How Do Stereotypical Representations Affect Judgments of New Product Success? An Empirical Investigation

Carlos Vazquez-Hernandez, Massimo Garbuio, and Betina Szkudlarek

Abstract—**Storytelling about success is a compelling strategy for communicating a new product's features, both internally to gain the support of key decision makers and externally to gain support for market launch. Yet, new product success stories often lean more toward stereotypes than facts, casting doubt on their accuracy and representativeness. This study examines the accuracy of innovation managers' judgments about new product success rates when faced with stereotypical information. We specifically explore the influence of the representativeness heuristic, hypothesizing that it leads managers to rely on stereotypical information and potentially results in erroneous judgments. Through two experimental studies, we assess how the valence and amount of information impact judgment accuracy. Our findings indicate that both factors predominantly drive intuitive judgments, which can be less accurate than deliberation. Additionally, we discover that a manager's level of expertise moderates this relationship. Even expert innovation managers, when influenced by stories about potential new product success, tend to disregard factual data about past success rates. These findings offer critical insights into how reliance on stereotypical representations can skew innovation managers' judgments about new product success.**

Index Terms—**Decision-making, expertise, heuristics, innovation, new product success, representativeness.**

I. Introduction

JUDGING the success of new products is a complex enterprise, even for experienced innovation managers [1]. Extensive research has been dedicated to identifying processes and systems that aid decision making in new product development, including the actual process of product development, prototyping [2], and design thinking [3]. The stakes are high, as launching a product that fails to resonate with the market can have lasting repercussions for a company's reputation [4]. Highlighting the unpredictability of market success, the Segway [5] and Google Lens [6] were both supported by tech giants, and the latter primarily found in niche markets. Recent advice suggests that crafting compelling stories can positively influence both internal decision makers and consumers [7]. While such stories can help navigate executive decision-making [7] and counter organizational resistance [8], especially when they have a positive spin, their effectiveness is unclear [9], [10]. Do exciting stories about new products truly help decision makers overcome the fear of "doing something we haven't done before" while considering all the evidence regarding the risks (and benefits) of a new product? Or do they promote a dangerous overreliance on intuition and a disregard for factual data in decision making? Factual data accurately represents real-world situations, and this is exemplified by historical success rates of newly introduced products.

One way to understand how stories and/or factual data help or hinder new product decision making is by considering the literature on stereotypical rather than factual representations of a new product's success. By stereotypical representations, we refer to oversimplified and belief-driven portrayals of new product success, as when the innovation team's excitement about a product in development is portrayed as an indicator that it is on track. Factual representations, by contrast, are grounded in data, such as historical success rates of comparable products. In the case of the Segway, data on past adoption rates in the electric scooter industry (or similar industries) would lead to a more accurate judgment of the products potential success.

Scholars have proposed that erroneous judgments are more likely when decision-makers are presented with stereotypical rather than factual information [11], [12], [13]. Stereotypical information triggers specific mental representations related to a given phenomenon, leading people to rely on heuristics, or "rules of thumb." A dependence on heuristics often reduces the capacity for rational and deliberative judgments. As a result, individuals frequently fall back on their expertise [14] and intuition to make sense of information [15]. One would expect more experienced individuals to make more accurate intuitive judgments due to their well-honed ability to effectively process limited information [16], [17], [18], [19]. However, this is not always the case.

Previous research has not investigated the impact of heuristics and expertise in judgments about the success of new products, including in screening decisions [20], innovation project investment [21], and pricing [22]. This knowledge is needed for two key reasons. First, subjective judgments (which

Manuscript received 31 July 2023; revised 26 November 2023 and 26 February 2024; accepted 25 March 2024. Date of publication 5 April 2024; date of current version 20 May 2024. This work was supported by the U.S. Department of Commerce under Grant 123456. Review of this manuscript was arranged by Department Editor G. Marzi. *(Corresponding author: Carlos Vazquez-Hernandez.)*

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the University of Sydney Research Integrity and Ethics Administration under Application No. 2019/092, and performed in line with the National Statement of Ethical Conduct in Human Research.

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Digital Object Identifier 10.1109/TEM.2024.3385359

are underpinned by heuristics and expertise) about uncertain situations [23] appear to be frequent in product launches [24]. This could contribute to erroneous assessments of market reactions, which could increase an organization's new product failure rate. Second, although heuristics are beneficial in certain innovation activities, such as selecting projects for investment during the screening stage, where data may be scarce [20], they can be misapplied or overused, supplanting necessary deliberation. This could be especially problematic when relevant data is available but ignored, leading to wasted corporate resources.

Two further aspects of judgment of new products and services are ripe for investigation. First, heuristics are often triggered by the valence of information—positive or negative—and its quantity [13], [25], [26], [27]. Such valence of information defines the emotional tone of innovation managers' stories about new product success. While the existing literature clarifies how narratives can help contribute to effective organizational strategies [8], it often overlooks the impact of valence and amount of information in those narratives on new product judgments. This is relevant since innovation managers may bias their stories to emphasize positive aspects of a new product to gain support or negative aspects to caution against new product features and ideas. Such bias makes it difficult to judge the success of new products, as individuals tend to prioritize positive over negative information [29], [30] as they seek to validate pre-existing beliefs [31]. This leads to a critical question: How do the valence and amount of information influence judgments of new product success? Second, while expertise in a field may increase reliance on heuristic-based judgments [23], [36], [37], [38], it remains unclear if such expert-driven judgments are more accurate when factual data are present. Lack of clarity around the susceptibility of judgments of new product success to bias [3], [36] further underscores the need for our research.

The present study aims to provide deeper understanding of the accuracy of judgments in the innovation space, particularly regarding the likelihood of success or failure of new products in the market. In particular, we aim to answer two main research questions: 1) Does the presence of different valences and amount of stereotypical representations about new product success triggers the use of heuristics? and 2) Does a higher level of expertise in innovation influence the accuracy of intuitive judgments regarding a new product's market success?

Our study includes two experiments and a questionnaire involving three distinct groups: innovation managers, noninnovation managers, and novices. In the two experiments, participants are exposed to varying valences and amount of stereotypical information regarding new product success. Additionally, since reliance on stereotypical information may be an innate trait, we employ an established scale to assess if participants are more inclined to deliberate and provide rational responses [13], [37], in the absence of valence and amount of stereotypical information.

Our study yields three key contributions. First, we critically examine the belief that (expert) innovation managers reliably make effective decisions concerning new products' market impact and success [38]. We also scrutinize findings that suggest an innovation manager's foresight into an idea's future value can enhance their decision-making [39]. Second, our results indicate that innovation managers' judgments are more rational—i.e., that they make more accurate judgements—when they are exposed to a great deal of positive information about a new product. Third, we provide evidence that individual expertise contributes to more rational judgments [33], [34], [35], [40], [41], but only in the absence of stereotypical representations.

By providing evidence of how established heuristics play out in innovation decisions, our study contributes to the broader literature on heuristics and decision making. It also contributes to the innovation and technology management literature by expanding our understanding of the role of information and heuristics in decision making [42]. Our work is especially relevant to the field of new product development, where it is widely acknowledged that accurately predicting the success of a new product is difficult [43] and often results in incremental advancements [44]. Our findings have implications for the composition of decision committees, training for expert decision makers, and the allocation of corporate resources (e.g., money, time) to innovation.

II. Theoretical Framework

A. Review of Extant Research on Judgment in New Product Evaluation

Research on intuitive judgments in new product management and innovation draws from theory in established heuristics and decision-making fields, including psychology, cognitive sciences, behavioral economics [17], [18], [41], [45], [46] sociology, organizational studies, and mathematics [47], [48], [49], [50], [51]. Intuitive judgments have been analyzed at various levels, from the individual [16], [34] to the team level [19], [33], [52], [53] to the organizational and institutional levels [54], [55], [56], [57]. Our research centers on the individual decision-making level, focusing on the pervasive influence of stereotypes encountered by innovation managers tasked with assessing the potential success of a new product.

In our study, we adopt a behavioral perspective, based on theory of bounded rationality [12], [58] to analyze the asymmetric relationship between heuristics and judgments of a new product success. That is, we start from the assumption that innovation managers adopt heuristics because their individual capacity to process information is limited [12], [58]. This results in decisions that are biased, affecting an efficient allocation of resources to the best new product ideas. Specifically, we seek to understand how the presentation of information affects individuals' ability to judge the potential success of new products [11], [37].

B. Conceptual Model and Hypotheses

Among the many heuristics explored in behavioral research [11], we focus on the representativeness heuristic and its role in shaping innovation managers' intuitive judgments regarding new product success. This heuristic, also referred to as the stereotyping heuristic, involves judging the likelihood of an event based on its similarity to what is typically expected of such events, and often relies on stereotypical information [23].

Despite several past investigations on heuristics and biases [11], [37] there is a notable gap in understanding the specific impact of the representativeness heuristic on decisions related to the development, launch, and success prediction of new products. Eling et al. [18] rigorously tested how different decision-making strategies—rational versus intuitive—affect the quality and speed of evaluating early-stage new-product ideas. They found that intuitive judgment was preferable for assessing the appeal of new product concepts, but they did not examine scenarios involving the launching of new products nor the impact of stereotypical versus factual information on judgment. We aim to build on their findings by examining the critical influence of intuition in innovation judgments, particularly in contexts where stereotypical information is presented and triggers heuristics in innovation managers.

West et al. [20] found that employing simple heuristics can be as effective as detailed analytical processes in the evaluation and selection of new product development. Unlike Eling et al., West et al. illustrate that considering positive attributes, like market potential and competitive advantage, can significantly influence the success of new product development. We are responding to their call for more experimental research on the role of positive attributes in product innovation by examining how a particular heuristic influences innovation judgments amidst the interplay of stereotypical and factual information.

Like Eling et al. and West et al., we explore the accuracy of judgments of new products, but differ from them by looking at the extent to which perceptions, whether based on positive or negative stereotypical information (i.e., valence) and the amount of information received, impact the accuracy of these judgments. This understanding is crucial for guiding investment and decision-making in innovation [73], while complementing the extant findings in the literature.

The valence of information is defined as its intrinsic attractiveness (positive) or averseness (negative) [60], [61], which influences decision-making, behavior, and internal judgment states. For example, research indicates that decision-makers are more impacted by negative events, such as losses, than by positive ones, like gains [26, p. 323]. Amount of information refers to the quantity of data/stimuli an individual receives and must process. A suboptimal amount of information can falsely bolster an individual's confidence in their judgments [62]. Too much information can lead to cognitive overload, resulting in reliance on heuristics and poor judgments, while too little information can lead to uninformed judgments.

In this study, we operationalize "valence" and "amount" of information in a manner similar to previous research on bounded rationality [18]. In essence, valence of information conveys that individuals process positive and negative information differently [26], and the amount of information influences the accuracy of their judgments [25].

We propose a conceptual model that incorporates valence and amount of information in the context of judging new product success. To this model, we add the concept of expertise, which moderates the effect of valence and amount of information on outcome variables. As theory has postulated, due to their own past experiences, perceptions, and cognitions, individuals tend to settle for a solution that is "good enough" (i.e., satisficing), rather than working toward the more rational, "best" solution (i.e., maximizing) expected from a deliberative process [64]. As a result, more expert managers tend to make better intuitive decisions [15], [65].

Our conceptual model presents a relationship of causality from the predictors (independent variables) operationalized as valence and amount of information, and the outcome (dependent variable) of judgment of the rate of new product success, operationalized in terms of rate of success. For example, when participants are presented with positive stereotypical representations, they might overestimate/underestimate their judgment about new product success rate.

We hypothesize that when innovation managers are estimating the success of a new product, valence of information representative of product success will affect their judgments. Specifically, a rational innovation manager would disregard irrelevant information (e.g., a comment about the product's likely contribution to the market that lacks supporting evidence) and focus solely on information that helps them increase accuracy of their judgment. We posit that when innovation managers are presented with positive/negative (yet irrelevant) information about a new product alongside base rate probabilities of success in its category, they will give more weight to the positive/negative information than to the base rate data due to a base rate neglect effect in their judgment processing [23]. Behavioral theory [11] established that the representativeness heuristic drives intuitive, rather than deliberative, judgments as a result of a base-rate neglect effect, or the tendency to dismiss relevant probabilities and make judgments based on stereotypical representations. Thus, we make the following hypotheses on valence of information:

H1a. If innovation managers are exposed to positive stereotypes regarding new product success (positive representativeness), then their judgments about a product being successful/unsuccessful will likely overlook the prior probabilities (base rates) of new product success that are presented to them.

H1b. If innovation managers are exposed to negative stereotypes regarding new product success (negative representativeness), then their judgments about a product being successful/unsuccessful will likely overlook the prior probabilities (base rates) of new product success that are presented to them.

The effect of information presented on the accuracy of judgement is not limited to its valence. We also propose that the amount of stereotypical information presented will significantly influence participants' judgments of a new product's success rates. Thus, the following hypotheses on amount of information:

H2a. If innovation managers are presented with more representations of stereotypical information about new product success, then their judgments about a product being successful/unsuccessful will likely overlook the prior probabilities (base rates) of new product success that are presented to them.

H2b. If innovation managers are presented with less representations of stereotypical information about new product success, then their judgments about a product being successful/unsuccessful will likely overlook the prior probabilities (base rates) of new product success that are presented to them.

Furthermore, we extend previous work on the base-rate neglect effect by examining whether innovation expertise has any moderating impact on the valence and amount of information

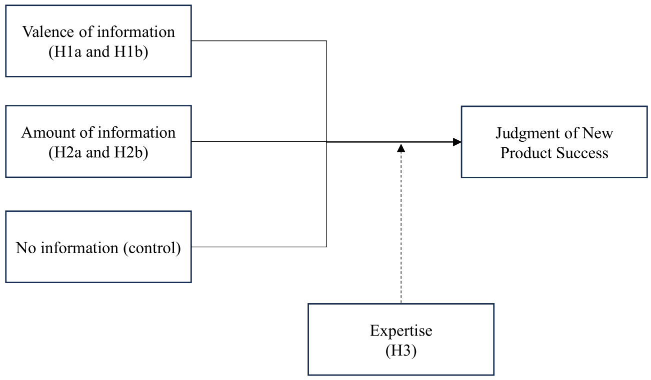

Fig. 1. Conceptual model.

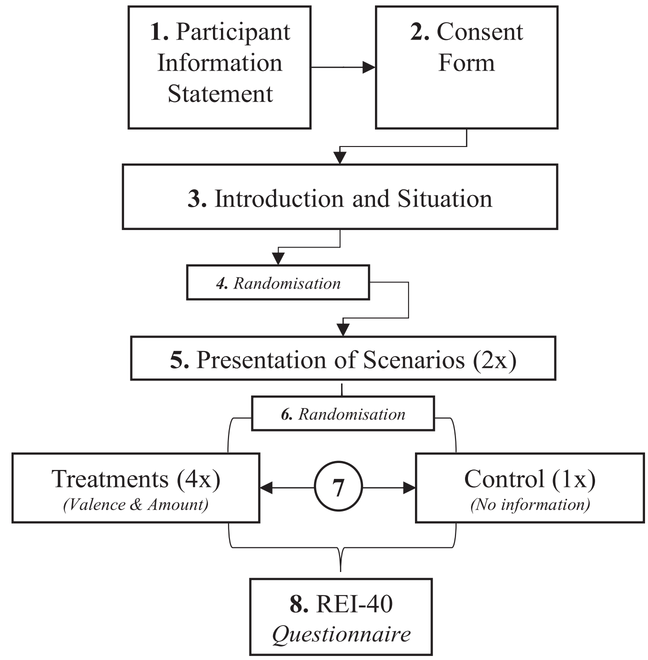

Fig. 2. Study procedure.

provided to participants. This is an important contribution, as it has been argued that more experience in innovation leads to better judgments, given limited knowledge of a situation [16], [57]. Hence, we further hypothesize that expertise is a moderating variable in the causal relationship between information and judgment.

H3. Innovation managers are likely to make intuitive judgments about a product being successful/unsuccessful, such that the valence and amount of information will be more representative to them than to other managers (with no experience in innovation) and to novices/students (with no previous relevant work experience). That is, innovation managers will tend to neglect base rates as much as other managers and novices/students do, and their expertise will offer minimal advantage in making more accurate judgments.

Fig. 1 outlines the conceptual model and shows how the representativeness heuristic, operationalized through valence and amount of stereotypical information, drives judgments about the rate of new product success.

III. Methodology

A. Experimental Design and Questionnaire

To test our hypotheses, we conducted two within-subjects experiments, for three reasons. First, the experimental method, which has been used by previous heuristics researchers, is best suited to gaining understanding of whether the representativeness heuristic is driving judgments in the context of new product success. Second, a controlled environment allows us to measure the likelihood that the causes reflected in our independent variables (valence and amount) are indeed driving our dependent variable—that is, judgments of new product success [66, p. 136]. Finally, within-subjects experiments allow individuals to act as their own control, thus reducing variability in results due to individual differences while improving statistical power, and requiring fewer participants to identify a significant effect [67].

We conducted two controlled experiments so that we could implement a randomization procedure, a treatment variable, and a control variable to better determine cause–effect relationships [68]. The first experiment (study 1) served as a pilot to assess validity and observe effects. The second experiment (study 2) replicated the first's design with a larger sample size to determine causal relationships more robustly. Our experimental setting was a controlled experiment using two online services. We used the Gorilla Experiment Builder[1] to create and host our experiment [69] and recruited participants via Prolific.[2] In our experimental design, we considered asymmetrical relationships where the manipulation at various levels (i.e., positive/negative valence and more/less information) of our independent variables would trigger a change in our dependent variable (i.e., rate of success of the new product) [66, p. 138] in any direction.

In addition to the experiments, and as a complementary data collection approach to increase robustness, we asked all participants to complete a questionnaire (i.e., a Rational-Emotional Inventory: REI-40) [70], [71] at the end of their experiment. We did so to better ascertain whether judging a new product success rate was correlated with the participants' natural disposition to make judgments from a cross-sectional perspective. Research has previously shown insightful results using similar data collection to evaluate dispositional information processing [17], and it is an appropriate given the variety of information processing styles in innovation [72]. Participants were also asked to provide key demographic information. Fig. 2 summarizes our study methodology for the experiments and questionnaire.

B. Study 1

To ensure our constructs, content, and procedures were valid, we first conducted an experiment with the following three different groups of participants:

[1]Online. [Available]: www.gorilla.sc
[2]Online. [Available]: www.prolific.co

TABLE I
SAMPLE DESCRIPTIVE STATISTICS

	N	*Range*	*Mean*	*SD*
Age (years old)	112	18—54	35	15
Work Tenure (years of experience)	112	1—10	5	4
Professional Domain Background				
Arts/Social Science	6			
Business/Finance/Marketing/Sales	29			
Design	2			
Education	5			
Engineer	2			
Government	1			
Health Management	8			
Hospitality	3			
IT/Digital	18			
Science	4			
Student	34			
Educational Background (at least)				
Bachelor's Degree	73			
Postgraduate certificate/diploma	8			
Master's Degree	25			
PhD	4			
Undisclosed (assumes BD per inclusion criteria)	2			

1) supervisors engaged in innovation activities, such as R&D and new product management (hereafter, innovation managers);
2) supervisors with no engagement in innovation activities (hereafter, other managers);
3) undergraduate students or recent graduates categorizing themselves as students with no previous relevant work experience (hereafter, novices/students).

The experiment provided participants in these three groups with different information about new products to be launched in the market. Such information reflected difference valences of information and different amounts of information, which were validated for content and context with five innovation professionals before launching the first experiment.

1) Sample: We recruited 27 participants for the first experiment: nine innovation managers, nine other managers, and nine novices/students. Given that our aim was to validate constructs, content, procedures, and, particularly, to minimize type one errors, we considered nine participants per group, sufficient to avoid a false-positive (more than 50% of Eling et al.'s main study and 22% of West et al.'s main study). For robustness, we include power calculations, as reflected in Section IV.

We issued a direct invitation to participate in the online experiment to individuals whom we previously screened to categorize them as innovation managers, other managers, or novices/students ($N = 27$, with 10 observations per participant, two belonging to control treatments, equally divided across the three groups). Our study produced 270 observations (or decision points). All participants from each group were presented with a participant information statement and a consent form.

2) Procedures: We conducted a (3) x (2) x 3 experimental design (i.e., within-subjects design). Participants were randomly exposed first to either the treatment or control conditions (as a counterbalance). After completing the experimental tasks, participants answered an open-ended questionnaire, where we asked for key demographic information, including age, professional domain, and work tenure (see Table I for more detail).

Each participant was presented with an introduction to the experiment (see Appendix A). Next, we presented different scenarios, treatment and control, that included two different base rates to counterbalance the treatments and to ensure participants' answers were not primed by the base rate presented to them (see Measures below and Appendix B for more detail). Participants in the treatment condition were then presented with a product description/information with a positive or a negative valence, and with less (two stereotypical representations) or more information (four stereotypical representations—double the amount than in the "less" condition); the control condition did not present such information (see Appendix C for more detail). The information about a new product came in the form of the types of stories that are usually encountered before launching a product. Then, based on the scenario randomly presented to participants, we asked them to estimate the probability that the product being described belonged to the category of products presented in the base rate for each scenario (see Appendix D for more detail).

3) Measures: Our experiment included two scenarios with two different base rates. The first scenario, the high-success category (Hs), presented a sample of products of which 70% were successful and 30% were unsuccessful. The second scenario, the low-success category (Ls), presented a sample of products of which 70% were unsuccessful and 30% successful. All participants were asked in both scenarios to judge the probability of the new product belonging to either the Hs or Ls category. For example, scenario 2 (the Ls category) mentions, "The set from which the 100 new products are sampled consists of 30% successful new products, and 70% unsuccessful new products." In this case, the base rate for unsuccessful products is set at 70%. After being presented with a new product description/information (see Appendix C), participants were asked to answer: "On a scale 0 to 100, the probability that this product is one of the 70 unsuccessful new products in the sample of 100 is: ___" All participants were asked to provide an answer in a range from 0% to 100% in 10% increments (e.g., 0%, 10%, 20%, etc.)

Our experimental design allows us to calculate how different patterns of judgments identify a product as belonging to either category. For instance, following Bayes' rule, when provided with a base rate and no other relevant information, all participants should answer according to normative probability [23], [73]. Here, we would expect that all participants would deliberate and analyze, rather than using their intuition, to make judgments about the probability that a new product belongs to the Hs or Ls category.

According to Bayes' rule, the likelihood that a new product being described belongs to the Hs or Ls category is subject to the previously provided base rate when there is no other relevant information to consider. Our new product descriptions did not provide any relevant information affecting the probability presented in the base rate and presented stereotypical information about them (see Appendix C for more detail). That is, all product descriptions/information used stereotypical statements of their success/failure.

C. Study 2

In our first experiment, we established initial relationships of causality, and we tried to minimize type 1 error. In the second experiment, our aim was to increase our sample per group, for two reasons. First, we identified an effect in our first experiment between valence and amount of information and overlooking prior probabilities of success. As a result, we wanted to further incorporate an appropriate number of participants per group to determine whether our experimental design was at risk for a type 2 error. Second, with a larger sample, we could administer the questionnaire to collect further information and rule out the possibility that our results derived from presenting stereotypical information to participants rather than from their own decision-making style. In this second experiment, our procedures (including treatments, controls, counterbalancing, and randomization strategies) remain unchanged from study 1 to ensure consistency and content validity.

1) Sample: For our second experiment, we recruited 112 participants via Prolific (www.prolific.ac), 44 of them innovation managers, 34 other managers, and 34 novices/students. Power calculations are presented in Section IV for this experiment below.

The common criteria for innovation managers and other managers included participants between 21 and 65 years old with at least an undergraduate degree. Only participants with supervisory responsibilities were considered. In terms of industry role, we included participants who described their role as either junior management, middle management, upper management, self-employed, or partner. In terms of tenure, each participant was required to have been in their position for at least 12 months. For novices/students, the common criteria included participants who positively answered as having student status, either working toward or having completed an undergraduate degree with no relevant working experience. Table I shows a summary of the age, work tenure, and professional and educational characteristics of the sample.

IV. Results and Findings

A. Results of Study 1

We analyzed each participant's responses and compared them with the base rate we provided in each scenario. Consistent with our initial hypotheses, individuals who were exposed to any type of treatment provided an answer driven by the representation made by our new product stereotypical information, and did not decide judge rationally that a new product belonged to either the Ls or Hs categories. That is, their answers were different from the base rate provided because of our experimental manipulations/interventions, which did not provide any relevant information that could have changed the rate. This was our first indication that stereotypical information might, indeed, influence their judgments.

To eliminate the possibility of confounding influences, we exposed the same individuals to the control scenarios and treatments, thus increasing the experiment's internal validity. In the control scenarios, all participants answered in line with the expected base rate, which suggested that our controls worked, and, without any manipulation, participants were likely to decide more rationally. These results are statistically significant. Fig. 3 illustrates the results of our controls in the first experiment across

Fig. 3. Results of control treatment.

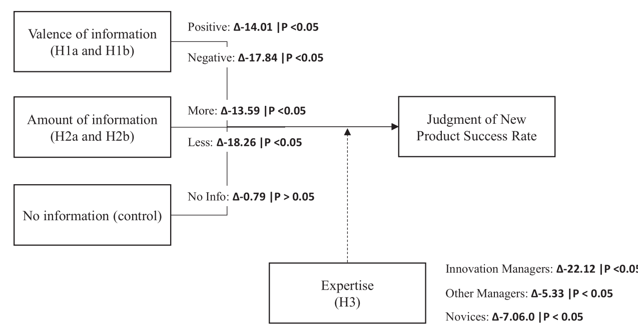

Fig. 4. Conceptual model and results of statistical analysis.

experimental groups. The base rate is represented in the line across the *X*-axis, which sits at 70% in both the Ls and Hs categories.

Once we statistically analyzed the observed answers across the groups' participants, we could establish that our control scenario and treatments were adequate (i.e., without any treatment, participants answering rationally on the given task).

Consistent with our preliminary hypotheses, the results suggest that there is an effect for valence and amount of stereotypical information across the different groups. Fig. 4 shows the conceptual model, overlaid by the results of our statistical analysis.

We conducted a series of two-tailed heteroskedastic *t*-tests across the different treatments of our experiment and compared the observations collected from participants' answers to the expected base rate in each scenario. Consistent with our initial hypotheses, we found that valence and amount of information affect the way participants judge and cast the new product success rate for either category of product in the experiment. However, when analyzing the different combinations of our treatments, we found no effect when we presented positive and more information. Per Bayes' rule, the mean in each case should not be statistically different from the 70% base rate provided across scenarios. Table II summarizes our results per experimental group and treatments in more detail.

The results of our first experiment demonstrate that our constructs, content, treatments/manipulations, and control scenarios were adequate. Furthermore, they suggest that there is, indeed, a representativeness effect caused by valence and amount of stereotypical information for judging the new product success rate of the given tasks, consistent with previous heuristics research [11], [37]. Additionally, the results suggest that we

TABLE II
SAMPLE MEAN AND STANDARD DEVIATION OF TREATMENT ACROSS EXPERIMENTAL GROUPS

	Innovation Managers*			Other Managers**			Students**		
Treatments	*N*	*Mean*	*SD*	*N*	*Mean*	*SD*	*N*	*Mean*	*SD*
Positive & Less Information	9	45	13	9	51	10	9	65	2
Postive & More Information**	9	56	7	9	64	3	9	64	3
Negative & Less Information	9	48	11	9	60	5	9	52	9
Negative & More Information	9	43	14	9	63	3	9	58	6

Note: Means are expressed as percentages. $*p < 0.05$ | $**p > 0.05$.

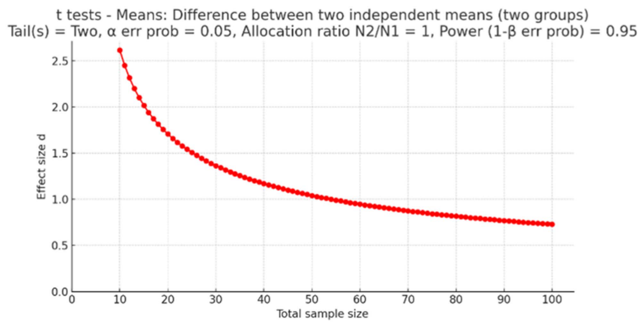

Fig. 5. Effect size chart as a function of total sample.

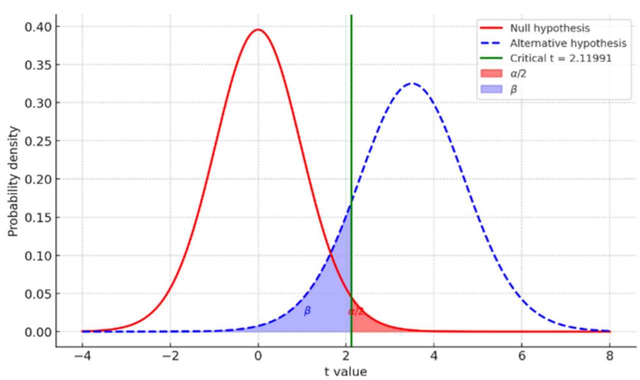

Fig. 6. Central and noncentral distributions of the first experiment.

appropriately addressed the risk of a type 1 error, as the results were analyzed through a predefined alpha value of $p<0.05$ in the case of the treatments, and $p>0.05$ in the case of the control.

Having found an effect, we wanted to understand its size, to make sure we included an appropriate number of participants for the second experiment (where we need to minimize the risk of a type 2 error). To address this, we used the information in the first experiment to calculate the effect size of the first experiment via G∗POWER software. Fig. 5 shows the plotted values, assuming a two-tailed test with an alpha of 0.05 and a sample of nine participants per experimental group.

Considering the results of the critical $t = 2.11991$ (with Df = 16, where Fig. 6 shows the central and noncentral distributions), we have an effect size $|p| = 1.812109$. These results suggest that the size of the representativeness heuristic effect in relation to judging new product success is very large [67], [74] per the experimental group.

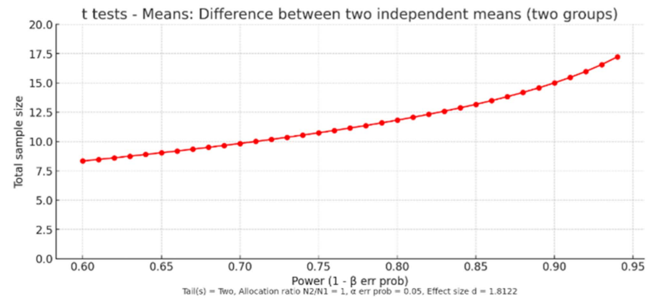

Fig. 7. Priori sample requirements.

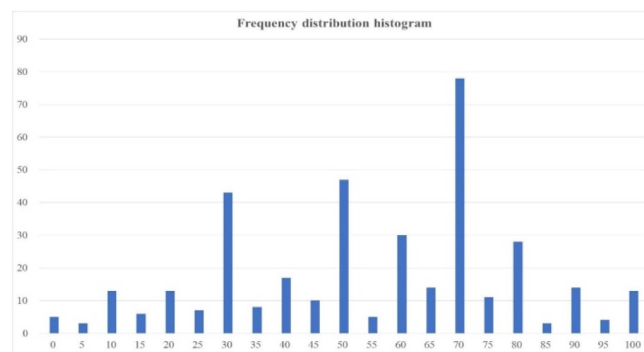

Fig. 8. Frequency distribution histogram.

B. Results of Study 2

After performing the effect size calculation, we were able to input the Cohen's coefficient back into G∗Power (i.e., 1.812109). In the power analysis, we used a 0.99 assumption as 1-β error probability that, in combination with the effect size, enables a more accurate sample size per group. This calculation resulted in a total sample of 13 participants required per group. Fig. 7 shows the plotted values for power analysis.

We revisited the information from the first experiment to understand whether the data were normal and to further estimate any adjustments to the sample. Fig. 8 shows the frequency distribution histogram based on information provided for the treatments and/or manipulation only; because all participants went through the control treatments, plotting this information would have created an artificial view of their answers.

As shown in Fig. 8, the data are positively skewed. This helped us to re-estimate the suggested sample size and increase it to at least 30 participants to normalize the data, as suggested by the central limit theorem, and as used by other experimental researchers [67], [75]. Our sample meets this re-estimation; as a result, we obtained 1120 experimental observations (ten per participant, two in the control scenarios).

We followed the same approach as in our first experiment (study 1). First, we looked at the results of the control scenarios and then those of the treatments to ensure that, without any manipulation, all participants performed the task rationally. Doing so allowed us to minimize the possible appearance of a confounding influence. Consistent with our first study, the second experiment further provided evidence that participants

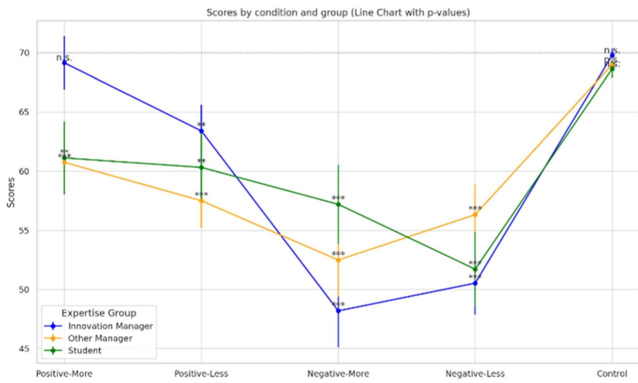

Fig. 9. *X*-axis in percentage. Mean results across experimental groups and treatments. Note: $*p < 0.05$ | $**p < 0.01$ | $***p < 0.001$ | n.s. indicates a nonsignificant difference (p-value ≥ 0.05). *T*-tests are based on a two-tailed, one-sample (observed, with a constant base-rate) with unequal variances analysis.

who are not exposed to any manipulation tend to answer along the lines of probability ($F = 0.7248$, $p > 0.05$).

We then looked more closely at the results of our treatments across experimental groups. We found a significant effect driven by both valence and amount of information in participants' answers. We analyzed the treatments applied to participants through ANOVA analysis and *t*-tests. We adopted these two analytical approaches to ensure our experiment was showing that innovation managers, other managers, and novices/students made judgments in the presence of representative (stereotypical) information, and that how a new product was judged as successful/unsuccessful depended on whether we presented positive or negative information, and less or more of that information.

The ANOVA between groups suggested both valence and amount of information influenced the likelihood of being asked across participants ($F = 4.04$, $p < .05$). The *t*-tests further suggested that the likelihood operated differently across experimental groups and was not the same for all conditions. Fig. 9 shows the results for the observed means and the *t*-tests across groups and across conditions to evaluate its statistical significance.

C. Complementary Results of the Rational–Emotive Questionnaire

To provide more context for the stated disposition to process information and for whether participants acted more rationally/intuitively, we complemented our experimental results by administering a rational–emotive questionnaire (REI-40) to participants. To ensure the REI questionnaire was anchored in an innovation context, we asked participants to answer questions while thinking about a time when they were involved in an innovation project or endeavor. We used a 5-point Likert answer-scale from "Strongly Disagree" to "Strongly Agree" (Cronbach $\alpha = 0.92$, low correlational items removed).

Based on their questionnaire answers, we profiled each participant as "rational," "intuitive," or "balanced." To do so, we summed items related to either rationality or intuitive information processing, and compared them to the maximum possible answer in each category. For example, if Participant A had a sum of 33 of the 50 possible points for the rational items, they received a score of 0.66. We continued this process across rational and intuitive items for all 112 participants in all experimental groups. Next, we compared participants' rational and intuitive scores. If Participant A had a rational score higher than their intuitive score, we profiled them as "rational." If Participant B had an intuitive score higher than their rational score, we profiled them as "intuitive." If there was no difference in their scores, we profiled them as "balanced." Next, we overlaid the participants' profiles onto their answers to determine whether their disposition to process information rationally/intuitively corresponded with more rational/intuitive judgments. Table III shows participants' answers to each treatment per experimental group, subdivided by their self-perceived decision-making disposition.

TABLE III
OBSERVED MEANS' (T-TEST, TWO-TAILED, WITH UNEQUAL VARIANCES) RESULTS PER TREATMENT AND CONTROL CONDITIONS

	Mean results per treatment and control				
N=112	*Postive-Less*	*Positive-More*	*Negative-Less*	*Negative-More*	*No Information*
Innovation Managers (N=44, p<0.05)	**63**	**68**	**51**	**49**	**70**
Rational (N=7)	59	61	41	41	69
Intuitive (N=31)	64	69	53	50	70
Balanced (N=6)	62	72	50	56	71
SD	*2*	*5*	*5*	*6*	*1*
p-value	*0.02*	*0.49*	*0.03*	*0.04*	*0.85*
Other Managers (N=34, p>0.05)	**59**	**61**	**57**	**54**	**69**
Rational (N=7)	55	60	55	50	70
Intuitive (N=25)	59	61	56	54	69
Balanced (N=2)	70	70	73	70	65
SD	*6*	*5*	*8*	*9*	*2*
p-value	*0.19*	*0.18*	*0.26*	*0.19*	*0.36*
Students (N=34, p<0.05)	**61**	**62**	**51**	**56**	**69**
Rational (N=7)	62	61	54	67	69
Intuitive (N=22)	60	59	53	55	69
Balanced (N=5)	62	77	40	47	68
SD	*1*	*8*	*6*	*8*	*1*
p-value	*0.01*	*0.52*	*0.04*	*0.14*	*0.07*

Note: p-values and standard deviations are at total level.

D. Summary of Results

Our results suggest that all participants make intuitive judgments when exposed to the different valences and amounts of information in our experiment. The representations provided by our experimental treatments affect how these experimental groups judged a new product belonging to the successful/unsuccessful category. Following Bayes' rule, we expected the probability of a new product's description belonging to the successful rather than unsuccessful category would be consistent with the actual base rate provided. For example, when we provided a base rate of 70% or 30% for the successful category, the odds would remain as 70/30 for the Hs category or 30/70 for the Ls category. In this regard, only when participants were not exposed to any new product information did they not show any statistically significant variation from the base rate, which suggests they make more rational judgments.

These results suggest there is a moderating effect of expertise on the representations presented across all three experimental groups but with a different magnitude across groups (see Section V). Overall, participants, including innovation managers, tended to answer intuitively, such that representations of what is successful triggered a recollection of what is new product success, and the information presented triggered the representativeness heuristic, as in other tests of the representativeness heuristic [23]. Table IV summarizes the hypotheses tested and the outcomes of our experiment.

TABLE IV
HYPOTHESES OUTCOMES

Hypothesis	Outcome
H1a: *If* innovation managers are exposed to positive stereotypes regarding new product success (positive representativeness), then their judgments about a product being successful/unsuccessful will likely overlook the prior probabilities (base rates) of new product success that are presented to them	Supported
H1b: *If* innovation managers are exposed to negative stereotypes regarding new product success (negative representativeness), then their judgments about a product being successful/unsuccessful will likely overlook the prior probabilities (base rates) of new product success that are presented to them	Supported
H2a: *If* innovation managers are presented with more representations of stereotypical information about new product success, then their judgments about a product being successful/unsuccessful will likely overlook the prior probabilities (base rates) of new product success that are presented to them	Supported
H2b: *If* innovation managers are presented with less representations of stereotypical information about new product success, then their judgments about a product being successful/unsuccessful will likely overlook the prior probabilities (base rates) of new' product success that are presented to them	Supported
H3: Innovation managers are likely to make intuitive judgments about a product being successful/unsuccessful, such that the valence and amount of information will be more representative to them than to other managers (with no experience in innovation) and to novices/ students (with no previous relevant working experience). That is, innovation managers will tend to neglect base rates as much as other managers and novices/'students do, and their expertise will offer minimal advantage in making more accurate judgments.	Partially supported (positive-more condition)

Note: Supported means that the null hypothesis has been rejected, as there is statistical information and evidence suggesting that the alternative hypotheses (H1 to H3, with the exclusion of the group of novices) are true.

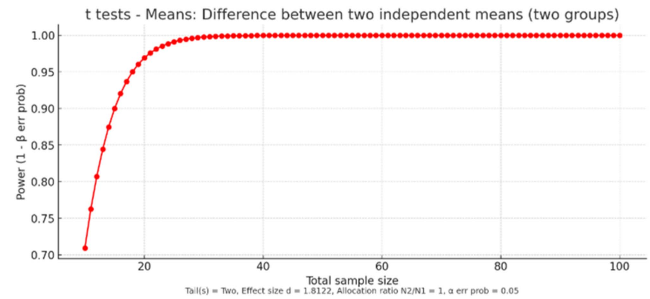

Fig. 10. Posthoc power analysis of decision-making experiment.

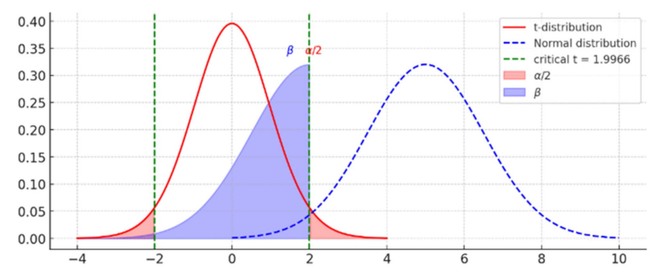

Fig. 11. Posthoc central and noncentral distributions.

E. Validity Checks

Following these results, we conducted a series of checks to ensure construct and content validity [76, p. 400]. This enriches the overall legitimacy of our experimental results and limits the possibility of false inferences [77, p. 688], [78]. Our validity checks consisted of four steps. First, for internal validity, we ensured that our second experiment followed the same variables and experimental treatments as our first study to ensure participants were clear about both the meaning and task of the second experiment [78]. Second, by observing participants' answers across experimental groups, we ensured that during the second experiment, the treatments of the independent variables happened ahead of measuring the changes in the treatments' dependent variable [77, p. 688]. Doing this allowed us to evaluate whether the levels of manipulation in valences and amount of information were appropriate. Third, we ensured that our statistical analysis yielded significant results as to the cause–effect under investigation. We looked at an asymmetrical relationship in the data distribution (two-tailed) in all directions, and at the analysis of the variances between the expected and observed means per and across groups to ensure both construct and context validity [76, p. 400]. To present the power of our experimental test on a posthoc basis, Fig. 10 shows the plotted values, considering a minimum of 34 participants per group, and Fig. 11 shows the central and noncentral distributions posthoc. We conclude that our study was adequately powered.

V. DISCUSSION

It is often argued that heuristic-based managerial decisions can match the accuracy of deliberate, analytical approaches, especially in the case of expert decision makers [29]. However, our analysis suggests they tend to lead to inaccurate judgments. Information about innovation projects shapes subsequent decision-making [79]. In our study, when such information carries a particular valence, and particularly a negative valence of information, it impacts all experimental groups, regardless of their level of expertise in the subject matter. However, when information is positively valenced and subject to the amount of information, innovation managers tend to make more accurate and rational decisions. This could be attributed to an overabundance of positivity, aligning with behavioral research suggesting skepticism towards overly positive stories [80], [81]. In all other interventions—specifically, when innovation managers are presented with the following:

1) positively valenced information (i.e., positive stereotypes) but less of it;
2) negatively valenced information (negative stereotypes) but more of it;
3) negatively valenced information but less of it—they exhibit the base rate neglect phenomenon discussed in the literature.

The representativeness heuristic's impact is further evidenced by our finding that in the absence of stereotypical representations, participants' judgments aligned closely with the base rate, indicating more deliberative judgments.

In summary, our research reveals that valence and amount of information about new product success led to inaccurate intuitive judgments, deviating from the base rate neglect bias. These findings have implications for understanding the role of expertise in heuristic-based decision-making, particularly in new product development and launch contexts. Contrary to previous studies [82], our results indicate that experience does not necessarily improve innovation managers' performance.

A. Implications for Scholars

Our study extends the conversation initiated by Eling et al. and West et al. by focusing on the nuanced effects of stereotypical information on innovation management judgments. Previous research suggests that a mix of careful deliberation and intuition enhances the accuracy and effectiveness of decisions in innovation [20]. Yet, despite Eling et al.'s recommendation to use a combination of reason and intuition, and West et al.'s assertion of the significant role of heuristics in producing good judgments, our empirical evidence reveals that seasoned managers are not immune to the effect of the representativeness heuristic. Indeed, our examination of both positive and negative stereotypical information, and various amounts of that information, generates a critical discovery: The representativeness heuristic skews perceptions of new products and their success rates. Consequently, our results challenge the assumption that expertise equates to better judgmental prowess in innovation contexts.

Our experimental investigation offers valuable insights for scholars in innovation, particularly those studying new product success. The evidence we provide can form the basis for new hypotheses about the role of heuristics in intuitive judgments during the development and launch of new products. Our findings indicate that while heuristics are a common aspect of new product development and innovation [79], they can lead to judgment and decision-making errors [3], thus highlighting their impact on evaluating new product success. It initiates a discussion of how context and cognition interact when making complex and uncertain judgments in innovation and suggests that a deeper understanding of expertise could enrich academic exploration in this area.

B. Implications for Practitioners

Our research reveals four major implications for innovation practice. First, we find that managers often use storytelling to highlight the potential success of new products and generate interest in their innovations. However, this storytelling risks oversimplifying definitions of success, leading to reliance on information that impairs decisions. Telling stories is a compelling means of winning over decision makers, as reflected in Aristotle's advice to include logos, ethos, and pathos in rhetorical appeals. However, the impact of doing so with stereotypical information may create too great a cost to bear. This highlights the importance of providing ways to highlight base-rate estimation for new products much more than we currently do. While past data cannot always predict future outcomes, it provides essential facts that can improve assessments of new product performance. Second, our findings emphasize that factual information (e.g., base rates) plays a more valuable role than stereotypes in making accurate judgments. When communicating about new products, it is crucial to include base rates that reflect the historical likelihood of success. This information should be presented as prominently as other types of data in product presentations. By doing so, innovation managers can balance their enthusiasm for a new product with hard data, leading to more informed decision-making processes. Third, and as we know from previous research, intuitive judgments might produce inaccurate answers. However, our study highlights that innovation managers' expertise may not be reliable, particularly when faced with information that is portrayed as relevant to their innovation project but that is actually stereotypical and irrelevant. Our results invite practitioners to envision decision-making processes that incorporate and balance deliberation with intuition. Fourth, and given our finding that expertise does not necessarily curb the use of heuristics, lifelong learning and training appear to be necessary to improve decision making in corporate settings and to improve the use of corporate resources in innovative initiatives. These changes would help shine a spotlight on innovation in companies that have not yet embraced it as a way to fuel growth. To reduce reliance on stereotypes that obscure rather than clarify decision-making processes, managers can establish evaluation criteria to guide their judgments [83] before receiving and reviewing information about an innovation project. In addition, emphasizing the practical value and utility of new products is crucial. Supporting these aspects with data, especially including base-rate information, can strengthen arguments for a product's success. This approach not only promotes more accurate assessments but also helps garner organizational support and acceptance for new products. Given that executives are biased toward the idea that innovation tends to fail, this approach will help build an organizational culture where innovative ideas are carefully scrutinized rather than discarded.

VI. Conclusion

A. Limitations and Future Research

As with any study, this one is subject to certain limitations. To begin with, our sample did not allow us to investigate whether there is a significant difference in decision-making between industries, across gender, and within teams. Replicating this experiment with different valences and amounts of information that reflect different sectors of the economy would be a fruitful avenue for future research. For example, the interpretation of success or failure may differ significantly between industries: in mining, for example, decision-making typically occurs within the framework of large-scale operations and long-term planning, whereas in the fast-moving consumer goods industry, decisions are influenced by rapid market feedback and require agility. As this is the first study of its kind, we deliberately investigated the phenomenon in a broader setting, within the realm of new product success.

Additionally, future research could investigate the representativeness heuristics in conjunction with other prominent heuristics, such as the recognition heuristic [84], [85], [86] and the availability heuristic [87]. There are reasons to believe that such heuristics may operate in conjunction with one another rather than in isolation, or that they can be a better way to reach judgments in some contexts. For instance, research has found that judgments made under uncertainty require the use of heuristics [84]. One reason for this could be that base rates provided to innovation managers may serve more as a measure for evaluating risk rather than uncertainty. From this viewpoint, heuristics are not considered a judgment flaw but rather a feature of reaching good judgments in uncertain situations. Determining when intuitive judgments are not prone to errors would assist innovation managers in making more informed, rapid, and accurate judgments. This would require them to take a new paradigmatic approach to the role of heuristics than that taken in this study.

Future studies might also reconceptualize the constructs of "less information" and "more information." For example, they should explore the less-is-more effect when dealing with innovation data [85], [86]. An open question is whether this effect is an underlaying mechanism (i.e., mediating variable) for producing more accurate judgments. Finally, exploring the role of serendipity presents an exciting avenue for research. This includes investigating how organizations might identify strategic opportunities that unexpectedly arise from judgment errors [88] and whether organizations can leverage these serendipitous discoveries [88] to enhance their innovation and decision-making processes. Such research could also consider how organizations use heuristics to make swift and effective decisions within this context, as suggested above.

B. Final Remarks

This study represents a first attempt to establish relationships of causality in the context of intuitive judgement in new product success. We contribute to the innovation literature by providing evidence that intuitive judgments are found in evaluations of new product success because innovation managers are influenced by stereotypical information representing the success or failure of a new product, which in turn leads to suboptimal outcomes. To foster effective innovation and superior firm performance, innovation scholars and practitioners alike should seek to balance stereotypical information with factual data.

Appendix

A. Introduction and Situation

WELCOME! - Please follow the instructions below:

You will be shown scenarios presenting the historical success rates of new products launched by Company X.

Within each scenario, there will be descriptions of the new products Company X is looking to commercialize.

These products are sampled from a set of 100 new products, which the company has categorized into two potential groups: 1) successful and 2) unsuccessful.

The task:

1) For each product description provide the probability that the product belongs to either the successful or unsuccessful category.
2) You have 30 s to provide your answer for each product description. A countdown will be shown to you at the 10 s mark. Regardless of whether you answer in this timeframe, the system will automatically take you to the next product description.

B. Scenarios

1) Treatment Scenarios:

1) The set from which the 100 new products are sampled consists of 30% successful new products, and 70% unsuccessful new products.
2) The set from which the 100 new products are sampled consists of 30% unsuccessful new products, and 70% successful new products.

2) Control Scenarios:

1) "The set from which the 100 new products are sampled consists of 30% successful new products, and 70% unsuccessful new products.
   In this scenario, no product description has been provided by the company"
2) "The set from which the 100 new products are sampled consists of 30% unsuccessful new products, and 70% successful new products.
   In this scenario, no product description has been provided by the company"

C. Example Descriptions/Information for Both Treatments and Controls

1) Treatments (New Product Descriptions): Positive description with less information (two new product descriptions). For example

1) the new product will disrupt the market through its innovative proposition;
2) the new product's profit-and-loss statement shows a positive position for the first three years of its launch.

Positive description with more information (four new product descriptions). For example

1) the new product has created a marketing strategy for its launch that has never been seen in the industry;
2) the new product has the full support of the brand team for its commercialization;
3) the new product will contribute to the company's portfolio without any detriment to its current negotiations with major clients;
4) the new product launch has made the C-suite excited about its revenue prospects.

Negative description with less information (two new product descriptions). For example

1) the new product has spent too much time in the commercialization stage and there are some doubts around its final functionality;
2) the new product's digital platform has some minor coding errors, which are unnoticeable to users.

Negative description with more information (four new product descriptions). For example

1) the new product has served as a "cautionary tale" for the company's innovation team;
2) the new product is struggling to find the sweet-spot for the final pricing for the company's customers;
3) the new product launch has made the operations team angry, and they are not in full agreement with its commercialization;

4) the new product will not be a disruptor in the market, and it is only expected to bring incremental benefits for the company

Control description (no new product descriptions). For example

1) no product description/information available to you.

D. Tasks

1) Treatment Tasks:

1) On a scale of 0 to 100, the probability that this product is one of the 70 successful new products in the sample of 100 is.
2) On a scale of 0 to 100, the probability that this product is one of the 70 unsuccessful new products in the sample of 100 is.

2) Control Tasks:

1) On a scale of 0 to 100, the probability that any given new product is one of the 70 successful new products in the sample of 100 is.
2) On a scale of 0 to 100, the probability that any given new product is one of the 70 unsuccessful new products in the sample of 100 is.

References

[1] A. Kock, H. G. Gemünden, S. Salomo, and C. Schultz, "The mixed blessings of technological innovativeness for the commercial success of new products," *J. Prod. Innov. Manage.*, vol. 28, no. s1, pp. 28–43, Nov. 2011, doi: 10.1111/j.1540-5885.2011.00859.x.

[2] V. Krishnan and K. T. Ulrich, "Product development decisions: A review of the literature," *Manage. Sci.*, vol. 47, no. 1, pp. 1–21, Jan. 2001, doi: 10.1287/mnsc.47.1.1.10668.

[3] J. Liedtka, "Perspective: Linking design thinking with innovation outcomes through cognitive bias reduction," *J. Prod. Innov. Manage.*, vol. 32, no. 6, pp. 925–938, 2015, doi: 10.1111/jpim.12163.

[4] V. P. Seidel and S. K. Fixson, "Adopting design thinking in novice multidisciplinary teams: The application and limits of design methods and reflexive practices," *J. Prod. Innov. Manag.*, vol. 30, no. S1, pp. 19–33, Dec. 2013, doi: 10.1111/jpim.12061.

[5] M. Garbuio and G. Gheno, "An algorithm for designing value propositions in the IoT space: Addressing the challenges of selecting the initial class in reference class forecasting," *IEEE Trans. Eng. Manage.*, vol. 70, no. 9, pp. 3171–3182, Sep. 2023.

[6] A. Klein, C. Sørensen, A. S. de Freitas, C. D. Pedron, and S. Elaluf-Calderwood, "Understanding controversies in digital platform innovation processes: The Google Glass case," *Technological Forecasting Social Change*, vol. 152, pp. 119883, 2020.

[7] N. A. Anaza, E. Kemp, E. Briggs, and A. L. Borders, "Tell me a story: The role of narrative transportation and the C-suite in B2B advertising," *Ind. Marketing Manage.*, vol. 89, pp. 605–618, 2020.

[8] W. H. Starbuck, "Five stories that illustrate three generalizations about radical innovations," *Ind. Marketing Manage.*, vol. 43, no. 8, pp. 1278–1283, 2014.

[9] Z. Wang, "Launching new products using storytelling as a powerful entrepreneurial tool," in *Proc. 2nd Int. Conf. Enterprise Manage. Econ. Develop.*, 2022, pp. 123–128.

[10] N. Sergeeva and A. Trifilova, "The role of storytelling in the innovation process," *Creative Innov. Manage.*, vol. 27, no. 4, pp. 489–498, 2018.

[11] K. Fiedler and M. von Sydow, "Heuristics and biases: Beyond Tversky and Kahneman's (1974) judgment under uncertainty," in *Cognitive Psychology: Revisiting the Classical Studies*, London, U.K.: Sage, 2015, pp. 146–161.

[12] D. Kahneman, "Maps of bounded rationality: Psychology for behavioral economics," *Amer. Econ. Rev.*, vol. 93, no. 5, pp. 1449–1475, 2003.

[13] A. Tversky and D. Kahneman, "Judgment under uncertainty: Heuristics and biases," *Science*, vol. 185, no. 4157, pp. 1124–1131, 1974.

[14] M. Heimstädt, T. Koljonen, and K. T. Elmholdt, "Expertise in management research: A review and agenda for future research," *Acad. Manage. Ann.*, vol. 18, no. 1, pp. 121–156, Jan. 2024, doi: 10.5465/annals.2022.0078.

[15] J. K. Phillips, G. Klein, and W. R. Sieck, "Expertise in judgment and decision making: A case for training intuitive decision skills," in *Blackwell Handbook of Judgment and Decision Making*, 1st ed., D. J. Koehler and N. Harvey, Eds. Oxford, U.K.: Blackwell Pub. Ltd, 2008, pp. 297–315.

[16] G. Calabretta, G. Gemser, and N. M. Wijnberg, "The interplay between intuition and rationality in strategic decision making: A paradox perspective," *Org. Stud.*, vol. 38, no. 3/4, pp. 365–401, 2017.

[17] R. Eliëns, K. Eling, S. Gelper, and F. Langerak, "Rational versus intuitive gatekeeping: Escalation of commitment in the front end of NPD," *J. Prod. Innov. Manage.*, vol. 35, no. 6, pp. 890–907, 2018, doi: 10.1111/jpim.12452.

[18] K. Eling, F. Langerak, and A. Griffin, "The performance effects of combining rationality and intuition in making early new product idea evaluation decisions," *Creativity Innov. Manage.*, vol. 24, no. 3, pp. 464–477, 2015.

[19] S. Feurer, M. C. Schuhmacher, and S. Kuester, "How pricing teams develop effective pricing strategies for new products," *J. Prod. Innov. Manage.*, vol. 36, pp. 66–86, 2018.

[20] D. C. West, O. A. Acar, and A. Caruana, "Choosing among alternative new product development projects: The role of heuristics," *Psychol. Marketing*, vol. 37, no. 11, pp. 1511–1524, 2020.

[21] X. Martin and W. Mitchell, "The influence of local search and performance heuristics on new design introduction in a new product market," *Res. Policy*, vol. 26, no. 7/8, pp. 753–771, 1998.

[22] A. B. Saab and D. Botelho, "Are organizational buyers rational? Using price heuristics in functional risk judgment," *Ind. Marketing Manage.*, vol. 85, pp. 141–151, 2020.

[23] D. Kahneman and A. Tversky, "Subjective probability: A judgment of representativeness," in *The Concept of Probability in Psychological Experiments*. New York, NY, USA: Springer, 1972, pp. 25–48.

[24] M. D. Packard, B. B. Clark, and P. G. Klein, "Uncertainty types and transitions in the entrepreneurial process," *Org. Sci.*, vol. 28, no. 5, pp. 840–856, Oct. 2017, doi: 10.1287/orsc.2017.1143.

[25] S. Ægisdóttir et al., "The meta-analysis of clinical judgment project: Fifty-six years of accumulated research on clinical versus statistical prediction," *Couns. Psychol.*, vol. 34, no. 3, pp. 341–382, 2006.

[26] R. F. Baumeister, E. Bratslavsky, C. Finkenauer, and K. D. Vohs, "Bad is stronger than good," *Rev. Gen. Psychol.*, vol. 5, no. 4, pp. 323–370, 2001.

[27] W. M. Grove, D. H. Zald, B. S. Lebow, B. E. Snitz, and C. Nelson, "Clinical versus mechanical prediction: A meta-analysis," *Psychol. Assess.*, vol. 12, no. 1, pp. 19–30, 2000.

[28] V. P. Rindova and L. L. Martins, "Futurescapes: Imagination and temporal reorganization in the design of strategic narratives," *Strategic Org.*, vol. 20, no. 1, pp. 200–224, Feb. 2022, doi: 10.1177/1476127021989787.

[29] D. Kahneman and A. Tversky, "Prospect theory: An analysis of decision under risk," *Econometrica*, vol. 47, no. 2, pp. 263–291, 1979, doi: 10.2307/1914185.

[30] P. Rozin and E. B. Royzman, "Negativity bias, negativity dominance, and contagion," *Pers.. Soc. Psychol. Rev.*, vol. 5, no. 4, pp. 296–320, 2001.

[31] C. Unkelbach, H. Alves, and A. Koch, "Negativity bias, positivity bias, and valence asymmetries: Explaining the differential processing of positive and negative information," in *Advances in Experimental Social Psychology*, vol. 62. Amsterdam, The Netherlands: Elsevier, 2020, pp. 115–187.

[32] L. Baldacchino, D. Ucbasaran, L. Cabantous, and A. Lockett, "Entrepreneurship research on intuition: A critical analysis and research agenda," *Int. J. Manage. Rev.*, vol. 17, no. 2, pp. 212–231, 2015.

[33] M. Dayan and S. Elbanna, "Antecedents of team intuition and its impact on the success of new product development projects," *J. Prod. Innov. Manage.*, vol. 28, no. s1, pp. 159–174, 2011, doi: 10.1111/j.1540-5885.2011.00868.x.

[34] K. Eling, A. Griffin, and F. Langerak, "Using intuition in fuzzy front-end decision-making: A conceptual framework," *J. Prod. Innov. Manage.*, vol. 31, no. 5, pp. 956–972, 2014, doi: 10.1111/jpim.12136.

[35] E. Sadler-Smith and E. Shefy, "The intuitive executive: Understanding and applying 'gut feel' in decision-making," *Acad. Manage. Exec.*, vol. 18, no. 4, pp. 76–91, 2004.

[36] D. Bardolet, C. R. Fox, and D. Lovallo, "Corporate capital allocation: A behavioral perspective," *Strateg. Manage. J.*, vol. 32, no. 13, pp. 1465–1483, 2011.

[37] D. Kahneman and A. Tversky, "On the psychology of prediction," *Psychol. Rev.*, vol. 80, no. 4, pp. 237–251, 1973.

[38] J. W. Dean and M. P. Sharfman, "Procedural rationality in the strategic decision-making process," *J. Manage. Stud.*, vol. 30, no. 4, pp. 587–610, 1993.

[39] M. Vettorello, B. Eisenbart, and C. Ranscombe, "The innovation system roadmap: A novel approach to instil futures-oriented reasoning in strategic decision making," *Creat. Innov. Manage.*, vol. 31, no. 1, pp. 5–18, Mar. 2022, doi: 10.1111/caim.12472.

[40] L. Baldacchino, "Entrepreneurial experience and opportunity identification: The role of intuition and cognitive versatility," Ph.D. thesis, Univ. Warwick, Coventry, U.K., 2013.

[41] K. Matzler, B. Uzelac, and F. Bauer, "Intuition's value for organizational innovativeness and why managers still refrain from using it," *Manage. Decis.*, vol. 52, no. 3, pp. 526–539, 2014, doi: 10.1108/MD-08-2013-0404.

[42] C. D. von Hippel and A. B. Cann, "Behavioral innovation: Pilot study and new Big Data analysis approach in household sector user innovation," *Res. Policy*, vol. 50, no. 8, Oct. 2021, Art. no. 103992, doi: 10.1016/j.respol.2020.103992.

[43] K. Matzler, C. Grabher, J. Huber, and J. Füller, "Predicting new product success with prediction markets in online communities," *RD Manage.*, vol. 43, no. 5, pp. 420–432, Nov. 2013, doi: 10.1111/radm.12030.

[44] G. Marzi, F. Ciampi, D. Dalli, and M. Dabic, "New product development during the last ten years: The ongoing debate and future avenues," *IEEE Trans. Eng. Manag.*, vol. 68, no. 1, pp. 330–344, Feb. 2021.

[45] K. R. Sarangee, J. L. Woolley, J. B. Schmidt, and E. Long, "De-escalation mechanisms in high-technology product innovation," *J. Prod. Innov. Manage.*, vol. 31, no. 5, pp. 1023–1038, 2014, doi: 10.1111/jpim.12142.

[46] C. W. Scheiner, C. V. Baccarella, J. Bessant, and K.-I. Voigt, "Thinking patterns and gut feeling in technology identification and evaluation," *Technological Forecasting Social Change*, vol. 101, pp. 112–123, 2015.

[47] D. Chatterjee, "Leadership in innovators and defenders: The role of cognitive personality styles," *Ind. Innov.*, vol. 21, no. 5, pp. 430–453, 2014, doi: 10.1080/13662716.2014.959314.

[48] U. De Brentani and S. E. Reid, "The fuzzy front-end of discontinuous innovation: Insights for research and management," *J. Prod. Innov. Manage.*, vol. 29, no. 1, pp. 70–87, 2012, doi: 10.1111/j.1540-5885.2011.00879.x.

[49] S. E. Reid and U. De Brentani, "The fuzzy front end of new product development for discontinuous innovations: A theoretical model," *J. Prod. Innov. Manage.*, vol. 21, no. 3, pp. 170–184, 2004, doi: 10.1111/j.0737-6782.2004.00068.x.

[50] Y.-C. Sun and O. G. Clark, "Implementing an intuitive reasoner with a large weather database," *Int. J. Comput. Intell.*, vol. 5, no. 2, pp. 85–102, 2009.

[51] T. Taura and Y. Nagai, "Creativity in Innovation Design: The roles of intuition, synthesis, and hypothesis," *Int. J. Des. Creativity Innov.*, vol. 5, no. 3–4, pp. 131–148, 2017.

[52] M. Dayan and C. A. Di Benedetto, "Team intuition as a continuum construct and new product creativity: The role of environmental turbulence, team experience, and stress," *Res. Policy*, vol. 40, no. 2, pp. 276–286, 2011.

[53] K. C. Kostopoulos, Y. E. Spanos, and G. P. Prastacos, "Structure and function of team learning emergence: A multilevel empirical validation," *J. Manage.*, vol. 39, no. 6, pp. 1430–1461, 2013.

[54] E. A. Elliot and C. Nakata, "Cross-cultural creativity: Conceptualization and propositions for global new product development," *J. Prod. Innov. Manage.*, vol. 30, no. S1, pp. 110–125, 2013.

[55] F. W. English and L. C. Ehrich, "Innovatus interregnum: Waiting for a paradigm shift," *Int. J. Educ. Manage.*, vol. 29, no. 7, pp. 851–862, 2015.

[56] D. Kandemir and N. Acur, "Examining proactive strategic decision-making flexibility in new product development," *J. Prod. Innov. Manage.*, vol. 29, no. 4, pp. 608–622, 2012, doi: 10.1111/j.1540-5885.2012.00928.x.

[57] P. R. Magnusson, J. Netz, and E. Wästlund, "Exploring holistic intuitive idea screening in the light of formal criteria," *Technovation*, vol. 34, no. 5, pp. 315–326, 2014.

[58] H. A. Simon, "Theories of bounded rationality," *Decis. Org.*, vol. 1, no. 1, pp. 161–176, 1972.

[59] R. K. Moenaert, H. Robben, M. Antioco, V. De Schamphelaere, and E. Roks, "Strategic innovation decisions: What you foresee is not what you get," *J. Prod. Innov. Manage.*, vol. 27, no. 6, pp. 840–855, 2010.

[60] L. F. Barrett, "Solving the emotion paradox: Categorization and the experience of emotion," *Pers.. Soc. Psychol. Rev.*, vol. 10, no. 1, pp. 20–46, Feb. 2006, doi: 10.1207/s15327957pspr1001_2.

[61] B. Osnes, S. R. Berrefjord, P. G. Poless, C. Sigrist, J. Koenig, and L. Sørensen, "Low heart rate variability is associated with a negativity valence bias in interpreting ambiguous emotional expressions," *Emotion*, vol. 23, no. 4, pp. 1040–1047, 2023.

[62] C. I. Tsai and M. Thomas, "When does feeling of fluency matter? How abstract and concrete thinking influence fluency effects," *Psychol. Sci.*, vol. 22, no. 3, pp. 348–354, 2011.

[63] C. Camerer, "Bounded rationality in individual decision making," *Exp. Econ.*, vol. 1, no. 2, pp. 163–183, 1998.

[64] B. Schwartz, A. Ward, J. Monterosso, S. Lyubomirsky, K. White, and D. R. Lehman, "Maximizing versus satisficing: Happiness is a matter of choice," *J. Pers. Soc. Psychol.*, vol. 83, no. 5, pp. 1178–1197, 2002.

[65] M. Ozer, "Factors which influence decision making in new product evaluation," *Eur. J. Oper. Res.*, vol. 163, no. 3, pp. 784–801, 2005.

[66] D. R. Cooper, P. S. Schindler, and J. Sun, *Business Research Methods*, vol. 9. New York, NY, USA: McGraw-Hill, 2006.

[67] P. G. Moffatt, *Experimetrics: Econometrics For Experimental Economics*. London: Palgrave Macmillan, 2016.

[68] D. T. Campbell and J. C. Stanley, *Experimental and Quasi-Experimental Designs for Research*. Boston, massachusetts, USA: Ravenio Books, 2015.

[69] A. Anwyl-Irvine, J. Massonnié, A. Flitton, N. Kirkham, and J. Evershed, "Gorilla in our Midst: An online behavioral experiment builder," *Behav. Res. Methods*, vol. 52, pp. 388–407, 2019.

[70] S. Epstein, R. Pacini, V. Denes-Raj, and H. Heier, "Individual differences in intuitive–experiential and analytical–rational thinking styles," *J. Pers. Soc. Psychol.*, vol. 71, no. 2, pp. 390–405, 1996.

[71] R. Pacini and S. Epstein, "The relation of rational and experiential information processing styles to personality, basic beliefs, and the ratio-bias phenomenon," *J. Pers. Soc. Psychol.*, vol. 76, no. 6, pp. 972–987, 1999.

[72] F. Schweitzer, T. Roeth, and T. Gillier, "The eye of the beholder: The influence of intuition, rationality, and leeway on the assessment of an idea's market-creation potential," *Ind. Marketing Manage.*, vol. 91, pp. 274–284, 2020.

[73] D. M. Grether, "Testing Bayes rule and the representativeness heuristic: Some experimental evidence," *J. Econ. Behav. Org.*, vol. 17, no. 1, pp. 31–57, 1992.

[74] J. Cohen, *Statistical Power Analysis for the Behavioral Sciences*. Evanston, IL, USA: Routledge, 2013.

[75] N. Bardsley, R. Cubitt, G. Loomes, P. Moffat, C. Starmer, and R. Sugden, *Experimental Economics: Rethinking the Rules*. Princenton, NJ, USA: Princeton Univ. Press, 2010.

[76] D. K. Hsu, S. A. Simmons, and A. M. Wieland, "Designing entrepreneurship experiments: A review, typology, and research agenda," *Org. Res. Methods*, vol. 20, 2016.

[77] J. Khan, "Validation in marketing experiments revisited," *J. Bus. Res.*, vol. 64, no. 7, pp. 687–692, 2011, doi: 10.1016/j.jbusres.2010.08.009.

[78] B. C. Perdue and J. O. Summers, "Checking the success of manipulations in marketing experiments," *J. Mark. Res.*, pp. 317–326, 1986.

[79] S. Magistretti, S. Sanasi, C. Dell'Era, and A. Ghezzi, "Entrepreneurship as design: A design process for the emergence and development of entrepreneurial opportunities," *Creativity Innov. Manage.*, vol. 32, no. 1, pp. 5–21, 2023.

[80] E. K. Vraga, M. Tully, H. Akin, and H. Rojas, "Modifying perceptions of hostility and credibility of news coverage of an environmental controversy through media literacy," *Journalism*, vol. 13, no. 7, pp. 942–959, Oct. 2012, doi: 10.1177/1464884912455906.

[81] C. Peacock, G. M. Masullo, and N. J. Stroud, "The effect of news labels on perceived credibility," *Journalism*, vol. 23, no. 2, pp. 301–319, Feb. 2022, doi: 10.1177/1464884920971522.

[82] C. B. Bingham, K. M. Eisenhardt, and N. R. Furr, "What makes a process a capability? Heuristics, strategy, and effective capture of opportunities," *Strategic Entrep. J.*, vol. 1, no. 1/2, pp. 27–47, 2007.

[83] D. Lovallo and O. Sibony, "The case for behavioral strategy," *McKinsey Quart.*, vol. 2, no. 1, pp. 30–43, 2010, Accessed: Feb. 8, 2024. [Online]. Available: https://www.mckinsey.com/capabilities/strategy-and-corporate-finance/our-insights/the-case-for-behavioral-strategy

[84] G. Gigerenzer, "Fast and frugal heuristics: The tools of bounded rationality," in *Blackwell Handbook of Judgment and Decision Making*, vol. 62. Hoboken, NJ, USA: Blackwell Publishing, 2004, pp. 88.

[85] T. Pachur and R. Hertwig, "On the psychology of the recognition heuristic: Retrieval primacy as a key determinant of its use," *J. Exp. Psychol., Learn. Memory Cogn.*, vol. 32, no. 5, pp. 477–501, 2006.

[86] C. Vazquez-Hernandez, "The recognition heuristic in innovation management: An experimental pilot study on fast and frugal heuristics for promoting innovation," Mar. 31, 2023. doi: 10.2139/ssrn.4405504.

[87] A. Tversky and D. Kahneman, "Availability: A heuristic for judging frequency and probability," *Cognit. Psychol.*, vol. 5, no. 2, pp. 207–232, 1973.

[88] M. Balzano, "Serendipity in management studies: A literature review and future research directions," *Manage. Decis.*, vol. 60, no. 13, pp. 130–152, 2022.

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