3-2016

The Technology Effect: How Perceptions of Technology Drive Excessive Optimism

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Recommended Citation

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Abstract

Purpose-- We propose that constant exposure to advances in technology has resulted in an implicit association between technology and success that has conditioned decision makers to be overly optimistic about the potential for technology to drive successful outcomes. Three studies examine this phenomenon and explore the boundaries of this "technology effect."

Design/methodology/approach-- In Study 1, participants (N = 147) made simulated investment decisions where the information about technology was systematically varied. In Study 2 (N = 143), participants made decisions in a resource dilemma where technology was implicated in determining the amount of a resource available for harvest. Study 3 (N = 53 and N = 60) used two implicit association tests (IATs) to examine the assumption that people associate technology with success.

Findings-- Results supported our assumption about an implicit association between technology and success, as well as a "technology effect" bias in decision making. Signals of high performance trigger the effect, and the effect is more likely when the technology invoked is unfamiliar.

Implications-- Excessive optimism that technology will result in success can have negative consequences. Individual investment decisions, organizational decisions to invest in R&D, and societal decisions to explore energy and climate change solutions might all be impacted by biased beliefs about the promise of technology.

Originality/value-- We are the first to systematically examine the optimistic bias in the technology effect, its scope, and boundaries. This research raises decision makers' awareness and initiates research examining how the abstract notion of technology can influence perceptions of technological advances.

The Technology Effect: How Perceptions of Technology Drive Excessive Optimism

Technological change and transformation touches almost all aspects of our daily lives. Prior research has demonstrated that technology influences numerous phenomena such as emotional response (Pinch & Bijker, 1987), value perceptions (Rindova & Petkova, 2007), and the quality of human relationships (Turkle, 2011). Yet to date we know very little about how perceptions of technology influence cognition in decision making. The pervasiveness of technology in nearly every aspect of society and business makes this a critical issue. Indeed, many important decisions that are made by individuals (e.g., purchasing new technology), organizations (e.g., investing in R&D), and governments (e.g., clean energy investments) about the allocation of scarce resources involve the notion of technology and forecasts of the likelihood that technology will improve our lives.

In this paper we argue that there is a tendency toward excessive optimism when making decisions involving technology. Because technological successes often produce dramatic and memorable results, such as revolutionizing industries and substantially altering our quality of life, such events are highly salient (Tversky and Kahneman, 1974). In contrast, technological failures are less salient because they often do not change the status quo (Golder & Tellis, 1993), and they are less likely to be discussed or publicized (Levinthal & March, 1993). As a result, we maintain that in decision making contexts, people develop a non-conscious or "implicit" association between technology and success (Greenwald, McGhee, & Schwartz, 1998), and that technology has become a diagnostic cue (Soll, 1996) for predicting success. We label the bias toward optimism in technology the "technology effect."

The technology effect has at its core the concept of overoptimism or overconfidence[1].

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[1] Overconfidence is conceptualized both as certainty that one's prediction (success or failure) is accurate (e.g., Klayman, Soll, González-Vallejo, & Barlas, 1999), and as certainty that a positive or successful outcome is more

Technology and overoptimism have been addressed extensively, but separately, by scholars in areas such as sociology, psychology, economics, and decision making. For example, technology research has explored questions of organizational structure (Rumelt, 1974), firm survival (Nelson & Winter, 1982), depth of relationships (Turkle, 2011), technology acceptance and phobia (Walczuch, Lemmink & Streukens, 2007), product preferences (Muthitcharoen, Palvia & Grover, 2011), value perceptions (Rindova & Petkova, 2007), and technology emergence (Chandy, Prabhu & Antia, 2003). Similarly, separate bodies of work have focused on overoptimism in research on entrepreneurial cognitions (Keh, Foo & Lim, 2002; Lowe & Ziedonis, 2006), social and resource dilemmas (Jager et al., 2002), market entry (Camerer & Lovallo, 1999), new product introduction (Hoeffler, 2003), and risk (Costa-Font, Mossialos & Rudisill, 2009).

However, to our knowledge, researchers have not yet examined the *intersection* of overoptimism and technology in the context of decision making. This oversight might be due to the fact that the tendency to be optimistic about technology is so pervasive that we take the association between technology and "success" for granted; people simply assume their optimism about the future success of technology is only rational. Indeed, there is ostensibly considerable reason for optimism. Like clockwork, Moore's law[2] has become a given for microprocessor advances (Moore, 1965). Physics, medicine, energy, global communications, and many other areas of technological and scientific inquiry have been revolutionized and revolutionized again. The fundamental assumption underlying the research we present here is that incredible

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likely than it actually is (e.g., Malmendier & Tate, 2005). The latter is akin to definitions of overoptimism (e.g., Jager, Janssen & Vlek, 2002) and is the type of overconfidence focused on in this manuscript. Hereafter, we refer to this as overoptimism.

[2] Moore's law is a description of the long-term trend that integrated circuits have tended to double in capacity every 2 years. This is most commonly linked to computer processing speed by the general public but also relates to things such as memory capacity and the number of pixels in digital cameras.

technological progress has conditioned us to *expect* technology to be a driver of success and progress. But this perspective has costs. Scholars and practitioners alike have long recognized that technology may alter our perceptions, noting the "seductive allure" of science and technology (Weisberg, Keil, Goodstein, Rawson & Gray, 2008), and have even publicly complained about the pitfalls of overoptimism towards technology (e.g., Silverstein, 2009). Despite these acknowledgements, however, the bias has not been empirically assessed, nor has the effect been described or its boundaries explored.

In this paper we present the results of three studies examining the core hypothesis that people associate technology with success, and that technology is used as a diagnostic cue for predicting success, which influences behavior. We also explore important contextual variables that help define the scope and boundaries of this effect. In Study 1 we examine whether information primes that denote past success make it more likely that people will use technology as a diagnostic cue in decision making. In Study 2, we test whether the technology effect is more likely to be active when the technology in question is unfamiliar rather than familiar. Finally, in Study 3, we explicitly examine our underlying assumption about the association between the notion of technology and "success" using an implicit association test (IAT).

Theoretical Mechanisms Underlying the Technology Effect

Definitions of the term "technology" are typically broad and abstract (e.g., Bain, 1937; Stiegler, 1998). The widespread use of terms like "technologically advanced" or "high tech" or "technologically savvy" suggest that although technology can take many forms, our society has developed considerable agreement that "technology" is something we encounter regularly, and is an important characteristic of things, processes, or the companies that use it. In this paper, one of our fundamental assumptions is that the abstract notion of technology has become a powerful

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and socially constructed quality that helps people make sense of their environment. Importantly, we also argue that because the abstract notion of technology has become so pervasive, it influences our judgment and decision making processes. Specifically, it provides people with a way of connecting one incidence of technology with past examples of technology. It is this overgeneralization of one technology context to others that is the basis of the underlying bias in judgment and decision making that we examine here.

At the center of our argument is the assertion that the abstract concept of technology has become associated over time with the notion of success, such that triggering the notion of technology can unconsciously trigger cognitions associated with success. These unconscious associations have become known as *implicit associations* (Greenwald & Banaji, 1995), and this literature has demonstrated that implicit associations between constructs can be powerful drivers of cognition and behavior (e.g., Greenwald, Poelman, Uhlmann, & Banaji, 2009). Consistent with the literature on implicit processing, we argue that people develop an implicit association between technology and success through accumulated experiences in which the two are paired.

We suggest that the process by which this occurs is related to the notions of salience and availability (Tversky & Kahneman, 1973). For example, the notion of salience suggests that individuals are more likely to notice examples of the successful application of technology, because those instances are more prominent (Hossain & Morgan, 2006) or relevant (John, Acquisti & Loewestein, 2009) relative to failed examples which are more easily overlooked (Golder & Tellis, 1993). The successes of emerging technologies are often highly dramatic (e.g., 3-D printing), while technological failures are relegated to the proverbial trash heap of collective memory. The notion of availability suggests that people might have disproportionate access to examples of successful implementations of technology due to a reluctance to discuss or publicize

failures (Levinthal & March, 1993). In other words, we suggest that frequent exposure to examples of technological successes gradually "bakes in" a cognitive association between technology and success.

Implicit associations are assumed to be learned slowly, and unconsciously, but once developed, they are thought to operate quickly and automatically with regard to cognition and behavior (Uhlmann, Leavitt, Menges, Koopman, Howe, & Johnson, 2012). Chaiken's (1980) heuristic-systematic model (HSM), suggests that information processing can occur along two routes: a more effortful systematic processing route, or a more automatic (or heuristic) route that does not involve complex information processing. People utilize the heuristic route when strong cues exist about the reliability of a message, which decreases motivation to engage in more effortful systematic processing. Chaiken and colleagues (1989) suggest that "the rules or heuristics that define heuristic processing are learned knowledge structures" (p. 213). In that regard, we argue that the implicit association between technology and success is such a learned knowledge structure. Specifically, we contend that the abstract notion of technology has become so powerfully associated with progress and achievement, or "success," that invoking technology in a decision context can trigger an automatic assumption that decision choices involving technology will be successful.

The notion of a *diagnostic cue* (Feldman & Lynch, 1988) provides a useful way of conceptualizing how an implicit association between technology and success can influence decision making. Diagnostic cues are recognizable signals or features of a decision context that prompt a decision maker to activate previously developed mental models that are relevant to the current context (Soll, 1996). A cue develops when decision makers perceive that its presence correlates with repeated outcomes of one type (Soll, 1996). We argue that technology,

particularly in contexts where it's success or failure are relevant, represents an important

diagnostic cue triggering "spreading activation" (Greenwald & Banaji, 1995) of associations

between technology and success that are represented in the implicit association mental model. In

the current paper, we use the notion of diagnostic cues in the development of our studies by

systematically varying the extent to which participants are exposed to decisions where

technology is presented as a prominent characteristic of the decision contexts they face.

In summary, we propose that continuous past exposure to evidence that technology has

resulted in myriad advances and positive outcomes for society has caused people to be overly

optimistic in their belief that technology will lead to success. As a result, when decision contexts

trigger the notion that technology might play a role in determining the outcome of some

situation, that reference to technology becomes a diagnostic cue that prompts an automatic

association with successful outcomes and behavior that assumes technology's success. We refer

to this as the technology effect.

Study 1

Theory and Hypotheses

As an initial examination of the technology effect, we chose financial investment

decisions as our context. Financial decision making has often been used to test cognitive

heuristics such as the recognition heuristic (Borges, Goldstein, Ortmann & Gigerenzer, 1999)

and the processing fluency heuristic (Alter & Oppenheimer, 2006). Financial decision contexts

are also relevant for exploring the technology effect because emerging technology attracts large

amounts of public and private investment, even though the returns on those investments are

frequently disappointing. For example, biotechnology alone attracted nearly $59 billion in the

United States from 4Q 2010 to 3Q 2011 (Burrill, 2011). While the promise of biotech has been

somewhat intoxicating, stimulating excitement and extreme levels of investment, the financial

reality has been ordinary at best (Pisano, 2006), with the sector underperforming both the Dow

Jones and Treasury bonds (Burrill, 2002; Hamilton, 2004).

We suggest that optimism toward technology investments might be influenced by the

implicit association between technology and success. We argue that when technology is a salient

feature of investment options, this represents a diagnostic cue that primes automatic associations

with success. Specifically, in the current study, guided by the results of a pilot study, we assume

that individuals will use information about industry to infer the presence of technology. We

predict that industries that are not considered technology industries will not trigger an automatic

association with success and will be perceived as less attractive investments. On the other hand,

the presence of technology will be perceived as a diagnostic cue that links that decision context

to a previously learned knowledge structure where technology is automatically associated with

success. Importantly, we believe this will occur even when information provided regarding

future performance is explicitly held constant. We therefore hypothesize the following:

> *H1: Investment in technology industries will be greater than investment in non-*
> *technology industries, when keeping financial return prospects constant.*

The utilization of a diagnostic cue is based on perceptions of relevance, thus cues become

more likely to be used when decision contexts are perceived as similar to the experiences from

which the cue originated (Simon & Houghton, 2003). Information regarding current or prior

success of a company and its stock should be somewhat diagnostic for predicting future success

(all other things being equal), and thus for making investment decisions. However, if technology

tends to stimulate associations with success, priming participants by providing information about

current or prior success should stimulate the implicit technology-success association. This

would, in turn, augment the perceived utility of technology as a diagnostic cue, resulting in an increased likelihood that the technology effect will be manifest. In other words, signals of recent success will increase expectations of future success more for technology investments than for non-technology investments.

H2: Past performance will moderate the relationship between investment in technology vs. non-technology industries such that an indication of high past performance will further increase the preference for technology investments.

Method

Pilot procedure. Prior to conducting the primary study, in which participants were asked to make investment choices in technology vs. non-technology, a pilot study was conducted in order to identify industries that were widely considered to be "technology" industries. Doing so is important because technology is not easy to define, but is something that is perceived by the decision maker. Having a pilot procedure enabled us to identify and validate our assumption that certain industries are perceived to be associated with technology. Because prior literature finds that people have a preference for investing in familiar companies (Huberman, 2001) we chose not to use real companies' stocks. We identified 9 industries we considered high tech, and 9 we believed were not high tech, and asked 40 undergraduate business students to rate the degree to which they believed each industry was a high-technology industry. Of the 18 examined in the pilot, we identified 12 industries for use in the study. The 6 technology industries, in descending order of the degree to which pilot participants considered them to be a "technology" industry, were Aerospace (4.85/5), Medical Devices (4.78), Nanotechnology (4.78), Biotechnology (4.77), Quantum Cryptography (4.53), and Semiconductors (4.25). The 6 non-technology industries, in ascending order of the degree to which they are considered to be a "technology" industry, were

Insurance (2.50/5), Restaurant (2.53), Retail Apparel (2.60), Food products (2.88), Textile goods (2.98), and Commercial Banks (3.26). Technology ratings for all 6 technology industries were significantly higher than the ratings for all 6 non-technology industries ($p < .01$). The use of multiple industries across multiple sectors for each category is helpful in attenuating the potential biasing influence of any one industry or sector (Baca, Garbe & Weiss, 2000). To rule out any reputation effect, pilot participants rated the reputation of each industry in terms of integrity, benefit to society, ethical approval, and importance. Across those dimensions, the average rating of the 6 technology industries (3.7/5) was not significantly different than the average of the 6 non-technology industries (3.6/5). Furthermore, to rule out the alternative explanation that the 6 technology industries are simply higher performing in the real world, the combined performance of the technology industries was compared to that of the non-technology industries. The difference in performance of stocks within the technology and non-technology industries during the fiscal year prior to data collection (8.15% vs. 8.04%) was not statistically significant and was practically equivalent. In addition, and perhaps most importantly, we fixed the probabilities for given future returns in our study materials by providing participants with information indicating the prospects for future returns for each stock, and that information was kept constant across the high and low technology stock groups. In other words, although the reputations and actual past returns of the industries among which participants could choose were equivalent, and participants were provided with information suggesting that prospects for future returns were equivalent, we predicted that participants' optimistic bias toward technology would still lead them to invest more in the technology stocks that they implicitly believed should do better.

Participants and procedure. We used two samples to test our hypotheses. Sample 1 was used for both hypotheses and Sample 2 was used to test Hypothesis 1 under different conditions

in order to extend generalizability.

Sample 1 included sixty-three undergraduate participants (73% male). Each participant was asked to complete a series of six financial decisions. In each decision, participants decided how much of $100,000 they would invest in a certificate of deposit (CD) that yields a fixed 5% annual return, and how much they would invest in an industry stock that has the potential to yield either a positive or negative return with a 6.5% annual return as the probability weighted average. For each of the six decisions they were provided information that stated the guaranteed return of the CD and the probabilities of a range of potential returns for the stock. The potential stock returns and their probabilities were equivalent across all industries.

Technology was manipulated by labeling the stock in each decision as either one of the technology industries or one of the non-technology industries identified in our pilot. For each participant, three of the six decisions required an investment allocation between a CD and one of the technology stocks and the other three between a CD and one of the non-technology stocks. *Investment* was calculated as the percentage of the money that was invested across the three technology stocks and non-technology stocks instead of the CD. Therefore, each participant had two investment measures: *technology investment* and *non-technology investment*.

Past Performance was a between subjects variable manipulated by including a graph of past stock performance in the information provided for each decision. Half of the participants saw computer-generated graphs with a relatively regular upward trend representing high past performance, and the other half saw graphs with a comparatively flat trend representing low past performance. All six graphs were distinct (to increase realism) but were generated to display mathematically equivalent trends. Each graph included two non-dated years (i.e., only months were indicated) of past performance of daily stock price with a superimposed trend line. Each

stock begins at $40 with the high performance computer-generated graphs showing an annual return ranging from 17.4% to 22.4% with an average of 19.9% and the low performance graphs showing an annual return ranging from 2.5% to 4.5% with an average of 3.5%. The past performance graphs provide our manipulation, but also further aid in ruling out the possibility that study results are biased by actual industry performance. About half of the participants saw high performance graphs for all six investment decisions while the other half saw only low performance graphs. This was done so that technology could be isolated as the sole manipulated within-subjects variable. To control for order effects, and specific industries, various versions of the materials were utilized. Six technology industries were separated into two lists of three, with half of the participants receiving one list and half receiving the other. Similarly, the six non-technology industries were divided into two lists of three, with half of the participants receiving each list. In addition, six high past performance graphs, and six low past performance graphs were split into two groups of three with half of the participants receiving one set or the other. Finally, order was counterbalanced such that about half of the participants received materials with three technology industries followed by three non-technology industries, while the other half received them in the reverse order. In all, this accounted for 16 versions of the materials wherein no stock list went first more than the other lists, each list was matched with the various graphs equally often, and each technology industry list was paired with each non-technology industry list equally often.

Participant gender was used as a covariate in the repeated measures analysis because past research has suggested that gender influences overoptimism in stock trading (e.g., Barber & Odean, 2001) and risk taking in general (Byrnes, Miller & Schafer, 1999).

In Sample 2, instead of simple pairwise decisions between a stock and a CD, we

presented participants with 10 industries (5 technology and 5 non-technology) in which they could invest. We asked the participants to make decisions about how much to invest in each industry simultaneously across the 10 options. Not only does this procedure introduce additional complexity to the decision context that more closely mirrors real-life investment decisions, it also directly pits technology and non-technology investments against one another, which was not done in Sample 1 where stock investments were chosen against CD investments. Importantly, we also note that people tend to use an equal weighting rule (i.e., invest the same amount in all stocks) in order to simplify complex decisions with multiple options (Einhorn & Hogarth, 1975). As a result, the modified decision context in Sample 2 represents a stronger test of our hypothesis, because in order for a technology bias to be detected, it must be strong enough to overcome an equal weighting strategy.

Eighty-four undergraduate student participants (65% male) were asked to allocate a sum of money among ten industries; 5 technology (Medical Devices, Nanotechnology, Biotechnology, Quantum Cryptography, and Semiconductors) and 5 non-technology (Restaurant, Retail Apparel, Food products, Textile goods, and Commercial Banks). To control for a potential magnitude effect of dollar quantity, half of the participants were given a theoretical $250,000 to invest while the others were given $25,000 to invest. Likewise, to avoid potential order effects, half of the participants received the list of ten industries in a particular order and the other half received the reverse order. *Technology Investment* was calculated as the percentage of dollars allocated to the five technology industries.

Results and Discussion

Means, standard deviations, and correlations for Sample 1 variables are provided in Table 1. Analysis of the individual industries revealed that five of the six technology industries were

invested in more heavily than all 6 of the non-technology industries. Prior to examining our hypotheses, we confirmed that there were no effects for the order in which technology or non-technology stocks were presented, nor effects for the different versions of the graphs or industry lists. Amounts invested in technology and non-technology industries were analyzed using a mixed-model ANOVA, with past performance (the graph manipulation) as a between subjects variable and gender as a covariate. In our model, there was a significant within-subjects interaction between Gender and Technology ($F(1,59) = 5.64$, $p<.05$, $\eta_p^2 = .09$), whereby women invested less in low technology industries than in high technology industries relative to men. Hypothesis 1 predicted that technology industries will attract greater investment than non-technology industries even when the financial prospects are equivalent. Results indicated a significant within-subject difference in investment percentage between the technology and non-technology industries ($F(1,59) = 9.13$, $p<.05$, $\eta_p^2 = .13$), with participants investing more money in technology industry stocks (M = 43.24%) than non-technology stocks (M = 38.65%). Thus, Hypothesis 1 was supported by Sample 1.

We also used Sample 2 to test Hypothesis 1. Sample 2 analyses indicated that the initial amount of money to be allocated ($25,000 or $250,000) did not affect standardized allocation decisions. Thus, we discuss allocations to technology and non-technology industries in terms of percentage of investment. Analysis of the individual industries revealed that three of the five technology industries were more heavily invested in than all five of the non-technology industries. The mean percent invested in technology industries was 60% (N = 84, SD = .20). We predicted that investment in high-technology would be greater than low-technology. To test Hypothesis 1 we compared the mean investment in technology (60%) to the null hypothesis that there is no difference in investment between the two types of stocks (i.e., 50% each). Results

indicated significantly greater investment in technology ($t(83) = 4.59$, $p < 0.05$). This result

provides evidence of the robustness of the technology bias in individuals, because of its ability to

overcome the simplifying strategy of equal weighting.

Sample 1 was used to test Hypothesis 2, which posited that information about past

performance will moderate the relationship between technology and investment such that there

would be a stronger preference for technology investments over non-technology investments

when past performance information indicated high past returns. Results indicated that the within-

subjects interaction term for technology and past performance was significant ($F(1,59) = 4.08$, p

$< .05$, $\eta_p^2 = .06$). The form of the interaction is plotted in Figure 1, which illustrates that the

interaction was driven by a clear preference for investing in technology industries only when past

performance was high, in support of Hypothesis 2. In light of the significant interaction, simple

effects analyses were also conducted and suggested that the combination of technology industries

(T) and high past performance (HPP) ($M_{T,HPP}=.461$) received significantly greater investment

than the other three combinations of technology/non-technology and high/low past performance

($p < .05$ for each comparison, $M_{T,LPP}=.405$, $M_{NT,HPP}=.384$, $M_{NT,LPP}=.389$).

Insert Table 1 and Figure 1 about here.

Our results suggest that Hypothesis 1 is qualified by the interaction of technology and

past performance, such that participants invested the *same* amount of money in non-technology

stocks whether past performance was high or low, while the amount they chose to invest in

technology stocks varied significantly according to the past performance success prime. This

finding is particularly interesting considering that decision makers had no forward-looking

indication that any industry would outperform any other industry (this was explicitly held

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constant in the materials by presenting a specific range of anticipated future returns). Despite being provided with unambiguous figures regarding past stock performance that were equivalent across all six (tech and non-tech) decisions, participants still invested in technology industries at a higher rate. It seems that seeing an upward sloping graph representing past performance triggers optimism in a technology context, but does not in a non-technology context.

The fact that the graphs indicating past success had a strong impact in the technology condition, but no impact in the non-technology condition is notable. If people use information in the graphs to inform their decisions, we would have expected *some* influence of high past performance graphs on all investment decisions, even for the non-technology stocks. With respect to the current study, information about high past performance for the non-technology stocks might have been inconsistent with existing beliefs about performance in those industries, and thus disregarded. In contrast, consistent with our assertion that technology can be a diagnostic cue due to its automatic association with success, we suggest that information about high past performance for the technology stocks was consistent with existing associations between technology and success, and thus attended to and acted upon (i.e., higher investment).

In light of these findings, our explanations for the results of Study 1 are that participants employed technology as a diagnostic cue and thus were more optimistic about investing in technology. Moreover, the use of technology as a cue for predicting future success was only triggered in the presence of an indication of prior success. The fact that past success was held constant within each condition and that there is a significant interaction across conditions, both strongly suggest that indicators of past performance are not responsible for the results. Indeed, because "actual" past performance and expected future performance were controlled, only variation in perceptions and beliefs about these particular stocks remain as explanations for our

findings, and our pilot study allows us to be confident that the primary dimension along which the stocks vary is high vs. low technology.

Study 2

Theory and Hypotheses

Thus far, we have conceptualized technology as representing an abstract characteristic that individuals can identify within a decision context. In Study 2, we explore whether familiarity with technology is a potential boundary condition for the technology effect, and ask the question, do familiar technologies generate the same optimism as unfamiliar technologies? Specifically, we explore the possibility that it is not just technology in general, but *unfamiliar* technology that elicits the technology effect.

Our fundamental argument is that individuals might not use a familiar technology as a diagnostic cue for predicting success because it differs in critical ways from their perceptions of the events from which the cue originates. Decision makers consider a cue to be diagnostic to the degree that the current context is perceived as similar to their past experience (Simon & Houghton, 2003; Soll, 1996) and are unlikely to use a cue when the current context does not match closely. We suggest that the familiar or mundane might not *feel* like technology in the abstract, socially constructed sense of the term, because the abstract notion of "technology" is a manifestation of the previously unimaginable. In contrast, familiar technologies (e.g., the telephone) are, by definition, imaginable. They have been experienced and integrated into our daily lives. Thus, when decision contexts involve familiar technologies, it is less likely that a decision maker will consider that context to match past instances where the more abstract "technology" impacted success, and thus less likely to utilize the familiar technology as a diagnostic cue.

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In other words, familiarity facilitates the recognition that the current decision context is *not* like other experiences with abstract and exotic technologies. For instance, one may be less likely to believe the statement "solar technology will revolutionize your future" than one would the statement "nanotechnology will revolutionize your future." Familiarity with solar technology, thus, might reduce the likelihood that the presence of solar technology in a decision context will serve as a diagnostic cue triggering the technology effect.

For this reason, the degree of optimism in the ability of a technology to drive success should be inversely related to one's familiarity with it. Therefore, we predict that there will be a greater degree of optimistic decision making in regard to unfamiliar technologies than regarding familiar technologies, even when objective probabilities for the success of unfamiliar and familiar technologies is held constant. Additionally, because familiarity with technology is likely a continuous variable, we suggest that decisions involving familiar technologies will still be subject to the technology effect to a greater degree than non-technology decisions. Hence, we hypothesize the following:

> *H3: Decision behaviors reflecting optimism will be the greatest in contexts of unfamiliar technology, followed by familiar technologies, followed by contexts employing no technology.*

In Study 1 we found that the preference for technology investment was stronger when past successful performance was primed. Similarly, in Study 2 we expect that a signal of *future* success will have a greater impact when the notion of technology is invoked in the decision context than when it is not. We base this expectation on the finding that diagnostic cues are more likely to be used when a current decision context is perceived as being similar or relevant to the past experiences from which the cue originated (Simon & Houghton, 2003). We argue that a

signal of success (past or future) will prime the association between technology and success, and

particularly so when the technology being invoked is unfamiliar.

> *H4: Likelihood of future success will interact with technology familiarity such that*
>
> *increased likelihood of success will result in the biggest increases in optimism in*
>
> *unfamiliar technology contexts, followed by familiar, then non-technology contexts.*

Study 2 utilizes the resource dilemma as a new context within which to examine the

technology effect and extend the generalizability of our findings. In a resource dilemma,

individuals are asked to make decisions about how much to harvest from a collective resource.

Individual decisions must weigh the desire to "harvest" a large amount for oneself (self-interest)

against the possibility that the other members of the collective will also harvest a large amount

with the risk that the resource will be depleted and unavailable for harvesting in the future. Thus,

people are more likely to harvest a resource when they believe that it will regenerate in the

future. In the current study, we designed a scenario for a resource dilemma in which the rate of

regeneration of the resources was supposedly contingent on the use of a technology (i.e., familiar

or unfamiliar) or based on random fluctuations (i.e., the non-technology option).

One specific benefit of exploring the technology effect in a resource dilemma is that it

allows us to address a potential rival hypothesis explaining our earlier results. In particular, one

might be overly optimistic about a technology stock because one believes *others* are overly

optimistic about the technology, and thus an individual will purchase the stock because he or she

believes that the unfounded optimism of *others* will lead to good returns for their own

technology investment. In a resource dilemma, however, if one expects others will be overly

optimistic about how much a technology might be useful in replenishing a resource, one would

assume overharvesting by others, which would actually reduce estimates of how much of the

collective resource will be available for them to harvest. This dynamic precludes the rival

hypothesis and addresses a potential alternative explanation present in Study 1.

Methods

Pilot procedure. We conducted a pilot study to identify technologies that can be

categorized a priori as familiar and unfamiliar. As in the investment scenarios of Study 1, we

avoided using options such as specific companies or locations that can induce bias in favor of the

familiar (Huberman, 2001). However, unlike our first two samples that held familiarity constant,

we sought to identify a particularly familiar and unfamiliar technology. Thirty-three

undergraduate students (70% male) participated in a pilot study. Each participant received a

questionnaire containing a list of 21 emerging technologies that were compiled based on a search

of various technology-related websites and were asked to rate their level of familiarity with each

technology on a 5–point scale. Across all 21 technologies, the average familiarity score was 2.2,

with a range from 1.3 (programmable matter) to 3.6 (electric/hybrid vehicles). Solar technology

and swarm robotics were selected for use in Study 2 because they could be adapted to our

hypothetical scenario and were significantly different in familiarity in our pilot sample ($p < .01$).

Furthermore, because we manipulate both familiarity and likelihood of success, we sought to

check the initial success expectation for each technology to ensure that unfamiliarity and initial

expectations for success are not confounded and explanatory of any findings that link

unfamiliarity and optimism. Pilot study participants indicated their expectation of future success

for each technology, and the familiar technology (solar technology: 4.6/5) was actually rated

significantly higher ($p < .01$) than the unfamiliar technology (swarm robotics: 2.4/5), suggesting

that the hypothesized relationship between unfamiliarity and overoptimism would be observed in

spite of, and not due to, preexisting expectations of success (i.e., a bias against supporting our

hypothesis).

Participants and procedure. Study 2 was completed by 152 undergraduate students (58% male). Nine participants (6%) failed or omitted the manipulation check, resulting in a final sample of 143. Participants were presented a resource dilemma stating that each of them was to imagine they were employed at a mining company and were required to make a one-time harvesting decision for mining the rare earth metal thorium. The size of the available resource was variable such that there was a guaranteed baseline amount available for harvest one year in the future, with some percent chance that the available amount would increase within a specified range of possibilities. *Likelihood of future success* was manipulated by assigning either a 20% or 50% probability to the likelihood that the future resource available for harvest would be greater than the baseline amount. This manipulation served two purposes. First, the probability that the available amount of the resource will increase served as our indicator of future success: the higher probability that the resource will be greater (i.e., 50%) corresponded to a higher likelihood of future success. Second, assigning a specific probability exactly defined the amount of outcome uncertainty participants faced within each condition. This allowed us to distinguish methodologically between the notions of unfamiliarity and uncertainty. A statement about the precise amount of outcome uncertainty compelled participants to assume that any uncertainty caused by the unfamiliarity was already included in the stated amount of outcome uncertainty (i.e., either a 20% or 50% chance of a greater resource from which to harvest).

In describing the probabilities of future success and the range of possible outcomes, the possibility of harvesting additional amounts of the resource beyond the baseline amount was described as being conditional upon one of three things: new solar technology (familiar technology), new swarm robotics technology (unfamiliar technology), or simply random

fluctuations in the mining process (non-technology explanation). In the technology conditions, it was explained that solar energy and swarm robotics technologies may or may not have progressed to the point where they would help increase the amount of thorium available for harvest by the year's end. Hence, a 2 (Low vs. High Success Indicator) x 3 (No Technology vs. Familiar Technology vs. Unfamiliar Technology) factorial design was used.

Participants were gathered in sessions of 20-40 where each participant was randomly assigned to one of the 6 conditions. They were informed that they had been randomly assigned to be a member of a 5-person group, although group members made individual decisions in private and could not communicate with each other. The participants were then presented with the resource dilemma in which they were told that each of the 5 anonymous members of their (fictitious) group would harvest some amount from the collective resource. It was explained that after the harvest decisions were collected and tallied and the resource size was simulated (based on the parameters included in the resource dilemma), if the group's collective request was greater than the available resource size all group members would receive nothing. If the collective request was less than or equal to the resource size, each group member would be rewarded an amount of candy proportionate to the harvest amount they personally requested. Two training examples were described in detail to ensure that participants fully understood the task and how their decision could impact the group and themselves.

Harvest was measured as the one-time harvest decision of each individual in "units of thorium." Possible harvest amounts ranged from 0 to 125 units of thorium. However, 125 was the theoretical maximum for the entire 5 person group, so more realistic harvest maximums would be considerably lower than 125 units. The manipulation check consisted of a single multiple choice question, administered at the end of the procedures that asked whether the

variability in possible thorium production outcomes was because: (a) mining can be

unpredictable, (b) wind power, (c) solar power, (d) genetic engineering, or (e) swarm robotics.

Results and Discussion

The 6 cell means and marginal means are displayed in Table 2. To test Hypothesis 3 we

performed post hoc contrasts and determined that harvesting decisions were higher in the

Unfamiliar Technology condition (M = 20.14) than the Familiar Technology condition (M =

16.67) (d = 3.47, F(1,137) = 2.75, p < .05) in support of Hypothesis 3 and the notion that

participants would be more optimistic about the ability of the unfamiliar technology to

successfully replenish the resource. However, contrary to this hypothesis, Familiar Technology

did not result in higher harvest decisions than the Non-technology condition (M = 17.32, p >

.05). Thus, we received mixed support for Hypothesis 3.

Insert Table 2 and Figure 2 about here.

To test Hypothesis 4 we examined the interaction term from the two-way ANOVA

(technology x future success) which was significant (F(2,137) = 4.00, p < .05, η_p^2 = .06). As seen

in Figure 2, we found the pattern of results to be generally consistent with our expectations. We

observed that the interaction was driven by relatively high harvest decisions in the unfamiliar

technology and high likelihood of success condition. To further test our predictions we

conducted post hoc contrasts to see whether the three technology conditions differed across the

high and low likelihood of future success conditions. The unfamiliar technology condition had

significantly higher harvests when paired with high likelihood of success (d = 11.07, F(1,46) =

13.97, p < .05), in support of Hypothesis 4. However, contrary to expectations, the familiar

technology (d = 1.60, F(1,48) = 0.30, p > .05) and non-technology (d = 0.20, F(1,46) = 0.01, p >

.05) conditions did not differ significantly across the high and low likelihood of future success conditions.

These results support our theorizing that unfamiliar technology fits more closely with the pervasive and biased-towards-success mental model of technology that drives the technology effect. The results also suggest that a familiar technology may not be perceived to be "technology" in the abstract sense of the term. Instead, industries utilizing familiar technologies might be perceived the same as non-technology industries. Additionally, our unanticipated finding that unfamiliar technology did not have a significantly higher relative harvest in the low likelihood of future success condition suggests a possible boundary condition for the technology effect. It seems that priming the association between technology and success is important, as technology is less likely to impact decision making when additional success indicators are absent. That is, without some cue for success, the presence of technology by itself might not be a diagnostic cue that influences behavior.

It is important to note that our dichotomous operationalization of familiar and unfamiliar technology may have precluded familiar technology from being a middle ground between unfamiliar and non-technology. There may be various technologies that would fall along a familiarity continuum such that there *is* a middle ground, but we didn't achieve it with our specific choice of technologies to fit the scenario. We intentionally focused on establishing a strong dichotomy of familiar and unfamiliar that made it more likely that we could determine whether familiarity matters or not. Having made such a choice, our results speak clearly only to the influence of the combination of unfamiliar technology and indicators of high future success condition as driving overoptimism.

Study 3

Theory and Hypotheses

A key assumption underlying both Study 1 and Study 2 was that there is a pervasively held automatic and nonconscious or "implicit" association (Greenwald & Banaji, 1995) between technology and success. In Study 1, we argued that this implicit association drove preferences for stocks from technology-intensive industries relative to stocks from industries that were not technology intensive. Also consistent with this underlying assumption, we found that the technology bias was pronounced when the association between technology and success was primed by information about past successful stock performance. In Study 2, we showed that people were most optimistic about the replenishment of a resource when the replenishment was thought to be caused by an unfamiliar technology with high success potential. This result provides some evidence consistent with our contention that the implicit association between technology and success generalizes to various technology contexts, and perhaps especially when technology is unfamiliar and abstract.

To this point, however, although our results are consistent with our predictions, we have not provided evidence for the existence of this underlying implicit association between technology and success. In this final study, we use a procedure called an implicit association test (IAT) to examine this key underlying assumption. Specifically, we hypothesize the following:

H5: The concept of technology has an implicit association with the notion of success.

Methods

Development of the IAT instrument. The implicit association test (IAT) has been used extensively in the literature on racial and gender-based biases and stereotypes (e.g., Hekman, Aquino, Owens, Mitchell, Schilpzand, & Leavitt, 2010), and has also been extended to examine behavior in other domains, including ethical behavior (Reynolds, Leavitt, & DeCelles, 2010),

and linkages between implicit job attitudes and work performance (Leavitt, Fong, & Greenwald, 2011). However, the methodology is easily adaptable to any context in which an implicit association is thought to operate between a category and an attribute (Uhlmann et al., 2012), such as our presumed association between technology and success. An IAT involves a series of timed sorting tasks, administered through computer software. Participants are asked to quickly sort exemplars of a category (i.e.., technology vs. non-technology), exemplars of attributes (i.e., success or failure), and various double-configuration combinations of the category and an attribute (e.g., technology + success OR non-technology + failure) (see Lane, Banaji, Nosek, & Greenwald, 2007, for an extended discussion of IAT use and development). Using this method, an implicit association is thought to exist when participants can more quickly sort exemplars into categories that are more easily associated with an attribute (i.e., theoretically congruent categories like technology + success, or non-technology + failure), than into categories that are not congruent with the attribute (i.e., technology + failure, or non-technology + success).

We created two separate IATs to examine our hypothesis. For the first IAT (IAT-1), paralleling Study 1, we created a list of exemplars of technology intensive industries (e.g., Robotics) and non-technology intensive industries (e.g., Trucking) to present as category stimuli. For the second IAT (IAT-2), we generated a list of exemplars of the technological items or products (e.g., lasers), and non-technology items (e.g., hammer). In addition, we generated a list of words to be exemplars of the attributes "success" (e.g., achievement) and "failure" (e.g., defeat) to be used in both IATs. Initial stimuli lists were generated by the authors using various web-based resources, including lists of technology industries, and thesaurus programs. We also enlisted the assistance of 8 colleagues who were asked to evaluate whether the exemplars in each category and attribute were prototypical or ambiguous. Their feedback was used to refine the

items lists until all 8 were comfortable with the prototypicality of the remaining exemplars. Lists

of the final stimuli used in each of the IATs are provided in the Appendix.

Participants and procedure. Students in two sections of the same upper-level

undergraduate management course were recruited to participate in the study in return for course

credit. Of 78 eligible participants, 60 agreed to participate and completed IAT-1, and 53 went on

to complete IAT-2. Participants were sent a link to our study, which used the web-based Inquisit

4 program hosted by Millisecond software (http://www.millisecond.com). Each participant was

asked to complete two IATs, which were administered in the standard 7-block sequence

(Greenwald, Nosek & Banaji, 2003). The sequence includes both practice blocks used to train

participants in the procedure (blocks 1, 2, & 5), as well as test blocks that combine attributes that

are theoretically congruent or incongruent. As recommended by Lane et al. (2007), the order of

the double configuration sorting tasks was counterbalanced such that half of the participants

received the congruent pairs in trials 3 and 4 (i.e., technology + success, and non-technology +

failure), and the incongruent pairs in trials 6 and 7 (i.e., technology + failure, non-technology +

success), and the other half received the reverse ordering.

Results and Discussion

Data from IAT-1 and IAT-2 were analyzed using the "improved algorithm" developed by

Greenwald et al. (2003), which creates a *d* score for each participant. The *d* score, which is

analogous to Cohen's *d*, represents the difference in average response latencies between the non-

congruent pairs (which are expected to take participants longer to categorize) and the congruent

pairs, divided by the standard deviation of the latencies for each participant. Latencies were

adjusted by removing latencies for trials in which there was an error, and replacing that latency

with the block mean plus a 600 ms penalty (Greenwald et al., 2003; Nosek et al., 2005).

Greenwald et al. (2003) also recommend eliminating trials with latencies above 10,000 ms, and participants for whom more than 10% of trials had latencies below 300 ms, but neither of those criteria were reached in the present study.

Thus, d scores are within-person scores that account for differences in overall response latencies between individuals (i.e., slow or fast responders) as well as individual variability in responses. A d score of 0 for a given participant, or as an average across participants, indicates no differences in response latencies between the congruent and incongruent pairs. Average d scores across participants that are greater than .2, .5, and .8 are considered to represent small, medium, and large effect sizes (Nosek, Greenwald, & Banaji, 2005).

Consistent with Hypothesis 5, results indicated that d scores for the congruent categories were indeed shorter for the theoretically congruent categories (i.e., technology + success), with mean d scores of 0.68 (SD = 0.05) in IAT-1 (technology industries) and 0.53 (SD = 0.07) in IAT-2 (technology products). Both mean d scores were significantly different from 0, with $t(59) = 13.12$, $p < .0001$ for IAT-1, and $t(52) = 7.15$, $p < .0001$ for IAT-2. In other words, the interference cause by asking participants to categorize stimuli that were incongruent (e.g., technology + failure, or non-technology + success) caused participants, on average, to be much slower when asked to make the categorization relative to when they were asked to categorize stimuli into congruent categories (e.g, technology + success). Moreover, out of 60 participants who completed IAT-1, 58 had a positive d score, and 49 out of 53 participants had a positive d score in IAT-2, indicating that the bias was almost universally present in our participants.

These results provide evidence for the implicit association we assumed to be underlying the technology bias we observed in Study 1 and Study 2. Moreover, as indicated by both the magnitude of the d-scores, and the proportion of participants who demonstrated an implicit

association between technology and success, we believe these results represent strong evidence.

In addition, we demonstrated that the bias was not only present when the technologies were

described in terms of technology industries, but also in terms of technology products (e.g.,

lasers). Thus, the findings from IAT-2 help support the notion that the technology-success

association and resulting bias generalizes more broadly to technology in general, and not just

industries that are technology intensive.

General Discussion

"Any sufficiently advanced technology is indistinguishable from magic" Arthur C. Clark

Technological advancements have clearly had an enormous influence on modern business

and society. From medical advancements, to information technology, energy, communications,

agriculture, and other domains, it is impossible to ignore the role of technology in shaping

human existence. However, because technologies have advanced to such an extent that only

those of us with the most intensive experience or training can begin to grasp how individual

technologies work, most of us just accept that they *do* work.

We have argued that the fact that technological wonders are so ubiquitous, that they

affect our lives so profoundly, and that most of us have so little understanding of how they all

work, has given rise to an abstract, socially constructed, and powerful concept that enables us to

make some sense of them: we label it all "technology." We also argue that the socially

constructed meaning of "technology" has become implicitly associated not only with positive

advancements, but with optimism for what they will bring in the future. Indeed, the fact that

most adults have seen technological advances become mainstream that they perhaps only

dreamed about as children (e.g., nearly everyone has a Star Trek-like "communicator" in their

pocket) has significantly (rose-) colored our collective belief that technology not only can, but

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will, continue to advance and improve our lives.

In this paper, we began to explore what we believe is an important consequence of what we have labeled the "technology effect," which is the tendency toward excessive optimism in decision contexts where the impact of "technology" is made salient. The goals of this paper were to describe the technology effect, to examine the implicit assumptions underlying it, to test the basic predictions relating to excessive optimism, and then to probe its scope and boundaries. Toward this end we conducted three studies. In Study 1, we supported the basic prediction underlying this paper by demonstrating that individuals were more optimistic about technology-related stocks than they were about stocks of companies that were not technology intensive. This finding was obtained despite the fact that the industries represented by the stocks were equivalent in performance, the past performance of each stock was held constant across high and low-technology options, and we provided explicit information indicating that prospects for future success were the same across high and low-technology stocks. Moreover, by manipulating signals of success between subjects we demonstrated that the technology effect is triggered by providing participants with information consistent with optimism in the prospect of technology's future success (i.e., good returns in the past). Importantly, the interaction pattern we obtained was driven by the fact that high past performance significantly increased the selection of technology stocks more than non-technology stocks.

We also tested our first hypothesis with an additional sample under modified conditions, as technology and non-technology stocks were directly pitted against each other, and participants were asked to make selections across a range of industries. As we predicted, participants invested more in the technology than the non-technology stocks, replicating our core finding.

Study 2 shifted the decision context to a resource dilemma to extend the generalizability

of our findings and to explore additional boundary conditions. We found that harvesting

decisions in a one-shot resource dilemma, which were tied to future prospects of technological

innovations, were influenced not only by prospects for future success (similar to Study 1's

implications for signals of past success), but also by the familiarity of the technology involved.

Specifically, we found that harvesting quantities were high, reflecting optimism in the future

quantity of the resource, only when prospects for the future performance of the technology were

relatively high, *and* only when the technology involved was unfamiliar to participants (i.e.,

swarm robotics). This result provided new and additional support for our underlying theoretical

rationale. Specifically, we replicated the notion that the technology effect is triggered or

enhanced when signals of optimism are present, and additionally, that the technology effect is

triggered most when the technology involved is unfamiliar, or mysterious, and remains imbued

with all of the abstract promise of technology that is facilitated by lack of understanding.

Finally, Study 3 allowed us to examine the assumption underlying the effects observed in

the other two studies: namely, that people have a relatively strong and pervasive implicit

association between technology and success. Two IATs linking technology industries and

technology products with success provided support for the idea that through slowly collected

experience, people begin to believe that technology is a harbinger of good things to come.

Limitations and Future Directions

In this paper, we have proposed that the technology effect is both a general tendency

toward optimism when technology is involved in a decision context, and that this effect is most

notable, or triggered, when paired with indications of technology's success, and unfamiliar

technologies. To some extent, this reflects a traditional approach to examining moderating

characteristics of effects, or boundary conditions, which tends to use language implying that "the

effect exists, but only when *x* happens." However, we wanted to acknowledge a somewhat different perspective that might also explain our results. Specifically, it is possible that instead of unfamiliar technologies and success indicators being "triggers" of the technology effect, the technology effect has become "baked in," and always exists in the general sense, but is *suppressed* when the context implies that the technology is familiar, or links it more concretely to unimpressive past performance. Indeed, the results of our Study 3, which strongly supports the existence of an implicit association between technology and success even in the absence of success indicators, is consistent with this perspective. While this alternative lens does not substantively change the interpretation of the present studies' findings, it might offer future researchers useful perspective, particularly with regard to identifying other conditions that might suppress the technology effect (some of which are discussed below).

Using a series of laboratory-based studies allowed us to manipulate "technology," as well as signals of success and familiarity, and to measure concrete behavioral responses to those variables. That being said, laboratory research has important weaknesses, including high artificiality, and the possibility that participants' behavior is influenced by the knowledge that they are being studied (Griffin & Kacmar, 1991). In addition, our research used college students as participants, which raises questions about generalizability to "real" decision making contexts.

Given that the current research is the first of which we are aware to test the technology effect, we felt that controlled laboratory studies were most well-suited to testing the hypotheses. An important first step in describing and testing the technology effect was to demonstrate that it is *possible* to identify patterns consistent with our underlying theory (Ilgen, 1986). One of the challenges we faced in designing laboratory studies was trying to manipulate technology cues cleanly, without making the task excessively artificial. To do this, in Study 1 we presented

participants with multiple stocks from technology and non-technology industries, in order to mitigate the possible influence of unknown participant attitudes toward particular industries. Even though our results (in terms of investment decisions) did not indicate that participants preferred all technology investments to all non-technology investments, there was a strong tendency in that direction in both Sample 1 and Sample 2. Extending research into field settings and using real decision makers facing real decisions could also provide valuable additional insights. For example, it might be possible to explore patterns of actual stock-picking behavior, possibly examining how various characteristics of the technology employed by companies (e.g., new versus old technology, R & D intensiveness) might influence investment decisions.

Multiple research avenues exist for examining the influence of the technology effect in specific decision making contexts. For example, decisions made by entrepreneurs, medical professionals, patients, lawmakers, and scientists all might be influenced by individuals' perceptions of the technological aspects of their environment, and their optimism about technology. Such research might help provide even greater definition of the scope and boundaries of decision making biases arising from the technology effect.

Finally, we focused on some key situational characteristics that might prime the technology effect (or suppress it), but there might be others that are important. For example, individuals in contexts where they are experiencing high cognitive load (Evans, 2008) might be more susceptible to the technology effect and heuristic processing. In addition, the technology effect might be influenced by individual-level moderators that could be fruitfully explored. For example, the likelihood of engaging in heuristic processing should be lower for those with a high epistemic motivation (Van Kleef, Homan, Beersma, van Knippenberg, van Knippenberg, & Damen, 2009), as such individuals might engage in more active search for and interpretation of

existing information. We also believe that potentially interesting individual-level variables such as investment experience or risk taking (Jackson, 1994) might influence investing behaviors, and possibly suppress the technology effect. Others, such as technology phobia, tolerance for ambiguity (Herman, Stevens, Bird, Mendenhall & Oddou, 2010), might influence additional cognitions and behaviors concerning technology. Lastly, consistent with previous literature on risk-taking, our results from Study 1 suggested that women might be more risk averse overall (lower rates of investment in stocks relative to CDs), but somewhat more susceptible to the technology effect than men, in that they demonstrated a stronger preference for technology industry stocks. Future research might develop this distinction more thoroughly to examine the nature of any possible gender differences.

Implications

We believe that the technology effect has the potential to impact decisions across a wide range of domains and at individual, institutional, and societal levels. For example, at the individual level, although areas such as nutrition science and medicine have greatly increased our knowledge about healthy diets, lifestyles, and exercise, the behavior of many people who are familiar with nutritional basics (e.g., more vegetables, less bacon) is inconsistent with those principles. Although some of that inconsistent behavior is undoubtedly due to other factors (e.g., education, the physiological draw of bacon), the decisions made by individuals might be influenced, in part, by the promise of future technology to solve the myriad maladies that can arise from bad diet. If scientists will develop devices that can strip my arteries of plaque in the future, what harm will this one indulgence really cause me? Relatedly, the success of products such as nutritional supplements, 5-minute exercise regimes, and wrinkle-creams, often advertised as being based on "scientific breakthroughs," might be driven by the technology effect, and

individuals' tendency to believe that not only are such breakthroughs possible, they are inevitable.

There are also important implications of our results for organizations and their decision makers. For example, within organizations, decision makers such as CEOs often delegate the role of expertise in core technological or scientific knowledge arenas to a direct report while retaining the decision making role themselves. If a decision maker is personally unfamiliar with a technology about which he or she must make judgments, there is greater potential for those judgments to be influenced by the technology effect and to be biased toward optimism. Our findings that primes of past or future success can create a conflict for the expert advisor who may have real incentive to upsell the technology area that they represent. Therefore, considerable care should be taken to develop well-grounded predictions, especially when dealing with unfamiliar technologies or unknowledgeable decision makers.

Finally, it is also important to note that although our discussion of the technology effect has focused exclusively on the negative effects of excessive optimism, an alternative perspective is that technological breakthroughs have been made by people who had high levels of optimism about the potential of technologies and their ability to develop them. It is certainly possible that such optimism drives goal-oriented behaviors, energy, and perseverance, and that without those qualities, many of the technological advancements we now enjoy would have never come to fruition. This logic suggests that although perhaps very few entrepreneurs end up benefiting directly from excessive optimism, as a society we might benefit from the fact that the technology effect and attendant optimism leads some to doggedly pursue those longshots.

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Table 1

Descriptive Statistics and Correlations: Study 1

Variable	Obs	Mean	SD	1	2	3
1. Tech Investment (%)	63	43.24	22.59			
2. Non-tech Investment (%)	63	38.65	19.56	.62*		
3. Gender	63	0.73	--	.09	.34	

Note. Gender = 1 for male, and 0 for female

p < .05

Table 2

Average Harvest by Condition: Study 2

Technology	Likelihood of Future Success		
	Low	High	(Row Mean)
Unfamiliar	**14.63**	**25.70**	20.14
Familiar	**15.92**	**17.52**	16.67
Non-Tech	**17.22**	**17.42**	17.32
(Column Mean)	15.90	20.17	17.99
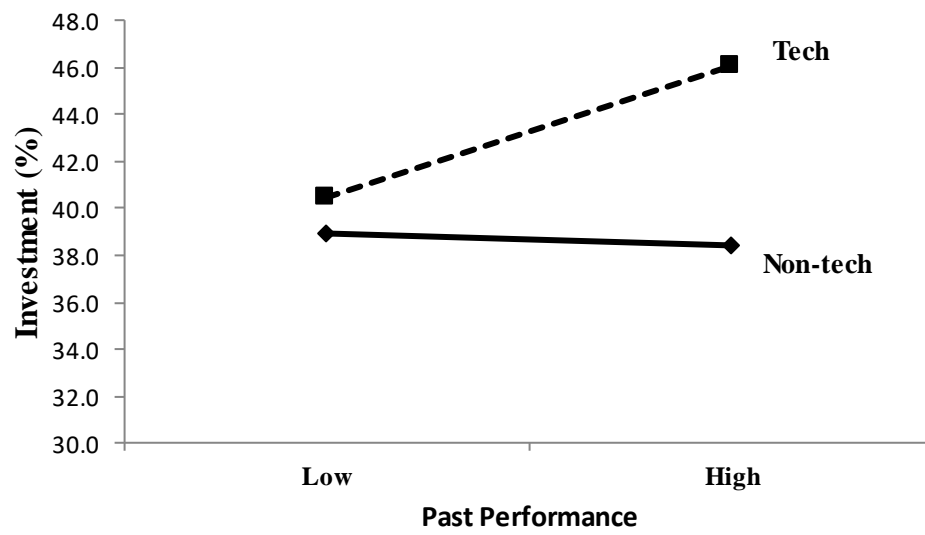
Figure 1. Interaction of Past Performance and Technology on Investment (Study 1)
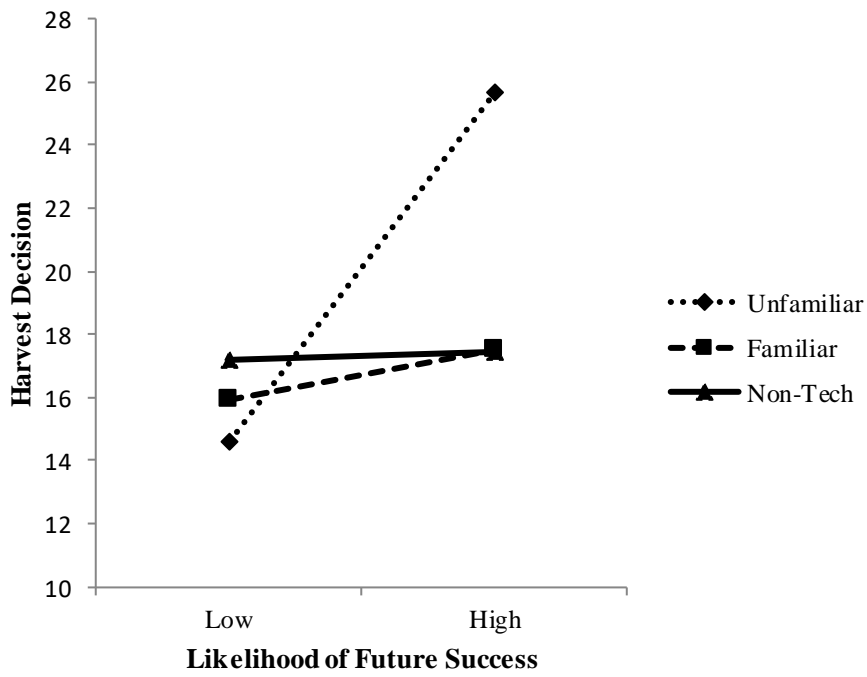
Figure 2. Interaction of familiarity and likelihood of future success on harvest decisions (Study 2)

Appendix

Category Exemplars (IAT-1: Technology Industries)

"Technology": Robotics, Semiconductors, Biotech, Pharmaceuticals, Aerospace, Nanotech, Genetics

"Non-Technology": Trucking, Livestock, Restaurants, Groceries, Textiles, Insurance, Apparel

Category Exemplars (IAT-2: Technological Products)

"Technology": Laser, Fiber Optics, Wifi, Satellite, Software, Nuclear Energy, Solar Cells

"Non-Technology": Soap, Ruler, Shoe, Chair, Backpack, Hammer, Brick

Evaluative Exemplars (Both IAT-1 and -2)

"Success": Victory, Solution, Achievement, Triumph, Win, Accomplishment, Advancement

"Failure": Defeat, Flop, Lose, Breakdown, Fiasco, Malfunction, Disaster