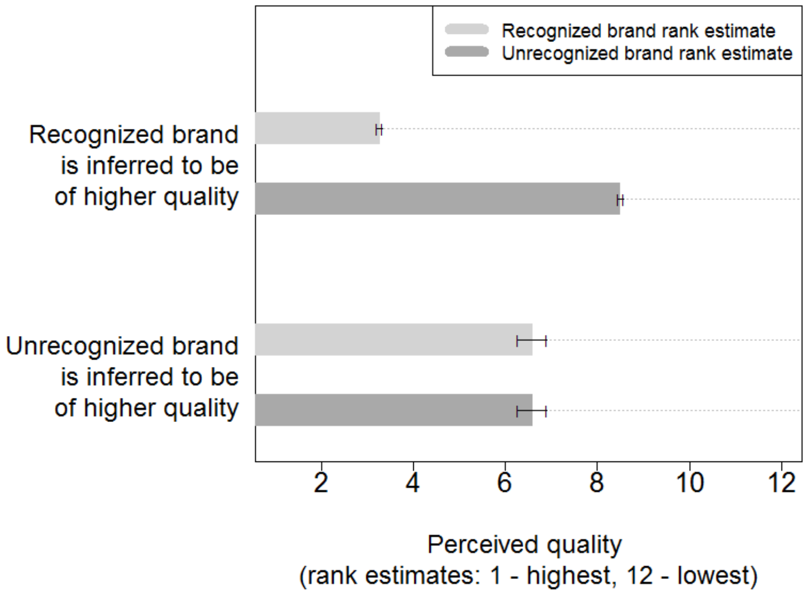
B. Vacuum cleaners



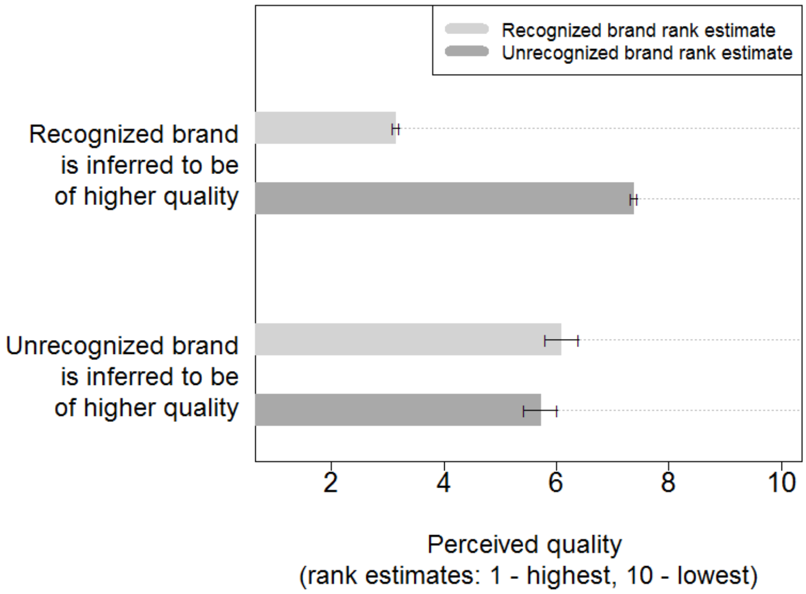
C. Refrigerators



D. Headphones



E. Walking shoes



Interestingly, the unrecognized brands in violating pairs differed from those in confirming pairs as well: they were believed to be of better quality in violating pairs than in confirming pairs (business schools, 4623 responses from 107 respondents, β = .76, SE = .18, t = 4.32; vacuum cleaners, 4685 responses from 202 respondents, β = .46, SE = .08, t = 5.41; refrigerators, 6574 responses from 203 respondents, β = .77, SE = .08, t = 9.34; walking shoes, 1033 responses from 48 respondents, β = 1.45, SE = .18, t = 8.05; headphones, 1634 responses from 47 respondents, β = .59, SE = .22, t = 2.69).

Were the unrecognized brands in violating pairs ranked higher than recognized brands when respondents were asked to estimate the brand quality of individual brands in a separate task (that is, in Question Set 2)?

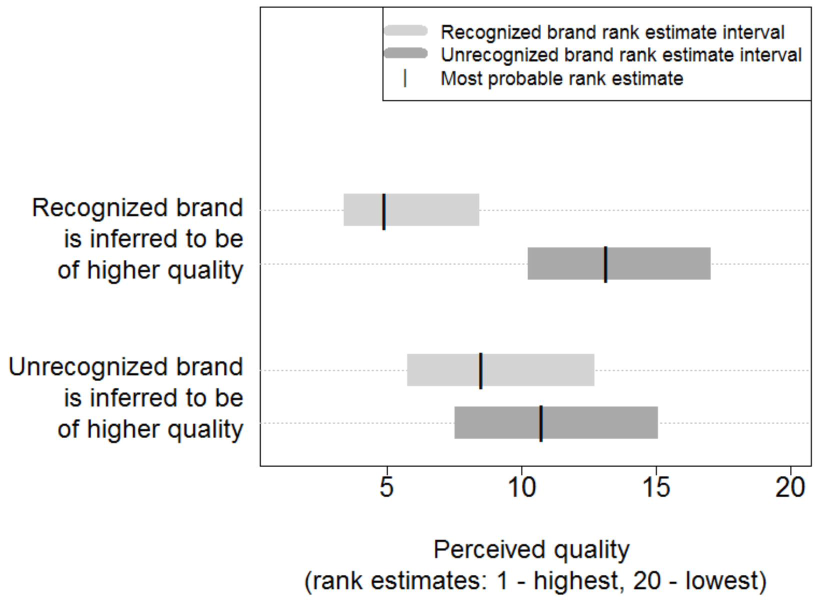
Participants' rank estimates of individual brands, elicited in a separate individual brand quality estimation task, show that, on average, unrecognized brands involved in violating pairs were still not ranked higher than recognized brands. In fact, the output of a mixed-effect linear model testing the relationship between the estimated ranks and recognition (with recognition as a fixed effect dummy variable and respondent as a random effect variable, as described on page 47) confirms that in the business school, vacuum cleaner, and refrigerator domains, the recognized brands in such cases were ranked significantly higher than unrecognized ones: business schools, 958 responses from 95 respondents, $\beta = 2.23$, $SE = .25$, $t = 8.99$; vacuum cleaners, 770 responses from 102 respondents, $\beta = 1.34$, $SE = .15$, $t = 9.19$; refrigerators, 1504 responses from 140 respondents, $\beta = .74$, $SE = .12$, $t = 6.42$ (the estimates for recognized and unrecognized brands in similar pairs of headphones and walking shoes were not different: walking shoes, 156 responses from 23 respondents, $\beta = .37$, $SE = .30$, $t = 1.23$; headphones, 152 responses from 17 respondents, $\beta = .00$, $SE = .40$, $t = .00$). Obviously, point estimates of perceived quality are not successful in explaining why people sometimes infer that an unrecognized brand is of higher quality. Could belief distributions explain that?

Figures 5A-E confirm the assumptions stated in this chapter that the quality belief distributions of recognized and unrecognized brands do not overlap (or overlap only slightly) in confirming pairs, but they overlap almost completely in violating ones. This suggests that the hypothesis 1, which states that the probability of a recognized brand being of higher quality than an unrecognized brand should be higher in confirming pairs than in violating pairs, should be supported as well.

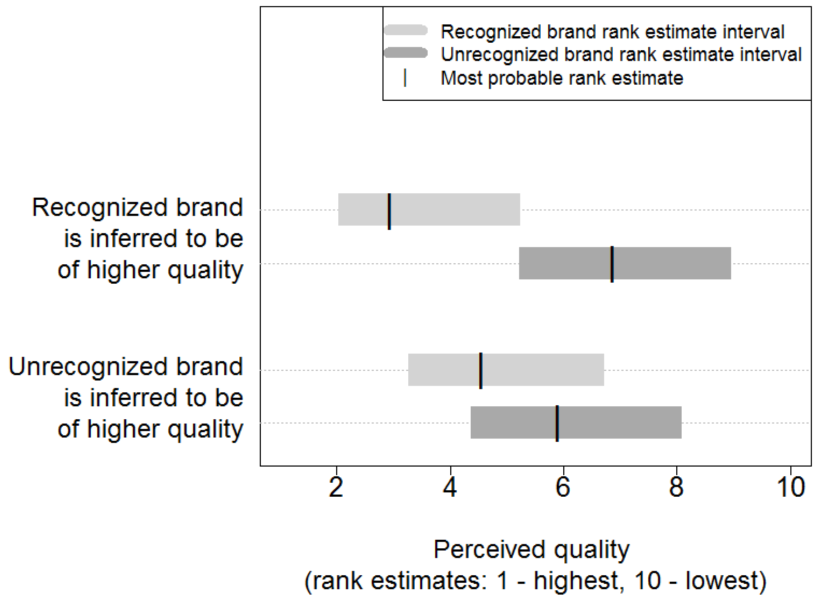
To quantify the degree of overlaps and test that hypothesis, the probability of the recognized brand being of higher quality than the unrecognized one was calculated based on the belief distributions stated by the respondents (appendix H provides a detailed explanation of how that probability was calculated).

Figures 5A-E. Stated quality belief distributions for recognized brands and unrecognized brands involved in paired comparisons

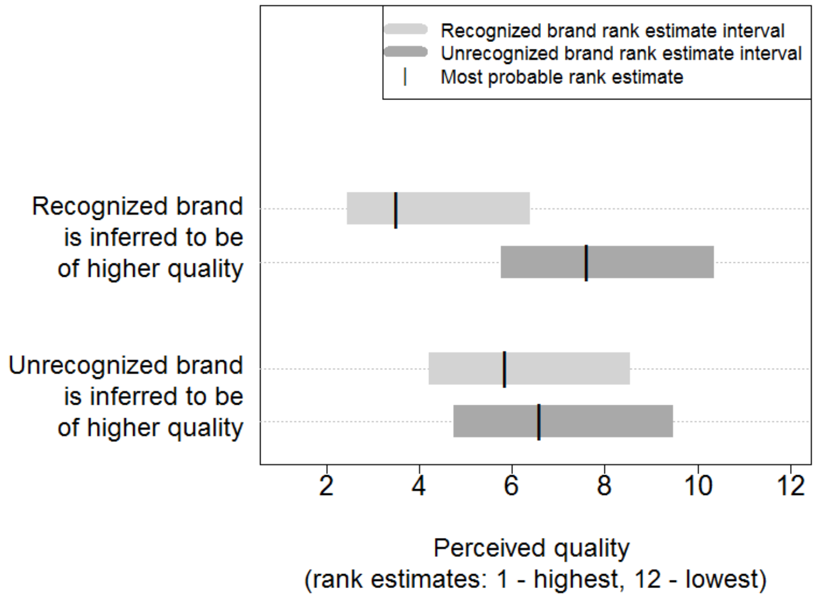
A. Business schools



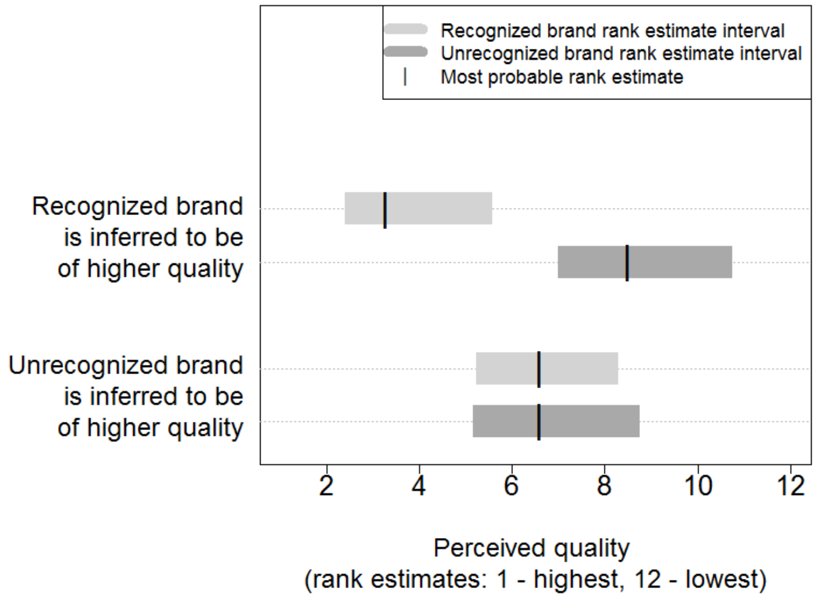
B. Vacuum cleaners



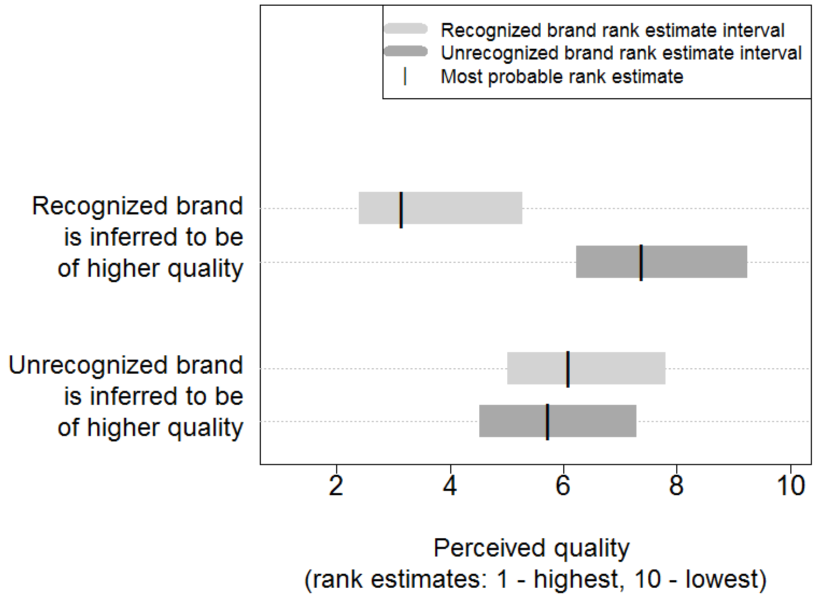
C. Refrigerators



D. Headphones



E. Walking shoes



The results in table 13 demonstrate that hypothesis 1 was supported: the probability of the recognized brand being of higher quality, derived from the degree of distribution overlaps, was significantly lower in violating pairs than in confirming pairs in all five domains.

Table 13. Probability of a recognized brand being of higher quality derived from the degree of distribution overlaps

		Confirming pairs			Violating pairs		
Domain	N of respondents	N of pairs	Mean	SE	N of pairs	Mean	SE
Business schools	107	4144	.90	.00	479	.62	.02
Vacuum cleaners	202	4300	.90	.00	385	.65	.02
Refrigerators	203	5822	.87	.00	752	.57	.01
Walking shoes	48	955	.92	.01	78	.43	.04
Headphones	47	1558	.93	.00	76	.50	.05

The output of a mixed-effect linear model testing the relationship between the afore mentioned probability and pair type (with pair type as a fixed effect dummy variable and respondent as a random effect variable) confirms these findings[8] (business schools: β = .16, SE = .01, t = 14.79; vacuum cleaners: β = .14, SE = .01, t = 13.96; refrigerators: β = .23, SE = .01, t = 25.44; walking shoes: β = .39, SE = .02, t = 16.07; headphones: β = .32, SE = .02, t = 14.66). These findings resonate with the results of the analysis of confidence levels (see table 2 in chapter 4): self-reported confidence in violating pairs was significantly lower than in confirming pairs.

6.4. Discussion

The purpose of this chapter was to test the "belief distribution" model's ability to explain some puzzling phenomena in decision making. In particular, by analysing the belief distributions of recognized brands involved in confirming and violating pairs, it shed light on why people sometimes infer that recognized brands are of lower quality that unrecognized ones, why people deviate from the recognition heuristic more often when they compare unrecognized objects with merely recognized objects or objects associated with conflicting information, and why people state different levels of confidence for different pairs of recognized and unrecognized brands.

Analyses reported in this chapter show that recognized brands involved in violating pairs are perceived to be of lower quality than recognized brands in

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[8] The following describes the model used to test this relationship for the fixed effect variable, type of inference, and the random effect variable, respondent.

$$BDO_{ij} = \beta_0 + \beta_1 * ITPC_{ij} + b_{ij} * z_i + \varepsilon_{ij},$$

where BDO represents probability of one brand being of higher quality derived from the degree of the belief distribution overlap for respondent i and paired comparison j, β_0 is the intercept, β_1 is the slope estimated for all respondents and comparisons, b is the vector of coefficients specific for respondent i, ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, ITPC is the dummy variable for the type of inference made by respondent i for paired comparison j, and z is the random effect for observations for respondent i.

confirming pairs. Typically characterized with low perceived frequency or mixed quality information, recognized brands in violating pairs have wider belief distributions than recognized brands in confirming pairs. Combination of lower perceived quality and higher uncertainty about quality for the recognized brands in violating pairs leads to "overlaps" of their belief distributions with those of unrecognized brands. These overlaps in quality belief distributions lower the chances of recognized brands being perceived as of higher quality, and unrecognized brands can be inferred as superior in quality due to mere chance.

Interestingly, the findings reported in this chapter suggest that such overlaps in belief distributions may also happen due to "shifts" in belief distributions for unrecognized brands: unrecognized brands involved in violating pairs were perceived to be of higher quality than unrecognized brands in confirming pairs. What could be the reasons for some unrecognized brands to be perceived differently from typical unrecognized brands?

The findings on the phonetic effect of brand names imply that unrecognized brands can be treated differently depending on their phonetic structure (Leclerc, Schmitt, and Dubé 1994; Meyers-Levy, Louie, and Curren 1994; Klink 2000, 2001; Yorkston and Menon 2004; Lowrey and Shrum 2007; Wänke, Herrmann, and Schaffner 2007), but is this effect large enough to increase the perceived quality of an unknown brand to that of a known one? How much do the peculiarities of a name matter, and how much does a lack of recognition matter?

Due to the scope of this thesis, these questions have not been explored. Instead, the current work focused on another possible reason for atypical perceptions for recognized and unrecognized brands: humans' restricted ability to identify whether or not they have seen or heard of an object.

Mistaken recognition. Could the unrecognized brands that were inferred to be of higher quality than the recognized brands, be deemed unrecognized due to an error? On the other hand, could the recognized brands be deemed recognized by mistake? If people sometimes make mistakes in calling something recognized or unrecognized, can inaccuracy in stated recognition explain why people sometimes infer that recognized brands are of higher quality than unrecognized brands?

One reason for such inaccuracy is the way recognition is measured in the studies. When asked “Have you seen or heard of the brand before?” respondents only had two options to choose from: positive and negative answer. If the respondents are not sure whether or not they have encountered the brands (see Erdfelder et.al. 2011), a pair of brands may include a brand that is labelled as recognized or unrecognized erroneously. In that case, a pair of two recognized brands or a pair of two unrecognized brands could be mistakenly classified as a pair containing a recognized and an unrecognized brand. In most extreme and rare situations, both brands could be “mislabelled”, in which case an opposite prediction of the inference would be made based on the brand recognition.

If the inability to correctly indicate recognition is one of the reasons some inferences are not in line with the recognition heuristic, correction for that inconsistency may increase the success of the heuristic as a predictor of inferences. To test that idea, the probability of a brand being recognized before the study was predicted for all brands involved in paired comparisons. Appendix E provides a detailed description of how these probabilities were derived and presents a summary statistics for these analyses.

The results showed that even though the overall number of cases of mistaken recognition was not high (8.41%), some violations of the recognition heuristic may be due to mistakes in indicating recognition: 51% of the violating pairs involved "mislabelled" brands (vs. 16% in confirming pairs, Fisher's exact test $p < .01$). When adherence rates for these pairs were recalculated based on the predicted probability of being recognized (that is, based on predicted recognition as opposed to the stated recognition), the number of violating pairs decreased by 24%, further evidence that mistakes in participant labelling may create the illusion of the recognition heuristic violations.

Thus, deviations from the recognition heuristic can happen in the following cases:

1. Some recognized brands are perceived to be of lower quality than typical unrecognized brands, that is, belief distributions overlap due to the fact that the distribution for the recognized brand is located lower on the quality continuum.
2. Some unrecognized brands are perceived to be of higher quality than typical unrecognized brands, that is, belief distributions overlap due to the fact that the distribution for the unrecognized brand is located higher on the quality continuum.
3. Both 1 and 2 may happen.

In all three scenarios, belief distributions suggest that the compared brands are perceived to be fairly similar and are characterized with high uncertainty about quality levels. Overlapping distributions yield low levels of confidence in paired comparisons, which is confirmed by the findings in this thesis. Thus, belief distributions are capable of explaining why people sometime deviate from the recognition heuristic. However, the results presented so far are not sufficient for validating the idea that belief distributions can explain how people make inferences based on information in memory.

While they show the link between memory information and belief distributions, on one side, and the link between the belief distributions and inferences in paired comparisons, on the other, these findings are based on belief distributions reported by respondents and do not show how memory information is related to quality inferences via belief distributions. To test the link between memory information and inferences via belief distributions in paired comparisons, one must combine data on memory cues, belief distributions and quality inferences in paired comparisons in one model, which is the main goal of the next chapter. In particular, the ability of belief distributions to describe how people make quality inferences will be tested on belief distributions predicted based on memory information. If belief distributions are compelling mental representations of how memory information is related to quality perceptions, can belief distributions modelled as a function of memory cues predict inference and confidence in inferences?

7. CAN BELIEF DISTRIBUTIONS PREDICT INFERENCE AND CONFIDENCE IN INFERENCES?

7.1. Introduction

The purpose of this chapter is to test the ability of belief distributions to predict brand quality inferences for paired comparisons along with inference confidence and its covariate, response time. Findings reported in Chapter 5 demonstrated that belief distributions are capable of reflecting how information in memory is related to quality perceptions. Results in Chapter 7, on the other hand, suggested that belief distributions can explain how people make brand quality inferences and demonstrated how belief distributions can explain changes in inference confidence. Given these findings, one can hypothesize that, modelled as a function of memory cues, belief distributions should predict inference, confidence and response time for paired comparisons.

To compare the accuracy of predictions made by the belief distributions, as a benchmark, this thesis uses predictions of multiple regression models based on memory cues as inputs directly. Encompassing all available information, the latter should yield the most accurate predictions. However, due to restricted computational abilities of the human mind, such models, analogous to the weighted additive rule, appear to be less plausible psychological decision making mechanisms (Bettman et. al. 1991).

7.2. Methods

To test the "belief distribution" model as a predictor of inference decisions and confidence, quality belief distributions were modelled as a function of one or more memory cues, such as recognition, perceived environmental frequency, knowledge volume and valence, and response latency. These predicted distributions were used for modelling inference, confidence and response time for paired comparisons. The outputs of this “belief distribution” model were compared with those of a benchmark model predicting inference, confidence and response time based on memory cues directly. Appendix F describes the models used for testing the “belief distribution” model and the rationale for using them.

The data used for modelling were collected in randomly ordered tasks performed by each participant during the lab studies described in general Methods section (chapter 3). In one of the tasks, participants were asked about the information in memory for each brand: whether or not they had seen or heard of the brand (recognition), how frequently they had seen or heard about it (perceived environmental frequency), how much they knew about its quality (perceived knowledge volume), and what proportion of that knowledge suggested that the quality was good or bad (perceived knowledge valence). In the second task, quality belief distributions were elicited for each brand: participants guessed the most probable, highest possible and lowest possible ranks a brand could have according to a published quality ranking, such as Consumer Reports or U.S. News and World Report. Finally, they made inferences about quality for pairs of brands in a two-alternative forced choice task.

7.3. Results

Recall that the main goal of this chapter is to test the hypothesis that the “belief distribution” model can predict inferences, confidence and response time for paired comparisons. Before testing that idea, this chapter probes the assumption that belief distributions modelled as a function of memory cues (henceforth, *predicted* distributions) can reflect the relationship between the degree of distribution overlap and confidence. Can the results for overlaps of distributions stated by respondents (henceforth, *stated* distributions), demonstrated in figures 5A-E, be imitated by predicted distributions? If we calculate the probability of the recognized brand being of higher quality based on predicted belief distributions (appendix H describes how these probabilities were calculated), will these probabilities be higher in confirming pairs than in violating pairs?

The output of a mixed-effect linear model testing the relationship between these probabilities and the type of inference for the paired comparison (with pair type as a fixed effect dummy variable and respondent as a random effect variable) confirms that the probability of a recognized brand being inferred of higher quality is lower in violating pairs than in confirming pairs[9]: business schools, $\beta = .06$, $SE = .01$, $t = 8.65$; vacuum cleaners, $\beta = .04$, $SE = .01$, $t = 8.46$; refrigerators, $\beta = .11$, $SE = .01$, $t = 17.75$; walking shoes, $\beta = .04$, $SE = .01$, $t = 3.22$; headphones, $\beta = .14$, $SE = .01$, $t = 10.1$. The average predicted probabilities in the confirming (R+) and violating pairs (R-) in the five domains are as follows: business schools, $M_{R+} = .95$, $SE_{R+} = .00$, $M_{R-} = .87$, $SE_{R-} = .01$; vacuum cleaners, $M_{R+} = .96$, $SE_{R+} = .00$, $M_{R-} = .90$, $SE_{R-} = .01$; refrigerators, $M_{R+} = .92$, $SE_{R+} = .00$, $M_{R-} = .79$, $SE_{R-} = .01$; walking shoes, $M_{R+} = .94$, $SE_{R+} = .00$, $M_{R-} = .88$,

[9] The following describes the model used to test this relationship for the fixed effect variable, the type of inference, and the random effect variable, respondent.

$$PBDO_{ij} = \beta_0 + \beta_1 * ITPC_{ij} + b_{ij} * z_i + \varepsilon_{ij},$$

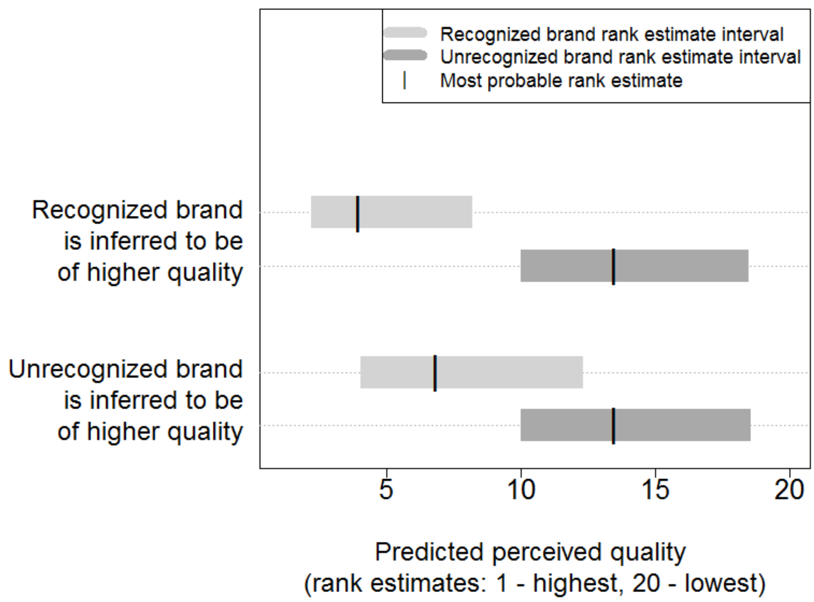
where PBDO represents probability of one brand being of higher quality derived from the degree of the predicted belief distribution overlap for respondent i and paired comparison j, β_0 is the intercept, β_1 is the slope estimated for all respondents and comparisons, b is the vector of coefficients specific for respondent i, ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, ITPC is the dummy variable for the type of inference made by respondent i for paired comparison j, and z is the random effect for observations for respondent i.

$SE_{R-} = .02$; headphones, $M_{R+} = .96$, $SE_{R+} = .00$, $M_{R-} = .81$, $SE_{R-} = .03$. That is, hypothesis 1 in chapter 6 predicting that the probability of a recognized brand being of higher quality than an unrecognized brand is higher in confirming pairs than in violating pairs is supported even when those probabilities are based on predicted distributions.

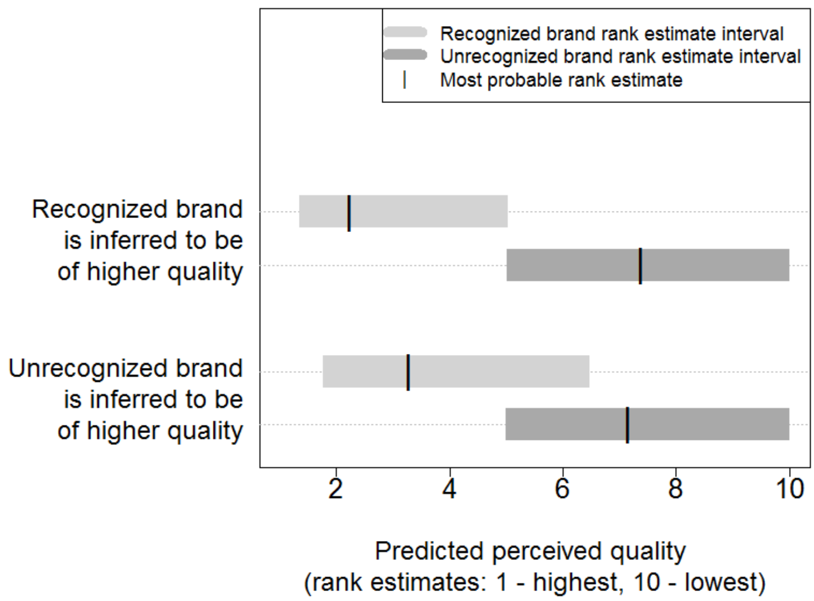
Figures 6A-E represent the visual demonstration of these results: the predicted quality belief distributions of recognized and unrecognized brands do not overlap, or overlap only slightly, when the recognized brand is inferred to be of higher quality. However, in cases when an unrecognized brand is believed to be superior, the degree of distributions overlap is much higher.

Figures 6A-E. Predicted quality belief distributions for recognized brands and unrecognized brands involved in paired comparisons

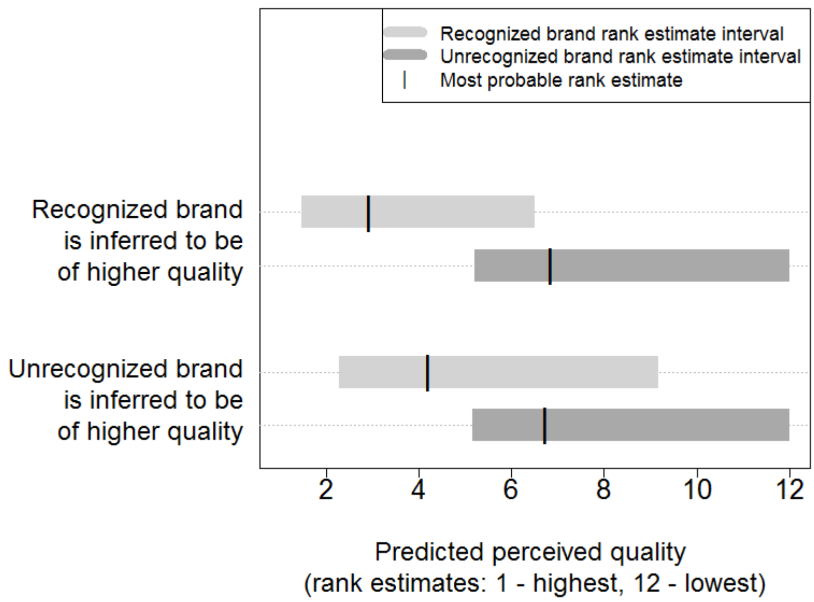
A. Business schools



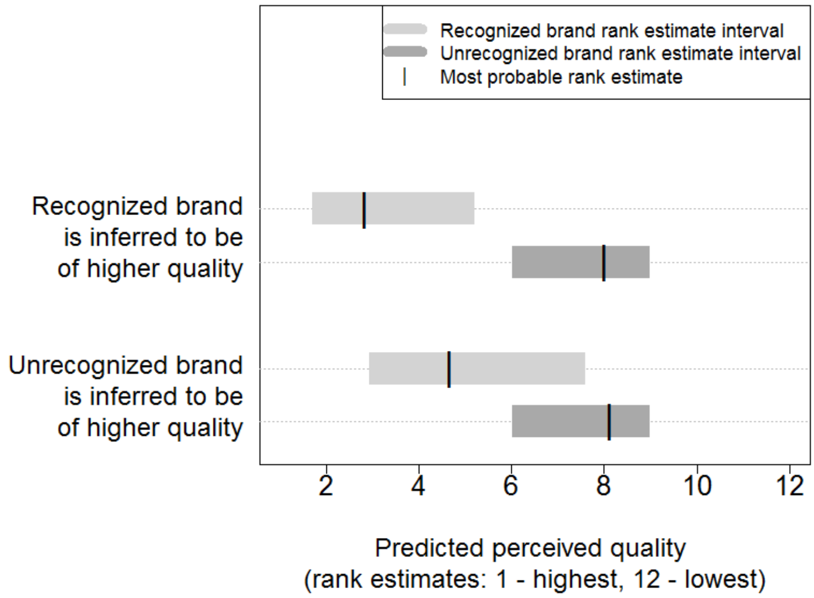
B. Vacuum cleaners



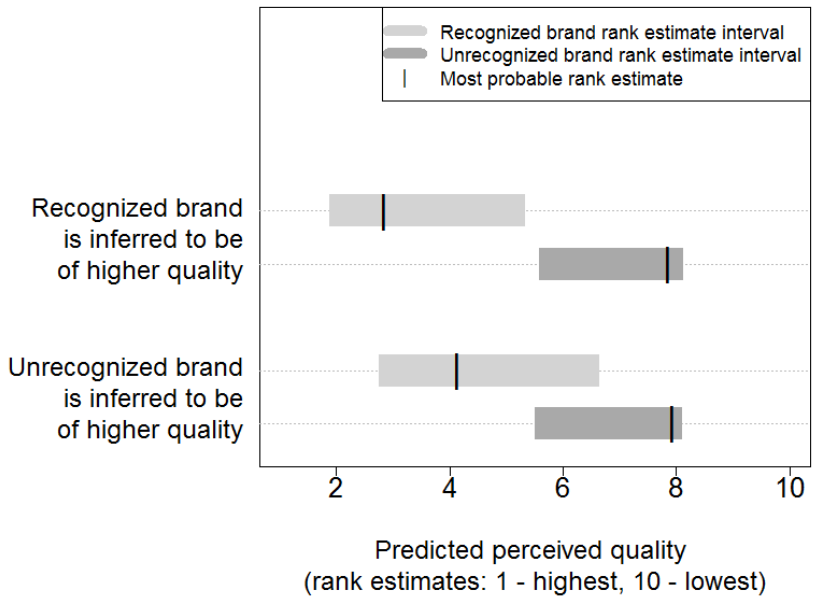
C. Refrigerators



D. Headphones



E. Walking shoes



These findings resonate with the results reported in table 2 of chapter 4 demonstrating that people report higher levels of confidence in confirming pairs than in violating pairs. This provides further support for the idea that belief distributions can reflect relationships between memory information and quality inferences. This idea was tested by modelling inference, confidence and response time for paired comparisons as a function of predicted belief distributions and comparing the predictive accuracy of this model to that of a benchmark model.

Predictive accuracy for inferences in paired comparisons. To calculate the accuracy of models used for predicting *decisions* in paired comparisons, the proportion of correct predictions, hit rates, were calculated. The output of models predicting decisions were compared based on average individual hit rates for all pairs included in the analysis. For *confidence* and *response latency* predictions, the models were compared in terms of their ability to make accurate prediction for confidence and response time for all paired comparisons included in the analysis, as well as particular groups of pairs: pairs including a recognized and an unrecognized brand, pairs of only recognized brands, and pairs of only unrecognized brands. The models' accuracy for predicting confidence and response time for all pairs was compared based on the individual level predictions. For comparing the models' predictive accuracy for the specific groups of pairs, aggregate statistics were used instead of individual ones, because the number of the pairs in the afore-mentioned three groups varied across individuals (that is, the same pair of brands could be classified as a pair of only recognized brands or a pair of only unrecognized brands depending on the respondents awareness of each of the paired brands). As a measure of models' accuracy in predicting confidence and response time for paired comparisons, the squared difference between the stated and predicted values was calculated. The main reason for this approach was the fact that, in order to model confidence (or response time) as a function of memory cues directly, different models were used for different types of pairs. As a result, fit statistics for these models could not be compared to those of the models based on belief distributions, which used one model for all pairs.

The results of predictive accuracy analyses show that, when inferences were predicted based on belief distributions modelled as a function of memory cues, mean individual hit rates calculated based on the modelled belief distributions were as high as the hit rates calculated based on the benchmark model, that is, the model based on differences in memory cues directly (tables 1-2 in appendix I)[10]. Furthermore, in terms of the accuracy of confidence and response time predictions, “belief distribution” model was at least as accurate as the benchmark model (tables 1-12 in appendix J and tables 1-4 in appendix K). When confidence was modelled after converting the stated confidence into 9-level category variable, the benchmark model was even less accurate than the “belief distribution” model, however, in the domains of headphones and walking shoes, that difference was not significant.

One particular group of paired comparisons can benefit from “belief distribution” models more than from the benchmark model. These paired comparisons include competing brands. Consider the following example. Brand A and brand B are two fairly popular brands with little difference in the frequency of encountering, on average. Brand C and brand D are two fairly unknown brands with the same little difference in the frequency of encountering. Because brands A and B are characterized

[10] Hit rates calculated based on these distributions are higher than the hit rates calculated based on the point (most probable) estimates, however the difference is not significant (see table 1 in the appendix I). This can be explained by the fact that, when making predictions for inference decisions, both types of models make predictions based on whether the probability of one brand to be of higher quality is higher than the probability of the other brand without considering how much these probabilities differ. For example, if according to two models, the probability of Dyson vacuum cleaners being of higher quality than Black&Decker vacuum cleaners is .6 and .8, both models predict that the quality of Dyson vacuum cleaners is higher. Next, since the probability of one brand being of higher quality than the other one is determined by the same factors in both models, the outputs of two models do not contradict each other (except for the rare cases, when the probabilities are very close to 0.5, in which case contradiction may happen due to chance).

with low variance in quality perceptions, inference confidence of the respondents comparing these brands should be higher. On the other hand, variance in quality perceptions for brands C and D would be high, which suggest a greater overlap of distributions, hence, lower confidence in inferences. One might hypothesize that the models predicting inference confidence based on memory cues directly will fail to predict different confidence levels for the two pairs, but the "belief distribution" models will not. To test this hypothesis, confidence levels for such pairs of brands were predicted based on the belief distributions or based on memory cues directly[11]. To ensure some (but not much) difference between brands A and B and between brands C and D, only the pairs with the difference in perceived environmental frequency of 4-6 were chosen for testing this hypothesis. Brands with frequency of encountering of 45 and above were chosen as brands A and B, and those below 25 were chosen as brands C and D. Average stated confidence levels for the brands A and B were 82%, and those for the brands C and D were 57%. Was the "belief distribution" model more accurate in predicting different confidence levels than the benchmark model predicting inferences as a function of memory cues directly?

To answer this question, confidence levels predicted based on the "belief distribution" model and benchmark model were analysed. Analysis of predicted confidence show that the models predicting confidence as a function of memory cues

[11] Due to the way the variables were measured in different domains, this idea could be tested on the inferences for business schools only. Perceived environmental frequency was collected using a single scale for both recognized and unrecognized brands in the business school domain, but not in the other domains. When respondents were asked about their perceived environmental frequency in the domains of consumer goods, they had an option of indicating that they had never seen or heard of the brand, in which case their response was coded as 0. If they did not choose that option, the participants could use a scale ranging from 1, corresponding to "I have seen or heard of it very rarely", to 50, corresponding to "I have seen or heard of it very often". As a result, in the domains of consumer goods, the difference between the perceived environmental frequency coded as 0 and 1 is not the same as the difference between the perceived environmental frequency coded as 1 and 2. Thus, unrecognized brands in the consumer good domains, which could only have "0" as a value for perceived environmental frequency, could not be included in the analyses of differences between the pairs of unknown brands and pairs of known ones, making these domains unsuitable for testing these differences.

directly yield the same prediction for the pairs of fairly known (brands A and B) and relatively unknown brands (brands C and D): $M_{AB} = .57$, $SE_{AB} = .00$, $M_{CD} = .57$, $SE_{CD} = .00$. In contract, forecasts based on belief distributions modelled as a function of memory cues predicted higher levels of confidence for the pairs of familiar brands than for the pairs of relatively unfamiliar ones: $M_{AB} = .74$, $SE_{AB} = .01$, $M_{CD} = .63$; $SE_{CD} = .01$, $t(38.94) = 7.12$, $p < .001$. This suggests that belief distributions can make predictions for pairs of fairly similar brands, which the benchmark model fails to make.

7.4. Discussion

The findings demonstrated in this chapter suggest that belief distributions modelled as a function of memory cues can explain why people sometimes consider the quality of unrecognized brands superior to that of recognized ones. They show that, while being a more psychologically plausible model, the "belief distribution" model is able to make at least as accurate predictions as the benchmark multiple regression models, which use all available memory information directly.

Thus, modelled as a function of memory cues, such as perceived environmental frequency and knowledge valence, belief distributions provide insight to how people make inferences about recognized and unrecognized brands. These models can be used for predicting consumers' inferences and their confidence in those inferences, and they are especially accurate for pairs of brands that are similar in terms of perceived environmental frequency.

In addition to the theoretical contributions, this portion of the current thesis provides methodological input by suggesting a model that allows for incorporating all the available data for the brands and for modelling inferences for different types of pairs using a single model. In contrast, the models predicting inferences in paired comparisons based on memory cues directly can only use data that are available for both objects in the pair and have to disregard rich data, such as knowledge volume and valence, for recognized objects, if they are compared with unrecognized or merely recognized ones.

8. CONCLUSION

The main query of this thesis, "*What psychological model can explain how consumers make inferences about brand quality using memory information?*" is addressed by positing a model based on quality belief distributions and by testing that model's ability to reflect the relationship between memory information and quality perceptions and its ability to predict inferences for paired comparisons along with inference confidence and decision time. More specifically, this dissertation answers the following research questions.

Do subjective belief distributions reflect the relationship between memory information and brand quality perceptions, documented in the marketing literature? The findings revealed in this thesis demonstrate that the belief distributions are reflective of that relationship: in line with the past research (Becknell, Wilson, and Baird 1963; Allison and Uhl 1964; Stang 1974; Pras and Summers 1978; Roberts and Urban 1988; Hoyer and Brown 1990; Laroche, Kim, and Zhou 1996; Rust et al. 1997; Erdem and Swait1998; Erdem and Swait2004; Goldstein and Gigerenzer 2002), the perception of quality, measured by people's estimates for the most probable rank a brand could have, was higher for the recognized brands than for the unrecognized brands. And the uncertainty about the quality, measured as a difference between the highest possible and lowest possible ranks, was lower for the recognized brands than for the unrecognized brands. Furthermore, the frequency of encountering the brand was positively correlated with the estimates of the most probable ranks and negatively correlated with the range of possible ranks. Belief distributions also reflected the positive relationship between the proportion of brand quality knowledge in memory and brand quality estimates.

Do people infer that recognized brands associated with mediocre reputation are of higher quality than unrecognized brands? By exploring the role of information valence as additional information in predicting inferences about brand quality, this thesis finds that recognition, as an inferential cue for brand quality, is so powerful that even the brands attributed with mostly negative quality information are perceived to be of higher quality than unknown brands. Analyses of the environmental relationship between quality and information available for brands revealed positive correlation between these two constructs, which suggests that people may realize that the frequency of encountering a brand can be as useful in predicting brand quality as deeper knowledge, such as information valence. Such an assumption is consistent with another finding from this thesis showing that inference predictions based on simpler cues, such as brand recognition and the frequency of encountering a brand, are as accurate as those based on more complex information, which, in addition to the simpler cues, includes brand knowledge valence and volume.

Can belief distributions explain why people sometimes infer that an unrecognized brand is of higher quality than a recognized brand? Analysis of the distributions reveal that, when comparing recognized brands with unrecognized ones, people deviate from their tendency to assign higher quality to recognized brands when their perceptions of quality for the recognized brands are fairly similar to those of unrecognized ones, which can be observed as an "overlap" of belief distributions. When these "overlaps" were quantified by calculating the probability of the recognized brand being of higher quality, such probability was lower in violating pairs (that is, when the respondents did not follow the recognition heuristic) than in confirming pairs (when the respondents made inferences in line with the recognition heuristic).

Interestingly, even in the violating pairs, people's brand quality perceptions for the recognized brands, measured in a separate task, proved to be higher than those for the compared unrecognized brands. In those cases, unrecognized brands were perceived to be of higher quality than unrecognized brands in confirming pairs, and recognized brands were perceived to be of lower quality than recognized brands in confirming pairs. As the closer examination of the brands involved in those pairs discovered, such shifts in perceptions could be driven by several reasons: low perceived environmental frequency of the recognized brands, low proportion of memory knowledge suggesting that the brands were of high quality, or people's inability to accurately determine whether or not they had seen or heard of the brands before the study. All these scenarios were characterized not only by fairly similar quality perceptions, but also by high uncertainty about quality of the compared brands, which led to an "overlap" of belief distributions and, hence, to low confidence in the inferences for the paired comparisons. These discoveries are consistent with the prior findings in psychology, demonstrating that people adhere to the recognition heuristic less often when they compare unrecognized brand with "merely" recognized ones (Marewski et al. 2010), and that they report different levels of confidence when making inferences for different pairs including a recognized and an unrecognized brand (Goldstein 1994).

Can belief distributions predict inference and confidence in inferences better than existing models? As an ultimate test of the "belief distribution" models' ability to make these predictions, this thesis compared the predictive accuracy of belief distributions, modelled as a function of memory cues, to that of the multiple regression models predicting from the memory cues directly. The findings demonstrate that the "belief distribution" models can predict inferences and response time in paired comparisons as accurately as the multiple regression models. However, the ability of the “belief distribution” models to predict confidence levels is higher than that of the benchmark regression models, although in two out of five domains that difference was not significant. “Belief distribution” models are particularly accurate in those cases when the compared brands are perceived as fairly similar.

The answers to the afore-mentioned questions demonstrate that the “belief distribution” model proves to be a compelling representation of what people believe about brand quality based on memory information. The initial attempt to address the main query of this thesis can be extended further by demonstrating, in experimental settings, how belief distributions change as a result of increased environmental frequency and knowledge volume and valence. The speculations about the belief distributions’ ability to reflect changes in information memory can be validated further by exploring, via direct manipulations, whether the quality estimates increase as a result of the exposure to unknown brands and/or as a result of accumulating more positive information about quality. How do the quality perceptions change as the proportion of negative knowledge increases? On the one hand, the quality perception should decrease because, according to the findings in this thesis, knowledge valence is directly correlated with quality perceptions. On the other hand, increased frequency of the exposure, stimulated by the negative information, should increase brand quality estimates. What will prevail in this situation: the frequency of exposure or knowledge valence? The findings in this thesis suggest that the effect of recognition is so strong that even the brands associated with negative knowledge valence are perceived to be of higher quality than unrecognized brands. However, it cannot affirm that unrecognized brands will benefit from negative information about them. Calling for further investigation, such speculation can be explored in future research along with other questions discussed later in this chapter.

Limitations. One of the unavoidable limitations of this work was the total duration of the study. To collect a sufficient number of observations for individual estimates and paired comparisons for the analyses, the studies involved answering a large number of questions, and while the respondents were tested on their comprehension of the tasks, some collected data may be inaccurate. In an attempt to determine the impact of such inaccuracy, all responses for the studies were checked for inconsistencies (for example, a respondent might state that he or she did not recognize brand X, but later he might indicate high frequency of encountering that brand), and the respondents with high rate of inconsistent answers were identified. However, the elimination of the inconsistent data did not change the results, and all collected responses were used for the reported analysis, unless stated otherwise.

Another potential inaccuracy could arise from the fact that, while answering the questions about a particular category of products, for example, business schools, the study participants could make inferences about "umbrella" brands, which, in case of schools, are universities. That is, when asked to make inferences about the business school at Harvard University, they might make inferences about Harvard University, in general. Even though the respondents were repeatedly reminded that the questions were about a particular category and were tested on their comprehension of what product category was involved in the task, they might subconsciously attribute their memory for a brand as a whole to that for a particular product labelled by that brand. This, however, should not affect the validity of any results, except those related to the environmental validity of memory cues.

Future directions. This work has established that, modelled as a function of memory cues, belief distributions can be used to predict brand quality inferences. Can we go a step further and model belief distributions (and inferences) as a function of antecedents of memory cues? Individual frequency of encountering should be highly correlated with the environmental frequency, for example, the number of times the brand is mentioned by news or social media. If so, inferences can be predicted by using measures available in the environment, which can be obtained without gauging individual memory information. That is, belief distributions, used for predicting inferences, can be modelled based on actual environmental frequency rather than perceived frequency reported by consumers. Alternatively, the predictions can be made based on the averages frequency of encountering the brand or the proportion of people recognizing the brand.

Obviously, obtaining these measures is more cost effective than collecting consumer memory information data. But a greater advantage of using objective actual environmental frequency data or the proportion of people recognizing the brand, as predictors of brand quality perceptions, is the possibility of predicting inferences for any brands in the domain and not only those included in the analysis. That is, once the model estimates are obtained based on the set of brands with different levels of environmental frequency, these estimates could be used for a new set of brands.

The other benefit of using the actual environmental frequency data or proportion of people recognizing the brand for modelling belief distributions could be predicting market share of brands in paired comparison. Using the degree of overlap of “average” belief distributions predicted based on the environmental frequency, or the proportion of people recognizing the brand, or mean perceived environmental frequency, one could calculate the probability of one brand being of higher quality than the other, which should correspond to market share for the compared brands.

Another direction this research could take is exploring what factors affect people's tendency to infer that recognized brands are of higher quality than unrecognized brands. Findings in psychology suggest that people adhere to the recognition heuristic more often under time pressure and cognitive load and that they may use it as a strategy for risk reduction (Pachur and Hertwig 2006; Halberstadt and Catty 2008; Hilbig, Erdfelder and Pohl 2012). However, adherence to the recognition heuristic may depend not only on situational, but also individual factors, such as neuroticism (Hilbig 2008; Hilbig and Pohl 2008). One possible extension of this work could be testing whether such catalysts of the recognition heuristic adherence affect inferences about brand quality. Part b of appendix L describes the pilot studies conducted as an initial attempt at exploring the applicability of these findings to the inferences about brand quality.

Managerial implications. The outcomes in this thesis have several implications for brand managers and for those dealing with new brands, in particular: when companies have limited resources for brand promotion, they may consider investing in a higher number of exposures to the potential consumer rather than in developing deep knowledge about the brand via informative advertising. The fact that knowledge valence information does not improve the predictive accuracy of models based on memory information has further implications for marketing research professionals: companies can make predictions about relative quality of brands using solely the data on perceived environmental frequency. Since collection of perceived knowledge valence and volume data requires additional investment (both in terms of the time required to complete questionnaires, on consumers' side, and efforts required for analysis of the additional data, on the researchers' side), which ultimately increases the cost of market research, collection of knowledge data can be omitted without any loss of predictive accuracy. The findings regarding the knowledge valence also suggest that unknown brands can possibly benefit from negative publicity as long as it raises awareness about them, even if consumers remember this quality information. Of course, it is better for a brand, if consumers have positive knowledge about it, but the fact that recognized brands with predominantly poor quality reputation are still inferred to be of higher quality than unrecognized ones is consistent with the lay theory that "better the devil you know than the devil you don't".

Finally, "belief distribution" models can be useful in predicting market share (via predicting inferences) of competing products. The results in this thesis suggest that "belief distribution" models should be more precise than traditional models for such predictions, as they take into consideration not only the "mean" quality, but also "variance" in quality, which should vary with confidence in the mean estimate. Having proposed a new model for predicting confidence in inferences, this thesis contributes to addressing one of the central questions in the current brand marketing, which was posed by Keller and Lehman in their paper highlighting research priorities in that field (2006, p. 746): "To what extent is increased confidence in decision making a key or even a critical factor of brands and brand equity; i.e., are standard deviations more important than means?" The current work suggests that standard deviations are more useful than means in predicting confidence in quality inferences and are particularly important for predicting inferences about brands of the same quality levels.

The findings in this thesis suggest implications not only for the situations when customers use solely the information in their memory, but also for the situations when other product information is available, because consumers tend to select only limited amounts of available information and place substantial importance on brand name information (Jacoby, Szybillo, and Busato-Schach 1977). They may use these strategies as coping mechanisms, when facing difficulty in processing product information available from various sources while choosing among a large number of alternatives in a product category (Bettman et. al. 1991). Therefore, the outcomes from the current work have repercussions at several stages of the consumer decision making process (including information search, evaluation of alternatives, and purchase) and may particularly benefit marketing managers involved in branding, marketing communications, and product design (packaging and labelling).

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APPENDICES

A. List of brands and quality scores in the business school domain

Rank	Business schools	Score (US News and World Report)
1	Harvard University	100
2	Stanford University	100
3	Dartmouth College (Tuck)	89
4	Columbia University	88
5	Yale University	80
6	Duke University (Fuqua)	79
7	Cornell University (Johnson)	79
8	Carnegie Mellon University (Tepper)	77
9	Georgetown University (McDonough)	69
10	Emory University (Goizueta)	68
11	Brigham Young University (Marriott)	64
12	Purdue University (Krannert)	63
13	University of Notre Dame (Mendoza)	61
14	Vanderbilt University (Owen)	58
15	Rice University (Jones)	57
16	Babson College (Olin)	55
17	Tulane University (Freeman)	51
18	Temple University (Fox)	49
19	Wake Forest University (Babcock)	48
20	College of William and Mary (Mason)	46

When the names of the schools were shown to the participants, they were presented in the following way: the full name of the university and the name of the business school in parenthesis, for example, Dartmouth College (Tuck). If the university name is the only name the business school has, only the university name was presented.

B. Average cue validities in the business school domain

The validities presented in the following table represent the average of individual validities for 107 participants in Study 1.

Cue	Mean cue validity	SE
Recognition	.86	.01
Perceived environmental frequency	.77	.01
Perceived knowledge valence	.68	.02

The individual recognition validity is calculated as a proportion of times a recognized brand has a higher quality according to a published ranking than an unrecognized brand. That is, $\alpha = R/(R + W)$, where α is the recognition validity, R is the number of correct inferences one could make using the recognition as a cue, computed across all pairs in which one object is recognized and the other is not, and W is the number of incorrect inferences under the same circumstances (Goldstein and Gigerenzer 2002). Similarly, the perceived environmental frequency validity is calculated as the proportion of times a brand with a higher perceived environmental frequency has a higher quality according to a published ranking than a brand with a lower frequency. Finally, the knowledge valence validity is calculated as the proportion of times a brand with a higher knowledge valence has a higher quality according to a published ranking than a brand with a lower valence.

C. List of brands and quality scores in the consumer good domains

Refrigerator brands	Mean overall scores	Mean attribute ratings
Bosch	74.33	4.42
Samsung	72.55	4.20
Thermador	70.50	4.00
Sub-Zero	64.50	3.54
Ikea	64.00	3.63
Electrolux	63.80	3.90
Amana	58.38	3.47
Hotpoint	53.50	3.00
Sanyo	47.00	3.50
Fisher & Paykel	43.50	2.75
Marvel	36.00	1.67
Magic Chef	33.00	3.00

Vacuum cleaner brands	Mean overall scores	Mean attribute ratings
Black & Decker	80.33	3.87
Riccar	67.00	4.08
Panasonic	66.67	3.93
Hoover	66.16	3.95
LG	66.00	4.00
Dyson	63.13	3.78
Aerus	60.00	3.85
Metropolitan	59.00	3.57
Kalorik	49.00	3.00
Koblenz	41.00	3.17

Walking shoe brands	Mean overall scores	Mean attribute ratings
Asics	81.50	4.60
ProSpirit	73.00	4.00
Ryka	72.00	4.20
Saucony	71.00	3.80
Avia	70.00	3.80
New Balance	66.50	3.80
Nike	62.00	3.60
Spira	61.00	3.20
Rockport	57.00	3.20
Reebok	56.00	3.00

Headphone brands	Mean overall scores	Mean attribute ratings
Klipsch	78.00	4.00
Phiaton	66.00	4.00
Panasonic	63.50	3.25
Sony	62.80	3.60
Bose	62.40	3.80
Able Planet	60.00	3.75
Yamaha	60.00	3.00
V-Moda	56.00	3.00
Philips	51.00	3.00
Apple	46.00	3.00
Etymotic	46.00	3.00
Auvio	31.00	2.00

A pilot study was conducted to refine the initial list of brands so that both known and unknown brands of different levels of quality were equally represented. As a measure of quality, both overall and attribute scores published by Consumer Report were used. If the brand had more than one product model scored, the overall scores for the models were averaged to compute the brand score within a particular domain. To calculate the attribute scores, first, all the attribute scores except price were added. Then, for the brands that had more than one model scored, these cumulative attribute scores were averaged to compute a brand score within a particular domain. The number of attributes varied across domains. There was a significant positive correlation between the overall and attribute scores (vacuum cleaners: $r(8) = .82$, $p < .01$; refrigerators: $r(10) = .86$, $p < .01$; headphones: $r(10) = .89$, $p < .01$; walking shoes: $r(8) = .96$, $p < .01$).

D. Average cue validities in the consumer good domains

Refrigerator domain (N = 203)

Cue	Mean cue validity[12]	SE
Recognition	.70	.01
Perceived environmental frequency	.66	.01
Perceived knowledge valence	.57	.02

Vacuum cleaner domain (N = 202)

Cue	Mean cue validity	SE
Recognition	.76	.01
Perceived environmental frequency	.68	.01
Perceived knowledge valence	.40	.02

Walking shoe domain (N = 48)

Cue	Mean cue validity	SE
Recognition	.27	.02
Perceived environmental frequency	.31	.02
Perceived knowledge valence	.48	.05

Headphones domain (N = 47)

Cue	Mean cue validity	SE
Recognition	.52	.01
Perceived environmental frequency	.51	.01
Perceived knowledge valence	.56	.02

[12] The validities presented in this table represent the average of individual validities for participants in Study 2. Appendix B describes how the cue validity is calculated.

E. Modelling the probability of being recognized before study

Using a binary logistic regression model, the probability of a brand being correctly labelled as recognized was modelled as a function of the frequency of encountering the brand and recognition response latency. To account for individual differences in the probability of the respondents to recognize the brands and for individual differences in the probability of the brands being recognized, object and subject IDs were included in the model as random effect variables. Thus, the probability for the brands being recognized before the study was modelled the following way.

$$P_{ij} = \beta_1 * RL_{ij} + \beta_2 * PEF_{ij} + Bb_i + Ss_j + \varepsilon_{ij},$$

where P represents the probability of brand i to have been seen or heard of by respondent j, β_1 and β_2 are the slopes estimated for all respondents and brands, ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, RL is the response latency frequency of brand i for respondent j for the recognition task, PEF is the perceived environmental frequency of brand i for respondent j, Bb is the adjustment/intercept specific for brand i, and Ss is the adjustment/intercept specific for respondent j.

The derived probabilities were compared with the responses of participants for the recognition task, and the brands were labelled based on the differences between the stated and predicted recognition:

- “hits” - both the participant’s response and derived probability indicate that the respondent has seen or heard of the brand before the study;

- “misses” - respondent stated that he has seen or heard of the brand before the study, but the predicted probability of a brand being seen or heard of before the study is low;
- “false alarms” - respondent stated that he has not seen or heard of the brand before the study, but the predicted probability suggests otherwise;
- “correct rejections” - both the participant’s response and predicted probability indicated that the participant has not seen or heard of the brand before the study.

The following table demonstrates summary statistics for the proportion of observations classified into these four groups[13].

Participant response	I recognize this brand		I do not recognize this brand	
Probability of being recognized before the study	Above 50%	Below 50%	Above 50%	Below 50%
Category based on stated vs. predicted recognition	Hits	Misses	False alarms	Correct rejections
Percentage of observations	36.07	4.67	3.74	55.51

[13] Due to the way the variables were measured in different domains, this idea could be tested in the domain of business schools only. Perceived environmental frequency was collected using a single scale for both recognized and unrecognized brands in the business school domain, but not in the other domains. When respondents were asked about their perceived environmental frequency in the domains of consumer goods, they had an option of indicating that they had never seen or heard of the brand, in which case their response was coded as 0. If they did not choose that option, the participants could use a scale ranging from 1, corresponding to "I have seen or heard of it very rarely", to 50, corresponding to "I have seen or heard of it very often". As a result, in the domains of consumer goods, the difference between the perceived environmental frequency coded as 0 and 1 is not the same as the difference between the perceived environmental frequency coded as 1 and 2. Consequently, modelling of the probability of being recognized for both recognized and unrecognized brands using a single model was not possible in those domains. The alternative for the consumer good domains would be to model the probability of being labelled as a recognized brand correctly using recognition response latency as a fixed effect and subject and objects IDs as random effects. However, using response latency as a single memory cue is not optimal because of the insufficient accuracy of the resulting model.

F. Models

To test the "belief distribution" model as a predictor of inference decisions and confidence, the quality inferences and confidence were modelled as a function of one or more memory cues, such as recognition, perceived environmental frequency, knowledge volume and valence, and response latency, or as a function of different statistics derived from belief distributions (manipulation conditions were included in the models as independent variables were applicable). Both fitted and cross-validated values were calculated for all models and used in further analysis, but only cross-validated values were reported in the result sections.

a. Modelling rank estimates

Each of three rank estimates (most probable, highest possible and lowest possible) was modelled separately using ordinal logistic regression. One or more of the following measures were used as independent variables: recognition, perceived environmental frequency, knowledge volume, knowledge valence and recognition response latency[14].

The following models were used to predict quality rank estimates for individual i and brand j, using an ordered logistic regression[15].

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[14] Recognition response latency was transformed before it was used for analysis or modelling. Inverse recognition response latency = 1 / Recognition response latency

[15] Due to the way the variables were measured in different domains, some models could be used for modelling both the recognized and unrecognized brands, but others required separate models for modelling unrecognized brands and the recognized brand with different levels of knowledge volume. For example, models using perceived environmental frequency do not allow for combined modelling of recognized and unrecognized brands in the domains of consumer goods, but can do so for combined modelling of recognized and unrecognized brands in the domain of business schools. Perceived

Quality rank estimates for recognized brands attributed with brand quality knowledge were modelled as a function of recognition response latency, perceived environmental frequency and knowledge volume and valence.

(1) $QRERK_{ij} = \beta_0 + \beta_1 * RL_{ij} + \beta_2 * PEF_{ij} + \beta_3 * KVOL_{ij} + \beta_4 * KVAL_{ij} + \varepsilon_{ij}$,

where QRERK represents quality rank estimates of respondent i for *recognized* brand j attributed with quality knowledge, β_0 is the intercept, β_1, β_2, β_3, β_4 are the slopes estimated for all respondents and brands, ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, RL is response latency, PEF is perceived environmental frequency, and KVOL and KVAL are knowledge volume and valence.

Quality rank estimates for merely recognized brands, that is, recognized brands attributed with no knowledge about brand quality, were modelled as a function of response latency and perceived environmental frequency.

(2) $$QREMR_{ij} = \beta_0 + \beta_1 * RL_{ij} + \beta_2 * PEF_{ij} + \varepsilon_{ij},$$

where QREMR represents quality rank estimates of respondent i for *recognized* brand j, β_0 is the intercept, β_1, β_2 are the slopes estimated for all respondents and

environmental frequency was collected using a single scale for both recognized and unrecognized brands in the business school domain, but not in the other domains. When respondents were asked about their perceived environmental frequency in the domains of consumer goods, they had an option of indicating that they had never seen or heard of the brand, in which case their response was coded as 0. If they did not choose that option, the participants could use a scale ranging from 1, corresponding to "I have seen or heard of it very rarely", to 50, corresponding to "I have seen or heard of it very often". As a result, in the domains of consumer goods, the difference between the perceived environmental frequency coded as 0 and 1 is not the same as the difference between the perceived environmental frequency coded as 1 and 2.

brands, ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, RL is response latency, and PEF is perceived environmental frequency.

Finally, quality rank estimates for unrecognized brands were modelled as a function of response latency.

(3) $$QREU_{ij} = \beta_0 + \beta_1 * RL_{ij} + \varepsilon_{ij},$$

where QREU represents quality rank estimates of respondent i for *unrecognized* brand j, β_0 is the intercept, β_1 is the slope estimated for all respondents and brands, ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, and RL is response latency.

The outputs of the models predicting rank estimates were used for modelling inference decisions and confidence. Since the estimates for the most probable, highest possible and lowest possible ranks were modelled separately, in some cases, the predictions yielded inconsistent results, which could fall into one or more of the following categories:

- The predicted most probable estimate is higher than the predicted highest possible estimate;
- The predicted most probable estimate is lower than the predicted least possible estimate;
- The predicted highest possible estimate is lower than the predicted lowest possible estimate.

Any rank estimate predictions that fell into those categories were amended before being used for further modelling (see appendix G).

b. Modelling inference decisions for paired comparisons

Using binary logistic regression, brand quality inferences in paired comparisons were modelled

- as a function of differences in memory cues for the compared brands, or
- as a function of belief distributions predicted based on the memory cues (as described in section 4.3.1 Modelling rank estimates). In this case, inferences can be predicted based on the
    - differences in these predicted most probable and highest and lowest possible rank estimates, or
    - probability of one brand being of higher quality than the other, calculated based on the overlap of the belief distributions of the compared brands derived from these three predicted estimates. Appendix H provides a more detailed explanation of how this probability was calculated.

The following models were used to predict brand quality inferences for paired comparisons for an individual i and a brand pair j, using ordered logistic regression.

i. Modelling inference decisions for paired comparisons as a function of differences in memory cues for the compared brands

Inferences for pairs of two recognized brands both attributed with brand quality knowledge were modelled as a function of differences in recognition response latency, perceived environmental frequency and knowledge volume and valence for the compared brands.

(4) $ITPCRK_{ij} = \beta_0 + \beta_1 * \Delta RL_{ij} + \beta_2 * \Delta PEF_{ij} + \beta_3 * \Delta KVOL_{ij} + \beta_4 * \Delta KVAL_{ij} + \varepsilon_{ij}$,

where ITPCRK represents an inference made by respondent i about paired comparison j including two *recognized* brands attributed with quality knowledge, β_0 is the intercept, β_1, β_2, β_3, β_4 are the slopes estimated for all respondents and brands, ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, ΔRL is the difference in response latency for the compared brands, ΔPEF is the difference in perceived environmental frequency, and ΔKVOL and ΔKVAL are the differences in knowledge volume and valence.

Inferences for pairs of two recognized brands, of which at least one was a *merely recognized* brand not attributed with any brand quality knowledge, were modelled as a function of differences in recognition response latency and perceived environmental frequency for the compared brands.

(5) $ITPCMR_{ij} = \beta_0 + \beta_1 * \Delta RL_{ij} + \beta_2 * \Delta PEF_{ij} + \varepsilon_{ij}$,

where ITPCMR represents an inference made by respondent i about paired comparison j including at least one *merely recognized* brand attributed with no quality knowledge, β_0 is the intercept, β_1, β_2 are the slopes estimated for all respondents and brands, ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, ΔRL is the difference in response latency for the compared brands and ΔPEF is the difference in perceived environmental frequency.

Inferences for pairs including a recognized and an unrecognized brand were modelled as a function of differences in recognition and recognition response latency for the compared brands.

(6) $$ITPCRU_{ij} = \beta_0 + \beta_1 * \Delta R_{ij} + \beta_2 * \Delta RL_{ij} + \varepsilon_{ij},$$

where ITPCRU represents an inference made by respondent i about paired comparison j including a recognized and an unrecognized brand, β_0 is the intercept, β_1, β_2 are the slopes estimated for all respondents and brands, ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, ΔR is the difference in recognition for the compared brands and ΔRL is the difference in response latency.

Inferences for pairs including two unrecognized brands were modelled as a function of differences in recognition response latency for the compared brands.

(7) $$ITPCU_{ij} = \beta_0 + \beta_1 * \Delta RL_{ij} + \varepsilon_{ij},$$

where ITPCU represents an inference made by respondent i about paired comparison j including two unrecognized brands, β_0 is the intercept, β_1 is the slope estimated for all respondents and brands, ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, and ΔRL is the difference in response latency for the compared brands.

ii. Modelling inference decisions for paired comparisons as a function of belief distributions

Inferences for pairs of brands were modelled as a function of differences in most probable, highest possible and lowest possible rank estimates, predicted based on the memory cues, for the compared brands.

(8) $$ITPC_{ij} = \beta_0 + \beta_1 * \Delta QREMP_{ij} + \beta_2 * \Delta QREHP_{ij} + \beta_3 * \Delta QRELP_{ij} + \varepsilon_{ij},$$

where ITPC represents an inference made by respondent i about paired comparison j including two brands, β_0 is the intercept, β_1, β_2, β_3 are the slopes estimated for all respondents and brands, ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, $\Delta QREMP$ is the difference in the predicted most probable rank estimates for the compared brands, $\Delta QREHP$ is the difference in the predicted highest possible rank estimates, and $\Delta QRELP$ is the difference in the predicted lowest possible rank estimates.

Inferences can also be predicted based on the probability of one brand being of higher quality derived from the degree of the belief distribution overlap for the compared brands.

(9) $$ITPC_{ij} = \beta_0 + \beta_1 * BDO_{ij} + \varepsilon_{ij},$$

where ITPC represents an inference made by respondent i about paired comparison j, β_0 is the intercept, β_1 is the slope estimated for all respondents and brands, ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, and BDO is the probability of one brand being of higher quality derived from the degree of the belief distribution overlap for the compared brands.

One obvious methodological advantage of the models using belief distributions for predicting inferences is that they suggests a universal model for all types of pairs, while the modelling based on memory cues directly requires separate models for different pairs depending on the availability of memory cue data for the compared brands.

The outputs for models 4-9, which represent the probability of one brand being inferred as of higher quality, can be rounded to the nearest integer for predicting the inferences for paired comparisons, or can be used for predicting confidence in those inferences.

c. Modelling inference confidence and response latency for paired comparisons

The models used for predicting confidence and response times for paired comparisons are similar to those used for modelling quality inference described in section 4.3.2. Modelling inference decisions for paired comparisons. That is, the same sets of independent variables in models 4-9 were used to predict confidence and response times for quality inferences in paired comparisons. The dependent variables were entered in the models in the following ways.

Inference confidence

1. Stated confidence, converted to decimal fractions (from .01 to.99), was modelled as a function of the independent variables in models 4-9.
2. Natural logarithm of the stated confidence, converted to decimal fractions, was modelled as a function of the independent variables in models 4-9.
3. Stated confidence, converted to categorical variable, was modelled as a function of the independent variables in models 4-9. For this approach, stated confidence, converted to decimal fractions, was coded as a 9-level category data, corresponding to the following ranges of confidence levels: *1* - .01-.11; *2* - .12-.22, *3* - .23-.33, *4* - .34-.44, *5* - .45-.55, *6* - .56-.66, *7* - .67-.77, *8* - .78-.88, *9* - .89-.99.

Inference response time

1. Inference response latency[16] was modelled as a function of the independent variables in models 4-9. The output was compared with the recorded inference response time.
2. Natural logarithm of the inference response latency was modelled as a function of the independent variables in models 4-9. The output was transformed again to be compared with the recorded inference response latency.

[16] Inference response latency was transformed before it was used for analysis or modelling. Inverse inference response latency = 1 / Inference response latency.

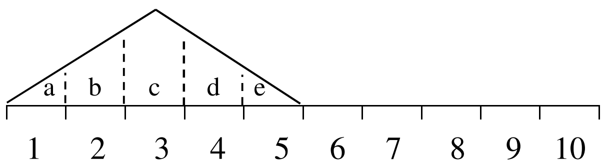
G. Amendment rules for inconsistent predicted rank estimates

<table>
<tr><th rowspan="2">Inconsistency type</th><th colspan="3">Amendment rules for the predicted rank estimates</th></tr>
<tr><th>Highest possible estimate</th><th>Most probable estimate</th><th>Lowest possible estimate</th></tr>
<tr><td>The most probable estimate is higher than the highest possible estimate</td><td colspan="2">Average of the predicted most probable and highest possible estimates</td><td>No changes</td></tr>
<tr><td>The most probable estimate is lower than the lowest possible estimate</td><td>No changes</td><td colspan="2">Average of the predicted most probable and lowest possible estimates</td></tr>
<tr><td>The most probable estimate is lower than the lowest possible and is higher than the highest possible estimate</td><td colspan="3" rowspan="3">Average of the predicted most probable, highest possible and lowest possible estimates</td></tr>
<tr><td>The highest possible estimate is lower than the most probable and the lowest possible estimates</td></tr>
<tr><td>The lowest possible estimate is higher than the most probable and the highest possible estimates</td></tr>
</table>

H. Calculating the probability of one brand being of higher quality than the other based on the overlap of the belief distributions of compared brands

The probability of one brand being of higher quality than the other was calculated based on the overlaps of triangular distributions, elicited during the rank estimation task, via the following four steps.

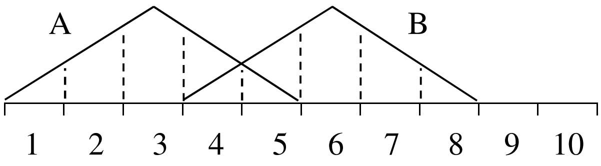
1. Using the most probable and highest and lowest possible rank estimates, stated by the respondents, calculate the probability of having a particular rank for each of the possible ranks for each observation. For example, if a respondent indicated that the most probable rank a particular brand could have was 3 out of 20, the highest possible was 1 out of 20, and the lowest possible was 5 out of 20, the probability of having ranks 6-20 is 0, and the probability of having a rank between 1 and 5 is 100%.



   The probability of having any rank between 1 and 5 is proportional to the percentage of geometrical area of the triangular distribution occupied by regions a to e, which is 8%, 24%, 36%, 24%, and 8%, or .08, .24, .36, .24, and .08, correspondingly.

2. For each pair, calculate the probability of having a particular combination of ranks for two compared brands, for instance, the probability of brand A being ranked 1st and probability of brand B being ranked 2nd, the probability of brand A being ranked 1st and probability of brand B being ranked 3rd, etc. This is calculated as a product of probabilities of having a particular rank for each of the

brands. For example, the probability of brand A being ranked 1st and brand B being ranked 5th is equal to the product of the probability of brand A being ranked 1st, which equals .08, and the probability of brand B being ranked 5th, which equals .24. The table below shows probabilities for each combination of ranks for two brands that can be ranked between 1 and 10.



			Brand B rank									
			1	2	3	4	5	6	7	8	9	10
Brand A rank		*Probability*	*0*	*0*	*0*	*.08*	*.24*	*.36*	*.24*	*.08*	*0*	*0*
	1	*.08*	0	0	0	.0064	.0192	.0288	.0192	.0064	0	0
	2	*.24*	0	0	0	.0192	.0576	.0864	.0576	.0192	0	0
	3	*.36*	0	0	0	.0288	.0864	.1296	.0864	.0288	0	0
	4	*.24*	0	0	0	.0192	.0576	.0864	.0576	.0192	0	0
	5	*.08*	0	0	0	.0064	.0192	.0288	.0192	.0064	0	0
	6	*0*	0	0	0	0	0	0	0	0	0	0
	7	*0*	0	0	0	0	0	0	0	0	0	0
	8	*0*	0	0	0	0	0	0	0	0	0	0
	9	*0*	0	0	0	0	0	0	0	0	0	0
	10	*0*	0	0	0	0	0	0	0	0	0	0

3. For each pair, calculate the probability of one brand being of higher quality than the other for each combination of ranks. To do that, multiply the probabilities calculated in the previous step by 1, .5, or 0. When calculating the probability of brand A being of higher quality than brand B, multiply by 1 for all combinations of ranks, where brand A is ranked higher, by .5 for all combinations, where both brands are ranked the same, and 0 for all combinations, where brand A is ranked lower, as in the following table.

		Brand B rank									
		1	2	3	4	5	6	7	8	9	10
Brand A rank	1	.5	1	1	1	1	1	1	1	1	1
	2	0	.5	1	1	1	1	1	1	1	1
	3	0	0	.5	1	1	1	1	1	1	1
	4	0	0	0	.5	1	1	1	1	1	1
	5	0	0	0	0	.5	1	1	1	1	1
	6	0	0	0	0	0	.5	1	1	1	1
	7	0	0	0	0	0	0	.5	1	1	1
	8	0	0	0	0	0	0	0	.5	1	1
	9	0	0	0	0	0	0	0	0	.5	1
	10	0	0	0	0	0	0	0	0	0	.5

The following table represents the probability of brand A of being higher quality than brand B for all combinations of ranks of brands in this example.

			Brand B rank									
			1	2	3	4	5	6	7	8	9	10
Brand A rank		*Probability*	*0*	*0*	*0*	*.08*	*.24*	*.36*	*.24*	*.08*	*0*	*0*
	1	*.08*	0	0	0	.0064	.0192	.0288	.0192	.0064	0	0
	2	*.24*	0	0	0	.0192	.0576	.0864	.0576	.0192	0	0
	3	*.36*	0	0	0	.0288	.0864	.1296	.0864	.0288	0	0
	4	*.24*	0	0	0	.0096	.0576	.0864	.0576	.0192	0	0
	5	*.08*	0	0	0	0	.0096	.0288	.0192	.0064	0	0
	6	*0*	0	0	0	0	0	0	0	0	0	0
	7	*0*	0	0	0	0	0	0	0	0	0	0
	8	*0*	0	0	0	0	0	0	0	0	0	0
	9	*0*	0	0	0	0	0	0	0	0	0	0
	10	*0*	0	0	0	0	0	0	0	0	0	0

4. For each pair, calculate the probability of one brand being of higher quality than the other by adding the probability of one brand being of higher quality than the other for each combination of ranks. For this example, it equals .9744.

I. Predictive accuracy of models for predicting inference decisions

Table 1. Individual level proportion of correct predictions for models with different predictors

Domains	N of participants	Predictors					
		Memory cues		Most probable estimate		Belief distributions	
		Mean	SE	Mean	SE	Mean	SE
Business schools	107	.746	.018	.707	.017	.715	.016
Vacuum cleaners	202	.772	.016	.752	.014	.761	.015
Refrigerators	201	.748	.014	.718	.013	.730	.014
Headphones	46	.795	.021	.730	.031	.776	.031
Walking shoes	47	.771	.032	.715	.040	.718	.038

Table 2. Aggregate level proportion of correct predictions for pairs including a recognized and an unrecognized brand for models with different predictors

Domains	N of observations	Predictors		
		Memory cues	Most probable estimate	Belief distributions
Business schools	4623	.899	.862	.886
Vacuum cleaners	4685	.926	.919	.925
Refrigerators	6511	.895	.865	.880
Headphones	1598	.955	.947	.944
Walking shoes	1008	.929	.911	.914

J. Predictive accuracy of models for predicting inference confidence

Table 1. Individual level squared deviations between the stated confidence and probability of one brand being of higher quality than the other predicted based on binary logistic regression models

Domains	N of participants	Predictors					
		Memory cues		Most probable estimate		Belief distributions	
		Mean	SE	Mean	SE	Mean	SE
Business schools	107	0.052	0.004	0.066	0.003	0.053	0.003
Vacuum cleaners	202	0.051	0.003	0.054	0.002	0.051	0.002
Refrigerators	201	0.056	0.003	0.057	0.002	0.054	0.003
Headphones	46	0.045	0.005	0.053	0.004	0.050	0.004
Walking shoes	47	0.045	0.006	0.050	0.005	0.049	0.006

Table 2. Aggregate level squared deviations between the stated confidence and probability of one brand being of higher quality than the other predicted based on binary logistic regression models

A. Pairs including a recognized and an unrecognized brand

Domains	N of observations	Predictors		
		Memory cues	Most probable estimate	Belief distributions
Business schools	4623	0.059	0.050	0.052
Vacuum cleaners	4685	0.060	0.051	0.056
Refrigerators	6511	0.065	0.049	0.057
Headphones	1598	0.044	0.039	0.042
Walking shoes	1008	0.048	0.042	0.044

B. Pairs including two recognized brands

Domains	N of observations	Predictors		
		Memory cues	Most probable estimate	Belief distributions
Business schools	2147	0.068	0.088	0.082
Vacuum cleaners	1649	0.084	0.088	0.087
Refrigerators	2536	0.083	0.086	0.091
Headphones	620	0.088	0.091	0.092
Walking shoes	360	0.080	0.083	0.087

C. Pairs including two unrecognized brands

Domains	N of observations	Predictors		
		Memory cues	Most probable estimate	Belief distributions
Business schools	3930	0.037	0.072	0.038
Vacuum cleaners	2756	0.021	0.042	0.024
Refrigerators	4219	0.028	0.053	0.029
Headphones	818	0.020	0.051	0.033
Walking shoes	747	0.026	0.042	0.038

Table 3. Individual level squared deviations between the stated and predicted confidence

Domains	N of participants	Predictors					
		Memory cues		Most probable estimate		Belief distributions	
		Mean	SE	Mean	SE	Mean	SE
Business schools	107	0.047	0.003	0.061	0.003	0.048	0.003
Vacuum cleaners	202	0.039	0.002	0.041	0.002	0.038	0.002
Refrigerators	201	0.042	0.002	0.048	0.002	0.041	0.002
Headphones	46	0.037	0.003	0.043	0.003	0.041	0.004
Walking shoes	47	0.036	0.004	0.042	0.004	0.040	0.005

Table 4. Aggregate level squared deviations between the stated and predicted confidence

A. Pairs including a recognized and an unrecognized brand

Domains	N of observations	Predictors		
		Memory cues	Most probable estimate	Belief distributions
Business schools	4623	0.047	0.053	0.040
Vacuum cleaners	4685	0.037	0.035	0.034
Refrigerators	6511	0.040	0.044	0.035
Headphones	1598	0.028	0.031	0.030
Walking shoes	1008	0.036	0.036	0.034

B. Pairs including two recognized brands

Domains	N of observations	Predictors		
		Memory cues	Most probable estimate	Belief distributions
Business schools	2147	0.067	0.097	0.086
Vacuum cleaners	1649	0.083	0.097	0.090
Refrigerators	2536	0.075	0.086	0.083
Headphones	620	0.092	0.100	0.099
Walking shoes	360	0.077	0.094	0.092

C. Pairs including two unrecognized brands

Domains	N of observations	Predictors		
		Memory cues	Most probable estimate	Belief distributions
Business schools	3930	0.037	0.053	0.037
Vacuum cleaners	2756	0.019	0.023	0.019
Refrigerators	4219	0.026	0.033	0.026
Headphones	818	0.018	0.025	0.020
Walking shoes	747	0.020	0.027	0.025

Table 5. Individual level squared deviations between the stated and predicted confidence levels modelled via natural logarithmic transformation

Domains	N of participants	Predictors					
		Memory cues		Most probable estimate		Belief distributions	
		Mean	SE	Mean	SE	Mean	SE
Business schools	107	0.049	0.003	0.067	0.003	0.050	0.003
Vacuum cleaners	202	0.040	0.002	0.044	0.002	0.040	0.002
Refrigerators	201	0.043	0.002	0.049	0.002	0.043	0.002
Headphones	46	0.037	0.004	0.044	0.003	0.041	0.004
Walking shoes	47	0.037	0.005	0.044	0.005	0.043	0.005

Table 6. Aggregate level squared deviations between the stated and predicted confidence levels modelled via natural logarithmic transformation

A. Pairs including a recognized and an unrecognized brand

Domains	N of observations	Predictors		
		Memory cues	Most probable estimate	Belief distributions
Business schools	4623	0.053	0.050	0.047
Vacuum cleaners	4685	0.041	0.037	0.039
Refrigerators	6511	0.044	0.042	0.039
Headphones	1598	0.030	0.030	0.031
Walking shoes	1008	0.038	0.037	0.037

B. Pairs including two recognized brands

Domains	N of observations	Predictors		
		Memory cues	Most probable estimate	Belief distributions
Business schools	2147	0.063	0.087	0.081
Vacuum cleaners	1649	0.078	0.091	0.085
Refrigerators	2536	0.074	0.084	0.084
Headphones	620	0.084	0.094	0.092
Walking shoes	360	0.074	0.085	0.082

C. Pairs including two unrecognized brands

Domains	N of observations	Predictors		
		Memory cues	Most probable estimate	Belief distributions
Business schools	3930	0.037	0.075	0.038
Vacuum cleaners	2756	0.019	0.030	0.020
Refrigerators	4219	0.026	0.041	0.027
Headphones	818	0.018	0.034	0.024
Walking shoes	747	0.020	0.034	0.032

Table 7. Individual level squared deviations between the stated and predicted confidence levels

Domains	N of participants	Predictors					
		Memory cues		Most probable estimate		Belief distributions	
		Mean	SE	Mean	SE	Mean	SE
Business schools	107	5.300	.332	7.966	.266	4.675	.276
Vacuum cleaners	202	5.157	.257	4.531	.171	4.243	.178
Refrigerators	201	5.429	.237	5.200	.185	4.382	.199
Headphones	46	4.354	.425	4.314	.299	3.927	.315
Walking shoes	47	4.125	.506	3.906	.425	3.777	.423

Table 8. Aggregate level squared deviations between the stated and predicted confidence levels

A. Pairs including a recognized and an unrecognized brand

Domains	N of observations	Predictors		
		Memory cues	Most probable estimate	Belief distributions
Business schools	4623	5.806	4.896	4.536
Vacuum cleaners	4685	5.436	4.974	4.548
Refrigerators	6511	6.380	5.676	4.590
Headphones	1598	3.342	3.798	3.363
Walking shoes	1008	4.320	4.028	3.848

B. Pairs including two recognized brands

Domains	N of observations	Predictors		
		Memory cues	Most probable estimate	Belief distributions
Business schools	2147	8.443	8.719	8.102
Vacuum cleaners	1649	11.343	9.319	8.794
Refrigerators	2536	8.888	8.197	8.009
Headphones	620	11.261	9.896	9.007
Walking shoes	360	9.391	8.871	8.381

C. Pairs including two unrecognized brands

Domains	N of observations	Predictors		
		Memory cues	Most probable estimate	Belief distributions
Business schools	3930	2.998	11.122	2.998
Vacuum cleaners	2756	1.517	1.517	1.517
Refrigerators	4219	2.182	2.971	2.182
Headphones	818	1.476	1.476	1.476
Walking shoes	747	1.641	1.641	1.698

K. Predictive accuracy of models for predicting inference response time

Table 1. Individual level squared deviations between the recorded and predicted inverse response time

Domains	N of participants	Predictors					
		Memory cues		Most probable estimate		Belief distributions	
		Mean	SE	Mean	SE	Mean	SE
Business schools	107	5.7e-08	6.3e-09	5.8e-08	6.5e-09	5.8e-08	6.6e-09
Vacuum cleaners	202	5.8e-08	3.3e-09	5.9e-08	3.3e-09	5.9e-08	3.3e-09
Refrigerators	201	5.5e-08	2.8e-09	5.6e-08	2.8e-09	5.6e-08	2.8e-09
Headphones	46	4.6e-08	3.5e-09	4.8e-08	3.4e-09	4.8e-08	3.4e-09
Walking shoes	47	5.0e-08	3.2e-09	5.0e-08	3.3e-09	5.0e-08	3.3e-09

Table 2. Aggregate level squared deviations between the recorded and predicted response time

A. Pairs including a recognized and an unrecognized brand

Domains	N of observations	Predictors		
		Memory cues	Most probable estimate	Belief distributions
Business schools	4623	5.0e-08	5.1e-08	5.1e-08
Vacuum cleaners	4685	5.0e-08	5.2e-08	5.2e-08
Refrigerators	6511	5.4e-08	5.5e-08	5.5e-08
Headphones	1598	4.4e-08	4.5e-08	4.6e-08
Walking shoes	1008	4.3e-08	4.3e-08	4.4e-08

B. Pairs including two recognized brands

Domains	N of observations	Predictors		
		Memory cues	Most probable estimate	Belief distributions
Business schools	2147	5.1e-08	5.2e-08	5.3e-08
Vacuum cleaners	1649	6.3e-08	6.1e-08	6.1e-08
Refrigerators	2536	5.6e-08	5.7e-08	5.7e-08
Headphones	620	5.8e-08	5.8e-08	5.8e-08
Walking shoes	360	5.2e-08	5.2e-08	5.2e-08

C. Pairs including two unrecognized brands

Domains	N of observations	Predictors		
		Memory cues	Most probable estimate	Belief distributions
Business schools	3930	6.9e-08	6.9e-08	6.9e-08
Vacuum cleaners	2756	6.3e-08	6.4e-08	6.4e-08
Refrigerators	4219	5.5e-08	5.6e-08	5.6e-08
Headphones	818	4.5e-08	4.6e-08	4.5e-08
Walking shoes	747	5.7e-08	5.7e-08	5.7e-08

Table 3. Individual level squared deviations between the recorded and predicted response time modelled via natural logarithmic transformation

Domains	N of participants	Predictors					
		Memory cues		Most probable estimate		Belief distributions	
		Mean	SE	Mean	SE	Mean	SE
Business schools	107	6.0e-09	7.9e-09	6.0e-08	8.0e-09	6.1e-08	8.1e-09
Vacuum cleaners	202	6.0e-08	3.9e-09	6.2e-08	4.0e-09	6.2e-08	4.0e-09
Refrigerators	201	5.9e-08	3.4e-09	5.9e-08	3.4e-09	5.9e-08	3.5e-09
Headphones	46	5.0e-08	4.7e-09	5.0e-08	4.5e-09	5.0e-08	4.5e-09
Walking shoes	47	5.4e-08	4.0e-09	5.3e-08	4.2e-09	5.3e-08	4.1e-09

Table 4. Aggregate level squared deviations between the recorded and predicted response time modelled via natural logarithmic transformation

A. Pairs including a recognized and an unrecognized brand

Domains	N of observations	Predictors		
		Memory cues	Most probable estimate	Belief distributions
Business schools	4623	5.3e-08	5.6e-08	5.6e-08
Vacuum cleaners	4685	5.2e-08	5.6e-08	5.7e-08
Refrigerators	6511	5.8e-08	6.0e-08	6.0e-08
Headphones	1598	4.7e-08	4.9e-08	5.0e-08
Walking shoes	1008	4.5e-08	4.6e-08	4.7e-08

B. Pairs including two recognized brands

Domains	N of observations	Predictors		
		Memory cues	Most probable estimate	Belief distributions
Business schools	2147	5.5e-08	5.2e-08	5.2e-08
Vacuum cleaners	1649	6.4e-08	6.4e-08	6.4e-08
Refrigerators	2536	6.0e-08	6.1e-08	6.1e-08
Headphones	620	6.1e-08	6.0e-08	5.8e-08
Walking shoes	360	5.5e-08	5.2e-08	5.1e-08

C. Pairs including two unrecognized brands

Domains	N of observations	Predictors		
		Memory cues	Most probable estimate	Belief distributions
Business schools	3930	7.3e-08	7.2e-08	7.2e-08
Vacuum cleaners	2756	6.6e-08	6.3e-08	6.3e-08
Refrigerators	4219	5.9e-08	5.7e-08	5.7e-08
Headphones	818	4.8e-08	4.6e-08	4.5e-08
Walking shoes	747	6.3e-08	6.1e-08	5.1e-08

L. Pilot studies

a. Pilot studies for the current research

Two pilot studies were conducted to select consumer good categories for Study 2. First, from the initial list of 27 domains with a sufficient number of different brands rated by the Consumer Report magazine, those with the balanced number of recognized and unrecognized rated brands were selected. This selection was made based on the results of the first pilot study conducted on Amazon Mechanical Turk. During this study, each respondent was presented with a list of brands in a particular product category and asked to indicate whether or not he/she recognized each brand.

Next, a pilot study was conducted to determine the environmental validity of recognition and other memory cues for the domains selected based on the results of the first pilot study. Ninety seven participants from the London Business School Behavioural Lab panel took part in the study. All participants were paid 10 British pounds ($16USD) for participating. Each participant answered a set of questions for five consumer goods. The participants were instructed on how to answer each question and tested for comprehension before they could start the actual tasks. If participants answered any of the comprehension test questions incorrectly, they were redirected to the instructions and answered the training questions again. For training purposes, all participants answered the full set of questions for printer brands before each participant answered the same set of questions for other four consumer good domains. Participants were asked several questions about each brand presented on the same page. The order in which the brands were presented was randomized for each question. First, participants indicated whether or not they had seen or heard of each brand. On the second page, the participants indicated how familiar they were with each brand on a 7-point scale: 1 - “Very unfamiliar” to 7 - “Very familiar”. When answering that question, participants were asked to think how often they had heard of or seen each of the brand names before the study. On the last page, they were asked questions about their knowledge on the quality of those brands presented side by side: “How much do you know about the quality of the following brands?” and “Of what you know about the academic quality of the following brands, how much suggests that it is good or bad?” The responses to the first question were measured using 1 to 10 scale, corresponding to ”I know little about it” and “I know a lot about it”, respectively. If the respondent did not recognize the brand, he could indicate that by selecting “0”. The responses to the second question were measured on an 11-point scale, ranging from “0% good, 100% bad” to “100% good, 0% bad”. If the respondent did not recognize the brand, he could indicate that by selecting “NA” option. The following tables represent the memory cue validities for the pre-tested domains. Appendix B describes how mean cue validities were calculated.

Washing machine domain (N = 24)

Cue	Mean cue validity	SE
Recognition	.74	.02
Perceived environmental frequency	.67	.03
Perceived knowledge valence	.53	.05

Fast food restaurant domain (N = 24)

Cue	Mean cue validity	SE
Recognition	.13	.02
Perceived environmental frequency	.21	.03
Perceived knowledge valence	.47	.08

Walking shoe domain (N = 24)

Cue	Mean cue validity	SE
Recognition	.34	.04
Perceived environmental frequency	.32	.03
Perceived knowledge valence	.54	.06

Digital SLR camera domain (N = 23)

Cue	Mean cue validity	SE
Recognition	.76	.04
Perceived environmental frequency	.69	.03
Perceived knowledge valence	.62	.06

Refrigerator domain (N = 23)

Cue	Mean cue validity	SE
Recognition	.67	.02
Perceived environmental frequency	.65	.02
Perceived knowledge valence	.67	.04

Vacuum cleaner domain (N = 25)

Cue	Mean cue validity	SE
Recognition	.71	.02
Perceived environmental frequency	.66	.02
Perceived knowledge valence	.33	.06

Athletic shoes domain (N = 25)

Cue	Mean cue validity	SE
Recognition	.21	.02
Perceived environmental frequency	.29	.04
Perceived knowledge valence	.56	.04

Headphones domain (N = 24)

Cue	Mean cue validity	SE
Recognition	.50	.02
Perceived environmental frequency	.51	.03
Perceived knowledge valence	.47	.05

Camcorder domain (N = 24)

Cue	Mean cue validity	SE
Recognition	.79	.02
Perceived environmental frequency	.76	.02
Perceived knowledge valence	.63	.03

Microwave domain (N = 19)

Cue	Mean cue validity	SE
Recognition	.66	.02
Perceived environmental frequency	.63	.06
Perceived knowledge valence	.60	.08

LCD TV domain (N = 24)

Cue	Mean cue validity	SE
Recognition	.80	.03
Perceived environmental frequency	.74	.04
Perceived knowledge valence	.61	.04

Portable DVD player domain (N = 24)

Cue	Mean cue validity	SE
Recognition	.64	.01
Perceived environmental frequency	.58	.02
Perceived knowledge valence	.47	.04

Kitchen knives domain (N = 18)

Cue	Mean cue validity	SE
Recognition	.33	.05
Perceived environmental frequency	.36	.05
Perceived knowledge valence	.44	.12

Bed mattress domain (N = 13)

Cue	Mean cue validity	SE
Recognition	.46	.06
Perceived environmental frequency	.53	.07
Perceived knowledge valence	.69	.13

b. Pilot studies for future research

The following pilot studies were conducted as an initial attempt to explore what factors affect adherence to the recognition heuristic. Does people's tendency to attribute recognized brands with higher quality change under time pressure, cognitive load, or the potential risk of losses? Is that tendency related to personality traits and individual-level recognition validity?

Adherence to the recognition heuristic and exogenous factors. The decision making literature suggests that people adhere to heuristic strategies more often under time and cognitive constrains (Pachur and Hertwig 2006; Hilbig, Erdfelder and Pohl 2012; Halberstadt and Catty 2008). According to Pachur and Hertwig, recognition memory is more accessible than other inferential cues and, therefore, it can be utilized faster. As a result, its use increases under time pressure or limited processing capacity. Prior research in marketing has demonstrated that people often choose recognized brands to reduce uncertainty, as brand names can communicate unobservable quality (Erdem and Swait 1998; Kirmani and Rao 2000; Keller and Lehman 2006). Therefore, people may use the recognition heuristic more often when they risk losses as a result of poor judgments.

Individual differences in adherence to the recognition heuristic. According to prior literature, reliance on recognition as an inferential cue depends not only on exogenous, but also endogenous factors. For example, Hilbig has revealed a relationship between individual differences and the use of recognition as a primary cue (Hilbig 2008; Hilbig and Pohl 2008). One such endogenous factor is neuroticism, which, according to Hilbig motivates people to adopt recognition-based decision making instead of using additional knowledge in an attempt to avoid a failure caused by their knowledge, which they usually do not trust. On the other hand, findings from the decade of research on the recognition heuristic suggest that adherence to that strategy depends on the validity of the recognition as an inferential cue (Gigerenzer and Goldstein 2011). That is, people should rely on recognition only if they learn that it helps making accurate decisions. Such recognition validity can vary among individuals, and should be positively correlated with their adherence rates (Goldstein and Gigerenzer 2002). Are people sensitive to other's reliance on recognition as a cue for making brand quality inferences? It seems perfectly reasonable for consumers to follow the recognition heuristic, if they observe others applying it successfully. Moreover, in some domains, such as business schools, people's preference for recognized brands may stem from others' tendency to infer that a recognized brand is of higher quality.

The effect of exogenous factors was tested by manipulating time pressure, cognitive load, and risk loss during the paired comparison task. To test the relationship between adherence to the recognition heuristic and individual factors, the respondents answered 44 questions from the BFI personality questionnaire (John, Donahue and Kentle 1991; McCrae and John 1992; John, Naumann and Soto 2008), which can be found in appendix M.

Time pressure, cognitive load, and risk manipulations. Different groups of randomly assigned respondents performed the paired comparison task either under time pressure, or cognitive load, or loss risk[17].

[17] All participants in Study 1 were randomly assigned to one of the following two conditions: time pressure vs. control. All participants answering the questions about refrigerators and vacuum cleaners in Study 2 were randomly assigned to one of the following four conditions: time pressure, cognitive load, loss risk, and control. No manipulation was used for the headphone and walking shoe domains.

In the time pressure condition, during the estimation and inference tasks, participants were asked to answer the questions for each business school within a very short period of time (three seconds per pair of schools for the inference task, and eight seconds per school for the estimation task), though participants could take as long as they wanted to answer the questions[18]. The time limit within which they were asked to answer was not specified. Instead, the participants could see a simple countdown device, which would indicate when the time, during which they were supposed to answer the question, had elapsed.

In the cognitive load condition, during the estimation and inference tasks, participants were asked to answer the questions for each business school while recording the colour of flash cards periodically appearing on the screen. Each flash card was shown for 2 seconds. There were 10 second intervals between the time the previous card disappeared and the new one appeared on the screen.

In the loss risk condition, during the inference task, participants were told that for every question in this task, they would lose a number of points proportional to how wrong they were. The scoring was set up the following way: if the inference made by the respondent was wrong, he/she would lose a number of points equal to the rank of the lower-ranked brand; no points were awarded if the inference was correct. For example, if according to a published ranking, Brand A was ranked forth and Brand B was ranked eleventh, and the respondent chose Brand B, he/she would lose 11 points. All respondents were given 500 points to begin with and were told that, at the end of the

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[18] During the inference making question in Study 1, the respondents answering the question under time pressure spent on average 1921ms per question, and the respondents in the control condition spent on average 2385ms ($t(53, 54) = 20.46$, $p < .05$). In study 2, the respondents answering the question under time pressure spent on average 1839ms per question, and the respondents in the control condition spent on average 2021ms ($t(138, 136) = 9.19$, $p < .05$). Though under time pressure, participants spent less time answering the questions, the results indicate that they had more time to answer a question than it took participants in the control condition, on average.

experiment, a randomly chosen participant would receive £0.20 for each point they had at the end of that task.

To analyse the relationship between people's tendency to adhere to the recognition heuristic and the factors affecting that tendency, two measures were derived for each participant in the study: the proportion of cases when a recognized brand was inferred to be of higher quality than an unrecognized brand, *recognition adherence rate*, and the proportion of cases when a recognized brand was ranked higher than an unrecognized one according to expert-judged quality, *recognition validity*. The regression analyses were conducted to test the relationship between individual-level recognition heuristic adherence, on one side, and the personality traits and the individual level recognition heuristic validity, on the other, for the data including all five domains.

$$RHA_i = \beta_0 + \beta_1 * \text{Domain} + \beta_2 * E_i + \beta_3 * A_i + \beta_4 * N_i + \beta_5 * O_i + \beta_6 * C_i + \beta_7 * RV_i + \varepsilon_i,$$

where RHA represents recognition heuristic adherence rate of respondent i, β_0 is the intercept, β_1, β_2, β_3, β_4, β_5, β_6, β_7 are the slopes estimated for all respondents, ε_{ij} is the residual, normally distributed with a zero mean and variance σ^2, E is extraversion, A is agreeableness, N is neuroticism, O is openness, C is conscientiousness, and RV is recognition validity.

The results of the analysis showed that actual adherence rates were positively related with agreeableness, $\beta = .02$, $t = 2.26$, $p < .05$, neuroticism, $\beta = .02$, $t = 3.00$, $p < .05$, extraversion (marginally significant), $\beta = .01$, $t = 1.82$, $p = .07$, and recognition validity, $\beta = .3$, $t = 7.51$, $p < .001$ ($R^2 = .13$, $p < .001$). These relationships were also analysed for the subset of domains used for exploring the effects of time pressure, cognitive load, and risk of loss. When these factors were added to the independent variables included in the previous model, the regression analysis revealed that the actual adherence rates were positively related with agreeableness, $\beta = .03$, $t = 2.19$, $p < .05$, neuroticism, $\beta = .03$, $t = 2.75$, $p < .01$, extraversion, $\beta = .03$, $t = 2.66$, $p < .01$, and recognition validity, $\beta = .31$, $t = 5.65$, $p < .001$, and that people adhere to the recognition heuristic less when they face risk of losses in case of making inaccurate inferences, $\beta = -.04$, $t = -2.18$, $p < .05$ ($R^2 = .14$, $p <.001$).

Thus, while analysis of the respondents' individual-level adherence rates confirm the relationship between the individual level of recognition validity and neuroticism, the effect of manipulations is either not found, like in the case of time pressure and cognitive load, or is found to have an opposite effect. The latter refers to the loss risk manipulation that decreased the reliance on the recognition heuristic, even though one might predict that the respondents would adhere to it more because they often choose recognized brands as a risk reduction strategy. Obviously, this effect may be caused by the way the manipulation was administered, in particular, by the scoring rule used to generate the perception of risk. Therefore, the findings of this study cannot be generalized without testing other scoring rules, or other techniques for manipulating risk perception, in general. Furthermore, using different degrees of time pressure or cognitive load could be more effective in establishing the effect of these factors. On the other hand, the findings revealed new effects: individual-level adherence rates were positively correlated with agreeableness and extraversion. These revelations call for further research that would explain the reasons for such relationship.

M. BFI personality questionnaire and scoring instructions

How I am in general

Here are a number of characteristics that may or may not apply to you. For example, do you agree that you are someone who likes to spend time with others? Please indicate the extent to which you agree or disagree with that statement.

1 - Disagree Strongly

2 - Disagree a little

3 - Neither agree nor disagree

4 - Agree a little

5 - Agree strongly

I am someone who…

1. _____ Is talkative
2. _____Tends to find fault with others
3. _____Does a thorough job
4. _____Is depressed, blue
5. _____Is original, comes up with new ideas
6. _____Is reserved
7. _____Is helpful and unselfish with others
8. _____Can be somewhat careless
9. _____Is relaxed, handles stress well.
10. _____Is curious about many different things

11. _____Is full of energy

12. _____Starts quarrels with others

13. _____Is a reliable worker

14. _____Can be tense

15. _____Is ingenious, a deep thinker

16. _____Generates a lot of enthusiasm

17. _____Has a forgiving nature

18. _____Tends to be disorganized

19. _____Worries a lot

20. _____Has an active imagination

21. _____Tends to be quiet

22. _____Is generally trusting

23. _____Tends to be lazy

24. _____Is emotionally stable, not easily upset

25. _____Is inventive

26. _____Has an assertive personality

27. _____Can be cold and aloof

28. _____Perseveres until the task is finished

29. _____Can be moody

30. _____Values artistic, aesthetic experiences

31. _____Is sometimes shy, inhibited

32. _____Is considerate and kind to almost everyone

33. _____Does things efficiently

34. _____Remains calm in tense situations

35. _____Prefers work that is routine

36. _____Is outgoing, sociable

37. _____Is sometimes rude to others

38. _____Makes plans and follows through with them

39. _____Gets nervous easily

40. _____Likes to reflect, play with ideas

41. _____Has few artistic interests

42. _____Likes to cooperate with others

43. _____Is easily distracted

44. _____Is sophisticated in art, music, or literature

To score the BFI, first, all negatively-keyed items were reverse-scored (that is, subtracted from 6). Next, scale scores were created by averaging the following items for each B5 domain (where R indicates using the reverse-scored item).

- Extraversion: 1, 6R 11, 16, 21R, 26, 31R, 36
- Agreeableness: 2R, 7, 12R, 17, 22, 27R, 32, 37R, 42
- Conscientiousness: 3, 8R, 13, 18R, 23R, 28, 33, 38, 43R
- Neuroticism: 4, 9R, 14, 19, 24R, 29, 34R, 39
- Openness: 5, 10, 15, 20, 25, 30, 35R, 40, 41R, 44