Impact of Extreme Decisions and Extreme Probabilities on Attribute Framing Effects

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Abstract

This study examines attribute framing in a capital budget decision-making scenario. In an experiment utilising 183 participants, we test the impact of extreme probabilities on the investment decision making process.

Results indicate that the presence of attribution frames may be problematic in certain decision-making scenarios and that framing effects may be stronger and more persistent than prior theory suggests.

This research adds to the literature through an extension of the understanding of the attribute framing phenomenon on capital budgeting decisions. it is important in that it highlights the potential for sub-optimal decision-making in that attribute framing is not easily moderated, even when utilising extreme probabilities in the capital spending approval process.

Keywords

Framing effects
Attribute framing
Extreme frames
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Introduction

Attribute framing is when an equivalent piece of information is worded, or framed, either positively or negatively. In both cases, the information is the same but the *manner* in which it is presented varies. Prior research in a variety of settings have consistently found attribute frames affect decisions, including accounting decisions (e.g., Fukukawa & Mock, 2011), business judgments (e.g., Dunegan et al., 1995), capital budgeting decisions (e.g., Kerler et al ., 2012 and 2014), consumer decisions (e.g., Kim et al., 2014), gambling judgments (e.g., Levin et al., 1989), environmental survey construction (e.g., Kragt & Bennett, 2012), and medical judgments (e.g., Biswas & Pechmann, 2012). Further, Levin et al. (1998) provides a review of framing research and presents over 30 research studies that find an attribute framing effect.

Levin et al. (1998) also identify two circumstances when attribute framing effects may be moderated. First, they posit “[t]opics involving issues of strongly held attitudes or high personal involvement are less susceptible to attribute framing effects” (p. 160). In a capital budgeting context, Kerler et al. (2012) find that framed financial information impacts capital budgeting decisions when a project is of low importance but not when a project is of high importance. The authors state, consistent with Levin et al. (1998), that projects of high importance increase the personal involvement of the decision maker and results in a more thorough processing of the evidence items, thus allowing the decision maker to “see through” the attribute frames. Second, Levin et al. (1998) posit “[a]ttribute framing effects are also less likely when dealing with extremes” (p. 164). For example, Levin et al. (1986) show stronger framing effects on gamble evaluations when the probabilities of winning/losing were intermediate compared to more extreme probabilities. Beach et al. (1996) show no attribute framing effects on toaster evaluations when toasters were missing most key attributes but show attribute framing effects on toaster evaluations when toasters were missing only minor attributes.

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This study examines Levin et al.'s (1998) second circumstance where attribute framing effects may be moderated. Specifically, this study will investigate two types of "extremes." One interpretation of the "extremes" would be extreme decisions – when the decision itself is clearly supported by the evidence. This interpretation of an extreme decision would be consistent with Beach et al. 1996. In a capital budgeting scenario, this would suggest attribute framing would not affect decisions when the financial data clearly suggests the project should be approved or rejected. For the remainder of this paper we refer to this variable as extreme decision. Another interpretation of the "extremes" would be extreme probabilities – when the framed data used to make the decision contains extreme probabilities. This interpretation of extreme probabilities would be consistent with Levin et al. 1996. In a capital budgeting scenario, this would suggest attribute framing may not affect decisions when the framed financial data includes probabilities significantly greater than or less than 50 percent. For the remainder of this paper we refer to this variable as extreme probabilities.

To test the research hypotheses, an experiment was conducted utilising 183 participants. Participants were asked to read over information concerning a capital budgeting investment decision. After reviewing financial data related to a potential new project, participants were asked to assess the likelihood of approving the project. The results indicate the strength and persistence of attribute framing effects may be greater than prior theory suggest. We find that attribute frames impact extreme decisions, where the financial data clearly suggests a project should be approved or rejected, with positively framed information resulting in a greater likelihood of approval. We also find attribute frames involving extremely low and extremely high probabilities significantly impacted participants' assessments. These results indicate attribute framing effects may be more persistent than prior theory suggests. These results also identify how simple attribute frames can create potential significant costs to companies by increasing the likelihood of approving poor projects and rejecting quality projects.

The remainder of this paper is organised as follows. The next section presents the relevant literature and research hypotheses. The research methodology and study's results are discussed next. The paper concludes with a discussion of the study's contributions to literature and potential areas for future research.

Prior Literature

Attribute framing effects occur when evaluations or decisions differ based on a positive or negative description of otherwise equivalent information. A popular example of this type of effect is based on a study from Levin and Gaeth (1988) where they study consumer preference by asking participants to rate the taste and quality of meat. They describe the meat as either "75% lean" (positive frame) or "25% fat" (negative frame), and find that the "75% lean" meat is assessed as better tasting and higher quality. Research across various disciplines and contexts have shown these attribute frames to have a significant effect on evaluations, as positive attribute frames result in more favorable evaluations and negative attribute frames result in less favorable evaluations.[1] Levin et al. (1998), summarising 30 years of framing effect literature, note the robustness and consistency of this "valence-consistent" shift due to attribute framing effects.

While attribute framing effects have consistently been shown across decision domains, attribute framing research has begun to seek possible moderators to this effect. Recent research in persuasive advertising (Putrevu, 2010), taxation (Fatemi et al., 2008), business education (Dunegan, 2010), and capital budgeting (Kerler et al., 2012) have shown partial or complete moderation of attribute framing effects based on factors, such as need for cognition, prior attitude, GPA, and decision importance. The current study considers another potential moderator to these

[1] Attribute framing effects have been shown in accounting decisions (Fukukawa & Mock, 2011; Rutledge & Harrell, 1994 and 1993), business judgments (Dunegan et al., 1995; Duchon et al., 1989), capital budgeting decisions (Kerler et al., 2014 and 2012), consumer decisions (Kim et al., 2013; Park & Kim, 2012; Levin et al., 1996; Johnson, 1987), gambling judgments (Levin et al., 1989; Loke, 1989), environmental survey construction (Kragt & Bennett, 2012), and medical judgments (Biswas & Pechmann, 2012; Levin et al., 1988; Wilson et al., 1987).

effects, extreme values. Based on two past studies (Levin et al., 1986 and Beacher et al., 1996), Levin et al. (1998) posit "[a]ttribute framing effects are also less likely when dealing with extremes" (p. 164). First, Levin et al. (1986) consider gambling evaluations, and find that the attribute framing effect is weaker when dealing with probabilities closer to 100 percent. Second, Beach et al. (1996) find that framing effects do not occur when important information is missing. The current study considers the impact of extreme probabilities, similar to Levin et al. (1986), and extreme decisions, similar to Beach et al. (1996) on attribute framing effects in the context of a capital budgeting decision.

This is important since capital budgeting decisions are vital decisions for the success of companies (Dutton & Fan, 2009), and past research has shown that these decisions are often problematic (Castellion & Markham, 2013; Dillon, 2011). Uncertainty is inherent in these decisions based on a project's future cash inflows and outflows, and estimates must be made. These estimates are naturally communicated with positive or negative attribute frames. Allport et al. (2010) find individuals may utilise attribute frames as a method of persuasion when summarising capital budgeting. For example, when presenting their recommendation and project data, individuals may use positive frames when they believe a project should be approved and negative frames when they believe a project should be rejected. Kerler et al. (2012 and 2014) analyse attribute frames in capital budgeting decisions and find a consistent framing effect. In addition, they consider the ability of capital budgeting decision characteristics to moderate these framing effects. Kerler et al. (2012) find that investment importance can serve to moderate attribute framing effects with framed data impacting decisions of low importance but not impacting decisions of high importance. The authors state, consistent with Levin et al. (1998), that projects of high importance increase the personal involvement of the decision maker and results in a more thorough processing of the evidence items, thus allowing the decision maker to "see through" the attribute frames. Kerler et al. (2014) find the requirement to justify one's decision to a superior did not moderate the effect of attribute frames. The current study extends the attribute framing literature by considering the moderation of attribute framing effects by other characteristics of some capital budgeting decisions, extreme decisions and extreme probabilities.

We define an extreme decision as a judgment where the evidence clearly indicates the best choice. While there is always uncertainty with capital budgeting decisions, some decisions are easier than others. If a project is clearly more likely to generate positive cash flows over its useful life, the information is more extreme in that the decision to approve is more obvious. If a project is clearly more likely to generate negative cash flows over its useful life, the information is more extreme in that the decision to reject is more obvious. In such extreme decisions, it is plausible decision makers will see through the attribute frames and approve (reject) projects where the evidence clearly suggests approval (rejection) regardless of how the evidence is framed. However, due to the lack of prior research on extreme decisions we stay consistent with the general attribute framing literature and hypothesise the following:

H1: Evidence attribute frames will affect investment decisions when financial data clearly suggests a project should be approved (extreme approve decision) or rejected (extreme reject decision) with positive frames resulting in higher project approval assessments.

H2: Evidence attribute frames will affect the proportion of participants approving a potential investment when financial data clearly suggests a project should be approved (extreme approve decision) or rejected (extreme reject decision) with positive frames resulting in a higher proportion of approvals.

In addition to extreme decisions, capital budgeting decisions can also include financial data that contains extreme probabilities. In this case, the financial data may or may not clearly indicate the most appropriate decision, but the likelihoods could be very high or very low. For instance, the net present value of future cash flows may be extremely likely (e.g., 90 percent) to satisfy the company's desired amount, but the payback period may be extremely unlikely (e.g., 10 percent) to satisfy the specified goal. In a situation such as this, the investment decision is certainly not obvious, but the likelihoods make the interpretation of each individual evidence item clearer. In the above example, it is plausible that the extreme probabilities will heighten decision makers' awareness of the true meaning of each individual piece of financial data and will allow them to "see through" the attribute frames. For example, a ten percent chance of success (a positive frame) will be viewed as a negative evidence item despite the positive (success) frame. Similarly, a ten percent chance of failure (a negative frame) will be viewed as a positive evidence item despite the negative (failure) frame. Due to the lack of prior research on extreme probabilities we stay consistent with the general attribute framing literature and hypothesise the following:

H3: Evidence attribute frames will affect investment decisions when the framed financial data involves extremely high or extremely low probabilities with positive frames resulting in higher project approval assessments.

H4: Evidence attribute frames will affect the proportion of participants approving a potential investment when the framed financial data involves extremely high or extremely low probabilities with positive frames resulting in a higher proportion of approvals.

Research Methodology

Research Case

The experimental case utilised in this study was adapted from prior attribute framing research (Kerler et al., 2012 and 2014). The case centers around HER Apparel, Inc., a manufacturer and distributor of women's clothing. The first section of the case provides background information about HER and presents information related to a potential new clothing line. Participants are informed that in order to give appropriate consideration to information risk when making new product and product improvement decisions, HER uses a Monte Carlo simulation program to estimate three popular financial indicators: net present value, payback period, and the accounting rate of return.

The Monte Carlo program performs 10,000 simulations and presents three important pieces of information for each financial indicator: the stated goal for each indicator, the percentage of simulation successes (simulations that met or exceeded the goal) or failures (simulations that did not meet the goal)[2], and the expected value for each indicator (average of all 10,000 simulations). Participants were then informed that they had the final authority to make new product and product improvement decisions at HER. The case information is presented in Appendix A.

The second section of the experimental case presents the results of the Monte Carlo simulation program for the potential new clothing line. For each financial indicator participants were presented a description of the indicator, the stated goal, the expected value, and the simulation success or failure rate.[3] The Monte Carlo results presented to participants for each of the six experimental cases are presented in Appendix B.

The third section of the experimental case required participants to assess the likelihood of approving the potential new product and the fourth section of the case gathered a variety of demographic data from the participants (e.g. gender, age, years of business experience). Finally, participants were asked how long they worked on the case (in minutes) and how clear the instructions were for the case. Participants reported the experimental case took an average of 9.72 minutes (standard deviation of 3.50).

Overall, participants indicated the case instructions were clear with an average assessment of 7.56 (standard deviation of 1.39) on a nine-point Likert-type scale with anchors of 1 – "Not Clear" and 9 – "Very Clear." This

[2] Simulation success rates were presented for the positive evidence frame manipulation group and simulation failure rates were presented for the negative evidence frame manipulation group. When the Monte Carlo simulation program was described to participants in the positive evidence frame manipulation group they were told the program presents the simulation success rate while participants in the negative evidence frame manipulation group were told the program presents the simulation failure rate.

[3] The results represented a fictitious capital budgeting case with fictitious numbers as a proxy for a real-world case.

assessment is significantly ($p < 0.001$, two-tailed) greater than the scale midpoint of five.

Independent and Dependent Variables

Decision Version

Hypotheses one and two predict that attribute frames will affect extreme investment decisions, both when financial data suggests the project should be approved (extreme approve decision version) and when financial data suggests the project should be rejected (extreme reject version). The expected values, stated goals, and simulation success/failure rates used in Kerler et al. (2012 and 2014) were designed to create a neutral project with no clear indicator as to whether the project should be approved or rejected. Specifically, in the two Kerler et al. (2012 and 2014) studies, the net present value (NPV) indicator had mixed evidence with an expected value ($2.50) greater than the stated goal ($0) but a simulation success rate (49 percent) less than the simulation failure rate (51 percent). The payback period (PBP) indicator suggested rejection with an expected value (3.6025 years) greater than the stated goal (3.5 years) and simulation success rate (48 percent) less than the simulation failure rate (52 percent). [4]

The accounting rate of return (ARR) indicator suggested approval with an expected value (17.225 percent) greater than the stated goal (17 percent) and simulation success rate (53 percent) greater than the simulation failure rate (47 percent). The extreme decision version was manipulated in the current study by varying the expected values and simulation success/failure rates used in the Kerler et al. (2012 and 2014) studies.

For the extreme approve decision version, both the expected values and simulation success/failure rates for all three financial indicators suggest the project should be approved. In the extreme approve version the NPV indicator had an expected value ($2.50) greater than the stated goal ($0) and simulation success rate (55 percent) greater than the simulation failure rate (45 percent). The PBP indicator had an expected value (3.4025) less than the stated goal (3.5 years) and simulation success rate (58 percent) greater than the simulation failure rate (42 percent). Finally, in the extreme approve version the ARR indicator had an expected value (17.225 percent) greater than the stated goal (17.0 percent) and the simulation success rate (56 percent) greater than the failure rate (44 percent). The extreme approve decision version is presented in Appendix B.

For the extreme reject decision version, both the expected values and simulation success/failure rates for all three financial indicators suggest the project should be rejected. The NPV indicator had an expected value ($-2.50) less than the stated goal ($0) and simulation success rate (45 percent) less than the simulation failure rate (55 percent). In the extreme reject decision version, the PBP indicator had an expected value (3.6025) greater than the stated goal (3.5 years) and simulation success rate (42 percent) less than the simulation failure rate (58 percent). Finally, the ARR indicator had an expected value (16.225 percent) less than the stated goal (17.0 percent) and the simulation success rate (44 percent) less than the failure rate (56 percent). The extreme reject decision version is presented in Appendix B.[5]

Evidence Frame and Extreme Evidence Frame

All four hypotheses predict that evidence attribute frames will impact investment decisions. To test the hypotheses, the data for each of the three financial indicators was framed either positively or negatively. The success (positive) evidence frame manipulation presented the simulation success rate while the failure (negative) evidence frame manipulation presented the simulation failure rate. This evidence frame manipulation is the same used in prior literature (Kerler et al., 2012 and 2014).Hypotheses three and four predict that evidence attribute frames will

[4] The payback period represents the amount of time before the cash inflows from the investment will equal the amount of the initial cash outflow. Therefore, when choosing an investment one would desire an expected value *equal to or below* the stated goal (i.e. initial cash outflow will be recouped as quickly as or quicker than desired).

[5] An alternative manipulation for extreme decisions would be to vary just the stated goals of each financial item (e.g. make stated goals well above or below the expected values) instead of varying both the expected values and simulation success/failure rates for each item.

affect investment decisions when financial data contains extremely high or extremely low probabilities. The extreme evidence frames were manipulated as either extremely high or extremely low by varying the simulation success and simulation failure probability rates. For the extreme evidence frame versions we followed Kerler et al. (2012 and 2014) and used a neutral decision version with some financial indicators suggesting approval of the potential project while others suggest rejection. We utilised Kerler et al.'s (2012 and 2014) expected values, stated goals, and the direction of the simulation success/failure rates (e.g. more successes than failures, or vice versa) but we varied the probabilities to be extreme (90 percent or 10 percent). Specifically, the NPV indicator had mixed evidence with an expected value ($2.50) greater than the stated goal ($0) but a simulation success rate (10 percent) less than the simulation failure rate (90 percent). The PBP indicator suggested rejection with an expected value (3.6025 years) greater than the stated goal (3.5 years) and simulation success rate (10 percent) less than the simulation failure rate (90 percent). The ARR indicator suggested acceptance with an expected value (17.225 percent) greater than the stated goal (17 percent) and simulation success rate (90 percent) greater than the simulation failure rate (10 percent). The evidence frame and extreme evidence frame manipulations presented in Appendix B.

Project Approval Assessment

Hypotheses one and three predict evidence attribute frames will impact project approval assessments. Participants' project approval assessment was measured by asking participants the likelihood they would approve or reject the development of the new clothing line for young women. The assessment was done on a nine-point Likert-type scale with anchors of 1 – "Definitely Reject" and 9 – "Definitely Approve." Hypotheses two and four predict evidence attribute frames will impact the proportion of participants that approve the potential project.

Participants whose project approval assessment was below five (the scale midpoint) were categorised as rejecting the project while participants whose project approval assessment was above five were categorised as approving the project. Participants whose project approval assessment was five were excluded from the analyses for hypotheses two and four.

Participants

One hundred eighty-three students from upper-level accounting courses at two large south-eastern U.S. schools participated in the study. Ninety-three (50.8 percent) participants were female and 90 (49.2 percent) were male. One hundred seventy-nine (97.8 percent) were undergraduate accounting majors with 167 (91.3 percent) being seniors, 12 (6.6 percent) juniors, and four (2.2 percent) other (e.g. students taking courses to prepare for a masters in accounting program, students taking courses to prepare for the CPA exam).

Participants had an average age of 24.3 years and an average of two-and-a-half years of business experience. Participants reported an average GPA of 3.35 and indicated they had completed, on average, 4.4 credit hours of finance courses and 5.25 hours of managerial accounting hours. While by no means a perfect proxy for professionals, upper-level accounting students have the required educational background and training (two to four years of focused business study) to analyse financial data, make investment recommendations, and understand the impact of capital projects on company performance and success. Also, as indicated, many participants have relevant business experience (mean of 2.5 years). Finally, upper-level accounting students have been used in prior research investigating framing effects in the management accounting literature (Kerler et al., 2012 and 2014).

Results

Primary Analysis

The first hypothesis predicts that evidence attribute frames will impact extreme investment decisions when the financial data clearly suggests a project should be approved and when the data clearly suggests the project should be rejected. Specifically, H1 predicts positive evidence frames will result in higher project approval assessments. To examine this hypothesis a 2 x 2 analysis of variance (ANOVA) was performed with evidence frame (success or failure) and decision version

(extreme approve or extreme reject) as the two independent variables and project approval assessment as the dependent variable
.

Table 1: Sample Descriptive Statistics

	N[a]	Mean	SD
Years of Business Experience	178	2.47	4.05
Age	182	24.31	5.62
GPA	179	3.35	0.42
Finance Hours	182	4.41	3.45
Managerial Accounting Hours	182	5.25	1.45
Time to Complete Case (min.)	178	9.72	3.50
Clarity of Case Instructions	183	7.56	1.39
Gender:	**Count**	**Percentage**	
Male	90	49.2%	
Female	93	50.8%	
Academic Level:			
Senior	167	91.3%	
Junior	12	6.6%	
Other	4	2.2%	
Program of Study:			
Undergraduate Accounting	179	97.8%	
Other (accounting certificate, Masters prep, CPA exam course hours)	4	2.2%	

A Final sample consisted of 183 participants. “N” not equal to 183 indicates some failed to provide information.

As shown in panels A and B of Table 2, the extreme decision version significantly impacted participants’ project approval assessments ($p < 0.001$, one-tailed) with participants receiving the extreme approve version providing a greater mean approval assessment (5.53) than participants receiving the extreme reject version (4.05). This suggests the two different versions had the desired effect of creating one project that clearly suggested approval and another project that clearly suggested failure. As shown in panels A and B of Table 2, the evidence attribute frame significantly impacted participants’ approval assessments ($p = 0.004$, one-tailed) with success (i.e. positive) evidence frames resulting in greater approval assessments (5.19) compared to failure (i.e. negative) evidence frames (4.40). The insignificant interaction ($p = 0.891$, two-tailed) between evidence frame and decision version indicates both main effects are consistent across the other variable’s levels. Overall, these results support H1 indicating that attribute frames significantly impact assessments even in extreme decision scenarios where all evidence clearly suggests a project should be approved or rejected.

The second hypothesis predicts that evidence attribute frames will impact the proportion of participants approving a potential new project with positive frames resulting in a higher proportion of project approvals. To test this hypothesis, a Mann-Whitney U Test (nonparametric) was performed for both the extreme approve decision version and the extreme reject decision version to compare the proportion of project approvals between participants in the success and failure evidence frame groups. As discussed previously, participants were categorised as approving (rejecting) the potential project if their project approval assessment was greater than (less than) the scale midpoint of five. Participants with an approval assessment of five were not included in this analysis. As shown in table 3, in the extreme approve decision version, the proportion of participants approving the project was significantly (p = 0.027, one-tailed) greater when evidence was framed positively (81.8 percent approval) compared to when evidence was framed negatively (55.6 percent approval). Similarly, in the extreme reject decision version, the proportion of participants approving the project was significantly (p = 0.096, one-tailed) greater with positively framed evidence (33.3 percent approval) compared to negatively framed evidence (17.9 percent approval). Together, these results support H2 and suggest the frame of evidence can significantly alter individuals' decisions as to whether a potential new project should be approved or rejected even in extreme decision scenarios where all the evidence clearly suggests the project should be approved or rejected.

Consistent with the first hypothesis, H3 predicts that evidence attribute frames will impact project approval assessments even when the framed data contains extremely high or extremely low probabilities. To examine this hypothesis a one-way ANOVA was performed with evidence frame (extreme success or extreme failure) as the sole independent variable and project approval assessment as the dependent variable. As shown in panels A and B of Table 4, even when evidence contains extreme probabilities (e.g. 10 percent and 90 percent) evidence frames on those extreme probabilities still significantly (p = 0.010, one-tailed) impact approval assessments with success frames resulting in greater (5.65) assessments than failure frames (4.39). This result supports H3 and suggests that attribute frames, even on extreme probabilities, can impact individuals' assessments.

Table 2: Effect of Evidence Frame and Decision Version on Project Approval Assessments

Panel A: 2 x 2 analysis of variance with evidence frame (success or failure) and decision version (extreme approve or extreme reject) as the independent variables and project approval rating as the dependent variable.

Source	df	Mean Square	F-score	P-value[d]
Evidence Frame	1	19.16	7.36	0.004
Decision Version	1	67.28	25.84	<0.001
Evidence Frame * Decision Version	1	0.05	0.02	0.891
Error	117	2.60		

Panel B: Descriptive Statistics (mean [standard deviation]) for Project Approval Rating

	Decision Version					
	Extreme Approve		Extreme Reject		Total	
Evidence Frame	**n**	**Mean [std. dev.]**	**n**	**Mean [std. dev.]**	**n**	**Mean [std. dev.]**
Success	29	5.97 [1.38]	30	4.43 [1.76]	59	5.19 [1.75]
Failure	31	5.13 [1.75]	31	3.68 [1.54]	62	4.40 [1.79]
Total	60	5.53 [1.62]	61	4.05 [1.68]	121	4.79 [1.80]

(a) Evidence frame was manipulated by framing the financial indicators' output either in terms of simulation success or simulation failure. The success (failure) manipulation provided participants with the number of Monte Carlo simulations that met (did not meet) the company goal.

(b) Decision version was manipulated by having all three financial indicators suggest the potential project should be approved (extreme approve) or rejected (extreme reject).

(c) Project approval assessment is participants' assessment of the likelihood they would approve or reject the potential capital budgeting project. This assessment was done on a nine-point Likert-type scale with anchors of 1 "Definitely Reject" and 9 "Definitely Approve."

(d) P-value is one-tailed for hypothesised main effects, two-tailed for interaction.

Table 3: Effect of Evidence Frame on Proportion of Projects Approved

Decision Version	Evidence Frame: Success	Evidence Frame: Failure	Is the Distribution of Approved/Rejected Decisions the Same Across Evidence Frames?
Extreme Approve	18 out of 22 (81.8%) Approved project 4 out of 22 (18.2%) Rejected project	15 out of 27 (55.6%) Approved project 12 out of 27 (44.4%) Rejected project	No: p = 0.027 (one-tailed)
Extreme Reject	9 out of 27 (33.3%) Approved project 18 out of 27 (66.7%) Rejected project	5 out of 28 (17.9%) Approved project 23 out of 28 (82.1%) Rejected project	No: p = 0.096 (one-tailed)

(a) Evidence frame was manipulated by framing the financial indicators' output either in terms of simulation success or simulation failure. The success (failure) manipulation provided participants with the number of Monte Carlo simulations that met (did not meet) the company goal.

(b) Projects were considered approved if participants' project approval assessment was six or greater. Projects were considered rejected if participants' project approval assessment was four or less. Participants' with project approval assessment of five (the midpoint of the scale) were removed for this analysis.

(c) Decision version was manipulated by having all three financial indicators suggest the potential project should be approved (extreme approve) or rejected (extreme reject).

(d) The distribution of projects approved and rejected between the success evidence frame group and the failure evidence frame group was examined with the Mann-Whitney U Test (nonparametric).

Table 4: Effect of Evidence Frames with Extreme Probabilities on Project Approval Assessments

Panel A: One-way analysis of variance with evidence frame (success or failure) as the independent variable and project approval assessment as the dependent variable.

Source	df	Mean Square	F-score	P-value[d]
Evidence Frame	1	24.53	5.83	0.010
Error	60	4.21		

Panel B: Descriptive Statistics (mean [standard deviation]) for Project Approval Rating

Evidence Frame	n	Mean [std. dev.]
Extreme Success	31	5.65 [1.94]
Extreme Failure	31	4.39 [2.16]
Total	62	5.02 [2.13]

(a)Evidence frame was manipulated by framing the financial indicators' output either in terms of simulation success or simulation failure. The success (failure) manipulation provided participants with the number of Monte Carlo simulations that met (did not meet) the company goal.

(b) Frames with extreme probabilities utilised simulation success or failure rates of 90 percent and 10 percent.

(c) Project approval assessment is participants' assessment of the likelihood they would approve or reject the potential capital budgeting project. This assessment was done on a nine-point Likert-type scale with anchors of 1 "Definitely Reject" and 9 "Definitely Approve."

(d) One-tailed for hypothesised main effect, two-tailed for interaction.

Consistent with the second hypothesis, H4 predicts that evidence attribute frames will impact the proportion of participants approving a potential investment even when the framed date contains extremely high or extremely low probabilities.

To test this hypothesis, a Mann-Whitney U Test (nonparametric) was performed to compare the proportion of project approvals between participants in the extreme success and extreme failure evidence frame groups. As shown in table 5, the proportion of participants approving the project was significantly ($p = 0.007$, one-tailed) greater when evidence containing extreme probabilities was framed positively (72.4 percent approval) compared to when evidence containing extreme probabilities was framed negatively (40.0 percent approval).

This result supports H4 and suggests that even when data contains extreme probabilities, evidence frames can significantly alter individuals' decisions to approve or reject a project.

Supplemental Analysis

The purpose of the supplemental analysis is to examine the robustness of the parametric statistical findings regarding the impact of evidence frames on project approval assessments (H1 and H3) across various demographic data reported by participants.[6] The six demographic variables analysed include participants' gender, age, years of business experience, GPA, finance hours, and managerial accounting hours. To examine the impact of gender on the first hypothesis, we performed a 3 x 2 ANOVA with evidence frame (success or failure), decision frame (extreme approve or extreme reject), and

[6] The parametric statistical analyses performed to test H1 and H3 allow us to include the demographic variables individually as an additional independent variable (for the gender categorical variable) or as a covariate (for the other five continuous variables) to see if their presence impacts the effects of the main variables of interest. For the nonparametric statistical analyses performed to test H2 and H4 we are not able to include additional variables.

Table 5: Effect of Evidence Frames with Extreme Probabilities on Proportion of Projects Approved

Evidence Frame: Extreme Success	Evidence Frame: Extreme Failure	Is the Distribution of Approved/Rejected Decisions the Same Across Evidence Frames?[d]
21 out of 29 (72.4%) Approved project 8 out of 29 (27.6%) Rejected project	12 out of 30 (40.0%) Approved project 18 out of 30 (60.0%) Rejected project	No: $p = 0.007$ (one-tailed)

(a) Evidence frame was manipulated by framing the financial indicators' output either in terms of simulation success or simulation failure. The success (failure) manipulation provided participants with the number of Monte Carlo simulations that met (did not meet) the company goal.

(b) Frames with extreme probabilities utilised simulation success or failure rates of 90 percent and 10 percent.

(c) Projects were considered approved if participants' project approval assessment was six or greater. Projects were considered rejected if participants' project approval assessment was four or less. Participants' with project approval assessments of five (the midpoint of the scale) were removed for this analysis.

(d) The distribution of projects approved and rejected between the success evidence frame group and the failure evidence frame group was examined with the Mann-Whitney U Test (nonparametric).

gender (male or female) as the independent variables and project approval assessment as the dependent variable. The gender main effect and all of its interactions with the other variables did not significantly affect participants' approval assessments (all p >= 0.190, two-tailed). Further, the inclusion of gender did not impact the main findings that decision version (p < 0.001, one-tailed) and evidence frame (p = 0.005, one-tailed) impact approval assessments while the decision version * evidence frame interaction is not significant (p = 0.901, two-tailed).

To test the impact of the five continuous demographic variables (age, years of business experience, GPA, finance hours, and managerial accounting hours) on H1 we performed five separate 2 x 2 analysis of covariance (ANCOVA) with evidence frame (success or failure) and decision frame (extreme approve or extreme reject) as the independent variables, each continuous demographic variable as the covariate, and project approval assessment as the dependent variable. In all five ANCOVAs, the inclusion of the demographic variable as a covariate did not alter the main findings that decision version (all p < 0.001, one-tailed) and evidence frame (all p <= 0.007, one-tailed) significantly affect approval assessments while the decision version * evidence frame interaction is not significant (p >= 0.716, two-tailed). In the five ANCOVAs, the number of finance hours was the only demographic variable significantly related to participants' approval assessments (p = 0.012, two-tailed).

A Pearson correlation of finance hours and approval assessments shows the variables have a negative relationship (-0.195, p = 0.033, two-tailed) indicating more hours of finance courses was related to lower approval assessments.

To examine the impact of gender on the third hypothesis, we performed a 2 x 2 ANOVA for participants that received financial data with extreme probabilities with evidence frame (extreme success or extreme failure) and gender (male or female) as the independent variables and project approval assessment as the dependent variable. The gender main effect and its interaction with evidence frame were not significant (p = 0.618, two-tailed and p = 0.454, two-tailed, respectively). Further, the inclusion of gender did not impact the main finding that evidence frames significantly impact (p = 0.009) approval assessments even when the framed data contains extremely high and extremely low probabilities. Finally, to test the impact of the five continuous demographic variables on H3 (age, years of business experience, GPA, finance hours, and managerial accounting hours) we performed five separate one-way ANCOVAs with evidence frame (extreme success or extreme failure) as the sole independent variable, each continuous demographic variable as the covariate, and project approval assessment as the dependent variable. In all five ANCOVAs, the inclusion of the demographic variable as a covariate did not alter the main finding that evidence frames significantly affect approval assessments (all p <= 0.017). In the five ANCOVAs, GPA was the only demographic variable significantly related to participants' approval assessments (p = 0.031, two-tailed). A Pearson correlation of GPA and approval assessments shows the variables have a negative relationship (-0.257, p = 0.049, two-tailed) indicating higher GPA was related to lower approval assessments.

Conclusion

This study investigates two types of "extreme" attribute frames introduced into a capital budgeting exercise, extreme decision and extreme probabilities, and the impact upon the decision maker. The results of the study indicate that evidence attribute frames will impact the decision maker's approval assessments and will impact the proportion of participants approving a potential new project even in an extreme decision scenario where the financial data related to the new project clearly suggests the project should be approved or rejected (hypotheses H1 and H2). Further, the results of the study indicate that evidence attribute framing impacts the decision maker's approval assessment even with the inclusion of extreme probabilities of the project's potential success or failure (hypotheses H3 and H4). These findings suggest that the presence of attribute frames may be problematic in certain decision-making scenarios and the framing effect may be stronger and more persistent than prior theory suggests.

Like all experimental studies, this study has its limitations. In order to specifically investigate the effects of only the variables of interest (increase the internal validity of our study) we needed to restrict the amount and type of information provided to participants (decrease the external validity of our study). While the experimental case was a fictitious case it was designed to provide realistic information utilised in real world capital budgeting decisions. Another limitation of the study is the use of student participants as proxies for professionals. We believe the participants' educational background and work experience makes them suitable proxies. We also believe the different distribution of approval/rejection decisions across the different versions supports that our participants were able understand the financial information presented and were impacted by the experimental manipulations. Future research should investigate the robustness of our results by examining the effects of extreme decisions and extreme probabilities on professionals.

This study contributes to the literature through the extension of the understanding of the attribute framing phenomenon on capital budgeting decisions. Levin et al. (1998) notes that attribute frames impact decision making, and Kerler et al. (2012 and 2014) demonstrate an impact upon capital budgeting decisions. The importance of this prior research is that it shows a potential sub-optimal decision-making scenario for which greater understanding is desired. Levin et al. (1998) also posits that attribute framing effects may be moderated in the presence of extremes. The current research does not support this theory for extreme decisions and for extreme probabilities and highlights the strength and persistence of attribute framing effects. Attribute framing impacts judgments even when financial data clearly suggests approval/rejection and even with the inclusion of extreme success/failure probabilities within the data. The results suggest that attribute framing contained within the capital budgeting process, as presented in the current experiment, may be difficult to moderate.

This study also contributes to recent research by Freling et al. (2014). Applying construal level theory (Liberman and Trope, 1998) to attribute framing research, Freling et al. (2014) perform a meta-analysis of 107 published articles and find attribute framing is most effective when there is congruence between the construal level of the information and the subject's psychological distance from the framed event. The construal level of information is "the degree of perceived abstractness that an event holds for an individual" (Freling et al., 2014, p. 97) and the psychological distance from an event is an individual's "perceptions of temporal distance (when an event occurs), spatial distance (where it is likely to occur), social distance (to whom it occurs), or hypothetical distance (whether it occurs)" (Freling et al., 2014, p. 97). Attribute frames should have the strongest effect when both the construal level and psychological distance are low or when they are both high. Therefore, "extremes" may have the greatest moderating impact on attribute framing when there is a lack of congruence between the construal level of information and the psychological distance of the framed event.

The current study's design and execution was prior to the publication of Freling et al. (2014), however, the manipulation used did "stack the deck in our favor" of supporting Levin et al.'s (1998) theory that attribute framing effects are less likely when dealing with extremes. Specifically, we utilised an experiment with a low construal level of information and a high psychological distance from the framed event. The low construal level of information is created by the use of specific dollar amounts and specific probabilities of success/failure. Having students make decisions that they have no direct experience making created a high hypothetical distance scenario, and therefore created a task with a high psychological distance. Despite the lack of congruence between the construal level of information and the psychological distance from the event, our results indicate that attribute frames significantly impacted decisions even in the presence of extreme decisions and extreme probabilities. The inability to identify a moderating effect in this scenario, where theory suggests the attribute framing effect is the least effective, indicates to us that the strength and persistence of attribute frames may be greater than prior theory suggests. Given that the study highlights the strength and persistence of attribute framing, future research may seek to identify mechanisms to moderate this effect and to continue to explore the boundaries of this phenomenon. Future research should also seek to utilise the work of Freling et al. (2014) when exploring the boundaries of attribute framing effects and when seeking to identify mechanisms to moderate the effect.

The major importance of these psychological finding upon the capital budgeting process is the identification of potential significant costs to management and firm owners. The process and manner in which information is presented may potentially impact project evaluation and approval. Perhaps the most alarming result of the current study is that in a project where all the financial data clearly suggests the project should be rejected, positively framed data still significantly increased participants' evaluations of the project and even resulted in a significantly higher percentage of approvals (33 percent approved when positively framed and only 18 percent approved when negatively framed). This suggests that low quality capital investment projects with a low chance of acceptable profitability may be approved by companies simply due to the framing of the evidence. Equally alarming, in a project where all financial data clearly suggests the project should be approved, negatively framed data significantly decreased participants' evaluations of the project and even resulted in a significantly lower percentage of approvals (56 percent approved when negatively framed and 82 percent approved when positively framed). This suggests that quality capital investment projects with a high chance of acceptable profitability may be passed on by companies simply due to the framing of the evidence. De-biasing the capital budgeting process through careful attention to attribute frames may improve the success rate of capital budgeting decisions and reduce the long-term cost (funding poor investments and passing up profitable investments) to the firm.

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Appendix A: Information Provided In Research Instrument

Case Information

HER Apparel, Inc. is a manufacturer and distributor of women's clothing. HER has historically focused on professional and casual clothing styles for women between the ages of 25 and 45. In 2009, HER recorded $100 million sales, with 2009 profits of $12 million and total assets of $140 million. While HER has generally had steady growth in terms of both sales and profits, the board of directors and management have noted that HER's major clothing lines are approaching product cycle maturity. Therefore, the company has been in the process of considering new product lines and new target markets. While many possibilities have been considered, the company is currently giving serious consideration to a new clothing line for young women between the ages of 15 and 25. All levels of management have been involved in considering the possibilities for the potential line, and extensive market research has been performed. Based on the collective knowledge obtained via these diverse sources, financial estimates for the new product line have been developed.

Several years ago the management of HER Apparel realised that they were not giving appropriate consideration to information risk when making new product decisions. Specifically, these decisions were based on popular financial indicators (Net Present Value, etc.) that required several subjective estimates, but no consideration was given to the possibility of inaccurate estimates or the impact these inaccuracies could have on the financial indicators. To remedy this problem, HER developed a Monte Carlo simulation program. Monte Carlo techniques quantify the impact of discrepancies in the timing of cash flows, the amount of competition, unexpected production difficulties, and many other contingencies on financial indicators, such as Net Present Value. The program provides this information by calculating the desired financial indicator thousands of times, making different assumptions about the amount and timing of cash flows in each calculation. The range of assumptions used by the computer program is generally based on the expected cash flows provided through market research and the likely frequency distribution of these cash flows. With this information, the decision maker can not only consider the expected value of a financial indicator, but also its variation.

The Monte Carlo program provides the decision maker three important information items relating to each financial indicator. One information item provided by the program is the ***target or goal*** for each financial indicator. For instance, if calculating the Net Present Value for the new clothing line, the program output would first provide the company goal of greater than $0. *[Failure (negative) evidence frame group received the following:] In addition, the output provides the simulation failure rate (number of simulation failures divided by total number of simulations). Considering the Net Present Value example above, the program would consider simulations that did not achieve the greater than $0 goal as simulation failures. [Success (positive) evidence frame group received the following] In addition, the output provides the simulation success rate (number of simulation successes divided by total number of simulations). Considering the Net Present Value example above, the program would consider simulations that achieved the greater than $0 goal as simulation successes.* Finally, the output provides the ***expected value*** for each financial indicator. This expected value is calculated by taking the average of all simulation outcomes.

Assume you have the final authority to make new product and product improvement decisions at HER. The next page presents financial information pertaining to the potential new product line created by the Monte Carlo program. Please review this information and determine whether you would approve the development of the new clothing line for young women. After you have formed an opinion, turn to the next page and respond to the questions.

Financial Information for Potential New Clothing Line for Young Women

Net Present Value:

Description: The present value of cash inflows and outflows for the life of the project. Cash flows are discounted to present value based on the company's required rate of return and the company goal is to have a net present value greater than $0. This measure is generally believed to be the most effective measure of overall investment value, and it is the only measure included that controls for the time value of money.

Monte Carlo Simulation Output:

Stated Goal:	Greater than $ 0.00
Expected Value (average of all 10,000 simulations):	*Varies depending on manipulation (see Appendix B for manipulations)*
Simulation Success Rate (10,000 total simulations): *(or Failure Rate, depending on manipulation)*	*Varies depending on manipulation (see Appendix B for manipulations)*

Payback Period:

Description: The number of periods/years before the cash inflows from the investment will equal the amount of the initial cash outflow. These cash flows are not discounted to present value. The company goal is less than 3.5 years. This measure is important for two reasons. First, it provides information relevant to future investment decisions; the sooner the company gets back the invested capital, the sooner the company can invest in additional projects. Second, conventional wisdom suggests that as cash inflows extend further into the future, they become more speculative (i.e., less certain).

Monte Carlo Simulation Output:

Stated Goal:	Less than 3.5000 years
Expected Value (average of all 10,000 simulations):	*Varies depending on manipulation (see Appendix B for manipulations)*
Simulation Success Rate (10,000 total simulations): *(or Failure Rate, depending on manipulation)*	*Varies depending on manipulation (see Appendix B for manipulations)*

Accounting Rate of Return:

Description: The average annual income of the project divided by the initial investment. This calculation employs revenue and expenses, rather than cash inflows and outflows. The company goal is a greater than 17% accounting rate of return. This measure is also a holistic assessment of investment value (like NPV), but the focus is on revenues and expenses rather than cash inflows and outflows. Revenue and expense measures can vary substantially from cash inflows and outflows.

Monte Carlo Simulation Output:

Stated Goal:	Greater than 17.000%
Expected Value (average of all 10,000 simulations):	*Varies depending on manipulation (see Appendix B for manipulations)*
Simulation Success Rate (10,000 total simulations): *(or Failure Rate, depending on manipulation)*	*Varies depending on manipulation (see Appendix B for manipulations)*

Appendix B: Financial Information Manipulations for Each Version

Decision Version **Evidence Frame**	***Extreme Approve*** ***Success***	***Extreme Approve*** ***Failure***	***Extreme Reject*** ***Success***	***Extreme Reject*** ***Failure***	***Neutral*** ***Extreme Success***	***Neutral*** ***Extreme Failure***
Net Present Value Stated Goal:	Greater than $0.00	Greater than $0.00	Greater than $0.00	Greater than $0.00	Greater than $0.00	Greater than $0.00
Expected Value (average of all 10,000 simulations):	$2.50	$2.50	(Negative $2.50)	(Negative $2.50)	$2.50	$2.50
Simulation Success Rate (10,000 total simulations): *[for positive evidence frame version]*	55% of simulations had a Net Present Value greater than $0.00		45% of simulations had a Net Present Value greater than $0.00		10% of simulations had a Net Present Value greater than $0.00	
Simulation Failure Rate (10,000 total simulations): *[for negative evidence frame version]*		45% of simulations did not have a Net Present Value greater than $0.00		55% of simulations did not have a Net Present Value greater than $0.00		90% of simulations did not have a Net Present Value greater than $0.00
Payback Period Stated Goal:	Less than 3.5000 years	Less than 3.5000 years	Less than 3.5000 years	Less than 3.5000 years	Less than 3.5000 years	Less than 3.5000 years
Expected Value (average of all 10,000 simulations):	3.4025 years	3.4025 years	3.6025 years	3.6025 years	3.6025 years	3.6025 years
Simulation Success Rate (10,000 total simulations): *[for positive evidence frame version]*	58% of simulations had a Payback Period of less than 3.5000		42% of simulations had a Payback Period of less than 3.5000		10% of simulations had a Payback Period of less than 3.5000	
Simulation Failure Rate (10,000 total simulations): *[for negative evidence frame version]*		42% of simulations did not have a Payback Period of less than 3.5000 years		58% of simulations did not have a Payback Period of less than 3.5000 years		90% of simulations did not have a Payback Period of less than 3.5000 years
Accounting Rate of Return Stated Goal:	Greater than 17.000%	Greater than 17.000%	Greater than 17.000%	Greater than 17.000%	Greater than 17.000%	Greater than 17.000%
Expected Value (average of all 10,000 simulations):	17.225%	17.225%	16.225%	16.225%	17.225%	17.225%
Simulation Success Rate (10,000 total simulations): *[for positive evidence frame version]*	56% of simulations had an Accounting Rate of Return greater than 17.000%		44% of simulations had an Accounting Rate of Return greater than 17.000%		90% of simulations had an Accounting Rate of Return greater than 17.000%	
Simulation Failure Rate (10,000 total simulations): *[for negative evidence frame version]*		44% of simulations did not have an Accounting Rate of Return greater than 17.000%		56% of simulations did not have an Accounting Rate of Return greater than 17.000%		10% of simulations did not have an Accounting Rate of Return greater than 17.000%