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Antonie J. Jetter
Portland State University, ajetter@pdx.edu

Fatima M. Albar
Portland State University

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An Investigation on Fast and Frugal Model for New Project Screening

Fatima M. Albar, Antonie Jetter
Department of Engineering and Technology Management, Portland State University, Portland, OR 97207-0751 USA

Abstract-- **Research in psychology is increasingly interested in decision-makers' use of heuristics or rules of thumb because they have accuracies close to more complex decision rules and seem particularly useful in difficult decision-making contexts when uncertainty is high and speed is of the essence. One particularly difficult decision setting is the fuzzy front-end of new product development because a large number of product ideas need to be screened to identify the few that should be developed further. This process is currently poorly supported through decision tools and mainly occurs on the basis of managerial "gut-feel".**

This study explores managerial "gut-feel" by investigating the performance of simple project screening heuristics: two so-called Fast and Frugal (F&F) heuristics, Take-the-Best and Tallying, and three logistic regression models with 3, 5, and 7 decision variables are used to screen a simulated dataset of 52 projects. Each model's ability to recognize successful projects and correctly reject poor projects is compared against the predictions of the other decision models. The results how that the logistic regression models outperform the F&F models in overall prediction quality and in the ability to predict project failure. However, the Tallying model has an overall performance that is close to the logistic regression and both F&F models are better at predicting success than the logistic regression model. Furthermore, the regression model that only takes 3 decision variables into consideration performs better than the regression models with 5 and all 7 decision variables. This indicates that a simple "less is more" decision approach, which is the basis of managerial "gut-feel", can be a successful strategy for front-end screening.

I. INTRODUCTION

At the first gate of new product development—the fuzzy front end (FFE)—product opportunities and product ideas are screened to identify ideas that are promising success and should be developed further into product concepts. Despite the strategic importance of this stage, front-end decisions are currently oftentimes made *ad hoc*, based on non-analytical factors, and poorly documented [1-4]. Furthermore, the front-end phase stretches over long periods of time in which product ideas "linger around" without evaluation, rather than being actively pursued or abandoned [5, 6]. Uncertainty, complexity, and unreliable information at the fuzzy front end threaten the effectiveness of using traditional quantitative techniques in evaluating new product ideas. Consequently, many practitioners express dissatisfaction with the front-end process [2, 7], which is presently not fast and not successful enough. As a result, new decision-making approaches are urgently required.

Recent research is increasingly interested in decision-makers' use of heuristics. Heuristics are simple strategies and rules of thumb that people employ for solving problems without guaranteeing an optimal solution [12]. Process tracing studies repeatedly show that individuals employ simple strategies that minimize the amount of considered information and mental effort invested in the decision [8-11]. Research on these heuristics shows that heuristic decision approaches have accuracies close to more complex decision rules and seem particularly useful in difficult decision-making contexts, especially when the level of uncertainty is high or when a quick decision is needed [16]A class of very simple decision heuristics, the so-called "F&F" (fast and frugal) heuristics [17], found their way into practitioners' literature [16, 18]. They have been proposed to help decision makers make decisions in difficult situations that involve high levels of uncertainty [13-15] . These simple decision heuristics are potentially useful for some front-end project screening. This research attempts to explore these potentials and test the validity of using F&F decision models for project screening, based on simulated data.

This paper begins by examining heuristics in general and well-known F&F decision models in particular. It then covers the research methodology. A simulated data set of 52 new product development projects is created which is used to test the performance of alternative decision heuristics: two well-known F&F heuristics, Take the Best and Tallying, and three variations of a regression model. The paper ends with a discussion about classes of problems that can be judged using heuristic models.

II. HEURISTICS

Even with the limitations of the human cognitive system, humans have the capability to understand and analyze obscure events and factors. As the complexity of making choices rises, people tend to simplify their decision-making processes by relying on simple heuristics and only processing a subset of the available information [18-21]. Heuristics are "the general problem solving strategies people apply for certain classes of situations" [22]. Heuristics can also be interpreted as "rules follow behavior and logic quite different than the consequential logic" [23]. People usually trade off the effort involved in making a choice against the accuracy of that choice, and choose simple decision strategies that would achieve the desired balance [24, 25]. The term heuristics in the industrial world does not exactly match the term in psychology; while industry defines heuristics as mathematical models, with specified procedures that are used to find the best solution for a well-structured environment [26, 27], in behavioral decision making, the term heuristics is used to refer to simple strategies, or rules of thumb, that are part of a decision maker's repertoire of cognitive strategies for solving judgment problems [28]. In this paper, we will use the term heuristics to mean the behavioral problem solving strategy unless we specify other meanings.

In 1996, Gerd Gigerenzer proposed examining simple alternatives to full rational analyses as a mechanism for decision-making; he called these methods the fast and frugal (F&F) decision models. Research followed to show that when there is a high level of uncertainty and limited time, simple heuristics frequently lead to better decisions than the theoretically optimal procedure that involves many calculations [13-15, 29-35]. F&F heuristics are simple algorithms that specify certain guiding principles or rules to make a decision [9]. They are ecologically rational because they exploit structures of information in the environment [36]. They claim to be fast, frugal, and simple enough to operate when time and information are limited because they do not search for the optimal solution; instead they look for a "good enough" solution that fits the needs and satisfies the decision maker [33, 37].

At the fuzzy front-end stages of product development, where information tends to be incomplete, not accessible, and sometimes inconsistent, and decisions often have to be made under time constraints [38-40], fast and frugal heuristics might be a good fit. This research proposes to use F&F models to screen projects by designing two popular heuristics models, "Take the Best" and "Tallying", and test the validity of using them for the FFE of NPD screening. Take the Best's judgment is based on the most important criterion that most validly predict judgments about alternatives, where criteria are ordered in descending order from the most important criterion to the least [33]. Tallying gives all or some of the criteria the same level of priority and chooses the alternative that is supported by the most reasons, by computing the score of each option, adding up the number of its pros, and subtracting its cons. The option with the highest score wins [36].

III. RESEARCH METHODOLOGY

The aim of this study is to test the potential of using F&F decision models for new product screening. To achieve this goal, we will compare the performance of two F&F models against regression models for forecasting project success. Regression models are statistical models, widely used for predicting and forecasting, and for understanding which among the independent variables are related to the dependent variable [41, 42]. Studies have used regression models to compare the fit of F&F models with regression models on both simulated judgment data [33, 34] and human judgment data [11, 30, 43]. The "statistical significance" of the estimated relationship gives the degree of confidence of the estimated relationship [41, 44], and the Pearson's correlation is used to measure the linear associated relationship between the variables in each model. Several performance measures, including the Pearson's correlation, will be used to estimate association and forecast errors. The comparison with a regression model

The comparison of the performance of the F&F models and the regression model will be made based on simulated project data. The simulation data takes current research on the success factors for new product projects into account. We do not intend to identify the method that best predicts project success, but want to compare the decision outcomes of alternative decision approaches. We assume that our simulated data set does not have any biases that would distort the results with this regard. *Research Process*

This research starts with identifying frequently used criteria for new product screening, and generates data for 52 projects, each of which is described through all important criteria. Since the heuristic models depend on minimizing the amount of tested information, the second phase of this research will select a subgroup of the criteria that are the most important ones and use them in testing the performance of the two heuristics models: Take the Best and Tallying. A statistical analysis will follow. The results of running a regression analysis of the data set will be compared with the results of the F&F models. Fig.1 is a flowchart of the research process.

IV. PREPARING THE DATA SET

A. Classify the important criteria for early NPD project screening

In prior research, many different criteria have been used in screening new products. Some researchers used 45 [45], other used 37 [45], 16 [46], or 13 [47, 48] criteria to evaluate the new product idea. Unfortunately, not enough attention was given to the critical criteria for forecasting a NPD project's success. Instead, more attention was given toward the innovation process, product selection process or market research methodology [31, 32, 45, 46, 48]. Copper [40] claims that product innovation does not happen as well as it should because the critical success factors are "indeed noticeably absent from the typical new product project". By analyzing existing research, we identified and grouped the important criteria and summarized them into 12 common criteria (Table 1).

At the fuzzy front end, no sufficient information is available to give quantitative data for each criterion; therefore, projects will be evaluated under each of the 12 selected criteria using linguistic variables [47], with four evaluation levels: "Very Good" when a project has a high probability to perform well in this criterion; "Good" when a project is evaluated to satisfy this criterion; "Neutral" when the project is expected to be fair in this criterion; or "Bad" if the evaluation of the project does not satisfy this criterion. When there is not enough information available about certain criterion for a certain project, the criterion will not have any value and will be left blank. Table 1 shows all the criteria that will be used, along with explanations of the evaluating values.

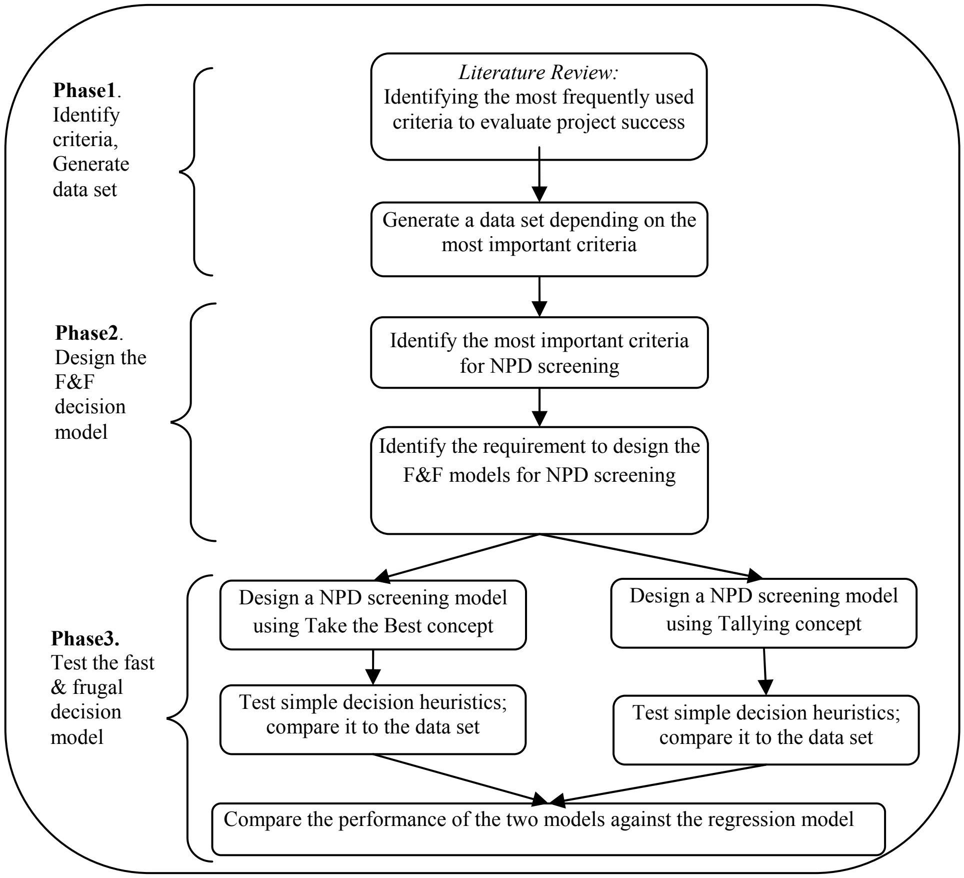

Fig 1 Research Design

TABLE 1. ALL CRITERIA USED BY FIRMS IN OUR SAMPLE

Criteria	**Explanation**	**Evaluation**	**Verbal Value**
Profitability	Expected to be profitable	• High probability/profit • Good profit • Hard to predict • Low profit/ low probability	• Very good • Good • Neutral • Bad
Risk	How much uncertainty in bringing it to the market	• Low risk • Medium risk • Unknown • High risk	• Very good • Good • Neutral • Bad
Superiority	Unique advantage to the customer	• New product idea and new function • Better performance • Just a new design, for a known product • Not new	• Very good • Good • Neutral • Bad
Technical Opportunity	Availability of resources and expenses	• Have resources and experience • Easy to get the needed resources or experience. • Have some of the resources or experience • Don't have enough resources or experience	• Very good • Good • Neutral • Bad
Market Demand	Demand size	• Big/grow • Medium/stable • Small/unpredictable • Shrinking	• Very good • Good • Neutral • Bad

Payback Period	How long will it take to get the capital investment back?	• Short period • Reasonable period • Acceptable or unknown • Long	• Very good • Good • Neutral • Bad
Protection	Strength of Competition?	• Strongly protected/ no strong competitors • Hard to imitate. • Can compete with others • Not protected and have other strong competitors	• Very good • Good • Neutral • Bad
Price	Is it an expensive product compared to competitors' products?	• Substantial economic advantage to customer • Priced like others, but more features • Same price as competition • More expensive	• Very good • Good • Neutral • Bad
Familiarity with the Product Concept	How much are customers familiar with the product concept?	• Familiar • New concept but there is need for it • Need to educate customer about the importance of the product	• Good • Neutral • Bad
Distribution	How hard is it to develop distribution channels?	• Ready or easy to develop through partners • Unknown • Expensive to develop	• Good • Neutral • Bad
Learning	How much training does the user need to use it?	• Easy to learn • Need some time • Need training	• Good • Neutral • Bad
Environmental impact	Might it harm the environment?	• Safe for the environment • Not proven to cause harm • Uncertain • May cause some harm	• Very good • Good • Neutral • Bad
• When no value is attached to a criterion, it means no sufficient information is available at this stage.			

TABLE 2. EXAMPLE OF DATA SET

	Profit	**Risk**	**Superiority.**	**Tech. Opp.**	**Market Demand**	**Pay Back**	**Protection**	**Price**	Familiarity	Distribution**.**	**learning.**	**Env. Imp.**	**Proj Performance**
P7	Good	Neut.	V.Good	Neut.	Good		Bad			Good			S
P8	Neut.	Good	Neut.	Good		Bad	Good	Neut.	Bad			V. Good	F

B. Data Set Generation

By considering the correlation between selection criteria and the project performance illustrated in previous research [32, 35], a data set of 52 project is generated that contains the value of each criterion and the final project result for each project.,

The data set is presented by assigning each project a number, then presenting the evaluation values of each project under all the 12 criteria. A criterion that has not been used in evaluating a certain project will be left blank. Project performance values (Succeed or 1, Fail or 0) will be generated to represent companies' evaluation of the project performance. Table 2 shows an example from the data set where the projects' weights under each criterion take linguistics values (very good, good, natural, and bad), and the project's final evaluation is presented in letter format (F for Fail and S for Succeed).

V. DESIGN THE FAST AND FRUGAL MODELS

Since F&F heuristics depend on a limited number of criteria, and we want to test the forecasting performance using less information, a smaller set of the most critical criteria will be selected and used in forecasting project performance [13, 30]. There is more than one technique that can be used to reduce the number of important criteria. Categorizing by elimination, collecting criteria that have higher correlation with project success, and classifying criteria that are more frequently used in making decisions are different techniques that can be used to reduce the number of criteria to a smaller set [32, 49].

Depending on the high correlation value between a criterion and project performance (Table 3) matching the most important criterion used by previous research, and covering the four factors for project evaluation addressed by Pinto [50]—risk, commercial, internal operating, and organizational factors—the authors identified a set of seven of the most important criteria: profitability, payback period, risk, superiority, opportunity, market demand and protection.

TABLE 3. CRITERIA WITH HIGHEST PEARSON CORRELATION VALUE WITH PROJECT PERFORMANCE

Criteria	**Pearson Correlation with Project performance**
Profitability	.534**
Risk	.218*
Superiority	.305**
Technical Opportunity	.223*
Market Demand	.211*
Payback period	.096
Protection	.109

N=105. ** Correlation is significant at the 0.01 level (1-tailed). *Correlation is significant at the 0.05 level (1-tailed).

Using the literature results [31, 32, 51], we order the criteria in the following descending order starting with the highest weight: profitability, risk, superiority, technical opportunity, market demand, payback period, and protection. This order for the criteria will be used in developing heuristics decision models. For the purpose and the scope of this research, we will assume that these seven criteria are truly the most important success factors for project selection and that their rank order is correct, without giving further study to prove this validity.

First proposed model: Take the Best

A useful Take the Best model has to evaluate projects individually and not through comparison with other projects. Selection models that compare project performance against others in the data set would choose the best of bad projects and not reject all of them, whereas the proposed F&F screening models will study and forecast each idea individually, and reject all projects with a high chance of failing.

The proposed "Take the Best" model for NPD screening is simple and follows the same concept Gigerenzer used [17, 33]. Starting by evaluating the most important criterion—in our case it will be the project *profitability*—if it has been evaluated as "Very Good" or "Good", then stop searching for more information, accept the project idea and move to the next stage of project screening. If the criterion has been evaluated as "Bad", then stop looking for more information, but in this case, reject the project idea. If the criterion has a "neutral" value since the expectation of profit is neither high nor low, or the project profitability is unknown because not enough market studies have been done, or because the product idea is a new innovative idea where results are hard to predict without further study, then the model will look at the next criterion – in our case it is *Risk* – and it will repeat the same scenario. After studying all criteria, if it is found that most of the criteria are neutral or unknown, then using Take the Best model will recommend giving further study to the project idea before making any decisions. Fig.2 shows the flow design of Take the Best model proposed for NPD screening. Table 4 shows an example of projects and their evaluation using Take the Best model.

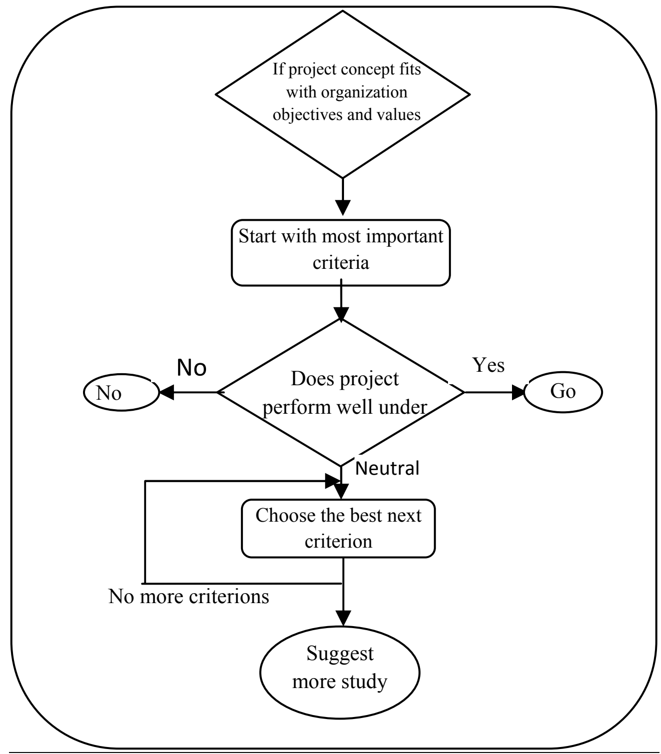

Fig. 2. Take the Best model for NPD screening

Second proposed model: Tallying model

A Tallying model does not test the criteria in any particular order, but makes a decision based on a minimum number of criteria *p* that indicate a positive project outcome or a maximum number of criteria *n* that predict a negative project outcome. Once the minimum or maximum is reached, it stops searching for more information.

To keep our proposed model simple, the model will cumulatively assess all seven criteria: $p=n=7$. Each "Very good" receives a score of (+2), "Good" a score of (+1), "Bad" a score of (-1) and "Neutral" a score of zero (0). If the total value is positive, then the Tallying model will recommend taking the idea to next stage. If the total value is zero or negative then idea will be rejected. Using the proposed Tallying method, the criteria will be randomly evaluated and a counter will be used to add one point for each "Good" criterion evaluated as "good" and subtract a point for each criterion evaluated as "Bad". The counter value will not change for any unknown value or any neutral evaluation. Fig 3 shows the process of this model, and Table 5 shows an example of projects with values of criteria.

TABLE 4. EXAMPLE OF PROJECTS EVALUATED USING TAKE THE BEST MODEL

	Profitability	Risk	Superiority	Technical Opportunity	Demand	Payback	Protection	Decision Using TTB
P7	Good	Bad	Good	Neutral		Neutral	Bad	Accept Idea
P8	Neutral	Neutral	Neutral	Good	Neutral	Good	Good	Accept Idea
P9			Neutral	Bad	Good	Neutral	Bad	Reject Idea

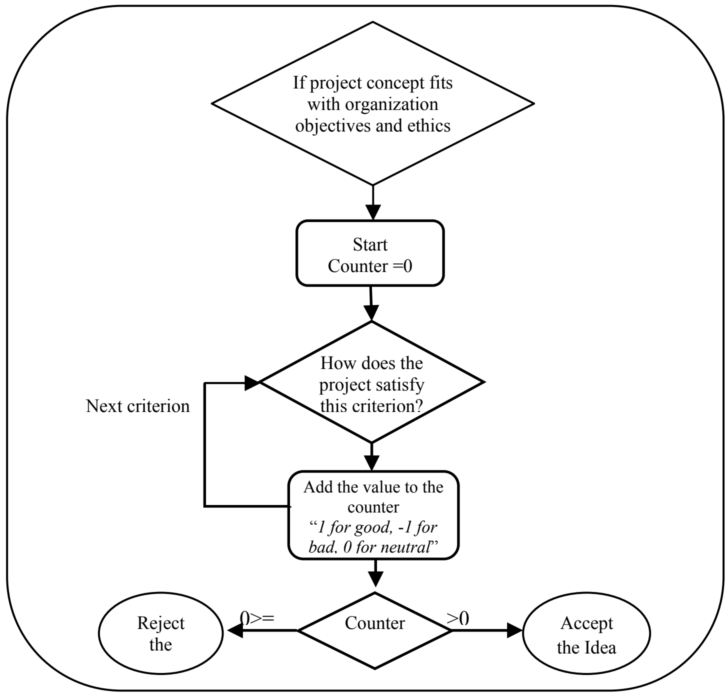

Fig. 3. Tallying decision model for early NPD Screening

TABLE**Error! No text of specified style in document.**5. EXAMPLE OF PROJECTS EVALUATED USING TALLYING MODEL

	Profitability	Risk	Superiority	Technical Opportunity	Demand	Payback	Protection	Counter for Tallying Model	Decision Using Tallying
P7	Good	Bad	Good	Neutral		Neutral	Bad	0	Reject
P8	Neutral	Neutral	Neutral	Good	Neutral	Good	Good	3	Accept
P9	Good		Neutral	Bad	Good	Neutral	Bad	0	Reject

VI. REGRESSION MODEL

Regression model is a statistical tool that is offered as evidence of reliability. It is widely used for investigating the relationships between variables in a data set and predicting future results [52]. Multiple logistic regressions is a technique that allows additional factors to enter the analysis separately so the effect of each factor can be estimated, when the outcome variable has a categorical (usually binary) value [41, 53].

In this study, since we have several explanatory (predictor) variables (the criteria), with a binary response (project success or failure), we will use the multiple logistic regression technique which is given as:

$$\pi(x_1, \ldots x_{p)} = P(Y = 1 \vdots \mathrm{X1} = \mathrm{x1}; \ldots.; \mathrm{Xp} = \mathrm{xp})$$

where, Y is Bernoulli with a probability that depends on covariates $f(X_1\ldots.;X_p)$ [53].

The logistic regression model uses the following equation:

$$\mathrm{P(y)} = \frac{1}{1 + \mathrm{e}^{-\mathrm{z}}}$$

In which:

P(y) is the probability of Y occurring

e is the base of natural logarithms

$z = b_0 + b_1x_1 + b_{2x2} + \ldots + b_px_p$

b_0 = a constant.

x_i = a criterion (predictor)

b_i = coefficient or weight attached to a predictor.

The result of the equation is a probability value represented by a number between 0 and 1. If the probability is closer to 0, it means Y (project success in our case) is very unlikely to occur, and if it is closer to 1, it means Y (project success in our case) is more likely to occur.

The object of multiple logistic regressions is to discover what combinations of explanatory variables provide the best fit for the observed proportions. Since some means for determining the significance of the estimates of the model parameters, and a means for assessing the fit, or lack of fit, of the logistic model are needed, correlations that may exist between explanatory variables will be studied [44]. The coefficients' values are estimated by fitting the model depending on the variable predictor to observed data [41]. "Inference for logistic regression is often based on the deviance (also known as the residual deviance). The deviance is twice the log-likelihood ratio statistic" [44]. The large value of the deviance (log-likelihood statistic) indicates a poor fit of the statistical model [41, 44].

This logistic regression model uses the seven most important criteria as the independent variables, and the response (predicting project success or failure) as the dependent variable. Criteria were entered simultaneously into the regression equation. The logistic regression analysis indicates the predicted probability of a project's success. Depending on the data, the logistic regression model equation for predicting project performance, using the same simulated data set, has the following values:

$$P(y) = \frac{1}{1 + e^{-z}} \qquad \text{where}$$

$$z = .14 + 2.5(\text{profit}) + .599(\text{sup}) + .616(\text{tech}) + .805(\text{mkt}) - .157(\text{pay}) - .663(\text{protect})$$

This model classified 45 failed projects correctly, and misclassified seven failed projects. In addition, it classified 37 successful projects correctly and misclassified 14 projects. It thus can predict project failure correctly 86.5 % of the time, project success correctly 72.5 % of the time, and overall, correctly classifies 79.6% of the projects, as summarized in TABLE6. Table 7 reports the chi-square statistics as 57.09, which is significant at p<.0001, followed by the model summary.

TABLE 6. CLASSIFICATION TABLE OF LOGISTIC REGRESSION MODEL USING 7 CRITERIA

			Predicted		
			Project performance		
	Observed		Failed	Succeed	Percentage Correct
Step 1	Project performance	Failed	45	7	86.5
		Succeed	14	37	72.5
	Overall Percentage				79.6
a. The cut value is .500					

TABLE 7. CHI-SQUARE AND MODEL SUMMARY FOR LOGISTIC REGRESSION MODEL USING ALL VARIABLES

Omnibus Tests of Model Coefficients

		Chi-square	Df	Sig.
Step 1	Step	57.094	7	.000
	Block	57.094	7	.000
	Model	57.094	7	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	85.685[a]	.426	.567

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001

VII. STATISTICAL ANALYSIS

A. Statistical analysis for TTB model

The TTB heuristic reaches a decision with little information: it searched through only 1 out of 7 criteria (K = 1) in 94% of the cases and through 2 criteria (k=2) in 5.7% of the cases in our data set. The maximum number of criteria that were considered was 3 (k=3). The heuristic predicted project performance correctly 57.69% of the time but was much more powerful at predicting project success than failure: while it correctly predicted failure at a rate of just 35.5%, it predicted project success correctly for 90.47% of all projects. A summary of the results is presented in Table 8.

TABLE 8. STATISTICAL ANALYSIS FOR TTB MODEL PERFORMANCE

		Predicted Project Performance		
		Wrong prediction	Right prediction	Percentage correct
Project Performance	Failed	20	11	35.5
	Succeed	3	19	90.47
Overall Percentage				57.69

Despite mostly using only one criterion, the model identifies successful projects with high accuracy. Its overall performance, however, is only slightly better than flipping a coin. It is therefore not suitable for making final project screening decisions - too many bad projects would receive funding. However, the projects that are selected by the heuristic have a much greater probability of success than the general pool of projects they come from. Using a simple heuristic can thus help decision makers to identify projects that should be studied further, when time to gather and evaluate information on all projects is in short supply.

B. Statistical analysis for Tallying model

The Tallying model goes through all the key criteria, adds the coded value of the project evaluation under each criterion to the counter, and then checks the final value of the counter. Despite giving all criteria the same weight, it predicts project performance correctly in about 77% of all cases. It is better at recognizing successful projects than unsuccessful ones and correctly predicted 81% of the successes and 74% of the failures. These results are summarized in Table 9.

TABLE 9. STATISTICAL ANALYSIS FOR TALLYING MODEL PERFORMANCE

Observed		Predicted Project performance: wrong prediction	right prediction	percentage correct
Project Performance	Failed	8	23	74.19
	Succeed	4	17	80.95
Overall Percentage				76.92

VIII. PERFORMANCE COMPARISON OF THE MODELS

The logistic regression and proposed tallying model weighted and integrated all available information on the seven project criteria in different ways to reach a decision, while TTB used a maximum (in our cases) of three criteria. A comparison of the performance of all three models, TTB, Tallying, and the logistic regression model is presented in Fig. 4. The results show that the logistic regression model outperforms the Fast and Frugal models in overall prediction quality and in the ability to predict project failure. However, with 77% correct predictions the Tallying model has an overall performance that is close to the logistic regression (79%). Furthermore, both F&F models are better at predicting success than the logistic regression model.

IX. EVALUATING PROJECTS USING LESS INFORMATION

A. Logistic regression model using a single variable

Researchers of F&F decision making argue that in some instances, "less is more" and decisions may improve when fewer criteria are considered [34]. Since TTB is using a single criterion most of the time, we tried to figure out how well the regression model would predict project performance, based on only a single criterion. Analyzing the project performance related to a single criterion, we got the following logistic regression equation:

$$\mathbf{P(y)} = \frac{\mathbf{1}}{\mathbf{1 + e^{-z}}}$$
$$\textbf{where } \mathbf{z} = -\mathbf{4.498} + \mathbf{1.825(prof)}$$

Using the logistic regression with a single variable, we can correctly predict a project's performance 77% of the time as shown in Table 10.

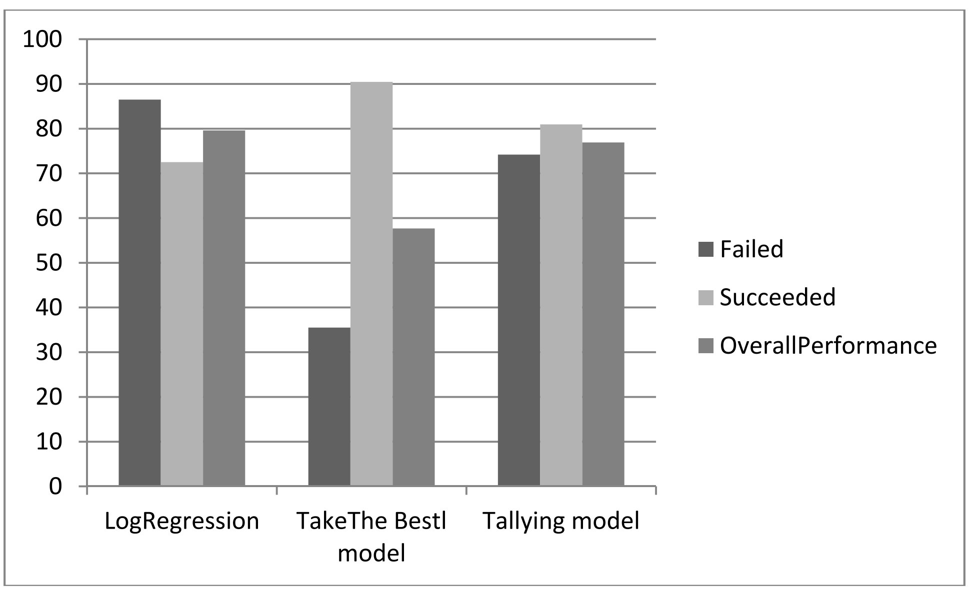

Fig.4. Percentage of Correct Project Performance Predictions, using Regression, TTB and Tallying Models

TABLE 10. PERFORMANCE ANALYSIS OF LOGISTIC REGRESSION MODEL USING SINGLE VARIABLE (PROFIT)

	Observed		Predicted: Project performance: Failed	Succeed	Percentage Correct
Step 1	Project performance	Failed	40	12	76.9
		Succeed	12	41	77.4
	Overall percentage				77.1
a. The cut value is .500					

TABLE 11. CHI-SQUARE AND MODEL SUMMARY FOR LOGISTIC REGRESSION MODEL USING ONE VARIABLE

Omnibus Tests of Model Coefficients				
		Chi-square	df	Sig.
Step 1	Step	34.634	1	.000
	Block	34.634	1	.000
	Model	34.634	1	.000

Model Summary			
Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	110.917[a]	.281	.375
a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.			

However, the log- likelihood statistic for this logistic regression with one variable is larger than it is for the same model with all 7 variables. When all 7 variables were included, -2LL= 85.68; when we have just one variable the -2LL= 110.2. The increase tells us that the model with one variable performs worse than the model with all 7 variables (Table11).

However, these results also show that the quality of decisions based on a single criterion is close to that of making the same decision using all criteria (77% compared to 79.6%). This yields the possibility to improve the TTB model to achieve good prediction results up to 77 %.

B. Logistic regression model using four criteria

This time we will run the same test using the logistic regression model on the same data set, but using just four criteria: profitability, risk, superiority, and technical opportunity of the project (variables coefficient values given in Table 12). With a correct prediction in 83.5% of the cases, the logistic regression model using four variables outperformed the regression models using one variable(76% correct predictions) and the model using all the seven variables (79.6% correct predictions), with -2LL= 89.28 and chi-square=53.49, as summarized in Table 14.

TABLE 12. VARIABLES COEFFICIENT IN THE LOGISTIC REGRESSION EQUATION WITH FOUR VARIABLES

		B	S.E.	Wald	Df	Sig.	Exp(B)
Step 1[a]	Profitability	2.191	.488	20.129	1	.000	8.945
	Risk	.671	.342	3.844	1	.050	1.956
	Superiority	.340	.244	1.945	1	.163	1.405
	Technical Opportunity	.733	.284	6.665	1	.010	2.081
	Constant	-9.140	1.778	26.433	1	.000	.000
a. Variable(s) entered on step 1: Profitability, Risk, Superiority, and Technical Opportunity.							

TABLE 13. PERFOMANCE ANALYSIS OF LOGISTIC REGRESSION MODEL USING 4 VARIABLES

			Predicted		
			Project performance		
	Observed		Failed	Succeed	Percentage Correct
Step 1	Project performance	Failed	46	6	88.5
		Succeed	11	40	78.4
	Overall percentage				83.5
a. The cut value is .500					

TABLE 14. CHI-SQUARE AND MODEL SUMMARY FOR LOGISTIC REGRESSION MODEL USING FOUR VARIABLES

Omnibus Tests of Model Coefficients				
		Chi-square	Df	Sig.
Step 1	Step	53.497	4	.000
	Block	53.497	4	.000
	Model	53.497	4	.000

Model Summary			
Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	89.282[a]	.405	.540
a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.			

X. SUMMARY

The performance of the two proposed F&F models, and the three logistic regression model with 7 variables, 4 variables, and 1 variable, are displayed in Fig.5. This figure shows that the logistic regression model using just four criteria has an overall prediction quality that outperforms the same model with more variables and outperforms the F&F models, although the Take the Best model outperforms all other models in predicting project success.

These results prove that evaluating projects using fewer criteria (less information) not only does not negatively affect the quality of the decision, but can actually give better results. The regression model has proven to be a very useful aid; however, decision makers might consider it to be an obscure mathematical model that can only be applied with the aid of a computer. Regression models are also difficult to apply to a new data set because they are based on variations in the criteria and judgments across the data set. Standardized weights are usually calculated by researchers, and application of these weights to a new case requires identification of where that case's criterion values fit in the range of criterion values that were used in the original data set on which the model was formed. In contrast, the two proposed fast and frugal models, Take the Best and Tallying, provide a transparent, non-mathematical description of judgment behavior. As a heuristic for decision making, they give adequate results, are simple to apply under time limitations, and do not require calculations and historical data.

XI. CLASSES OF PROBLEMS HEURISTICS MAY BE USED FOR

Attempts to make quick and accurate inferences in one domain may not work well in another. Different environments require different decision tools that exploit their particular information structure to make good decisions fitting with their situation. There are two fundamental goals for any problem-solving situation; finding solutions or algorithms that can solve the problem with 1) provable good run times and 2) with provable good or optimal solution quality. However, sometimes we trade between these two goals if it is impossible to get both, if we don't have enough time needed to sacrifice the quality of the results, and/or if we need highly accurate results we need to spend more time in solving the problem. F&F heuristics, with their simplicity, can be robust in the face of environmental change and can be generalized well to new situations by changing the criteria used or the rank of the criteria [54].

Heuristics are typically used when there is no known way to find an optimal solution in a short time either because of uncertainty, lack of information, or because the problem is not well structured and it is non-computational in nature. The other case where we may need to accept the good enough results by implementing the fast and frugal heuristics is when it is desirable to give up finding the optimal solution for an improvement in run time. For example, in the case of finding the best way to manage hotel reservations, which will increase revenue to its maximum potential and reduce the cost to its lowest level (what is called a yield management), this problem is well structured because even if the hotel managers are not sure if customers will show up, they still know the number of rooms they have, the revenue they gain from reserving a room, and they can calculate the costs from overbooking a room or leaving it empty [26]. This and similar problems do not need F&F heuristics; instead they need a mathematical algorithm that can give the best optimal solutions**.**

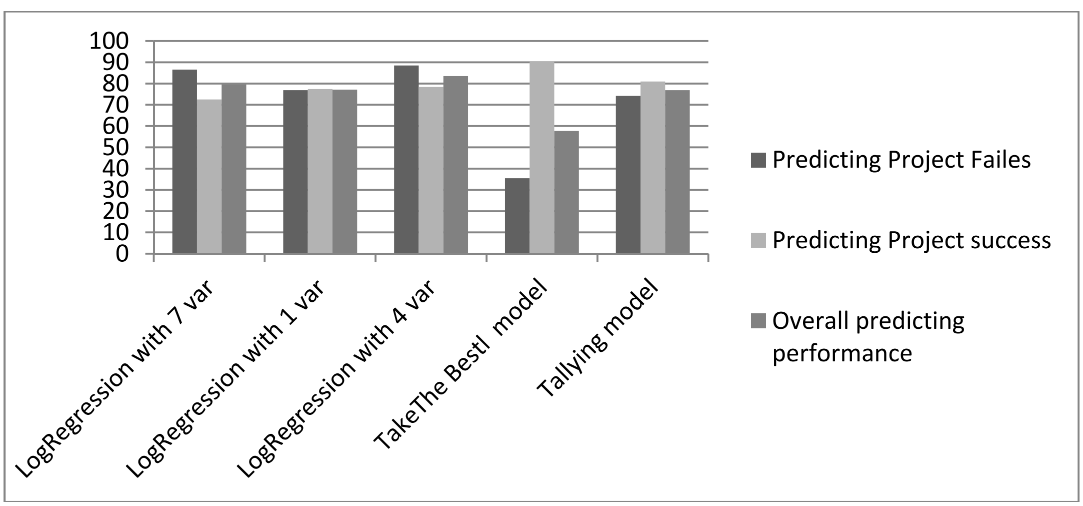

Fig.5. Performance of Five Models in Predicting Project Performance

XII. FUTURE STUDIES

It is clear that heuristic models have potential benefits. Decision models can be designed on different levels of a decision hierarchy by using simple or multiple heuristics. This would provide a different set of hypotheses; these hypotheses should be tested under different task conditions. In this review we have argued that F&F models are capable of screening projects at the early evaluation stages of new product development. Relying on previous studies in the last 10 years, we know that F&F strategies are useful tools. However, more studies are needed to find the fit of F&F models in a managerial business environment.

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