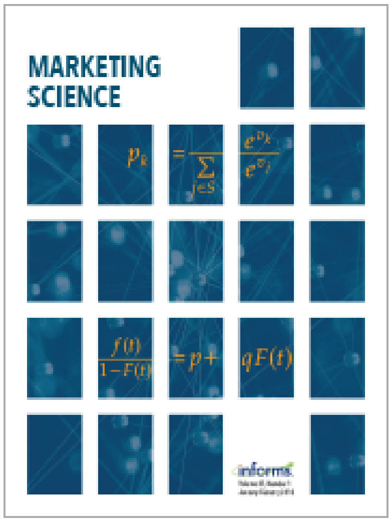

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Making Inclusive Product Design a Reality: How Company Culture and Research Bias Impact Investment

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Abstract. *Inclusive product design* enables consumers who hold commonly overlooked identities such as people of color, people with disabilities, and older adults to realize the benefits of a product. However, there is a mismatch between the spending power of overlooked consumers and the dearth of products for which companies have invested in inclusive product design. This paper develops an analytical model to examine how company culture and bias in the research process influence the investment in inclusive product design and the product's expected profitability. Interestingly, the results show that under specific company cultures, a research bias against finding the need for inclusive product design can actually increase the probability of investment in inclusive product design, relative to when there is no research bias. The results of the model define the conditions for when each direction of research bias (in favor or against) can lead to more investment or less investment in inclusive product design. The findings have implications for companies that are able to influence the research bias or the company culture in which the researcher works.

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Keywords: inclusive design • research bias • company culture • game theory

1. Introduction

Inclusive product design enables consumers who hold commonly overlooked identities, such as people of color, people with disabilities, and older adults, to realize the benefits of a product (Tauke et al. 2016, Patrick and Hollenbeck 2021). As an example, Mastercard successfully launched True Name to give nonbinary and transgender customers the opportunity to choose the name on their credit card, whereas previously only legal names were allowed. True Name customers felt "recognized, accepted, and empowered."[1] Evidence suggests that inclusive design can bring substantial economic benefits to companies.[2] However, products are often not inclusively designed. Examples include automatic soap dispensers that fail to detect darker skin, speech recognition software that is noticeably less accurate for Black speakers, and airport body scanners that lead to unnecessary patdowns for transgender individuals.[3] In fact, it seems many companies are missing out on lucrative opportunities associated with inclusive product design. For instance, consumers with disabilities, just one type of commonly overlooked consumers, have an estimated $8 trillion combined spending power, yet only 4% of companies include disability in their diversity efforts (Casey 2020). Although some products, such as Google's Pixel 6, are emphasizing "accessibility,"[4] other products fail to address the needs of commonly overlooked consumers. In this paper, we develop an analytical model to examine factors that affect whether a company is more or less likely to invest in inclusive product design than what would be optimal with full information.

We model a researcher's information collection about consumer needs and consider the company's decision to invest in an inclusive product based on the outcome of the research. Consider a common scenario of a firm deciding on product features to include in its new product. A researcher will often gather insights into user needs through customer interviews and observations.[5] The company will balance the needs of the user and the needs of the business to prioritize potential features to develop. We examine how bias in the research process interact with the company culture to influence the investment in inclusive product design and the product's expected profitability. We elaborate on each of these concepts later.

Bias in cognition and decision making is pervasive and can arise for many different reasons (Banaji and Greenwald 2016). In the product development context, a researcher's bias can influence the information collected or the outcome of the analysis. Common biases include the use of an *availability heuristic* (Tversky and Kahneman 1973) in which people tend to overweigh instances that more easily come to mind, an *anchor bias* (Tversky and Kahneman 1974) in which people anchor on immediately available information and adjust from there, and an *affinity bias* (Nalty 2016) in which people tend to gravitate toward others who are similar. As it relates to inclusive product design, a person's lived experiences and prior beliefs can affect whether these biases skew the research results in favor or against inclusive product design. For instance, a researcher assessing the need for inclusive product design may have easier or earlier access to exemplars from populations who would otherwise be excluded from the innovation (i.e., exhibiting a bias in favor of inclusive product design) or to exemplars from populations who do not need inclusive product design (i.e., exhibiting a bias against). In a renowned book on inclusive product design, Holmes (2018) wrote that when people "bring their own biases to the process, it can be challenging to make a solution that works well for all the people it is intended for" (p. 48). As another example of a research bias impacting investment in inclusive product design, Google's Head of Product Inclusion noted that an earlier version of the Pixel phone camera was not rendering images of nonwhite skin tones effectively, because "it wasn't tested enough to determine that the product designers themselves weren't unconsciously biased."[6] In this study, we explore how the presence and direction of a research bias in the researcher's information collection and interpretation procedures can increase or decrease the likelihood of firm investment in inclusive product design.

Our paper also examines the implications of company culture, which has been shown to be a key factor driving innovation (Tellis et al. 2009). Although there are many dimensions of company culture, we focus on elements of *psychological safety* (Edmonson 1999), a concept gaining prominence in practice. Clark (2020) describes four stages of psychological safety. Relevant to this research are the stages of *learner safety*, with which employees feel safe to experiment and make mistakes, and *challenger safety*, with which employees feel safe to speak up and challenge the status quo. Psychological safety has been shown to have positive influence on knowledge creation (Choo et al. 2007) and performance (Baer and Frese 2002, Lee et al. 2011). We operationalize elements of psychological safety by considering the researcher's perceived future rewards (i.e., recognition, employee awards, and promotion) if the research leads to successful firm investment in inclusive product design. Moreover, we operationalize the lack of psychological safety as the researcher's perceived future punishments (e.g., being berated for the failure, lack of promotions, or feeling ostracized from the group) if the research leads to failed investment. This is consistent with the behavior Edmondson (2011) found in which executives commonly treated failures as blameworthy. Although psychological safety has been argued as critical to creating a culture of innovation,[7] we also examine how a culture lacking psychological safety (e.g., either punishing failures or not rewarding experimentation) can interact with research bias to affect firm investment in inclusive product design as well as firm profit.

As companies such as Google begin to tout their inclusive products,[8] push toward a culture of psychological safety,[9] and acknowledge research bias exists in product teams,[10] it is clear these issues are of practical importance. Moreover, company culture provides the ecosystem where employees develop and is known to sway their motivations and performance (McGregor and Doshi 2015). It is thus natural to anticipate a researcher's effort and output to be affected by the culture. A firm, when interpreting the research report and evaluating the opportunity to invest in inclusive design, should consider the combined impact of company culture and research bias. In this study, we develop an analytical model to examine the following research questions: *First*, how do research bias and company culture affect investment in inclusive product design? *Second*, how do research bias and company culture affect expected firm profitability? *Last*, how do research bias and company culture interact in their impacts?

To address these research questions, we consider a model where a rational, profit-maximizing firm decides whether to invest in inclusive product design based on research about the needs for inclusive product design. The researcher can exert effort to get more accurate information. We consider three different types of researchers: a researcher without bias, a researcher whose research process is biased toward producing outcomes that suggest a limited need for inclusive product design (a case we referred to as "research bias-against"), and a researcher whose research process is biased toward producing outcomes that suggest a substantial need for in inclusive product design (a case we referred to as "research bias-in-favor"). We consider two types of cultures: a "reward-oriented culture" in which the researcher is rewarded if the research leads to a successful investment in inclusive design and a "punishment-oriented culture" in which the researcher is punished if the research leads to an investment in inclusive design for which the costs of development exceed the financial gains from broadening access to the product's benefits. We compare outcomes across the different types of researchers and cultures. The main findings of the analysis are as follows.

First, we find that a research bias-against can actually lead to a higher likelihood of investment than both unbiased research and a research bias-in-favor. One might expect that a research bias against the need for inclusive product design would reduce the likelihood of investment, which we confirm to be true in certain company cultures, but we show when and why the opposite is also true.

Second, we find that a research bias in favor of the need for inclusive product design can actually lead to a lower likelihood of investment in inclusive product design than when there is no research bias. This finding is another example that the investment likelihood can move in the opposite direction of the research bias. Again, the company culture (reward-oriented versus punishment-oriented) plays a critical role in determining when common intuition is confirmed or overturned.

Third, we find that a punishment-oriented culture can lead to greater profit than a reward-oriented culture under certain conditions. We find that research bias plays a critical role in determining which culture leads to greater profitability. As a consequence, any prescriptions regarding the optimal culture must account for research bias.

Our results are driven by how research bias impacts the firm's decision and how company culture impacts the researcher's effort in the research process. A research bias gives the firm a high degree of confidence in a research finding that is counter to the direction of the bias. Therefore, although a research bias-against decreases the probability that the research reports a high need for inclusive product design, the firm's heightened confidence in the finding can lead to an overall increased probability of investment relative to when there is unbiased research. The reverse is true for a research bias-in-favor. The counter-intuitive results regarding research bias and investment in inclusive product design arise when the company culture and prior beliefs about the need for inclusive product design are such that the unbiased researcher does not have incentive to exert enough research effort to mitigate the effect of research bias on firm confidence.

A company culture is most profitable when it motivates the researcher to produce a highly credible report that improves the investment decision. As one would expect, a firm's profit increases when its investment decision better matches the true state of the world (i.e., investing if there is a need for inclusive product design and not investing if there is no such a need). When the prior belief about the need for inclusive product design is such that over-investment is likely, a punishment-oriented culture can lead to a greater profit than a reward-oriented culture if the researcher has a bias-in-favor. In this case, the researcher, out of incentive to reduce the probability of receiving punishment, exerts substantial research effort and produces a highly accurate report that helps the firm reduce the probability of making a failed investment.

Overall, our results highlight an important interaction between research bias and company culture in determining the likelihood of investment in inclusive product design and the firm's expected profit. One might expect that psychological safety created by a reward-oriented culture and unbiased researchers would lead to the highest expected profit and a researcher's bias-in-favor of inclusive product design would lead to the highest probability that a firm invests in inclusive product design. However, our results challenge common intuition and inform company decisions regarding who to deploy to conduct research and how employees are rewarded or punished. Depending on the company, it may be difficult to change the direction of the research bias or it may be difficult to change the culture. Our results highlight that during a firm's attempt to increase expected profitability or likelihood of investing in inclusive design, careful attention should be paid to the underlying factors that are not possible to change.

Inclusive product design is the motivating factor for this research. That said, the model and insights apply to a broader range of contexts. The insights and modeling approach generalize to decisions made by a firm with an imperfect signal from biased research, provided that the researcher's payoff (and consequently equilibrium research effort) is affected by the company culture, firm decision, and the true state of the world.

The rest of the paper proceeds as follows. In Section 2, we discuss related literature to our study. We set up the model in Section 3 and solve the model in Section 4. Section 5 concludes with a discussion.

2. Literature

Our paper contributes to the growing research on "inclusive design" or product design that makes a product accessible to consumers who are traditionally overlooked based on their race, age, or disability. Existing studies on inclusive design are scant. Using data from Diaper.com, Choi and Bell (2011) found that offline retailers commonly tailor products to the needs of preference majorities and so preference minorities, facing high cost of offline shopping, are less price sensitive. Patrick and Hollenbeck (2021) developed a conceptual framework to explain the cognitive appraisals and emotional responses that inclusive design elicits among users. Van der Sluis et al. (2022) used a series of laboratory studies to show that observers infer disabled consumers prefer utilitarian products more, and hedonic products less, than nondisabled consumers. To the best of our knowledge, our research is the first modeling work to examine a firm's investment in inclusive design.

Broadly, our work belongs to the general area of research on firms' social responsibility. The majority of existing studies in this literature has examined firms' investment in developing "green products" (Baron 2001, 2009; Bagnoli and Watts 2003; Kotchen 2006), which do not directly generate profit but enhance the welfare of society. Examples of green products include Clorox's Green Works Line of nonsynthetic cleaning products and Levi's "Water < Less" jeans. Iyer and Soberman (2016) examined how consumers' intrinsic concerns about social responsibility and extrinsic social preferences interact to determine a firm's incentive to make research and development (R&D) investments in developing such products. Jiang et al. (2014) examined how a firm devises its pricing strategy when it has private information about whether it only cares about maximizing profit or truly cares for consumer welfare. Wu et al. (2020) considered both consumers' preferences and firms' preferences for a socially responsible product and examined how information transparency affects firms' investment in "greenwashing" or observable, as opposed to unobservable, aspects of socially responsible activities. Different from these works on green products, we do not model a firm's altruistic incentive to offer an inclusive product or mainstream consumers' altruistic motive to invite such a product. Instead, we build a model on classical assumptions that firms maximize profits and consumers maximize consumption utilities, and investigate how a firm's decision about whether to invest in inclusive design is driven by research findings about the demand of commonly overlooked consumers.

Our study considers the scenario where the firm relies on the research outcome of a researcher to decide whether to invest in inclusive product design. As such, our model contributes to existing research that examines how firms make product decisions based on unbiased research that truthfully reflect consumer needs. For example, Jovanovic and Rob (1987) examined how a firm gathers information about uncertain consumer demand before deciding its new product location. Ofek and Turut (2008) studied the incentives of a firm to conduct market research when it has to decide between innovation and imitation in entering a market. Iyer and Soberman (2000) examined competing firms' incentives to purchase information relevant for product modifications from a strategic vendor. Lauga and Ofek (2009) modeled how competing firms conduct costly market research before setting R&D strategy for innovation. Katona (2015) compared the outcomes from using market research versus inviting consumers to vote on new product designs on social media in a democratic design process, the latter of which serves as a commitment device that can impact competition. Similar to this literature, our model finds product decisions can be influenced by the outcome of the market research. In contrast, our model demonstrates how the research bias affects the firm's investment in inclusive product design and expected profit. Examining research bias allows us to explore some under-investigated aspects of a company's environment, such as company culture, that might affect the product development process through interactions with the research bias.

Our research relates to psychological safety. There are several extensive reviews of the literature on psychological safety (Frazier et al. 2017, Newman et al. 2017). Within a psychologically safe environment, failure can occur "without retaliation, renunciation, or guilt" (Schein and Bennis 1965). To the best of our knowledge, our research is the first to incorporate psychological safety into an economic model of the product development process.

3. Model

In this section, we first provide a conceptualization of the product development process on which our modeling is based and then describe each of the players, payoffs, decisions, and information structure.

3.1. Conceptualization

Design thinking is a common approach to product development and has five phases (Murtell 2021): (1) gathering high-quality consumer understanding, (2) creating a design brief for all stakeholders, (3) ideating and collaborating on solutions, (4) prototyping solutions, and (5) testing solutions with consumers who have a vested interest in the problem being solved. Research about users is needed in both phase 1 and phase 5, as we detail here.

In the first phase, a *researcher* will "observe and engage with human beings to truly internalize their experience on an emotional and even psychological level" (Murtell 2021). A researcher will study the customer journey (often conducting interviews and observing behavior) in an effort to identify pain points that real users have. Consider, for instance, when the inclusive product design is centered around accessibility. This first phase of the design thinking process may reveal that a sizeable number of users have a pain point around accessibility of the product. Although there are available statistics on the number of people with various disabilities, the researcher may have a bias affecting the determination of how many real users of the particular product will have the pain point.

In subsequent phases of the design thinking process, the various observed pain points will be prioritized in a design brief (phase 2), the team will think through potential solutions to the prioritized problem(s) in phase 3, and prototypes will be created in phase 4.

In the fifth stage of the design thinking process, the *researcher* is tasked with getting feedback on prototypes from real users who have a vested interest in the problem being solved (Murtell 2021). For instance, before investing in developing a fully functioning accessibility feature, the researcher may show users concept art, a video of how the feature would work, or a "Wizard of Oz" prototype in which the functionality is achieved by hand rather than an end-to-end working technology solution. In this phase, the researcher is asking questions such as "What problem could this solve for you?" or "How could this solution impact your experience?" (Murtell 2021). The response to the importance or usefulness of the inclusive design features will depend on the prototype developed, the questions asked, and the users with whom the prototype is tested.

To capture the impact of research in this design thinking process, we model the potential for *research bias* in the work of a *researcher*. We consider a *firm* that is given a signal from the researcher and makes a profit-maximizing decision of whether to invest in inclusive product design. This firm decision can occur in phase 2 of the design thinking process (i.e., the design brief that prioritizes finding solutions for user problems related to inclusive product design) or after phase 5 (i.e., fully developing solutions that were prototyped in phase 4 and tested in phase 5). Thus, the researcher's signal can be considered as the result of the research in phase 1 of the design thinking process or can be considered the result of testing potential solutions in phase 5 of the design thinking process.

Our modeling approach follows the tradition of Bayesian persuasion games (Kamenica and Gentzkow 2011, Kamenica 2019), where the decision maker's activity depends on the information provided by a sender. Importantly, the decision maker rationally anticipates the sender's information generation process and reacts to such information in a rational or Bayesian manner. Bayesian persuasion models have been applied to various business contexts such as price discrimination (Bergemann et al. 2015), organizational behavior (Jehiel 2015), and financial markets (Goldstein and Leitner 2018). In our context, a researcher (i.e., the sender) examines the need for inclusive product design and the firm (i.e., the receiver) observes the researcher's report and decides whether to make an investment in inclusive product design. In what follows, we describe the assumptions about *consumers*, the *firm*, the *researcher*, and the *research bias*.

3.2. Consumers

There are two consumer segments. Borrowing terminology from Shaw and Nickpour (2021) and Raviselvam et al. (2022), we refer to these two segments as extreme users and mainstream users. For instance, the extreme user may require a hands-free alternative to navigate a phone's interface, whereas a mainstream user may be able to navigate the phone as traditionally designed. Both segments of consumers derive a value from using the product, which follows a uniform distribution on $[0,1]$ if the product satisfies their needs. By default, the product satisfies the needs of mainstream users, but will only satisfy the needs of extreme users if it has an inclusive design. For example, Google researched and developed a feature called Camera Switches in the Pixel 6 smartphone that allows users to navigate the interface using certain gestures like looking in a direction, raising eyebrows, or opening a mouth. Without inclusive product design, extreme users obtain zero value from using the product.

We normalize the size of the mainstream user segment to one. The actual size of the extreme user segment is unknown before an inclusive product is developed and introduced. Ex ante, it is common knowledge that the size of the extreme user segment is $x\,(0 < x < 1)$ with probability $y\,(0 < y < 1)$ and zero with probability $1 - y$. Combined xy thus represents the ex ante expected size of the extreme user segment.

Several of the assumptions are made in the interest of parsimony without loss of generality. In reality, there is often a continuum of extreme users, these users can vary in the proportional value that would be unlocked with inclusive product design, and there may be varying probability densities of each point on the continuum. However, modeling such complexities would still lead to the key factors in this model: Inclusive product design unlocks value for extreme users by enabling them to access benefits that mainstream users experience. Key to our model is that there is an unknown benefit to the firm of investing in inclusive product design.

3.3. Firm

The firm decides whether to invest in inclusive product design to serve the extreme users, which involves a fixed development cost $c > 0$. We denote the firm's investment decision by an indicator variable I, which equals one if the firm invests and zero otherwise. In the interest of parsimony, we assume zero marginal cost of production. The firm chooses the product price p. We write the firm's profit function as $p \cdot q(p, I) - I \cdot c$, where q represents the sales quantity and is a function of the firm's price p and the investment decision I. Given consumer payoffs specified previously, it is easy to prove that the firm's optimal price is always $p^* = \frac{1}{2}$, which brings the firm a maximized profit of $\frac{1}{4}$ from selling to mainstream users when it does not invest in inclusive design (i.e., $I = 0$). When the firm invests in inclusive design (i.e., $I = 1$), its profit will realize as $\frac{1+x}{4} - c$ if the true size of extreme users is x, and $\frac{1}{4} - c$ if the true size of extreme users is zero. We focus on the interesting case of $x > 4c$, which ensures that investing in inclusive design is profitable when the extreme demand realizes as x. The probability y

that there is an extreme user segment thus gives a benchmark probability that a fully informed firm would invest in inclusive product design. Ex ante, the firm does not know the size of the extreme user segment and chooses I based on information shared by the researcher. When the firm invests in inclusive product design with a lower probability than y, we consider the situation "underinvestment." On the other hand, when the firm invests with a higher probability than y, we consider the situation "overinvestment."

3.4. Researcher

The researcher engages in a research effort to obtain a signal that indicates the size of the extreme user segment. We denote the two states of the world with H (i.e., the extreme user segment is of size x) and L (i.e., the extreme user segment is nonexistent), respectively. The researcher starts with the common prior that state H realizes with probability y, and conducts research to obtain a noisy signal, $sig \in \{H, L\}$, which is correlated with the truth. For example, the researcher may obtain $sig = H$ when a sufficiently large number of customer interviews suggest inclusive product design is necessary for that customer to access the benefits of the product and obtain $sig = L$ when the number is small. The researcher can improve the accuracy of the signal by making more research effort. We assume research effort of level k $(0 < k < 1)$ involves cost of k^2.

The researcher truthfully reports to the firm the obtained signal (Grossman 1981, Milgrom 1981, Milgrom and Roberts 1986). The researcher's effort level is also observable to the firm. For example, at the end of the research process, the researcher submits a report that includes details of the research method such as sample size, sampling method, questionnaire, and data analysis (which combine to suggest the effort level), together with the result from data analysis, which serves as the signal about the state of extreme users.[11] In what follows, we describe how we model research bias and then subsequently will describe how we model company culture.

3.5. Research Bias

We consider a research bias-against and a research bias-in-favor that skew the signal regarding the state of the extreme user segment. Additionally, we consider a benchmark case where there is no bias in the research process. We summarize in Table 1 the conditional probabilities of a signal given the true state in various conditions of research bias. The nature of the bias is common knowledge.

Table 1. Conditional Probabilities

	No research bias	Bias-against	Bias-in-favor
$Pr(sig = H\|H)$	$k + (1-k)y$	$k + (1-k)y$	1
$Pr(sig = L\|H)$	$(1-k)(1-y)$	$(1-k)(1-y)$	0
$Pr(sig = H\|L)$	$(1-k)y$	0	$(1-k)y$
$Pr(sig = L\|L)$	$k + (1-k)(1-y)$	1	$k + (1-k)(1-y)$

To understand the modeling approach described in Table 1, first consider the case of no bias, for which the model captures several important facets. First, if the researcher exerts the maximum possible effort (i.e., $k = 1$), then the signal is perfectly correlated with the truth. In practice, this effort can be in the form of developing the proper customer interview approach and in recruiting a broad, representative research sample. Second, if the researcher exerts no effort (i.e., $k = 0$), the signal is uninformative relative to the known prior that there is a probability y of the H state of the world. Third, the researcher's effort is equally likely to improve the accuracy of the signal in either state of the world since the researcher has no bias.

Connecting the modeling approach to the conceptualization, research bias can occur in phase 1 or phase 5 of the design thinking process. Researchers will commonly screen potential interviewees to make sure the interviews are conducted with current or future users of the product or service.[12] Consider an example of a productivity software targeted to small business owners. A researcher would conduct prescreening to ensure all the interviews are with small business owners who use productivity software.[13] Therefore, even if the number of people with a certain disability or demographic variable in the population at large may be known, the researcher does not know how many potential users of the product are extreme users.

Holmes (2018) writes "One important way to change invisibility is to seek out the perspectives of people who are, or risk being, the most excluded by a solution" (p. 32). In this spirit, a researcher with a research bias against inclusive product design may have the easiest access to users who do not have a need for accessibility features (e.g., current customers of an existing product that does not include accessibility features). If there are no users who have a need for accessibility features, none of the interviews would suggest that the need exists (i.e., $Pr(sig = L|L) = 1$)). If the need for accessibility features is pervasive, then even the biased sample may surface the need in user interviews. A researcher can exert effort to recruit a more diverse interview panel to increase the odds that an existing need for accessibility features would be revealed in the user interviews (i.e., $Pr(sig = H|H) = k + (1-k)y$).

Similar to a research bias-against, a researcher with a research bias-in-favor may have the easiest access to users who do have a need for accessibility features. If the need is pervasive, then it will surely surface during the customer interviews (i.e., $Pr(sig = H|H) = 1$). If the need is not widespread (though demand is set to zero in our model for parsimony, the logic applies to very small demand), the researcher's sample of user interviews may have an inordinately high proportion of users articulating a need for accessibility features given the researcher's easier access to these users. Greater research effort to recruit a more balanced sample of interviews can decrease the likelihood of a false signal of need (i.e., $Pr(sig = H|L) = (1-k)y$).

The previous examples are regarding the research sample. The same results can happen based on the researcher's propensity to ask leading questions biased in either direction. If the truth is consistent with the direction of the leading questions, then the signal will be consistent (i.e., $Pr(sig = H|H) = 1$ with research bias-in-favor and $Pr(sig = L|L) = 1$ with research bias against). If the truth is inconsistent with the direction of the leading questions, then greater research effort to improve the questions or their interpretation can increase the accuracy of the interviews.

In summary, we model research bias as the researcher's ease in finding information that is accurately consistent with the bias. This information gathering can occur when the goal is to understand consumer needs or when the goal is to test which potential solutions to implement. The bias may manifest itself in the process of choosing the research sample or in collecting information from the sample. Importantly, in our setting, the researcher does not intentionally hide or avoid collecting information that goes against the researcher's pre-existing bias. Rather, the researcher is more effective in rendering an accurate signal when the truth aligns with the researcher's bias but less effective when the truth conflicts with the bias. Costly research effort can mitigate this discrepancy. For example, researchers at Google have taken extra effort to identify whether there is a need for inclusive product design. This includes building a partnership with GLAAD to conduct "qualitative research interviews with trans individuals and community leaders,"[14] creating an inclusion champion group of "thousands of Googlers from historically marginalized backgrounds who test products regularly and provide feedback,"[15] and collecting data from people whose speech is difficult to understand such as people who have multiple sclerosis, are deaf, had a stroke, and stutter.[16]

3.6. Company Culture

We consider two types of company cultures: reward-oriented and punishment-oriented. In practice, many rewards or punishments are nonmonetary and also not immediately associated with a specific job task. We parsimoniously focus on psychological reward and cost, which have proven effective at motivating behavior. For example, a recent Globoforce survey found that 82% of employees said being recognized actually motivated them in their jobs.[17]

In a reward-oriented culture, the researcher is rewarded to experience a utility boost of $R \geq 0$ if both the research leads to investment in inclusive product design and the extreme user segment is sufficiently large to warrant profitable investment (as evidenced by the volume of sales). This is consistent with a culture with *challenger safety*, with which employees feel safe to challenge the status quo and are rewarded for taking bets that pay off. Companies with a high R might bestow strong psychological rewards such as promotions, awards, or recognition in company stand-ups.

In a punishment-oriented culture, the researcher is punished with a utility penalty of $N \geq 0$ if both the research leads to investment in inclusive product design and the extreme user segment is too small to ensure profitable investment. This penalty is consistent with a culture that lacks *learner safety* because employees do not feel safe making mistakes. This psychological cost may manifest itself through the employee being berated for the failure or feeling ostracized from the group.

The status quo of not investing in inclusive product design yields no punishment or rewards because the size of the extreme user segment is an unobservable counterfactual. The true state of the extreme user segment can only be observed after a product is made inclusive to this segment.

3.7. Game Sequence

The game proceeds as follows. In stage 1, the researcher maximizes the expected payoff by deciding the observable effort level k to research the size of the extreme user segment. The researcher obtains signal sig which is reported to the firm truthfully. In stage 2, upon receiving the signal, the firm decides whether to invest in inclusive product design, I, and also decides the product price to maximize its expected profit. In stage 3, the firm introduces the product to the market. The size of the extreme user segment is realized if the product has an inclusive design. Firm profit and researcher payoff are both realized.

Table 2 summarizes key model notations.

4. Analysis and Results

We solve three cases of the model: a benchmark *unbiased* case in which the research process has no bias, a *research bias-against* case and a *research bias-in-favor* case. In each of the three bias cases, we also consider a *reward-oriented* company culture where the researcher perceives a psychological reward if the firm's investment succeeds (i.e., state H realizes) but no psychological penalty if the investment fails (i.e., state L realizes) and a *punishment-oriented* culture where the researcher anticipates no reward for a successful investment but a penalty for a failed investment. We consider six cases in total and use backward induction to solve each case.

4.1. Firm's Investment Decision

We first derive the firm's investment decision upon receiving a signal from the researcher. In particular,

Table 2. Summary of Notation

Symbol	Description
$x \in [4c, 1]$	Size of extreme segment in state H
$y \in [0,1]$	Probability of extreme segment being in state H
$k \in [0,1]$	Researcher's effort to improve research accuracy
$sig \in \{H, L\}$	Signal that the researcher shares with the firm
$R \geq 0$	Researcher's psychological reward from successful investment
$N \geq 0$	Researcher's psychological cost from failed investment
$c > 0$	Firm's cost of investing in inclusive design
$I \in \{0,1\}$	Indicator of firm investment in inclusive design
$Pr(I) \in [0,1]$	Probability of firm investment in inclusive product design

the research may indicate $sig = H$ or $sig = L$. By Bayes rule, the conditional probabilities that the extreme segment is in state H are $Pr(H|sig = H) = \frac{Pr(sig=H|H)Pr(H)}{Pr(sig=H)}$ and $Pr(H|sig = L) = \frac{Pr(sig=L|H)Pr(H)}{Pr(sig=L)}$, respectively. The expressions $Pr(sig = H)$ and $Pr(sig = L)$ are probabilities that the research will result in the two signals. Using conditional probabilities specified in Table 1, we derive $Pr(sig = H) = Pr(sig = H|H)Pr(H) + Pr(sig = H|L)Pr(L)$. These probabilities depend on the research bias case (i.e., unbiased, bias-against, or bias-in-favor) and also the researcher's effort level k.

If the firm receives $sig = H$, its expected profit from investing is $Pr(H|sig = H)\frac{1+x}{4} + Pr(L|sig = H)\frac{1}{4} - c$. The firm invests in inclusive product design if and only if this expected profit is greater than its profit of $\frac{1}{4}$ from not investing. This happens only if $Pr(H|sig = H)$ is sufficiently high. On the other hand, if the firm receives $sig = L$, the firm invests in inclusive design if $Pr(H|sig = L)\frac{1+x}{4} + Pr(L|sig = L)\frac{1}{4} - c > \frac{1}{4}$. This happens when $Pr(H|sig = L)$ is sufficiently high. Moreover, because $Pr(H|sig = H) \geq Pr(H|sig = L)$ is always satisfied, if the firm invests upon observing $sig = L$, the firm will also invest if $sig = H$. The firm thus has three strategic options:

IA. Investing Always, that is, $I(sig = H) = I(sig = L) = 1$. This strategy is optimal when $Pr(H|sig = L)$ is sufficiently large. Upon investing, state H of the extreme segment realizes with probability $Pr(H) = y$.

IN. Investing Never, that is, $I(sig = H) = I(sig = L) = 0$. Without investment, the firm does not observe the state of the extreme segment.

IH. Investing only upon receiving $sig = H$, that is, $I(sig = H) = 1 \& I(sig = L) = 0$. Upon investing, state H of the extreme segment realizes with probability $Pr(H|sig = H)$.

In the full-information case, the firm invests with probability $Pr(H) = y$. Thus, we consider strategies that lead to investment probabilities greater than y as overinvestment and strategies that lead to investment probabilities less than y as underinvestment. By these definitions, strategy IA implies overinvestment and strategy IN implies underinvestment. In strategy IH, underinvestment occurs if $Pr(sig = H) < y$ and overinvestment occurs if $Pr(sig = H) > y$. We summarize the firm's profit under each of these strategies as follows:

$$\pi = \begin{cases} Pr(H)\dfrac{1+x}{4} + Pr(L)\dfrac{1}{4} - c = \dfrac{1}{4}(1 + xy - 4c) & \text{if} \quad I(sig = H) = I(sig = L) = 1 \\ \dfrac{1}{4} & \text{if} \quad I(sig = H) = I(sig = L) = 0 \\ Pr(sig = H)\dfrac{1}{4}(1 + xPr(H|sig = H) - 4c) + Pr(sig = L)\dfrac{1}{4} & \text{if} \quad I(sig = H) = 1 \& I(sig = L) = 0. \end{cases} \tag{1}$$

From Equation (1), we see that always investing is more profitable than never investing if and only if xy, the ex ante expected size of the extreme segment is sufficiently large. Moreover, investing upon $sig = H$ can be optimal if the firm is sufficiently confident that the signal reflects the true state of the extreme segment, that is, if $Pr(H|sig = H)$ is sufficiently high.

4.2. Researcher's Effort Decision

Rationally anticipating the firm's investment strategy, the researcher decides the effort level to maximize the researcher's expected payoff. We derive the researcher's payoff function as shown later. In a reward-oriented culture, $R > 0 \& N = 0$, whereas in a punishment-oriented culture $R = 0 \& N > 0$:

$$\Gamma(k) = \begin{cases} yR - (1-y)N - k^2 & \text{if} \quad I(sig = H) = I(sig = L) = 1 \\ -k^2 & \text{if} \quad I(sig = H) = I(sig = L) = 0 \\ Pr(sig = H)Pr(H|sig = H)R - Pr(sig = H)(1 - Pr(H|sig = H))N - k^2 & \text{if} \quad I(sig = H) = 1 \& I(sig = L) = 0. \end{cases} \tag{2}$$

In each bias case, we solve the optimal researcher effort level k^* for each type of company culture. We then plug

Table 3. Results with No Research Bias

Conditions		Equilibrium results		
Demand	Culture	k^*	$Pr(I)^*$	π^*_{nb}
$xy > 4c$	$R > 0$ or $N < N_{nb}$	0	1	$\frac{1}{4}(1 + xy - 4c)$
	$N > N_{nb}$	$\max\left\{\frac{xy-4c}{xy}, \min\left\{1, \frac{Ny(1-y)}{2}\right\}\right\}$	y	$\frac{1}{4}(1 + xy^2 + k^*xy(1-y) - 4cy)$
$xy < 4c$	$R < R_{nb}$ or $N > 0$	0	0	$\frac{1}{4}$
	$R > R_{nb}$	$\max\left\{\frac{4c-xy}{x(1-y)}, \min\left\{1, \frac{Ry(1-y)}{2}\right\}\right\}$	y	$\frac{1}{4}(1 + xy^2 + k^*xy(1-y) - 4cy)$

Note. $N_{nb} = \frac{(xy-4c)^2}{x(y-1)y^2(4c-x)}$, $R_{nb} = \frac{(xy-4c)^2}{4cxy(1-y)^2}$.

k^* back to Equation (1) to derive the firm's equilibrium investment strategy $Pr(I)^*$ and expected profit π^*. The equilibrium results are summarized in Tables 3–5. Subscripts *nb*, *bg*, and *bf* represent the cases of no research bias, bias against, and bias-in-favor, respectively. The following lemma summarizes the researchers' optimal decision on exerting research effort.

Lemma 1. *Across bias cases,* (i) *in a reward-oriented culture, a researcher exerts effort only if the ex ante expected size of the extreme segment, xy, is sufficiently small and the reward R for successful investment is sufficiently high.* (ii) *In a punishment-oriented culture, a researcher exerts effort only if both xy is sufficiently large and the punishment N for failed investment is sufficiently high.*

Lemma 1 summarizes the common impact across research bias cases of company culture on a researcher's research effort. We provide the intuition behind the result later, which will serve as a foundation for addressing our research questions. In a reward-oriented culture, the benefit for the researcher to make research effort is increasing the expected probability of a successful investment. If the ex ante expected size of the extreme segment, xy, is sufficiently large, research effort will not further increase the probability of successful investment that is at its highest possible level given the bias case. Thus, a reward for successful investment will have no impact on research effort in this parameter region. If xy is sufficiently small such that research effort will increase the probability of investment (and thus also the probability of successful investment), then the researcher will exert the research effort only if the reward for successful investment is sufficiently high to offset the effort cost.

In a punishment-oriented culture, the benefit for the researcher to make research effort is decreasing the expected probability of a failed investment. If the ex ante expected size of the extreme segment, xy, is too small, then the research effort will not further decrease the probability of failed investment, which is at its lowest possible level given each bias case. Thus, the punishment for a failed investment will have no impact on the researcher's effort level. On the other hand, if xy is sufficiently large, research effort will decrease the probability of failed investment. This happens when the researcher produces a signal that is accurate enough so that the firm will not invest upon receiving an unfavorable signal. In this case, the researcher will exert effort only if the penalty for failed investment is high enough to justify the effort cost.

As shown in Tables 3–5, research bias affects the cutoffs of xy such that the researcher exerts effort in obtaining more accurate signals and the equilibrium effort level. These cutoffs and effort levels play a pivotal role in determining the effects of research bias and company culture on investment in inclusive product design and firm profit. We compare outcomes across cases in the following section.

4.3. Research Bias-Against

We now consider the impacts of the researcher having a known research bias that makes it more difficult to

Table 4. Results with Research Bias Against

Conditions		Equilibrium results		
Demand	Culture	k^*	$Pr(I)^*$	π^*_{bg}
$xy > 4c(1+y)$	$R > 0$ or $N < N_{bg}$	0	1	$\frac{1}{4}(1 + xy - 4c)$
	$N > N_{bg}$	$\frac{4cy+4c-xy}{4cy-xy}$	$\frac{4c-xy}{4c-x}$	$\frac{1}{4}(1 + xy - 4c)$
$xy < 4c(1+y)$	$R > 0$	$\min\left\{1, \frac{1}{2}(1-y)yR\right\}$	$(k^*(1-y)+y)y$	$\frac{1}{4}(1 + xy^2 - 4cy^2) + k^*\frac{1}{4}(1-y)y(x-4c)$
	$N > 0$	0	y^2	$\frac{1}{4}(1 + xy^2 - 4cy^2)$

Note. $N_{bg} = \left(\frac{4cy+4c-xy}{4cy-xy}\right)^2 \frac{1}{1-y}$.

Table 5. Results with Research Bias-In-Favor

Conditions		Equilibrium results		
Demand	Culture	k^*	$Pr(I)^*$	π^*_{bf}
$xy > 4c(2-y)$	$R > 0$	0	$y(2-y)$	$\frac{1}{4}(1 + xy - 4cy(2-y))$
	$N > 0$	$\min\left\{1, \frac{Ny(1-y)}{2}\right\}$	$y(1 + (1-k^*)(1-y))$	$\frac{1}{4}(1 + xy - 4c(2-y)y) + k^*c(1-y)y$
$xy < 4c(2-y)$	$R < R_{bf}$ or $N > 0$	0	0	$\frac{1}{4}$
	$R > R_{bf}$	$\frac{4cy-8c+x}{4cy-4c}$	$\frac{xy}{4c}$	$\frac{1}{4}$

Note. $R_{bf} = \frac{1}{y}\left(\frac{4cy-8c+x}{4cy-4c}\right)^2$.

find information that accurately confirms state H. We draw comparisons across the equilibrium outcomes described in Tables 3 and 4. The proposition below presents the comparison of the firm's investment probability when there is a research bias-against versus when there is no bias.

Proposition 1. *When there is a research bias-against, the firm invests in inclusive product design with a greater probability than when there is no research bias if and only if the ex ante expected size of the extreme user segment is small (i.e., $xy < 4c$) and the company culture is either punishment-oriented or weakly reward-oriented $\left(\text{i.e., } N>0 \text{ or } R < R_{nb} = \frac{(xy-4c)^2}{4cxy(1-y)^2}\right)$.*

Proposition 1 brings two keys insights. First, it shows that a research bias against the need for investment can actually make the firm more likely to invest in inclusive design. This result is counter-intuitive because one might expect a research bias-against would make the firm less likely to invest. Second, this result highlights the important role that a company's culture plays in the outcome. To understand this result, consider the two mechanisms by which research bias impacts the probability of investment: Research bias impacts the confidence the firm has in each signal (i.e., $Pr(H|sig = H)$ and $Pr(L|sig = L)$) and impacts the outcome of the research in terms of the probability that the researcher reports $sig = H$. These two mechanisms, which operate in opposing directions, explain why research bias-against can increase the probability of investment in inclusive product design and when this will happen.

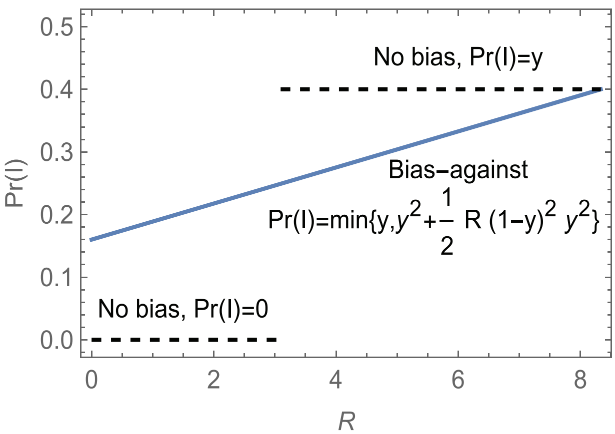
If the researcher with a research bias against investment reports $sig = H$, the firm has a high degree of confidence that the true state is H because the research is biased against such an outcome. Thus, the firm will invest in inclusive design when the researcher reports $sig = H$, even if the researcher exerts no effort. In contrast, if the researcher with no research bias exerts little effort and reports $sig = H$, the firm's confidence in investment is lower. As a consequence, a research bias-against can increase the probability of investment in inclusive product design by increasing confidence in the H signal.

On the other hand, the research is less likely to indicate a large extreme user segment when there is a research bias-against than when there is no research bias (i.e., $Pr(sig = H)$ is lower with research bias-against than no bias). Therefore, absent an effect on the firm's confidence in the signals, a research bias-against would diminish the probability of investment in inclusive product design. Thus, the counter-intuitive result holds only under conditions such that the improved confidence associated with a research bias-against relative to the case of no research bias is strong enough to change the firm's investment decision upon observing $sig = H$. If the ex ante expected size of the extreme user segment is small (i.e., xy is small) and the unbiased researcher exerts little effort, a firm will adopt strategy IN with an unbiased researcher (i.e., never invest) and will adopt strategy IH when there a research bias-against (i.e., invest if and only if $sig = H$). From the discussion of Lemma 1, a researcher with no research bias does not exert research effort when the reward is not enough to justify the effort cost, which is true in a punishment-oriented or weakly reward-oriented culture. This explains why in such demand and culture conditions a research bias-against increases the probability of investment in inclusive product design.

When the conditions in Proposition 1 are not met, however, the research bias-against weakly reduces the likelihood of investing in inclusive product design. A strong reward-oriented culture motivates the researcher to exert effort to improve signal accuracy, and as a result the firm is willing to invest upon receiving a favorable signal from the researcher with no research bias. Thus, a strong-reward can moderate the effect that bias has on the firm's confidence in investment. In this case, research bias-against leads to reduced investment probability because the researcher is less likely to produce $sig = H$. Last, if the ex ante expected size of the extreme user segment is very high (i.e., xy is large), the firm will always invest regardless of whether there is no research bias or a research bias-against.

Figure 1 illustrates this interaction between research bias, company culture, and the ex ante expected size of the extreme user segment in influencing the firm's investment decision.

Figure 1. (Color online) Firm Investment Probability in Case of No Research Bias vs. with Research Bias-Against in a Reward-Oriented Culture When $xy < 4c$ $(x = 0.2, y = 0.4, c = 0.055, N = 0)$



We next turn our attention to the profitability of the firm. The following proposition summarizes the impact of company culture on firm profit when there is a research bias-against.

Proposition 2. *When there is research bias-against, the reward-oriented culture is more profitable than the punishment-oriented culture if the ex ante expected size of the extreme user segment is relatively small (i.e., $xy < 4c + 4cy$). Otherwise, the reward-oriented culture or the punishment-oriented culture generate the same profit.*

When there is a research-bias against, Proposition 2 confirms common intuition that a culture with psychological safety in which employees are safe to take a risk and rewarded for challenging the status quo can improve performance (Baer and Frese 2002). Recall that the firm has confidence to invest in inclusive product design when the research indicates a large extreme user segment. When the ex ante expected size of the extreme user segment is small (i.e., $xy < 4c + 4cy$), the firm uses strategy IH (i.e., only investing upon $sig = H$). This strategy, however, leads to underinvestment in inclusive product design because the research bias-against makes the researcher less likely to obtain $sig = H$ than in a full information case (i.e., $Pr(sig = H) < Pr(H)$). As discussed in Lemma 1, in this market condition, only a reward-oriented culture will motivate a researcher with a research bias-against to exert research effort. This research effort increases the probability of investment, the probability of successful investment, and therefore firm profit. Thus, a reward-oriented culture is more profitable than a punishment-oriented culture. On the other hand, when the ex ante expected size of the extreme user segment is large (i.e., $xy > 4c + 4cy$), the firm uses strategy IA (i.e., always investing). The researcher never makes research effort in a reward-oriented or a punishment-oriented culture, and so the culture does not affect firm profit. In the following section, we will show that the direction of the bias is critical to the result of Proposition 2.

4.4. Research Bias-in-Favor

We now consider the bias-in-favor case when the firm uses a researcher who needs to exert more effort to find information that accurately confirms the true state of the world is L than to accurately confirm the state of H. The following proposition compares the firm's investment probabilities when the researcher has a bias-in-favor to when the researcher is unbiased.

Proposition 3. *When there is a research bias-in-favor, the firm invests in inclusive product design with a lower probability than when there is no research bias if and only if the ex ante expected size of the extreme user segment is large (i.e., $xy > 4c$) and the company culture is either reward-oriented or weakly punishment-oriented $\left(\text{i.e., } R > 0 \text{ or } N < N_{nb} = \frac{(xy-4c)^2}{x(y-1)y^2(4c-x)}\right)$.*

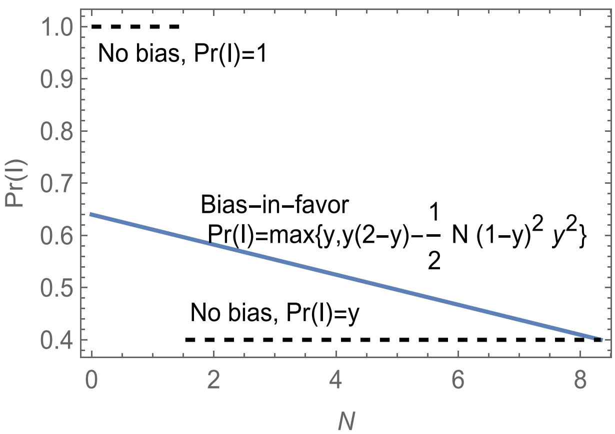
Proposition 3 highlights the interaction between a research bias-in-favor and company culture in determining the probability of investment in inclusive product design. One might expect that a research bias-in-favor would increase the probability of investment. Our findings suggest common intuition can be valid in some company cultures but invalid in others.

This result is again driven by how bias impacts the firm's confidence in the research outcome and the probability that the research suggests a large segment of extreme users. If the researcher with bias-in-favor reports $sig = L$, then the firm has a high degree of confidence that the state is L even if the researcher exerts no effort. Thus the firm will not make an investment. In contrast, if the researcher who has no research bias exerts little effort and reports $sig = L$, the firm's confidence in the signal is low and the firm may still invest if the ex ante expected size of the extreme user segment is sufficiently large (i.e., high xy).

On the other hand, the research is less likely to indicate a small extreme user segment when there is a research bias-in-favor. Therefore, absent an effect on the firm's confidence in the research outcome, the research bias-in-favor will lead to greater investment than an unbiased researcher. A strong punishment-oriented culture can motivate the unbiased researcher to exert enough effort to provide enough confidence such that the firm will not invest if $sig = L$. Moreover, a firm will not invest upon receiving $sig = L$ if the ex ante expected size of the extreme user segment is small. In these cases, a research bias-in-favor weakly increases the probability of investment, relative to an unbiased researcher, as one would expect.

Figure 2 compares the firm's investment probability under the researcher's optimal effort level when

Figure 2. (Color online) Firm Investment Probability in Case of No Research Bias vs. with Bias-in-Favor in a Punishment-Oriented Culture when $xy > 4c$ ($x = 0.2, y = 0.4, c = 0.001, R = 0$)



$xy > 4c$ with a research bias-in-favor versus unbiased research.

We next turn our attention to the effect of company culture on profitability.

Proposition 4. *When there is a research bias-in-favor, the punishment-oriented culture is more profitable than the reward-oriented culture if the ex ante expected size of the extreme user segment is large (i.e.,* $xy > 4cy(2-y)$*). Otherwise, the firm obtains the same profit in either culture.*

Proposition 4 runs counter to the industry's emphasis on the benefits of psychological safety. Whereas the safety to make mistakes and challenge the status quo is known to increase performance in general (Baer and Frese 2002), we find the interesting interaction between a research bias-in-favor of investment and a punishment-oriented culture can lead to the opposite effect. The reasoning behind the result is as follows. Recall that the firm has confidence to avoid investing in inclusive product design when the research indicates a small extreme user segment (i.e., when $sig = L$). When the ex ante expected size of the extreme user segment is large (i.e., $xy > 4cy(2-y)$), the firm uses strategy IH (i.e., only investing upon the research $sig = H$). This strategy, however, results in overinvestment because a research bias-in-favor makes the researcher more likely to obtain $sig = H$ than in the full information case. As discussed in Lemma 1, in this market condition, a researcher with a research bias-in-favor will only exert effort if the punishment for a failed investment, N, is sufficiently high. The effort induced by a punishment-oriented culture decreases the probability of investment in inclusive product design, and thus increases firm profit by decreasing the probability of failed investment. On the other hand, when the ex ante expected size of the extreme user segment is small, the firm adopts strategy IN (i.e., never investing). The researcher never exerts effort in either a reward-oriented or a punishment-oriented culture, and so the culture does not affect firm profit.

4.5. Comparing Impacts of Research Bias-Against and Research Bias-in-favor

In previous discussions, we have compared the research bias-against and the research bias-in-favor with the benchmark case of unbiased research separately. In this section, we directly compare the two types of research bias. Our comparison is made based on results in Tables 4 and 5.

First, we compare the impact of research bias on the firm's probability of investment in inclusive product design and summarize the results in Figure 3. Figures 4 and 5 illustrate the three-way interaction among company culture, research bias, and the ex ante expected size of the extreme user segment in determining the probability of investment in inclusive product design. In particular, when the ex ante expected size of the extreme user segment is large, a research bias-against leads to a greater probability of investment in inclusive product design than a research bias-in-favor within a reward-oriented culture, but the opposite is true in a punishment-oriented culture (Figure 4). When the ex ante expected size of the extreme user segment is small, the interaction between culture and bias is reversed (Figure 5).

Next, we compare the impact of bias on profitability and summarize the results in the following proposition.

Proposition 5.

(i) *When* $xy > 4c + 4cy$*, firm profit is lower with a research bias-against than research bias-in-favor within any culture;*

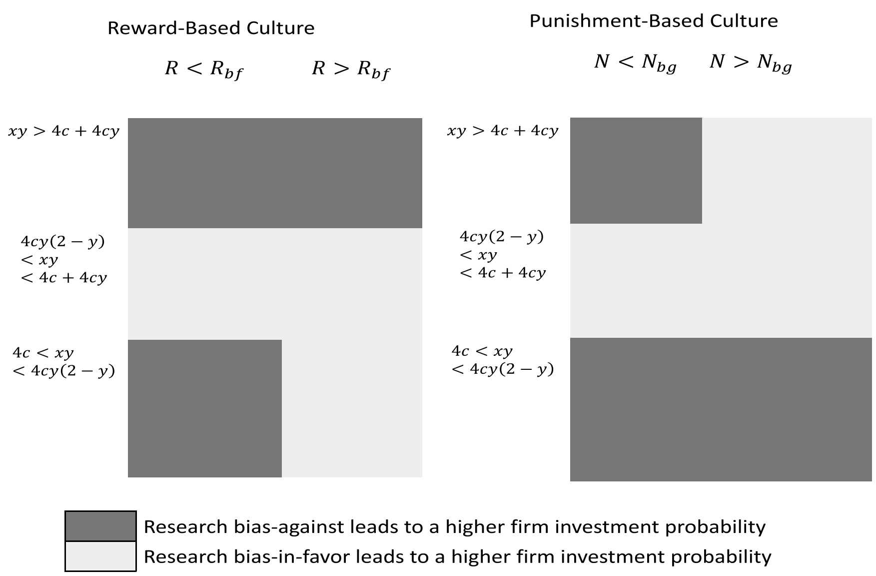
(ii) *When* $4cy(2-y) < xy < 4c(1+y)$*, firm profit is greater with a research bias-against than research bias-in-favor if the reward is sufficiently large, that is,* $R > \frac{2(8c-x)}{(4c-x)y(1-y)}$*, or the punishment is sufficiently small, that is,* $N < \frac{8c-x}{2cy(1-y)}$*. Otherwise, a research bias-in-favor researcher results in greater firm profit.*

(iii) *When* $xy < 4cy(2-y)$*, firm profit is greater with a research bias-against than a research bias-in-favor within any culture.*

Proposition 5 highlights the three-way interaction effect on expected firm profit between the direction of the researcher bias, the company culture, and the ex ante expected size from the extreme user segment, xy. This three-way interaction is summarized in Figure 6 and illustrated in Figure 7.

The intuition for this result is as follows. Overall when ex ante expected demand from the extreme user segment is sufficiently large, a research bias-in-favor is more profitable, because doing so helps alleviate overinvestment

Figure 3. Investment Probability with Research Bias-Against vs. Research Bias-in-Favor



(i.e., reducing investment probability from one to $(y + (1 - k)y(1 - y))$). On the other hand, when xy is sufficiently small, using a researcher with bias against investment is more profitable, because doing so alleviates underinvestment (i.e., increasing investment probability from zero to $(k + y - ky)y$).

When xy is intermediate, the firm invests only if receiving $sig = H$ from the researcher and obtains a greater profit if it receives a more accurate $sig = H$ with a greater probability. In this case, the research bias interacts with company culture to affect firm profitability. First, consider a researcher with research bias-in-favor of investment. Recall that a firm has confidence that the investment is not worthy when a biased-in-favor researcher reports $sig = L$. On the other hand, $sig = H$ from such a researcher is inherently noisy, and the researcher will exert effort to obtain a more accurate signal only to avoid penalty on a failed investment. Therefore, the researcher with a bias-in-favor exerts more effort and reports a more accurate

Figure 4. (Color online) Comparing Firm Investment Probability When $xy > 4c(1 + y)(x = 0.3, y = 0.4, c = 0.01)$

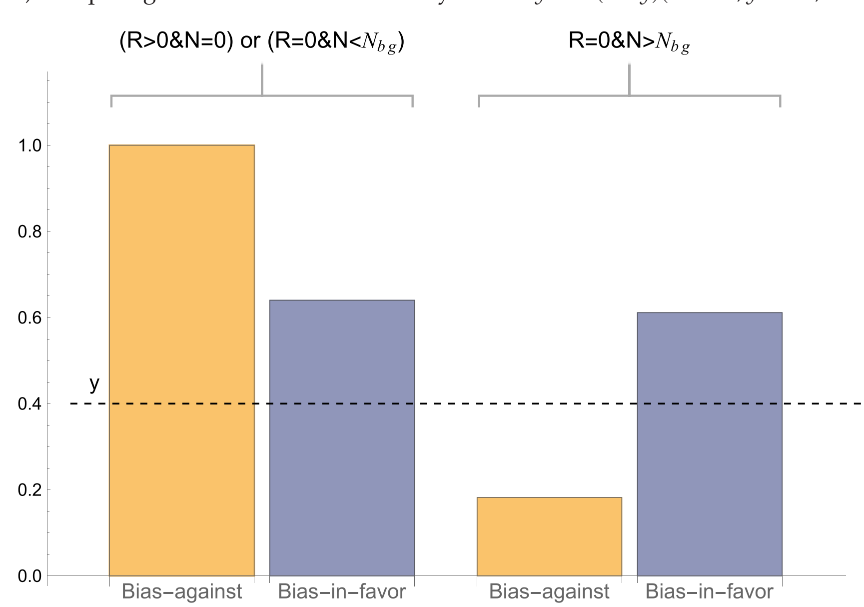
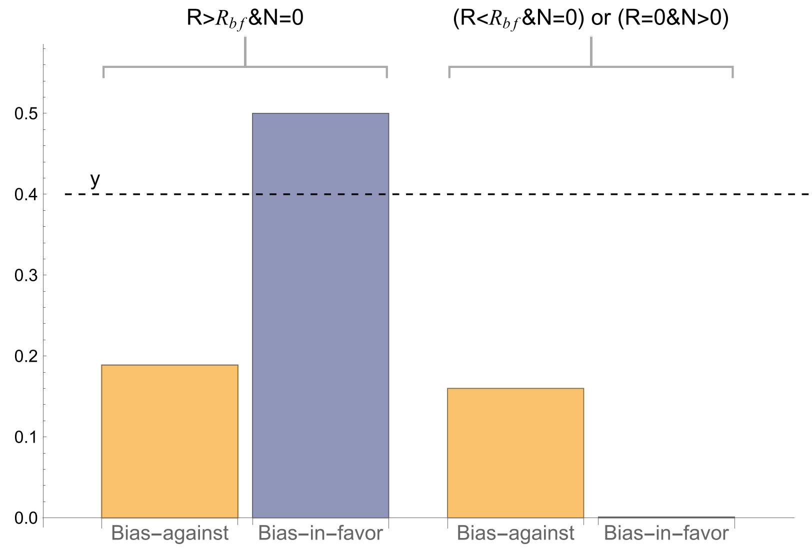


Figure 5. (Color online) Comparing Firm Investment Probability When $xy < 4c(2-y)y (x = 0.1, y = 0.4, c = 0.02)$



$sig = H$ when N increases, which consequently improves firm profit.

Next, we consider a researcher with a research bias against investment. The firm will always invest and enjoy a success when such a researcher reports $sig = H$. For the biased-against researcher, however, such a signal is costly to obtain. The researcher has incentive to exert effort in obtaining such a signal only if the reward for investment success is sufficiently large. The researcher exerts more effort and reports $sig = H$ with a greater probability when R increases, leading to enhanced firm profit. This is why the research bias-against results in greater profitability in a strong reward-oriented culture or a weak punishment-oriented culture.

Our result has important managerial implications. In particular, firms should pay careful attention to both the research bias and the company culture. When one factor is difficult to change, Proposition 5 shows the impact on the profitability of changing the other factor. Facing an inert culture, the company may hire researchers with certain lived experiences or may provide resources, tools, and training to alter the nature of the research bias. On the other hand, facing persistent research bias, the company may adapt the culture in

Figure 6. Firm Profit with Research Bias-Against vs. Research Bias-in-Favor

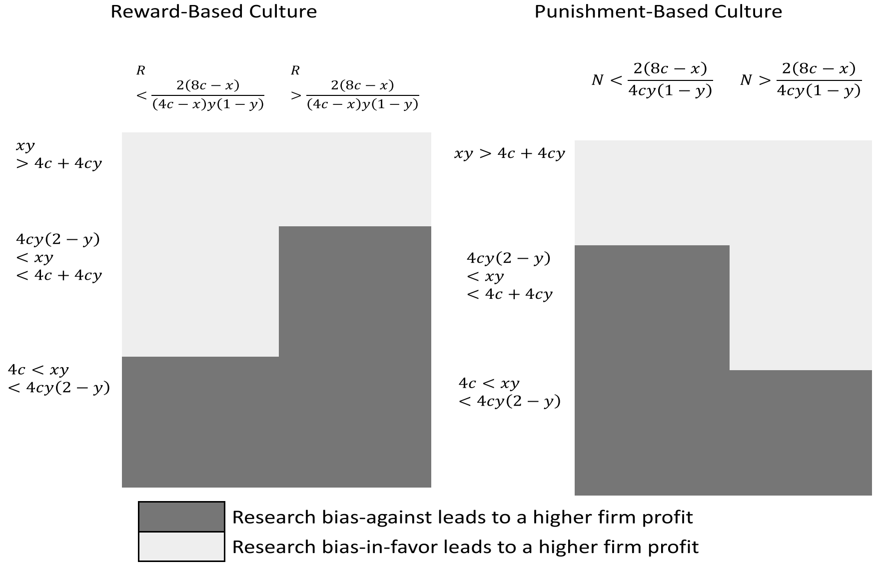
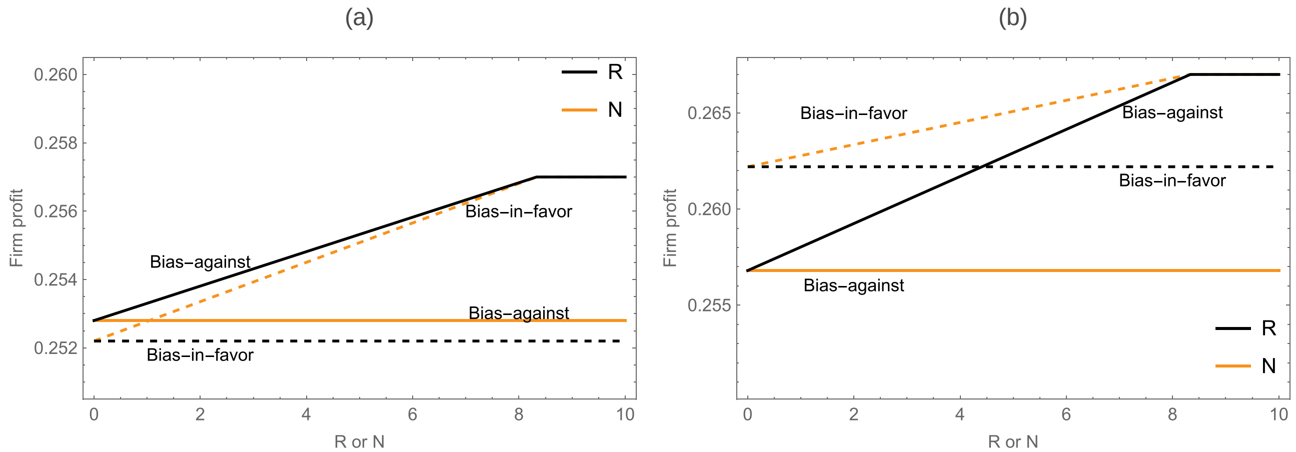


Figure 7. (Color online) Comparing Firm Profit When $4c(2-y)y < xy < 4c(1+y)$



Notes. (a) $x = 0.15, y = 0.4, c = 0.02$. (b) $x = 0.25, y = 0.4, c = 0.02$.

terms of how success is rewarded or failure is penalized. The result shows the prescriptions for improving profit or increasing the frequency of investments in inclusive product design critically depend on both the company culture and the research bias.

5. Model Extensions

In this section, we explore two extensions of our model to examine the robustness of the core insights. In the first extension, we allow for the offering of an inclusive product to influence the utility that a mainstream user derives from the product. In the second extension, we examine a company culture that is focused on effort rather than outcomes.

5.1. Consumer Preference Changes for the Inclusive Product

In our main model, a mainstream user has the same valuation distribution $[0,1]$ for the standard product and the inclusive product. In practice, by including features that are specifically designed for extreme users an inclusive product may present a different value for a mainstream user. Here, we consider this situation and demonstrate the robustness of our model results. We assume that consumer preference for the inclusive design follows a uniform distribution on $[0, 1+\alpha]$. Positive α indicates that the inclusive design enhances the value of the product for mainstream users, whereas negative α suggests that the inclusive design reduces the perceived value of the product for mainstream users. The main model can be viewed as a special case where $\alpha = 0$. We consider the interesting case when $|\alpha|$ is small.

A larger α enables the firm to charge a higher price (i.e., $\frac{1+\alpha}{2}$) for the inclusive product. Across all cases of research bias, if the firm receives $sig = H$, its expected profit from investing is

$$Pr(H|sig = H)\frac{(1+x)(1+\alpha)}{4} + Pr(L|sig = H)\frac{1+\alpha}{4} - c. \tag{3}$$

If the firm receives $sig = L$, its expected profit from investing is

$$Pr(H|sig = L)\frac{(1+x)(1+\alpha)}{4} + Pr(L|sig = L)\frac{1+\alpha}{4} - c. \tag{4}$$

In Equations (3) and (4), the conditional probabilities are the same as in the main model. The equilibrium results of each case of research bias can thus be obtained by replacing c in the main model with $\frac{c}{1+\alpha}$. It is easy to see that with a larger α the firm has stronger incentive to invest in inclusive product design. The qualitative results of Propositions 1–5 continue to hold.

5.2. Firm Rewards Effort

Our main model considers the company culture of rewarding or punishing based on outcomes, which is consistent with Google chief executive officer (CEO) Sundar Pichai's observation that "People tend to reward outcomes."[18] One argument for this outcome-based approach is that rewarding effort can "cultivate a workforce focused on looking good rather than doing good" (Russo 2010). Moreover, Sarin and Mahajan (2001) found empirically that outcome-based rewards (relative to process-based rewards) had a positive relationship with product quality.

We recognize that some companies choose to reward effort. In this section, we examine how research bias affects investment in inclusive product design within a company culture that focuses on effort-based rewards.

The extension is the same as the main model with the exception that we assume the firm offers a marginal reward on effort equal to $2E$ ($0 \leq E \leq 1$). The researcher chooses $k \in [0,1]$ to maximize $\Gamma_e(k) = 2Ek - k^2$, regardless of bias. This payoff is independent of the firm's investment decision because the reward is tied to effort rather than outcomes. As such, the researcher's payoff is maximized at $k^* = E$.

We consider exogenous E that reflects the culture of the organization and extends beyond the researcher's role and any single research project. Endogenizing E would require further assumptions regarding the firm's constraints and costs of providing intrinsic rewards based on effort; otherwise, E would be set such that there is maximum research effort and no uncertainty associated with the impact of investing in inclusive product design.

For each bias case, the preceding analysis of the main model defines the firm's investment decisions as a function of k. We summarize the equilibrium probability of investment for any given E in Table 6 (proof of the table is in the online appendix). We can see that when the firm rewards research effort rather than outcomes, research bias can have counterintuitive impacts on the probability of investment in inclusive product design that are similar to what is demonstrated in the main model. Notably, a research bias against can lead to a greater probability of investment than an unbiased researcher (see the third row of Table 6). Also, a research bias-in-favor can lead to a lesser probability of investment than an unbiased researcher (see the first row of Table 6). The intuition is as follows. When the company rewards effort, researchers will exert the same effort, regardless of research bias. However, the probability that a researcher will produce a high or low signal depends on the researcher's bias. Via the same mechanism as in the main model, the direction of a bias can have an opposite impact on the probability of investment as a result of the confidence a firm has in a signal that is counter to the bias.

In conclusion, this extension confirms the central thesis that there is a company culture-research bias interaction in determining firm investment in inclusive product design. This interaction is driven by the impact of company culture, as defined as high or low reward on effort, on the research effort and the impact of research bias on the firm's inference of the research outcome.

6. Conclusion

Recent successes in inclusive product design demonstrate the business potential of serving consumer segments who have been traditionally overlooked by innovations. For example, Herbal Essences piloted tactile markings on its products to help blind customers identify the product of their choice and the product's success led the company to roll out the feature on all shampoos and conditioners.[19] Google's Pixel 6 smartphone has made accessibility a point of emphasis in its design and in advertisements.[20] However, designs based solely on the needs of mainstream users commonly miss out on sales from extreme users. For instance, a recent study suggests that retailers lost out on \$828 million due to websites that were not inclusive to shoppers with disabilities.[21] Given the significant spending power of consumers who are overlooked when product design is not inclusive, it is a surprise that underinvestment in inclusive product design has persisted for years and continues to persist for some companies. Our paper examines two factors that can affect how often a firm invests in inclusive product design: research bias and company culture.

For constituents hoping to see investment in inclusive product design become more common, our paper shows an important interaction between research bias and company culture. This interaction produces several surprising results. First, a researcher whose process is biased against finding a large extreme user segment can result in a greater probability that the firm invests in inclusive product design than an unbiased

Table 6. Equilibrium Investment Probabilities Pr(I) When Effort Rewarded

Condition	No bias	Bias-against	Bias-in-favor
High xy, low E	$Pr(I) = 1$	$Pr(I) = 1$	$Pr(I) = y + (1-E)y(1-y)$
High xy, high E	$Pr(I) = y$	$Pr(I) = (E + y - Ey)y$	$Pr(I) = y + (1-E)y(1-y)$
Low xy, low E	$Pr(I) = 0$	$Pr(I) = (E + y - Ey)y$	$Pr(I) = 0$
Low xy, high E	$Pr(I) = y$	$Pr(I) = (E + y - Ey)y$	$Pr(I) = y + (1-E)y(1-y)$

Note. High xy, low E: $xy > \max\{4c, 4c(1+y), 4c(2-y)y\}$, $E < \min\left\{\frac{xy-4c}{xy}, \overline{k}_{bg} = \frac{4cy+4c-xy}{4cy-xy}\right\}$;

high xy, high E: $xy > \max\{4c, 4c(1+y), 4c(2-y)y\}$, $E > \max\left\{\frac{xy-4c}{xy}, \overline{k}_{bg}\right\}$;

low xy, low E: $xy < \min\{4c, 4c(1+y), 4c(2-y)y\}$, $E < \min\left\{\frac{4c-xy}{x(1-y)}, \underline{k}_{for} = \frac{4cy-8c+x}{4cy-4c}\right\}$;

low xy, high E: $xy < \min\{4c, 4c(1+y), 4c(2-y)y\}$, $E > \max\left\{\frac{4c-xy}{x(1-y)}, \underline{k}_{for}\right\}$.

researcher. This occurs when the company culture is punishment-oriented or offers limited reward in a reward-oriented culture. Second, a researcher whose process is biased in favor of finding a large extreme user segment can result in a lesser probability that the firm invests in inclusive product design than an unbiased researcher. This occurs when the company culture is not strongly punishment-oriented. As a consequence, if one is hoping a company increases the frequency of investing in inclusive product design, it is important to recognize both the company culture and the research bias.

Our results regarding the impact of company culture and research bias on the likelihood of firm investment in inclusive product design are driven by two opposing effects. On the one hand, research bias impacts the firm's confidence that the research outcome aligns with the true state of the world. On the other hand, research bias affects the likelihood that the outcome of the research suggests a large number of extreme users. The counter-intuitive results arise when the research bias materially affects the investment decision through an impact on the firm's confidence in the research outcome and are moderated when the company culture inspires substantial research effort of an unbiased researcher.

For companies looking to maximize profit, the research again finds an interaction between research bias and company culture. A punishment-oriented culture can be more profitable when the researcher's process is biased against finding a large extreme user segment. A reward-oriented culture can be more profitable when the researcher's bias is in favor of finding a large extreme user segment. Our results also identify conditions for when profit is greater with a research bias-against and when profit is more profitable with a research bias-in-favor. Our findings indicate that a firm's effort to change company culture or research bias to increase profit may not be fruitful and actually can be counterproductive. The impact of such a policy change has to be carefully evaluated in the context of bias-culture interaction.

As companies look to either increase the likelihood that their culture and research process will lead to inclusive product design or increase their profitability, our paper provides insights into how the factors interact. If company culture is immutable given the size of the organization or the mentality of leadership, our model shows when hiring decisions or training to change the direction of biases will be effective at increasing profit or investment in inclusive product design and when they will have adverse consequences. If the bias of the researcher is fixed given the team in place, our model shows when efforts to have a reward-oriented culture will succeed in increasing profit and when the efforts will backfire.

This research was inspired by the conundrum surrounding company investment in inclusive product design. Meanwhile, the mechanism plausibly applies to a broad range of decisions that can be informed by a biased research process. Future research can explore how generally the insights can be applied.

Moreover, inclusive product design is an important topic that deeply affects the lives of people from historically marginalized communities. A rigorous empirical study confirming the interaction between research bias and company culture in impacting investment in inclusive design is an interesting area for future research. Future research can consider whether long-term reputational effects or consumer fairness concerns can lead to an equilibrium investment in inclusive product design even if the market need is not large enough to justify the expense on its own. Future research can also explore the role of teams in influencing the equilibrium outcomes and explore an endogenous hiring process. Whereas our model considers bias manifesting itself in the signal researchers find, future research can consider intrinsically motivated bias that directly weighs into the researcher's payoff function. There is also an opportunity to examine continuous investments in inclusive product design that provides fractional benefits to commonly overlooked consumers. Further research is warranted to identify roadblocks to inclusive product design that can be profitably removed to create a more equitable future.

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Endnotes

[1] See https://www.bestcards.com/credit-card-news/citi-launches-true-name-feature/ (accessed March 22, 2023).

[2] See for instance, https://www.mckinsey.com/business-functions/mckinsey-design/how-we-help-clients/design-blog/accessible-design-means-better-design (accessed March 22, 2023).

[3] See https://www.userinterviews.com/blog/design-failure-examples-caused-by-bias-noninclusive-ux-research (accessed March 22, 2023).

[4] See https://gizmodo.com/the-pixel-6s-accessibility-features-make-me-hopeful-for-1847997736 (accessed March 22, 2023).

[5] See https://www.indeed.com/career/user-experience-researcher (accessed March 22, 2023).

[6] See https://www.fastcompany.com/90775141/for-tech-to-work-for-everyone-we-need-commitment-and-collaboration-on-product-inclusion (accessed March 22, 2023).

[7] See https://www.ccl.org/articles/leading-effectively-article/3-factors-that-drive-or-suppress-innovation/ (accessed March 22, 2023).

[8] See https://about.google/belonging/in-products/ (accessed March 22, 2023).

[9] See https://rework.withgoogle.com/guides/foster-an-innovative-workplace/steps/introduction/ (accessed March 22, 2023).

[10] See https://abcnews.go.com/Technology/exclusive-google-reveal-2000-person-diversity-inclusion-product/story?id=68154762 (accessed March 22, 2023).

[11] This assumption indicates that there is no information asymmetry between the firm and the researcher, which contrasts with a principal-agent relationship between a firm and its sales agent (Coughlan and Sen 1989, Prendergast 1999).

[12] See https://grain.com/blog/recruiting-participants-for-user-research (accessed March 22, 2023).

[13] See https://help.usertesting.com/hc/en-us/articles/115003370731-Screener-Questions-Best-Practices (accessed March 22, 2023).

[14] See https://blog.google/outreach-initiatives/diversity/transgender-awareness-week-2021/ (accessed March 22, 2023).

[15] See https://www.fastcompany.com/90775141/for-tech-to-work-for-everyone-we-need-commitment-and-collaboration-on-product-inclusion (accessed March 22, 2023).

[16] See https://about.google/belonging/in-products/ (accessed March 22, 2023).

[17] See https://www.remodeling.hw.net/business/leadership/stand-up-and-be-recognized (accessed March 22, 2023).

[18] See https://www.gsb.stanford.edu/insights/sundar-pichai-reward-effort-not-outcomes (accessed March 22, 2023).

[19] See https://www.businesswire.com/news/home/20191009005512/en/Herbal-Essences-Continuing-Commitment-Inclusive-Design-Accessibility (accessed March 22, 2023).

[20] See https://gizmodo.com/the-pixel-6s-accessibility-features-make-me-hopeful-for-1847997736 (accessed March 22, 2023).

[21] See https://www.forbes.com/sites/gusalexiou/2021/12/19/retailers-to-lose-828-million-of-sales-over-christmas-due-to-inaccessible-websites/?sh=2946f42d35b5 (accessed March 22, 2023).

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