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Extending an EconoPhysics Value Model for a Pre-Contract Award DoD Acquisition Investment Decision

November 5, 2018

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Overview

Department of Defense (DoD) acquisition professionals have a fundamental problem: There is no quantitative, accepted, comparable measure of value. Without this critical element, acquisition professionals cannot assess acquisition investment portfolios on the basis of the value that investment options bring to the DoD enterprise. This limits program managers (PMs) to using historical cost estimates to predict the future performance of their programs. While historical measures can be useful, particularly on relatively mature programs, these methods are lacking with regard to the reliability and perhaps even the validity of trying to determine future program outcomes and subsequent program performance. PMs need a more reliable predictive method that provides real insight into program performance from a return on investment strategy, not simply a cost method based upon comparing actual to estimated cost relative to work performed. Using the nexus between financial investment theory and physics, we hope to show that future performance of an information technology (IT) can be predicted more accurately than using historical cost data alone.

When there is no unique quantitative value metric with which to take advantage of commonly used financial performance ratios, the acquisitions PM is forced to use metrics that do not have the predictive power resident in metrics that incorporate quantitative value estimates. Examples of rigorous financial metrics that can be used when there is a quantitative (i.e., common units) estimate of value include productivity-based performance ratios, such as return on investment (ROI)[1] and benefits/cost ratios.

[1] The return on investment (ROI) is the ratio between the net profit and cost of investment resulting from an investment in some resource. A high ROI means the investment's gains compare favorably to its cost. As a performance measure, ROI is used to evaluate the efficiency of an investment or to compare the efficiencies of several different investments ("Return on Investment—ROI," 2013). In purely economic terms, it is one way of relating profits to capital invested.

The current research study focused on developing an extension of our basic econophysics model (Baer, Bounfour, & Housel, 2018; Baer & Housel, 2017; Housel, Baer, & Mun, 2015) to generate a quantitative value metric (i.e., protovalue) that can be used to optimize acquisition portfolios on the basis of the relative returns on, and potential adoption rate[2] of, DoD technology acquisitions. This extension includes parameters for cognitive biases that influence acquisition professionals and vendors' expectations about the risk to successful performance of IT acquisitions. Further, this study provides a potential extension of Earned Value Management (EVM) using the physics of the thermodynamics of a turbulent flow model.

Armed with a better understanding of the risks inherent in cognitive biases, a defensible econophysics-based quantitative value metric (i.e., protovalue) and the application of a turbulent flow model to the current EVM framework, the acquisition professional will be better prepared to develop more precise approaches to predicting the performance of IT acquisitions. In what follows, we review the basic econophysics model in a simplified form and in a more detailed form. Acquisitions decision-makers can use the simplified form to make rapid, rough-cut estimates of the future value of an IT application acquisition. A review of the more detailed basic econophysics model, in the context of an IT acquisition, provides the scaffolding for inclusion of the cognitive bias risk parameters in the proposed extended model. The report includes a review of prospect theory, which was used to develop the new cognitive bias parameters in the extended econophysics model.

The proposed extended econophysics model should lead to better prediction of the value and potential adoption rate of future IT applications. Understanding and developing uses for the econophysics model will require a major learning curve that may cause acquisitions professionals to eventually

[2] It can be argued that predicting adoption rate in the DoD context is not relevant because users are forced to use any new IT technology they are given. However, there is ample evidence that users are very good at finding ways to avoid or go around any new IT that they do not perceive as valuable in doing their jobs.

abandon the current EVM approach. However, the proposed extensions of the current EVM approach, including the phenomena of turbulent flow, will help acquisition professionals re-conceptualize EVM with the purpose of detecting cost, schedule, and value problems earlier than the current model permits. This extension of the current EVM approach may not require a major learning curve.

Study Context

The context of this research was early stage IT acquisitions decision-making before formal developmental contracts would be awarded. Focusing on the pre-developmental phases of a program will allow decision-makers to make more informed decisions on the overall acquisition strategy before making major investments in an IT project. With a more accurate predictive model for program performance, decision-makers can conduct more robust and informative trade-off decisions between user requirements, projected budget, value, and schedule, as well as the overall strategy for program execution. Without a value metric and a better understanding of decision-maker cognitive biases, however, forecasts of the potential performance and adoption of IT acquisitions will be problematic in a pre-contract award review context.[3]

The proof-of-concept case studies reviewed in this research will demonstrate how the extended econophysics value theory may be applied to support forecasts of the future value and adoption rate of DoD IT acquisitions. Predicting the value performance of future DoD IT acquisitions is necessary in optimizing acquisition investment portfolios before further investments in the more codified, restrictive acquisition stages. The results of this study provide a methodology for estimating the potential future value of any IT project at the pre-contract review stage of acquisition.

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[3] These challenges also apply to the private sector because early stage start-ups most often do not generate revenue, making estimates of the future value of such companies problematic. It follows that even though the focus of this research is the general acquisition context in the DoD, the results can also be applied to early stage start-up IT companies.

The behavioral finance and economics investment theories predominantly use prospect theory to explain and predict the effect of cognitive biases on investment decisions. For this reason, a section of this report includes a detailed review of prospect theory in terms of its relative effectiveness for use in the extension of the basic econophysics value theory.

This report proceeds with a description of the simplified and more detailed version of the original econophysics value theory. This is followed by a discussion of prospect theory research and how this theory can help shape our understanding of program decisions and outcomes. We then proceed to the extension of the basic econophysics value theory that includes cognitive bias parameters. Finally, a proof of concept example of how the econophysics theory can be used to improve on the current EVM approach.

The final section of the report includes recommendations for use of the proposed models in early stage acquisition decision-making, as well as limitations of the research. The limitations of these models include a call for future research.

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Introduction

This section of the report reviews the assumptions and tenets of the econophysics protovalue theory, including behavioral decision biases. The fundamental framework demonstrates how the physics concepts are used analogously to map to basic economic concepts. The conceptualization of the extended model, which follows a description of the simple and more detailed original basic econophysics model, will incorporate the cognitive bias parameters that populate the proposed extended econophysics value theory model. To develop the econophysics value theory, it was necessary to begin with a table that matched fundamental physics energy concepts and the economic value concepts. With this analogy table, it was possible to use energy theory from physics to map to the value concept in economics. Mirowski (1989) documented the use of the energy concept from physics to develop the value concept in economics over four centuries: “There is no way of understanding economics and social [i.e., value] theory in the twentieth century without first understanding ‘energy’ in some detail” (p. 11). The analogy between economics and physics is a fundamental relationship in that economics focuses on the phenomenon of behavior in the use of limited resources, while physics focuses on the physical interaction in the material due to changes in the value or form of energy. The use of resources in the economy is analogous to the change in value or form of energy. This analogy will be further extended with the introduction of fluid dynamics and complexity theory as we begin to show the relationship between econophysics theory and the performance of IT projects within a program life-cycle.

Using the analogy table, we created an econophysics value vector model that utilizes these concepts for the proof-of-concept application case examples. A vector space model is an algebraic model that allows us to represent text documents and variables as vector identifiers. The purpose of the analogy table, Table 1: Definition of Terms: Analogy Between Physics and Psycho-Economics, is to demonstrate how the physics concepts map to the economic concepts.

Table 1 also includes the mapping of physics concepts to psychological concepts that can be used to model behavioral investment decision biases.

Table 1. Definition of Terms: Analogy between Physics and Economics

Physics Concept	**Abbreviation**	**Economics Concept**
Kinetic Energy	KE	Actual rate of satisfaction
Work Energy	WE	Useful actual rate of satisfaction that fits a need
Potential Energy	PE	Potential rate of satisfaction, expected or hoped for satisfaction rate
Lagrangian Energy	(KE- PE)	Happiness, Difference between actual and hoped for rate of satisfaction. Positive values are pleasure. Negative values are pain
Hamiltonian Energy	H = KE+PE	Heftiness, Total capacity of an economic entity (consumer or business)
Einstein Mass	$m=H/c^2$	Another term for identifying the concept of heftiness
Speed of light in vacuum	c	Speed of Now in equilibrium economy
A bit of Kinetic Action	$KE \cdot dt$	a bit of Actual Satisfaction
A bit of Potential Action	$PE \cdot dt$	a bit Potential Satisfaction, a Need bit
Macroscopic Action	$S = \int (KE - PE) \cdot dt$	Satisfaction for a tangibly large size activity
Minimum Action Principle	$\delta S=0$	Minimum Pain or maximum pleasure Principle
Position vector of attributes in a physical quantity	q	Position of ownership in an economic quantity
Momentum vector	$p_q = dS/dq$	The rate of change of satisfaction when changing one's ownership of a quantity
Force in a quantity direction	$F_q = dp_q/dt$	The force felt by an economic entity when it feels the opportunity for changing ownership of a quantity
Equilibrium condition	$0 = \sum_i F_{qi}$	Vector sum of all forces of all quantities (qi) are zero
Unit vectors of quantities	u_q , u	Units of ownership (apples, dollars, etc.)
Measurement of a physical quantity	$q = \#_q \cdot u_q$	Measurement of an economic quantity
Generalized Physical space	x,y,z i,j,k	Quantity type dimensions define
Dimensions of measurement Vectors in physical space	q_x, q_y, q_z ...q_f q_i,q_j,q_k	Vectors in economic space
Maximum Quantity	$q_{f,max} = max\#_q \cdot u_q$	
Volume of physical space	$q_{x,max} \cdot q_{x,max} \cdot q_{x,max}$ $q_{f,max}$ $q_{i,max} \cdot q_{j,max} \cdot q_{k,max} \cdots q_{f,max}$	Volume of Economy
Behavioral-cognitive risk bias	bcR_i	Decision risk biases

The major challenge with such analogies is that concepts from different fields never match perfectly. Despite this limitation, the use of these concepts from physics to develop an extended theory of value model provided a comprehensive integrated approach. This avoids the mistake-laden borrowing of a few concepts that are most often out of context with a basic physics theory. Applying physics analogies to economics and ultimately to IT project development prediction methods is consistent with the use of physics as a basis for bridging between physical and social models. Physics models have been extensively applied in economics to include the kinetic theory of gas (called the Kinetic exchange models of markets), percolation models, chaotic models developed to study cardiac arrest, and models with self-organizing criticality such as scale-free networks (Chakrabarti, Chakraborti, Chakravarty, & Chatterjee, 2012).

This proposed use of the extended econophysics value model will be refined over time as more proof-of-concept case studies reveal its limitations and suggest improvements. This refining process will extend the current model to other contexts involving the investment in IT. The proposed model will also inform the fluid dynamics modeling of risk and value in an extension of the EVM approach.

The acquisitions management EVM approach, as well as the standard financial investment approaches, assume that decision-makers are motivated by rational inclinations. Rational economic person assumptions have not worked well in predicting investment decision-making behavior (for a general review of this literature, see Yazdipour & Neace, 2013). For example, the economic pundits predicted that the British voters would follow rational decision heuristics and reject the seemingly economically irrational option of leaving the European Union (EU) in favor of the rational option of remaining in the EU. The cognitive bias decision research of Kahneman and Tversky (1979) in the context of prospect theory is often cited as the basis for the biasing agent that leads decision-makers to irrational investment choices. These biases have been cited as the primary source of behavioral finance investment risk-taking.

Our report reviews the potential of the prospect theory risk bias framing assumptions for inclusion in the extended econophysics value theory. The goal for including the cognitive risk parameter(s) was to predict how the biases would impact the match of a set of user or decision-maker needs to a set of general vendor-provided needs solutions such as the needs for security, happiness, satisfaction, or a high ROI.

The current study focused on developing practical applications of the econophysics model that includes biases in order to predict the comparative value for non-monetized IT acquisition options while accounting for cognitive bias risks. The goals were to provide a methodology for predicting the adoption rate of new DoD IT applications by taking into account the features that provide the best fit for user needs relative to their cost and perceived riskiness.

The Basic Econophysics Model

The context for the basic model is provided in Figure 1. The protovalue framework in Figure 1 is meant to show how protovalue is required to estimate the other measures of interest. It is a critical parameter for estimating an IT application's potential adoption rate. As actual adoption rate becomes known over time, the result provides a feedback loop that can be used to adjust the estimates of value performance for the model attributes, and adoption rate predictions can be adjusted as a result. This is akin to the same phenomena in modern weather forecasting models that feed basics model parameters with new values for these parameters as they become known over time.

The raw data inputs for the protovalue estimate are based on a set of users' attributes, including their biases. These are attributes that suggest the value a user expects to receive based on an IT application's attributes. There are also a set of acquisition life-cycle attributes that affect the application adoption rate, which need to be considered in estimating the protovalue of a given application.

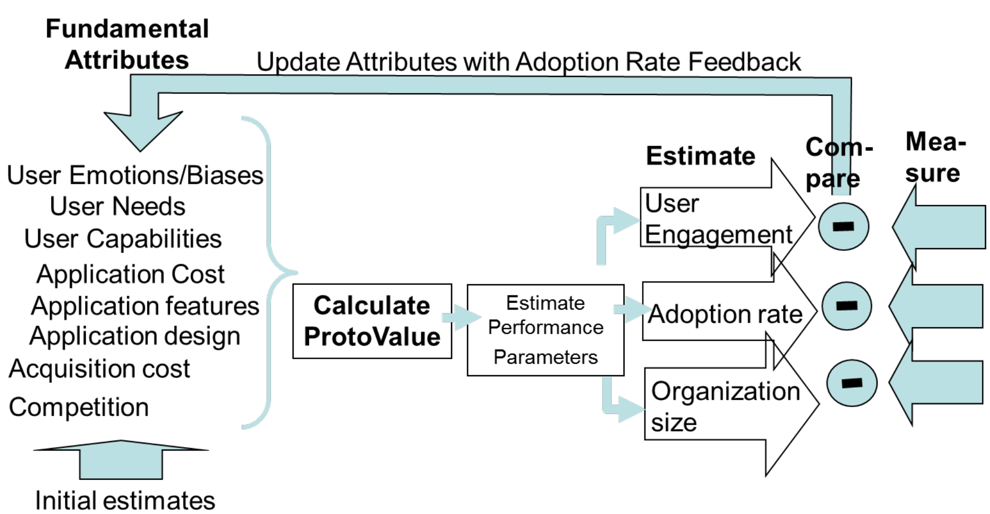

Figure 1. Econophysics Model: How to Calculate Protovalue Performance from Fundamental Parameters

One major difference of this econophysics approach for predicting the potential protovalue of an IT application is that it is not dependent on historical adoption rate behavior. Most future value investment estimating techniques require historical volatility rates to estimate risk when making capital asset price or portfolio forecasts. This concept is also important in the application to program performance prediction. The fundamental concepts of adoption rate are similar to the variables that effect program decision-making and performance. Using the attributes of the adoption rate model and applying these to more analytical variables that represent programmatic behavior will allow us to generate more precise forward-looking prediction models that do not rely on typical historical cost trends. This protovalue model adjusts parameter values as adoption rate information becomes available, in the same way a cannon's aim is adjusted based on where a projectile lands.

Using physics concepts from the analogy Table 1, the protovalue model attributes are derived from a number of different sources that document user behavior, application acquisition costs, design features, and competition. For example, Maslow's Hierarchy of Needs (Maslow, 1970) is a standard reference for the fundamental categories of user needs that could be included in a general protovalue model. These basic parameter values can be used to estimate the protovalue of an IT application for a given category of users.

Just as the physics model for potential energy specifies the strength of attraction between entities in a system, protovalue calculates the potential value (i.e., potential energy) for a given IT application to meet a set of user needs. In the non-profit context, if the protovalue of the application is higher than the comparative value of a user's time, then the adoption rate of the application will be positively affected. The application value to user need value difference among alternative options also will determine the potential adoption rate speed of an IT application.

In what follows, we provide a very simple protovalue model that aggregates many of the parameters listed in the analogy Table 1. The simplified model can be used to make very quick, rough-cut estimates of the potential value of a new IT application. A notional example is provided to demonstrate how the simplified model works. This section of the report is followed by a more detailed protovalue model that might be applied when an acquisition decision is made to proceed with a review of the potential of the IT application to produce future protovalue. The extended econophysics theory notional case example will demonstrate how the theory can be used to predict the adoption rate of a potential acquisition of a truly new IT application. The EVM case example will use historical EVM parameters, with the addition of several econophysics theory–derived value parameters, to demonstrate how EVM might be improved in forecasting variance with cost, schedule, or value risk.

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A Simplified Econophysics Value Theory Model

We begin with a simplified model that aggregates a number of physics concepts (including risk and distance) to derive the basic value model parameters. This model is useful in identifying problematic areas for further investigation using the more detailed econophysics model before acquiring an IT application. The description of the simplified model is followed by a more detailed and comprehensive basic model that includes distance and disaggregates model parameters with reference to the Table 1 physics to economic analogies.

The simplified model used economic analogies for the physics concepts of mass, potential field, force, momentum, velocity, total energy, and work extracted from total energy. These parameters were used to produce protovalue estimates. Table 2 provides the basis for populating the simplified model parameters. The more detailed model uses all of these concepts, as well as the concepts reviewed in Table 3, including the behavioral risk bias parameter(s) that will be offered in the extended model.

Table 2. Simplified Econophysics Theory Basic Concept Definitions

mass {**m**} = relative richness of services, measured in common units of complexity
Position of m = name of node in a network of the entity that is offering the service established by the force of the pull of the business and the pull of the customer for the service
Force = the pull of the mass of the company {**Mb**} – the pull of the customer {**Mc**} (**Force = m*Mc/r^{2} $^{\text{[distance squared]}}$ * K (constant) or customer desire/r^{2})**
Business Mass {**Mb**} has a given strength of pull on the service {m},
Customer Mass {**Mc**} pull on the service offered by the business
Number of services {**N**} = total number of services {**m**} at a given point in time (e.g., Net Mapping, Blogging, Video Sharing)
Total Potential Field (TPF) ≈ (**m*Mc*N/distance between the Mc and Mb**) the number of services of a given complexity (m) offered by an organization to a field of customers (TPF = total protovalue field)
Velocity (V) = Change in rate of position of **m**
Momentum {Mo}= rate at which service {m} moves from Mb to Mc
TPF*Mo = total Energy (E) ≈ protovalue
Work = total monetized value extracted from protovalue

The primary challenge in generating the simplified basic model was to maintain conceptual integrity with the more detailed model while providing an approach that would be appealing and simple to use by acquisition professionals. This necessitated compromises while maintaining the potential efficacy of the results of applications of the model. The simplified model is sufficiently flexible for acquisition professionals to modify operational definitions based on the specific context of the IT application, acquisition constraints, vendor markets, civilian company competitors, regulatory restrictions, and other relevant conditions.

In these models, protovalue is analogous to potential energy in the context of matching the IT application capabilities to a user's need for the application. Kinetic energy corresponds to the actual value delivered when the user produces work with the application. When the user need for the application becomes satisfied, protovalue is converted to actual value. Potential energy often is only partially converted into kinetic energy. It follows that potential protovalue is not always equal to the actual protovalue realized at the point in time when some level of satisfaction is achieved by using the application.

Simplified Example: Intelligence Using Social Media Application

Many terrorist groups and military groups use social media to influence targeted groups of terrorists, voters, and adversaries, as well as allies. By applying the econophysics concepts, it is possible to derive a rough-cut quantitative estimate of the potential protovalue of a series of three potential social media applications.

In this notional example, the military leadership was concerned about the innovativeness of their organization's talent pool and how quickly they could acquire new social media applications for niche uses to meet mission goals. This example requires populating surrogates for the following physics concepts in Table 3.

Table 3. Econophysics Framework for Estimating Organizational Innovativeness

mass[4] {**m**} = relative complexity of new services provided by IT applications
Number of services (**N**) = total number of IT applications at a given point in time (i.e., Net Mapping, Blogging, Video Sharing)
Potential **F**ield (**PF**) = (**m*N**) the number of IT applications of a given complexity (m) offered by the organization to a field of users
Velocity = Change in rate of **PF** over time period of three years

A great concern for military leaders is how quickly new IT innovations can be put into operational use. Non-profit organizations, such as those involved in homeland security, are equally motivated to stimulate innovation within their organizations in an effort to outsmart potential foes or competitors. This makes tracking the innovation cycle a high priority. The simplified econophysics framework can be used to structure this problem.

In the following example of social media applications, the military leadership is interested in how the new applications can become operational. The velocity (i.e., change in rate of introduction of new or modified applications) of the operational use of the new applications by users is of utmost importance to the leadership. Table 4 provides an example of the kind of raw data the simple econophysics value model would generate. This new form of quantitative raw data can be used for a variety of analyses, including potential velocity of the introduction of new applications (i.e., innovativeness).

By increasing the velocity of introduction of new, or modified, applications the potential field for users (i.e., protovalue) is increasing. A decreasing velocity would alert acquisition professionals that users are moving away from the potential offerings of the new applications. Figure 2 is an example of how this new form of raw value data can be used to measure the change in the rate of the potential value created by the introduction of new services. The velocity analysis indicates that the introduction of new applications is rising from Year 1 to Year 2

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[4] Mass is estimated on a 1–10 interval scale for purposes of this example. A more detailed approach could be used to estimate mass using a ratio scale, such as in terms of complexity bits or lines of code converted to bits.

and dropping sharply from Year 2 to Year 3. This new information may be troublesome to the military leadership because it indicates that relative innovativeness of the acquisition of new applications is apparently slowing and that acquisitions of the same may not have been a good investment.

Table 4. Social Media IT Applications Example

Year	Net Mapping (NM) **8*N**	Blogging (B) **6*N**	Video Sharing (VS) **4* N**	Potential Field (PF) **NM+B+VS**	V	Potential Users/ Uses (PU)	Total E, Protovalue **PF*PU**
1	56	12	100	168	90	100	16800
2	80	24	180	284	116	120	34080
3	80	18	150	248	-36	125	31000
Totals	216	54	430	700		345	81880

Mass per service weightings
NM=8 B = 6 VS = 4

Such a downward trend in the introduction of new applications would prompt leadership to make inquiries focused on determining the root causes for this negative change in the velocity of innovation.

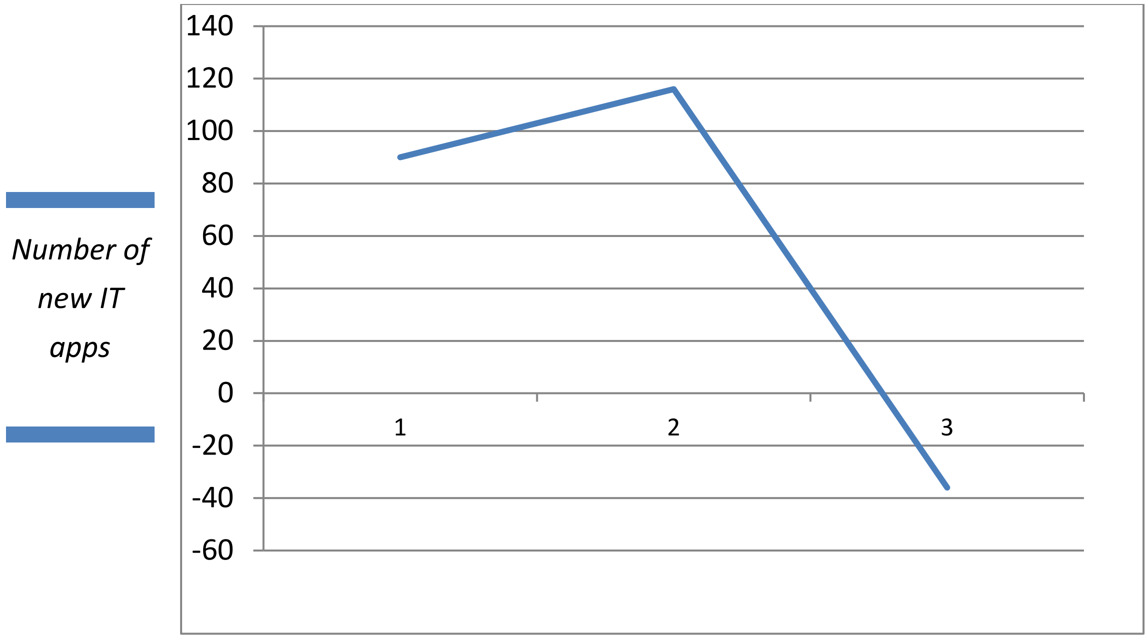

Figure 2. Velocity of Introduction of New IT Applications

Table 5 provides the parameters to calculate the yield from potential usage value to actual usage value. The **AU** parameter is representative of actual use of the IT applications that have a given **mass.** When actual usage (AU) is multiplied by potential field (PF), **AU * PF = W**, the result is the amount of work value extracted from the IT applications.

Table 5. Customer Usage of IT Application Offerings

number of potential uses of services (PU) (e.g., number of potential uses of service products within the time frame of the service offerings)
number of actual uses of the services (AU) (e.g., number of actual downloads, clicks, page views within the time frame of the availability of the services)
PU * PF = total potential energy = potential protovalue
AU * PF = Work = actual protovalue

The potential usage value and the actual usage value parameters provide management with a way to determine how much value is foregone because it is highly unlikely that the applications will be used to the fullest value possible. This is normally the case with IT applications that have more features than most users actually use.

Using the example of the social media company, we can generate a hypothetical table of values based on results from Table 6 and the results of the equations.

Table 6. Social Media IT Applications Example

Year	PU	AU	PF (from Table 2)	Total E. Protovalue	Total W, Kinetic E
1	100	40	168	16800	6720
2	120	60	284	34080	17040
3	125	90	248	31000	22320
Totals	**345**	**190**	**700**	**81880**	**46080**

Velocity of Usage

2010	40
2011	20
2012	30

Comparing total protovalue (i.e., potential energy) with total work (i.e., total kinetic energy) provides a ratio of 46080/81880 or 56% yield over the three-year period. The acquisition professional could compare this result with the same ratio value for other IT applications or an average benchmark yield to get some sense of the value added of these IT applications. In addition, the comparisons and ongoing value-added performance of these IT applications would be useful in monitoring the conversion of their protovalue to work value performance over time.

In Figure 3, the velocity of AU changed in a negative direction from Year 1 to Year 2. The increases in PU from the IT applications from Year 1 to Year 2 can be compared to the decreased AU yield during the same three-year period via Figure 4. There may have been a lag effect (i.e., actual value [work] lags production of potential value). Given these trends, management should consider trying to increase protovalue from Year 3 to Year 4 with the potential of monetized value increasing afterwards.

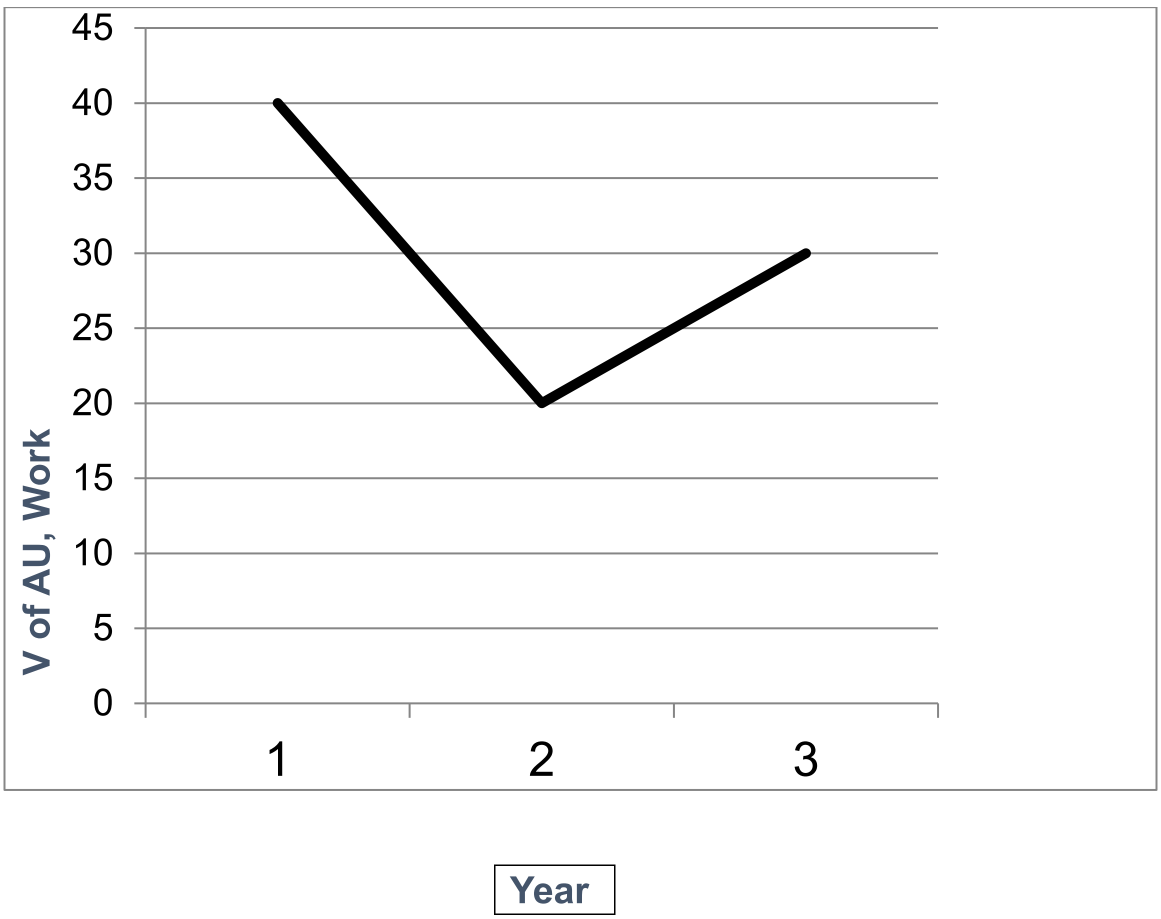

Figure 3. Value of Actual Usage (V of AU) or Work

This ongoing monitoring of the velocity of actual usage would be useful in computing the volatility of the potential to actual value conversion process. Many of the more sophisticated investment valuation techniques require a volatility metric and a value metric to measure the risk to reward ratio (i.e., Sharpe ratio) and to optimize a portfolio of investment options.

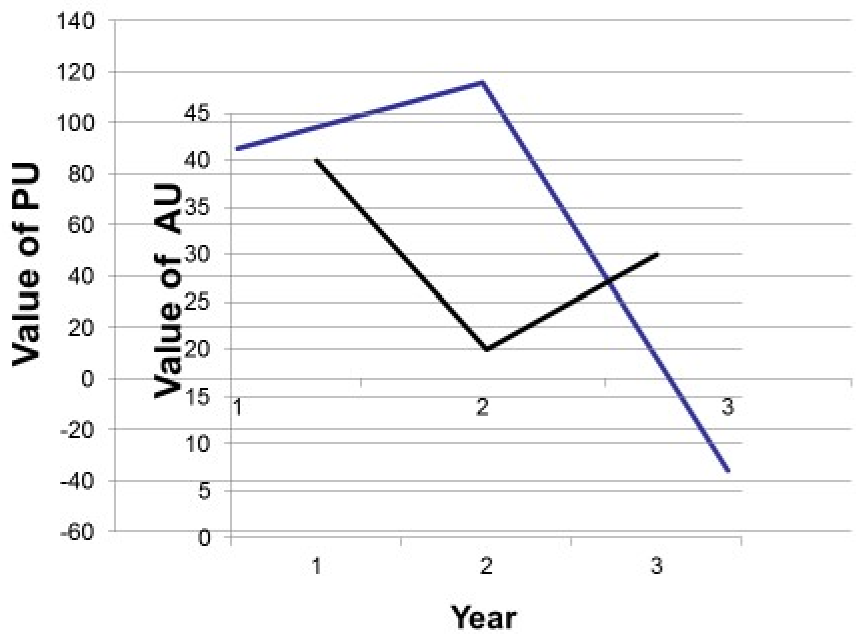

Figure 4. Velocities of Potential Usage (PU) and Actual Usage (AU) Compared

By superimposing the two graphs, AU and PU can be compared even though the scales are different. The two curves show that users were not able to absorb the application's new functions, or simply chose to ignore them. The resultant comparison might also lead the acquisition professionals to seriously consider the users' absorption capacity before rushing to support acquisition of new capabilities before checking with users. Even in an environment such as the DoD, users may resist using new IT acquisition capabilities if they feel overwhelmed by them.

Detailed Econophysics Value Theory Example

The example for the detailed econophysics value theory is based on the potential application of a new IT social media platform that would allow users to send text messages, images, video, audio, and their location information to other smartphone users.

The following is the fundamental value equation for the detailed approach:

Equation 1: Fundamental Value Equation $E[B,x] = Q_{f'}[B] \bullet K_{f',f'} \bullet q_f[x] / r[B,x]$

Where:

$Q_{f'}[B]$ = the quantity of potential value (i.e., f') provided by the IT application suite (i.e., B)

$q_{f'}[x]$ = the amount of user (i.e., x, need for f')

$K_{f',f}$ = the fit matrix that matches need, f', to potential value, f

r [B,x] = the distance between x and application suite B

E[B,x] = the potential energy (i.e., protovalue), between x and B

f = an index for the type of IT application.

The application suite includes text, image, video, audio, or location messaging services for this complex example. In this example, $K_{f',f'}$ is a matrix, and the potential value and need values can be represented as vector arrays. For this example, all the applications represent a single message (m) service and it follows that f =f'=m.

The distance between the IT application suite B and an average potential user, x, includes an initial installation of B coding on each user's device and the time required to learn how to use the suite B applications. Distance can be modeled by an exponentially decreasing function, Equation 2.

Equation 2: $r(n) = t_{exp} + t_{init} \bullet 2^{-n/lh}$

Where:

r(n) = a user's time using application suite B calculated by the number of service transactions

n = number of service transactions

lh= the number of service transactions resulting in a halving of the learning time for a potential user to learn how to use suite B

t_{exp} = time required to operationally use suite B for an expert user

t_{init} = initial first use time

The user has to take the time required to install and learn the new IT applications (t_{init}). This time represents a distance between the user and the applications. The time required to operationally use the applications is akin to a measure of cost (t_{exp}) and is dependent on, to a large extent, the ease of use of the application's interface.

In this example, we assume that an expert user will spend an average of 10 seconds per application transaction. It follows then that "$n = \infty$", $t_{exp} = 10$ seconds and $r(n) \Rightarrow r(\infty) = 10$ seconds.

The strength of the need of the user for the applications is represented by the parameter $q_m[x]$. In examining the need of users for the given applications under review, market-comparable applications from incumbent service providers gives a base point for comparison to the new IT applications. The time or cost a user is willing to pay for use of a given application provides a market-comparable empirically-based constant.

This market comparable cost can be represented by a demand curve. It follows that, if a typical price for the applications under review is available and the need strength varies only slightly from an equilibrium value, then the demand curve can be considered a reliable representation of a typical user's need for the applications.

The need users have for new services is complex because behavioral needs, such as need for novelty, cultural biases, peer group pressure, and risk aversion, may actually create the perceived need for a new application. This is especially true for new "free" applications where the demand curve would reach a use limit that would be determined by behavioral biases and not the forces that led to the market-comparable application need equilibrium point. The "free" application use limit is represented as the dashed vertical line in Figure 5.

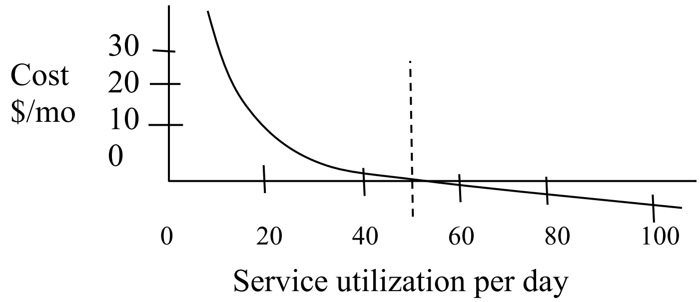

Figure 5. Typical Need-Based Demand Curve for Commercial Applications

The area to the left of the dashed line represents the applications usage the user is willing to pay for. As the application cost decreases, the use of the application increases until the equilibrium “free” use limit is reached. Beyond that equilibrium limit, the user needs to receive significant incentives to continue to use the applications that is limited because there are only a given number of hours in a day that the user can devote to utilizing the applications.

The values for the parameters of this example econophysics model were derived from a popular communications platform provider. The user need for messaging services from this provider was a single data point at the “free” use limit of the demand curve. Assuming that an average user devotes eight hours a day for their job, eight hours for sleep, several hours for eating, traveling, shopping and housekeeping, the remainder of the user’s day could be used for utilizing the applications on the provider’s platform. The actual time a user applies to use of the provider applications can be established based on behavioral studies. In this case example, we assume the user need estimate for the use of the “free” applications is a constant of ½ hour per Equation 3

Equation 3: User Applications Usage per Day = $q_m[x]$ = .5 hr/user-day.

User Applications Usage per Day is assumed to define the average amount of time the average customer is willing to pay in order for the satisfaction of the needs that the applications offer to fulfill. Additional cost for use of the applications is represented by the vertical axis in the demand curve and is included in the estimate of distance defined in the foregoing discussion. The $q_m[x]$ parameter is an estimate of the need the user has to expend on these applications.

The "B" parameter represents the amount of potential need satisfaction of type "f"=by the application, quality of service provided by the application "m." This parameter defines the amount of satisfaction that B is able to supply by m. This parameter was identified as the reciprocal of the amount of time required from the user to fulfill the quality of service need: m.

The effect of this parameter was negligible since the quality of the service was quite high. Measured by the reciprocal of the number of times the user used the platform to successfully access the application suite, there were very few usage failures due to high quality of service by the platform. The resulting ratio is the quality of service to the use of an application via the platform is represented by Equation 6: Quality of Service per Application Usage.

Equation 4: Quality of Service per Application Usage

$Q_f[B]$ = (Network delay)/((#of tries)*(delivery time per try)

If the platform service was slow and/or it lost application transactions, the user would be forced to spend more time to fulfill his/her needs via the applications on the platform, resulting in a lower value score. For example, if one out of 10 application transactions failed and the typical delivery time were two seconds with a network delay of one second, then the $Q_f[B]$ parameter is 1/2.2 seconds.

The fitness matrix $K_{f',f'}$ parameter represents the need for an application by a user and the ability of the business to provide an application that will satisfy that need. In general, this matrix represents how well B's application offering meets a user need that might be fulfilled by that application.

In the example, the assumption is that the user has a need to communicate with 10 colleagues during the half-hour per day he/she devotes to this application. If only three of his/her colleagues are using the application, then $K_{f',f'}$ = 0.3. If all 10 are using it, $K_{f',f'}$ = 1. If the application attracts more colleague, then the fitness matrix $K_{f',f'}$ could become greater than one. This possibility also could be addressed by an increase in the need parameter value because it could be considered an expansion of the original communication need.

Using the values suggested in the paragraphs above for Equation 1 (for an experienced user) yields the following protovalue score.

Equation 5: Fundamental Value Equation (applied)[5]

$E[B,x] = .3 \cdot .5 \cdot 360/2.2 = Q_{f'}[B] \cdot K_{f',f'} \cdot q_f[x] / r[B,x]$

Where:

$Q_f[B]$ = 1/2.2 the quantity of satisfaction delivered by the application

$q_{f'}[x]$ = 0.5 hours/day the quantity of need for the application

$K_{f',f}$ = 0.3 ratio of need to satisfaction by application fitness matrix

$r[B,x]$ = 10 seconds = 1/360 hours

$E[B,x]$ = 24.54 protovalue (potential energy) units

[5] Typically, a constant is required to convert these value units defined in terms of user time into units of monetary equivalents. As shown in the next subsection, however, the value is usually used in a comparison with values calculated for different situations, and it is the relative unit independent ratios that are of interest.

Units in the Energy-Value Analogy

Physics uses quantitative units of energy (ergs, Joules, KiloWatt-hours) that must be converted to common units of value for purposes of the econophysics theory approach. Thus, energy units must be converted to user value units in order to quantify E[B,x]. Traditional economics monetizes value measured in currency units (e.g., $, €). It is not necessary to measure value in terms of currency units. Common units of value can be derived from our measure of potential energy. This is important for non-profit, governmental, military organizations, such as the DoD. The following are quantitative units for estimating the parameters for Equation 1: Fundamental Value Equation.

$Q_f[B]$ = is a ratio of actual to ideal per satisfaction type-“f’ ” completion time (and the units of time in such a ratio cancel thus) units are(1/f’)

$q_{f'}[x]$ = is measured in hours per application need type “f” per day (hours/day-f)

r [B,x] = distance was also measured in hours

$K_{f',f}$ = .3 the fit matrix measured in satisfaction per need, f, per Satisfaction, f’. (Represented as units of Action/ f*f’)

E[B,x] = 24.54 protovalue (potential energy) units

Using these common units in Equation 1, the units of energy = action/day in physics terminology and value = satisfaction/day in psychoeconomic terms. It is traditional in physics to compensate for modifications in various units, for example, if time were measured in years instead days, and a need was measured in hours per year, then the units of value would change to need satisfaction/year.

Total Value Calculations Comparison for IT Application Alternatives

In this complex example, the value estimate of an IT application suite was calculated using Equation 1. In what follows, we compare the potential IT application suite to an alternative IT application suite. To do this, we use the results of the Equation 1 calculations across a very large number of potential users (i.e., based on the actual user population for the commercial IT application suite used for this complex example) compared to the potential acquisition of a new IT application suite. For the purposes of this comparison, the user need for the application suite is defined as $q_f[x]$ for an average user need, hence the number of users can be factored out of the summation in the equation.

The value of the IT application suite exists because it satisfies needs the users have even though it is not monetized in typical revenue terms as in commercial enterprises. However, the applications suite does have value that can be quantified in common units of value that we have labeled protovalue. Calculating the value of protovalue does require expanding the concept of value to include the value produced by non-profits such as the DoD.

In the next section of the paper, we describe extensions of the basic econophysics value theory that include behavioral risk using examples from a traditional acquisitions management approach (i.e., EVM) and also by demonstrating how it provides a means for predicting adoption rate.

Behavioral Cognitive Biases Effect on Investment Decision-Making

The emerging field of behavioral finance and economics is focused on the problem of how cognitive biases affect investor decision-making. The dominant theory to help explain behavioral biases is prospect theory. See, for example: Barberis and Huang (2008) and Barberis, Huang, and Santos (2001).[6] The

[6] While prospect theory is the dominant framework for behavioral finance, there remains an external validity problem with this theory due to the context of the classic experiments. For example, prospect theory also does not address the issue of the elapsed time between a first and second bet in the original experimental context of gambling scenarios. If there is considerable time between the first and second bet or first and second purchase of a service or product, consumers would forget or minimize the influence of the second investment, purchase decision. The proposed extension of the original econophysics model that incorporates some of prospect

standard financial model assume that investors are rational and will maximize their expected utility in investment decisions. This assumption appears to be supported in times of low volatility in capital markets but fails to predict investment behavior in times of high volatility. The acquisition model used in the DoD assumes a rational acquirer, investor. The model focuses on achieving sufficient detail in the requirements leading up to an acquisition to presumably ensure a “rational” acquisition program.

The problem comes in when acquiring information technology (IT) where detailed requirements do not translate well into an iterative building model that requires numerous adjustments over the acquisition life cycle. Given the long acquisition, and subsequent development, building period for IT projects, the standard program management techniques, such as EVM, do not work well in keeping a project on schedule and on budget. Another problem is that the performance of IT projects that are heavily software-dependent are hard to track because the outputs of the system build are in code. Unlike acquisitions of hardware that have clearly defined deliverables, software outputs are only relevant when an entire system is produced so that their functionality may be evaluated.

The acquisitions of IT systems are highly volatile as a result of these constraints. This lack of output transparency, until the entire system is up and running in a Beta model or production level system, creates a sense of high risk among the acquisition professionals (as well as the vendors). This paves the way for the introduction of cognitive biases that move them from a “purely” rational decision-maker to a biased decision-maker. These biases are largely based on risk aversion, especially as IT projects get “off- track” and the acquisition professionals become increasing alarmed at the negative direct of the project.

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theory’s primary tenets regarding risk aversion biases, addresses this external validity problem by using more realistic investment adoption rate scenarios.
This has been noted in recent research that attempts to apply the general concepts with more realistic situations.

Traditional financial investment models incorporate capital asset volatility (e.g., stocks, bonds, options) within their forecasting models. Volatility in these cases is operationally defined as the standard deviation and variance of the asset price over time. This volatility beta weight is a measure of the riskiness of the asset. In equity stock markets, risk provides opportunities because a stock price can increase in price dramatically or drop dramatically. However, in the non-profit DoD context, risk is always treated as a negative threat because there appears to be no potential upside to risk in an acquisition, especially an IT acquisition. This makes risk a negative threat and tends to elicit risk aversion responses by acquisition professional. This can create a positive feedback cycle in the acquisition life cycle of an IT system because as the failure to keep on schedule and on budget accelerates, the acquisition professional becomes more alarmed and begins to try to institute measures to return the project to the schedule timeline and budget projections. The result is often a death spiral for the IT acquisition.

The challenge is how to avoid this potential death spiral. One possibility is to obtain the schedule and budget deviations sooner, enabling program adjustments sooner. Another more complex possibility is to assume that risk is not necessarily a negative. This possibility is more challenging because budget and schedule deviations are a matter of grave concern and figure negatively in the EVM model. There are two reasons for the complexity of treating schedule and cost volatility as a potentially positive:

1. There is no quantitative value metric in the DoD acquisition context.[7]
2. IT projects, due to their iterative development nature, may provide even greater benefits (e.g., capabilities) than originally designed if the development team is allowed to adjust requirements to emerging defense contexts.[8]

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[7] EVM uses cost and schedule parameters to estimate value. It is illogical to use cost to estimate value as it is clearly in the denominator of any productivity ratio, such as ROI. EVM offers no raw, common unit of value for any of its equations.

[8] A good example of this is the emerging cyber threats to the operations of given weapon systems due to intrusions by hostile hacker.

In what follows, we review the dominant behavioral cognitive bias literature with a focus on how these biases can affect acquisitions decisions. We will also review how a new metric for volatility within the EVM context can be used to identify negative schedule and cost deviations based on existing EVM archival data. We conclude this section with a description of the extensions of the original econophysics model that includes parameters for the cognitive biases identified in prospect theory and risk aversion research.

Prospect theory was proposed to account for observed cognitive biases in decision-making under risk that rational decision-making models cannot explain (e.g., Allais paradox; Kahneman & Tversky, 1979), and has become widely accepted as the leading theory in individual decision-making under risk (Fox & Poldrack, 2009). Expected utility theory assumes that decision-makers will make rational choices among alternative investment options. Acquisition approaches, such as EVM, assume that decision-makers will apply rational thinking in making cost and schedule trade-offs to avoid risk. That this assumption has not been borne out in the many IT system acquisition failures is well documented in prior research (Jones & Housel, 2018).

One of the major contributions of prospect theory that is a distinct point of departure from expected utility theory is that the evaluation of gains and losses are made in relation to a reference point (Kahneman & Tversky, 1979), as opposed to an overall state of wealth. Reference dependence is thought of as analogous to the perceptual system perceiving the same stimulus as darker or lighter depending on the referenced stimulus in comparison (Kahneman, 2003).

The perception of value or utility based on gains and losses was introduced in the original prospect theory that was developed for decision under risk. However, it has carried through to subsequent versions (i.e., CPT), and is one of the most important contributions, extending to decisions under uncertainty (Tversky & Kahneman, 1992) and riskless choice (Tversky & Kahneman, 1991). Since gains and losses reflect changes in comparison to a reference point, the concept of framing becomes important. Information that can be framed as either a gain or a loss will elicit a different response depending on the chosen frame. When information is framed as a loss, the weight of the potential loss will be more significant than if the same information was framed as a gain. Acquisition professionals are vulnerable to these kinds of decision framing strategies employed by vendors to overcome objections to increases in cost and schedule. Unscrupulous vendor representatives often try to frame these overruns as actual reductions in risk because of the potential gains that the IT system will provide with potential added capabilities, that may have not been represented in the original requirements documentation. This framing is effective because it places the reference point in terms of a gain over the existing system instead of a loss, thereby minimizing the reluctance to invest in the new system.

Loss aversion and diminishing sensitivity give rise to the value and weighting functions described in what follows. Loss aversion describes the tendency for decision-makers to be more sensitive to losses than to gains. When gains are compared to losses, losses are given more weight than gains of the same magnitude. It is estimated that the loss-aversion ratio is 1.5 to 2.5, such that if one were to evaluate an even chance to gain or lose a IT system capability, they would need 1.5-2.5 times more gain to accept the option (Kahneman & Egan, 2011).

To use a simple example, evaluating a gamble that with a flip of a coin one could win $100 on heads or lose $100 on tails would be rejected by most people as the potential loss is weighted heavier than the potential gain, and therefore the perception of the potential loss amount is not equal to the perception of the potential gain amount. This inequality is captured by the kink in the value function at the reference line, showing the psychological value of a loss does not exactly mirror the psychological value of a gain when close to the reference point (see Figure 6).

The *value function* represents the perceived value of a gain or loss in relation to a reference point. The value function is essential to understanding how prospect theory predicts that value is reference-dependent and that people in general are loss averse (Kahneman & Tversky, 1979). Diminishing sensitivity can be seen in the value function as well. The farther from the reference point, the less sensitive one is to changes (Tversky & Kahneman, 1992). For example, a $10 difference is monetarily the same between when evaluating $10 to $20, and $100 to $110. However, the perceived difference is larger from $10 to $20 than it is from $100 to $110.

This general concept can be applied to acquisition professionals in making the necessary trade-off options of dealing with cost and schedule overruns. It follows from this concept that as costs increase and the value curve tapers off, further increases of the same magnitude in cost will not be perceived as significant as initial cost overruns. This non-rational investment decision bias represents a pathway to disastrous cost and schedule overruns.

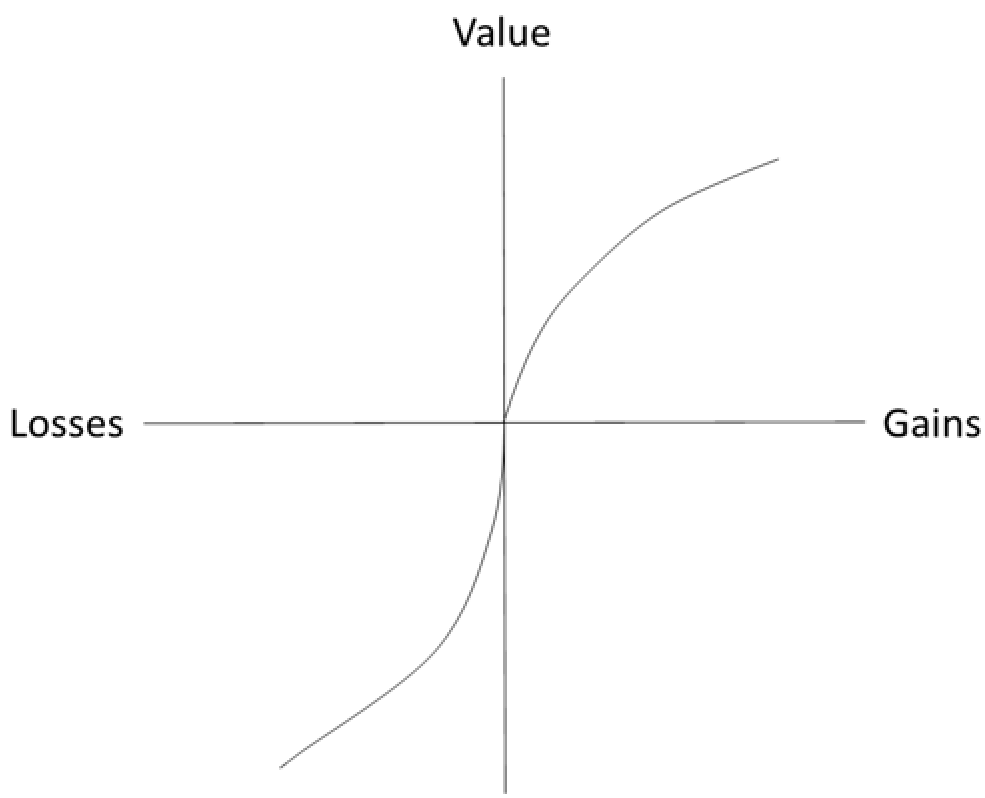

Figure 6. Value Function

Through experimental laboratory observations demonstrating loss aversion and diminishing sensitivity, prospect theory proposes a value function (as described above) and a weighting function (Tversky & Kahneman, 1992). The *weighting function* describes the decision weight a person assigns to the prospect, not the probability itself. Research on the weighting function shows that in general, people tend to overweight low probabilities, and underweight high probabilities (Tversky & Kahneman, 1992). Through both the value and the weighting functions, prospect theory can account for the fourfold pattern of risk attitudes that cannot be accounted for with expected utility theory:

1. Risk seeking for gains that are low in probability. For example, an acquisition professional may try to push a vendor to speed up development of an IT application to make their schedule metric look good when the probability of this outcome is remote and may cause cost overruns.
2. Risk seeking for losses that are high probability. For example, the acquisition professional may recognize that their management of an IT application's cost and schedule is very likely to result in negative outcomes and may overreact by ratcheting up the pressure on the vendor to meet cost and schedule targets that are virtually unattainable due to the volatility of the project.
3. Risk averse for gains that are high in probability. For example, an acquisition professional may avoid a vendor's suggested improvements to the capabilities or reliability of an IT application even when this results in demonstrable gains in the value of the application to the end-user warfighter.
4. Risk averse for losses that are low in probability. For example, a vendor may not undertake an opportunity to improve an IT application's reliability due to concerns about cost or schedule overruns even when such overruns are unlikely to occur. (Tversky & Kahneman, 1992).

The essential features of prospect theory have also been used to model consumer choice. Thaler (1980) first argued that traditional economic models are insufficient to explain consumer choice and that prospect theory offers more insight when trying to predict consumer choice. Tversky and Kahneman (1991) formally presented a theory of consumer choice largely based on reference dependence and loss aversion, which are essential elements in prospect theory.

In the case of considering between multiple options, the reference point becomes important as each option will become more or less attractive depending on where the reference point is placed (i.e., what attribute is weighted the heaviest at that point in time). If a vendor positions an upgrade option to an existing IT application on a capability that the warfighter has emphasized in public documents that reach the press, the acquisition program manager may feel compelled to pursue this option over other less expensive options that may actually provide greater benefits to the warfighter.

Loss aversion in consumer choice is largely an effect of framing, in that when the difference between options is presented as a loss, it has a larger impact than when it is presented as a gain. In a phenomenon known as the endowment effect (Thaler, 1980), loss aversion is seen in the difference one is willing to pay (WTP) to acquire a good, and the amount one is willing to accept (WTA) to sell the same good. The value of the same good is placed higher once one owns it, and therefore the WTA price is higher for the loss of that good, than it was to originally gain the same good. The endowment effect was first tested in a classroom using mugs. Some of the students were given mugs and how to fill out a questionnaire with varying amounts on it and asked whether they would be willing to accept that price or would prefer to keep the mug. Other students received a questionnaire with the same amounts asking if they would prefer the mug or that sum of money for each amount. In each scenario the student would either receive the mug or the cash. The only difference is the reference point, the sellers are losing an already owned good, and the buyers are deciding between two gains. The results reflected the difference framing can make in value, whereas the sellers were WTA $7.12, the buyers were WTP $3.12.

The endowment effect in the acquisition arena may be likened to the tendency of acquisition professionals and DoD leadership to stick with a given weapons platform, such as the A10, when a more capable system may be offered by a vendor. This can lead to the protection of legacy systems that have long outlasted the required capabilities of modern warfare contexts.

The term *status quo bias* was introduced by Samuelson and Zeckhauser (1988) and refers to a person's preference for their current state over an alternative. Samuelson and Zeckhauser found this effect in numerous studies involving different choices, including employees' choice of medical plans where new employees were more likely to choose a new medical plan over older employees when given the option to switch. The status quo bias also plays a large role in brand loyalty when people are hesitant to switch to a new brand, especially if the brand was the original product in the marketplace (Samuelson & Zeckhauser, 1988). Loss aversion has been implicated as a contributing factor in the preference for the status quo (Tversky & Kahneman, 1991). Changing from the status quo might mean losing an aspect that one is currently benefitting from. In addition to the status quo, loss aversion can also be seen when evaluating the advantages and disadvantages between multiple options; comparison of disadvantages will be weighted more than comparison of the advantages (Tversky & Kahneman, 1991).

In an experiment examining reference points and a comparison of advantages and disadvantages, participants were asked to choose between two hypothetical job options, with a description of a current job as the reference point (Tversky & Kahneman, 1991). The dimensions for comparison were commute time (20 minutes for job x, 60 minutes for job y) and amount of social contact (limited contact with others for job x, moderately sociable for job y). The two scenarios depicting the current job (reference point) were inferior in either the social contact (isolated for long stretches and 10-minute commute; scenario A), or commute time (much pleasant social interaction and 80 minutes of commute time; scenario B). Since loss aversion has a greater impact when evaluated in terms of losses, job x was preferred more when scenario A was presented, and vice versa (Tversky & Kahneman, 1991). This status quo effect can be seen in civilian DoD acquisition professionals and their leadership in preferences for working with vendors that they have significant experience with over years of acquiring IT systems. These inherent biases for given vendors can lead to the exclusion of smaller vendors that may offer greater system capabilities and development speed for new capabilities than large incumbent vendors with which the acquisition professionals have had dealings with over time.

One criticism of prospect theory is that most of the research has been carried out in a laboratory setting and therefore may have limited external validity. However, studies have applied the principles of prospect theory to real-world contexts, for example, in understanding why investors are more likely to sell stocks that have increased in value and hold on to stocks that have decreased in value (Odean, 1998). This has been proposed to be explained by the value function in prospect theory, where the value moves into the loss domain of the value function, and therefore induces more risk seeking behavior (see Barberis, 2013; Odean, 1998; Shefrin & Statman, 1985). Bendickson, Solomon, and Fang (2017) analyzed decision made in the National Football League (NFL) regarding the decision to pass when the team was either winning or losing. The reference point would be either in the gains or loss domain of the value function, respectively. They observed a tendency to engage in more risk-averse behavior when the team was winning, and more risk-seeking behavior if the team was losing, up to a certain point in which decision strategy shifted to risk neutral/averse. This aligns with the four-fold pattern of risk, where a risk-seeking strategy with losses is employed in with a higher probability outcome (the team losing, but not by much, representing a higher probability that the team could "come back"), and a risk-averse decision strategy with a lower probability outcome (the team losing by a lot representing a low probability that the team will be able to win).

The application of prospect theory to everyday decisions has also been seen in cabdrivers. Target daily income and expected hours driving have been analyzed and explained consistent with predictions of prospect theory (Camerer, Babcock, Loewenstein, & Thaler, 1997; Crawford & Meng, 2011; Kőszegi & Rabin, 2006). These studies find that, consistent with loss aversion and reference dependence, once the target income or the number of expected working hours is accomplished, they will stop working, even on days in which they are unexpectedly earning higher hourly wages. The expected or referenced number of hours and income sets up the expectations, and therefore any hours worked beyond those set up by the reference point are valued at a higher cost while extra income gained is valued lower, and therefore not worth the extra amount of time working. In addition, to account for initial limitations, prospect theory was later modified and extended to account for both decisions under risk and decisions under ambiguity[9] (cumulative prospect theory; Tversky & Kahneman, 1992).

Acquisition decisions within the DoD may also be evaluated in terms of gains and losses. The reference point in determining whether or not to invest in a new or updated option for a ship may be evaluated in terms of the status quo, or in weighting a particular dimension in the comparison between multiple options. Framing also comes into play in determining where to set the reference point. Current events and military priorities are going to weight what dimensions are important in the consideration of new equipment.

Loss aversion will also come into play in acquisition decisions. If the acquisition decision requires the retirement of an older option, there is a psychological cost that is attached to the overall investment, especially if older option is seen as not having fulfilled the initial investment (Okada, 2001). Loss aversion might also come into play with any doubts that the new acquisition might not be used to its potential (Knight, 2014). In evaluation of a new IT systems, potential adversarial capabilities might drive a shift in the reference point if there is an increasing concern about not having the same capabilities.

The reference point might be the capabilities that need to be met or exceeded to remain ahead of our adversaries, and loss aversion in this case would therefore be the fear of losing in battle. There are numerous historical examples of acquisition decisions based on perceived competition from emerging adversaries. Technological options that may have been evaluated in terms of a reference point in absence of this competition may have been deemed too risky

[9] Ambiguity is being used instead of uncertainty due to the most recent decision-making literature that defines uncertainty as a continuum that includes risk and ambiguity (e.g., Kothiyal, Spinu, & Wakker, 2014; Starke & Brand, 2016).

to buy. However, when a competitor comes into the picture with increasing capability in the same area, the reference point changes. The previously considered potential loss becomes weighted less in comparison to the potential loss faced when the reference point is shifted towards maintaining a competitive advantage. Figure 7 depicts how the options viewed by the different reference points will shift preferences.

When the options are viewed with reference point *a,* option 1 is preferred because option 1 results in an increase in the accepted use dimension and no change in the competitive advantage dimension, where option 2 results in a gain in the competitive advantage but a loss in the accepted uses. However, if the reference point was more weighted towards the competitive advantage, or from reference point *b,* option 2 is now preferred, as it results in a gain in the competitive advantage dimension and no change in the accepted uses dimension, where option 1 results in a gain in the accepted uses, but a loss in the competitive advantage dimension.

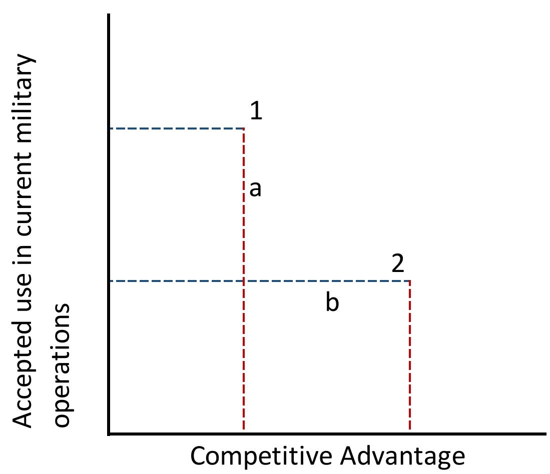

Figure 7. Loss Aversion and Competition in Warfighting Capabilities

Prospect theory can be applied to our extended econophysics model of protovalue. The econophysics protovalue model, proposed by Housel, Baer, & Mun (2015), is a model that applies physics to the field of economics with the aim of better predicting adoption rates. However, the model to date has not accounted for theories of human decision-making that deviate from the traditional rational value expectancy models. Incorporating the features of prospect theory into the model will help align the protovalue model with current theories of human decision-making. Reference dependence and loss aversion are the elements in prospect theory that have had the most impact in economics (Barberis, 2013), and therefore make the most sense to incorporate into the econophysics protovalue model.

Reference dependence and loss aversion as they have been applied to riskless, or consumer choice (Tversky & Kahneman, 1991) have obvious extensions to the user need space in the protovalue model. In the consideration of an IT application, there are various dimensions that the user will consider. These dimensions will be viewed in terms of a reference point. The framing of that IT application, and subsequently the reference point in that frame, will depict the dimension as either a loss or a gain in comparison to either a status quo or another competing IT application. The dimension(s) framed as a loss rather than gain will then carry more weight. Tversky and Kahneman's (1991) description of weighing advantages and disadvantages would apply in the need vector space.

The protovalue model has identified differences in consumer types using the Bass adoption rate model (Bass, 1969) that distinguishes between innovators and imitators. Innovators, according to Bass, represent 2.4% of the population, and act to predict the rate at which the rest of the consumers, imitators, will acquire the good. Research on prospect theory has noted differences in those that are more risk seeking and those that are more risk averse. Applying prospect theory to the innovators and imitators in the Bass Model, it follows that innovators are more risk seeking than imitators. The imitator group, as defined by Bass, includes those groups identified by Rogers (1962) as (a) early adopters, (b) early majority, (c) late majority, and (d) laggards. Bass (1969) then argued that these groups are influenced by the innovators and therefore grouped them as imitators.

While it may be best to view risk-seeking/risk-averse on a continuum (e.g., early adopters may be more risk-seeking than the early majority, but less risk-seeking than the innovators). The scope of the protovalue (PV) model includes predicting acquisition rates, and since innovators are said to influence imitators, the PV Model groups the various imitator categories into one and focuses on the difference between innovators and imitators.

Since innovators are the first to acquire a new good, they can be thought of as more risk-seeking than imitators. Howell and Higgins (1990) investigated the personality characteristics of what they termed "champions of technology," those that become invested in furthering the success of a new technological innovation. Howell and Higgins examined 88 companies that recently released a new technology product. They then identified those individuals who played a role in implementing the technology, and then they used snowball sampling to identify other individuals who were essential in championing that product.

The results of this review of prospect theory made it clear that it was sufficiently robust and extensible to justify its inclusion in our extended econophysics PV model to provide the cognitive decision parameters that should adequately account for risk-based biases in acquisition decision-making. The extended theory includes behavioral parameters that provide new insights to acquisition investment decision-making, leading to more accurate predictions of the future value of IT acquisitions, as well as the adoption rate of new applications. In what follows, we demonstrate how these new cognitive bias parameters affect the PV estimate, as well as adoption rate of truly new IT applications.

Extension of the Original Econophysics Model to Include Behavior Cognitive Biases

The failure of many new IT products and IT applications among consumer groups has been well documented in the past literature (e.g., characterized generically in the Hype Cycle; Gartner, n.d.). For example, MPesa, a microbanking/finance application, has been very widely adopted in Kenya but not in South Africa among the same customer segments (Baer, Bounfour, & Housel, 2018). Our original econophysics model found that the Kenyan consumer valued the application approximately eight times higher than the South Africa consumer.

Extended Model Econophysics Analogy

The economics-to-physics analogy provides a conceptual basis for the extensions to the original econophysics model described earlier in this report. This analogy focuses on the concept of exchange value rather than the static model of value embedded in the original theory. In what follows, we provide an explanation of the concepts in Table 7.

Organized potential energy is analogous to the potential protovalue of a product/service before it is purchased or used (in the case of a service offered by a non-profit such as the DoD). Organized kinetic energy is analogous to use of the product/service after it is provided to the user and is actually used. This is analogous to the physics concept of organized kinetic energy or work.

The total energy generated by potential and kinetic energy is analogous to the change in protovalue before and after a product/service is provided and actually used. The protovalue before and exchange can be subtracted from the protovalue after an exchange to get an estimate of the change in the exchange protovalue.

The amount of satisfaction, happiness, utility (i.e., value) a user expects to derive from the exchange before the use of the product/service is analogous to the change in potential energy (PE) multiplied times the time period. The actual satisfaction, happiness, utility a user experiences after the use of a product/service is multiplied times the time period, which is analogous to the action (A) generated by kinetic (KE) energy multiplied times the time period.

Table 7. Extended Economics to Physics Analogy

Economics to Physics Analogy

Economics	Physics
Protovalue: Useful Potential Value / Cost Barriers) **Work Energy**: Use or Work Value	Organized Potential Energy Organized Kinetic Energy
Exchange Energy **Point of Sale**: Δ in Protovalue (PV_a After Exchange – PV_b Before the Exchange) **Definition:** $PV_b = PV_p + WV_\$$ $PV_a = WV_p + PV_\$$	Δ Energy = Organized Potential Energy + Organized Kinetic Energy. Note: Surrogate Kinetic Energy is $
Satisfaction = Exchange Rate **Point of Sale**: Satisfaction = Expected Exchange Energy (E_x) * Length of Time in Hours **Actual Satisfaction** = Actual Exchange Energy (E_x) * Length of Time in hours.	Amount of Action: Action = Energy * Δ Time ΔA = Δ PE * Δ Time ΔA = Δ KE * Δ Time

This table provides the conceptualization of energy and its analog, value, that is applied in our extension of our original theory. In addition to the conceptualization of exchange protovalue, we include the impact of cognitive biases in the adoption rate of new products, services (i.e., IT services) in our extended value model.

DoD IT Application Using the Extended Model

In this notional example, we define the user need vector space that will include the cognitive bias of risk aversion variance. Many new IT applications introduced to the various DoD users generate a risk aversion–based apprehension about the performance of the application in various warfighting contexts. For example, in the context of the Advanced Concept Build (ACB) upgrades to the Aegis ship defense system, users are wary of the performance of new systems or modification to existing integrated weapons system software in spite of extensive testing before implementation in potential warfighting contexts.

Potential users of new IT applications can be categorized as those who are very willing to try the new applications and those who patiently wait for the early users to find any bugs in the systems. In the commercial environment where the adoption rate of introduction of new products and services has been studied for many years, a dominant model that is used in marketing is labeled the Bass Model after the originator of this adoption rate model. This model has identified early adopters, labeling them *innovators*, and late adopters, labeling them *imitators*. The innovators represent a very small segment of the general market population (i.e., 2.4%).

Given the absence of research that segments early and late adoptions in the DoD context, we have chosen the Bass Model to segment the potential DoD user population in our notional adoption rate model. In the future, if the structure of the comparable population of early and late adopters can be established in the potential DoD user segments, it will be a simple model to substitute the resulting segmentation values in our extended model.

As in standard physics models, distance is a critical component of our econophysics model. Distance represents potential and actual barriers between a user and the satisfaction, happiness, utility they will receive from adopting a new product or service. Distance is the denominator of the protovalue ratio. In our extended model, we have included uncertainty, from the prospect theory concept, as a parameter in our new distance estimate.

The notional example examines the effects of cognitive bias in terms of levels of user segment risk aversion and perceived gains in reducing distance, as explained by reference points and loss versus gain in prospect theory. In our notional example, users are segmented into innovators (2.4%) and imitators (97.6%), and each segment is assigned a level of risk aversion that moderates the level of fit in the protovalue numerator calculation.

The assumption is that perceived gains in reducing distance can generate a cognitive bias that influences the users' perceived distance between their need space and the general solution vector space in the protovalue numerator calculation. For example, when users have a reference point or baseline effort barrier for the time they believe they will need to devote to learn how to use a particular IT application and they are given an option to invest more time to reduce the distance barrier, then the ratio of the baseline to the additional time investment option would influence their decision to use the new IT application.

Incorporated in the need vector space, risk aversion and perceived gains in distance will modify the need-solution vector fit, as well as the distance parameters factored into the protovalue calculations. The results of the calculations are used to estimate the adoption curves for the innovators and imitators in the context of two acquisition reference points in our proof of concept example: $100 and $1,000, as well as a perceived gain that is described in the protovalue tables that follow. The impact of these new parameters and the notional values used in the example result in the adoption rate curves for both user segments.

Notional Extended Model Protovalue with Cognitive Biases Included

The level of risk aversion between innovators (less risk adverse) and imitators (more risk adverse) is operationalized as variability in each need space vector (i.e., vectors in Hilbert space). For example, the Canopy Penetration need vector can vary between 2–6 hours of their valuable time that are required to be able to identify an object at the bottom of a three-level canopy. We assume that an innovator is not as concerned as an imitator about whether a given acquisition cost will provide them with less than or greater than the level of their expected need on each of the three need vectors. As a result, the innovator will have a lower level of risk aversion toward a higher level of variability within a vector coordinate need space. Also, consider the notional example that might be rendered under uncertainty and under ambiguity (“not able to form any beliefs about probabilities”).[10]

For this notional example, we assume that ambiguity rather than uncertainly is in effect when assigning estimated probabilities because users may consider how much they would like to use a given number of valuable hours for a particular need vector rather than how many hours of need they might have in comparison to another vector. This individual vector estimation process led us also to consider innovator preference bias containing a wider range of variability in terms of need (measured in valuable need hours) for each vector in the need coordinate space. For this simplified notional example, we use a range of 2–6 valuable hours for innovators across all need vectors and assigned the same preference bias for all three vectors (in Figure 8) to make it easier for the reader to follow the math in the adoption rate estimates that follow the protovalue estimates. We understand this is a simplified example that uses the same range for each need vector and that, in many cases, innovator preference bias will vary among need vectors. This variability would result in variations among the length of each need vector.

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[10] See http://www.econport.org/econport/GlossaryPopup.jsp?glossaryWordID=1302 for the definitions of ambiguity and uncertainty that are used in this report.

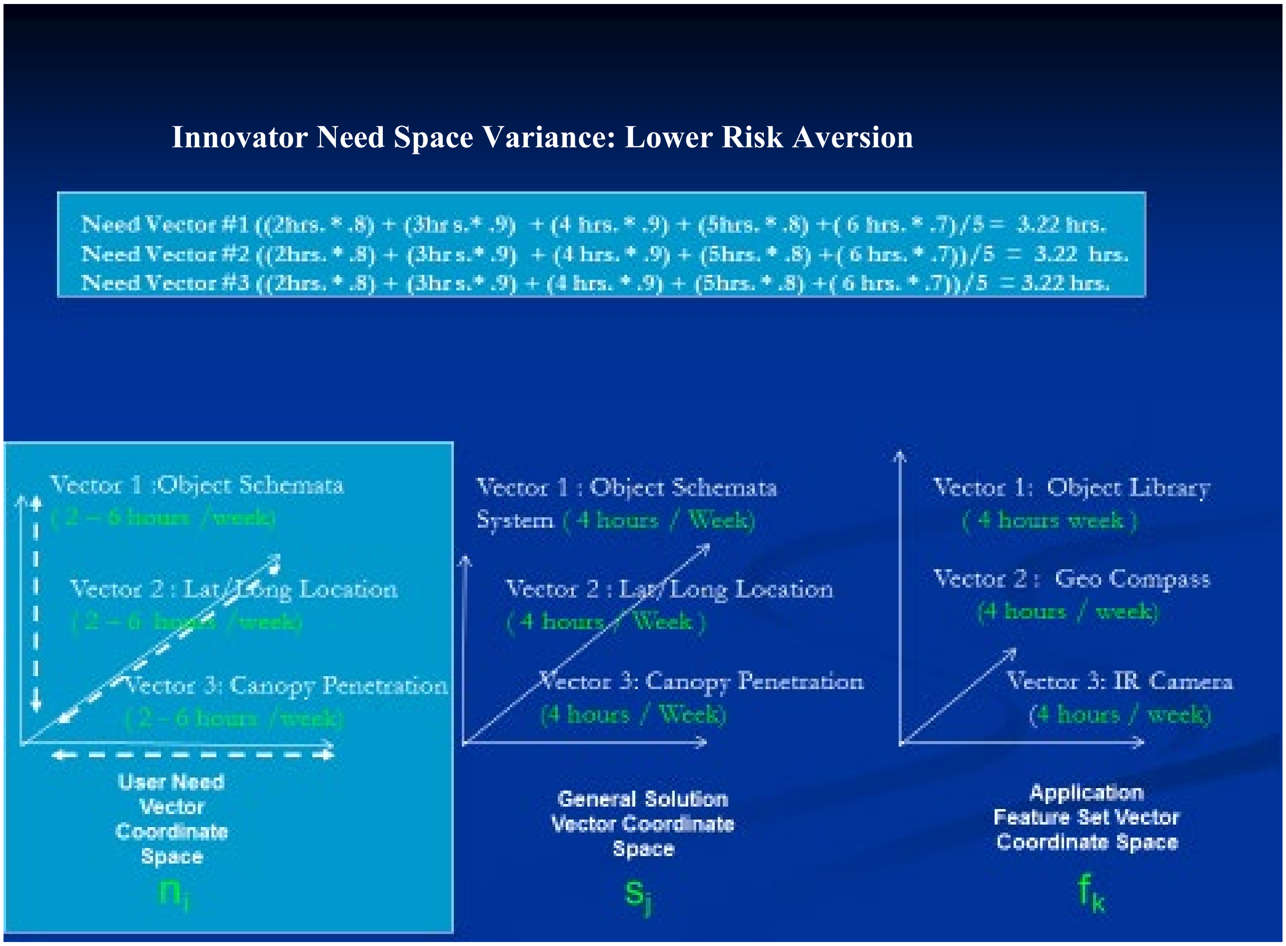

Figure 8. Protovalue Numerator—Innovator Notional Situational Awareness Application

For the imitator protovalue need vector coordinate space, we assume that an imitator is more concerned about whether a given number of valuable hours of their time in trying the new IT application will provide them with less than or greater than the level of their need on each of the need vectors. For example, their expectations for the amount of valuable time needed in each need vector will be narrower than for the innovators because they have waited to see how the innovators in their organizations have used the new IT application. As a result, the imitator will have a higher level of risk aversion resulting in a preference for a lower level of variability within a vector coordinate need space. Again, we must consider a notional example that could be rendered under uncertainty (based on possible available use data and "when the probabilities are not precisely known") and under ambiguity ("not able to form any beliefs about probabilities").

For this notional example, we assume ambiguity and rather than uncertainly when assigning probabilities because users may consider how much they desire a particular number of valuable hours for a particular vector rather and how many needed hours in comparison to another vector. This individual vector estimation process led us to consider imitator preference bias. Imitators are assumed to have a higher preference bias across a narrower range of vector variations because they perceive that they have become more certain about their needs by allowing the innovators to narrow their potential need for the application functions represented by each need vector. This results in a narrower range of variability in the need space since they have been observing or are aware of innovator use patterns as portrayed in Figure 9. For this simplified notional example, we used a range of 4–6 hours for imitator across all need vectors and assigned the same preference bias for all three need vectors. We realize that this is a simplified example that uses the same range for each vector and that, in many cases, innovator preference bias will vary among need vectors, resulting in a more complex protovalue calculation.

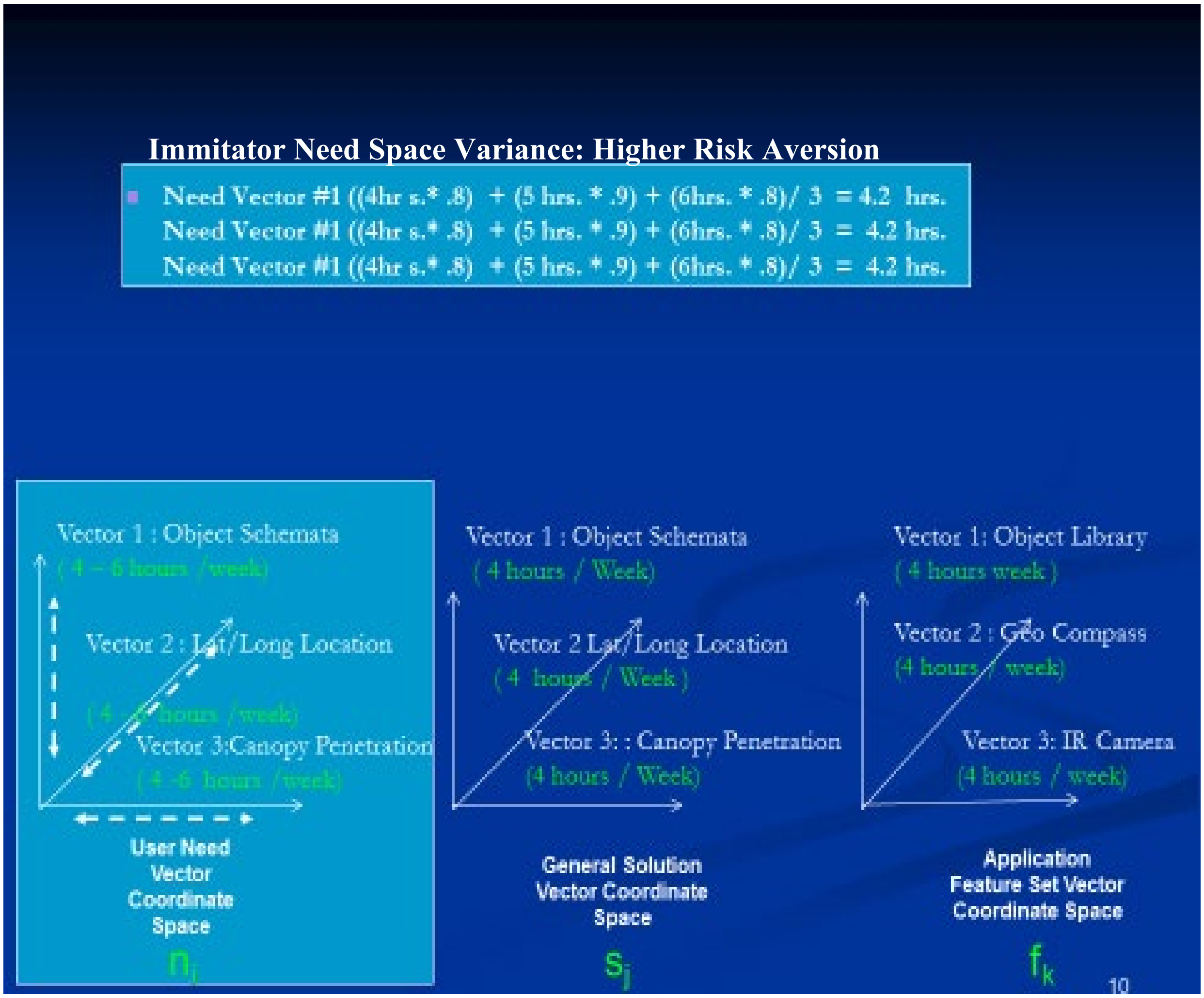

Figure 9. Protovalue Numerator—Notional Imitator Situational Awareness Application

In prior work, we have considered "Use Cost," "Acquisition Cost," and "Search Cost" in our operationalization of the denominator (i.e., Distance of the protovalue ratio). In the original protovalue model, distance was treated as a deterministic variable with the unit of analysis measured in hours. For this extension to the model, we include statistical parameterization of the cognitive biases resulting from decision-making under uncertainty and reference points as well as loss versus gain from prospect theory concepts.

We consider learning time to use the application's three functions as distance in terms of learning time and the application's three functions usage in terms of "Acquisition Cost." Both learning time and application usage costs appear to fit the idea of uncertainty where probabilities in the future can be estimated because baseline learning time and acquisition costs can used based on prior distance estimates and the probability of a typical user selecting from a range of alternative acquisition costs with varied learning times. These estimates can be based on prior experience in learning how to use new applications, as well as comparable IT application costs.

Rather than simply using assigned probabilities for the two reference points and related learning times for distance, we use the coefficient of gain and acquisition costs converted to hours based on an average wage of $25 per hour. Based on prior empirical work, reference point and gains versus losses from prospect theory have explained most of the variance and were selected for this extension to the original econophysics model to operationally define the distance parameter as portrayed in Figure 10.

The reference points for the distance parameters were operationally defined as follows:

- Two levels of acquisition costs that have a baseline cost of $100 and $1,000 per year respectively were selected based on prior empirical prospect theory research studies that suggested using a 10X difference in reference points.
- Reference points are $100 and $1,000 with a saving of $20 or spending $80 and $980 would result in potential decreases in learning times (i.e., time decreased from 0.20 hours to 0.10 hours.)
- Gain is represented in the distance parameter with the idea of saving $20 on learning time of 0.10 hour rather than a 0.20 hour decrease.
- Assigned notional probabilities were based on prior research in the cognitive biases domain with potential use of historical data related to reference point in prospect theory.
- Evidence from prospect theory research suggests the following probabilities considering the coefficient of gain, which has been reported as either .88 or .73–.68. For this notional example, we have selected a coefficient of .70.

Distance under uncertainty: Reference Point and Coefficient of Gain Coefficient of Gain X to .7 > or = 0

Fitness Club Baseline Cost	Scenario 1 (.1 hr. driving distance)	Scenario 2 (.2 hr. driving distance)	Distance: $ converted to hrs. based on an average wage of $25 per hour.
$100	Baseline $100 Coefficient of Gain = 25.12 (.20)	$80 Coefficient of Gain = 21.49 (.80)	(($25.12 * .20) + ($21.49 * .80)) = $22.2 or .88 hrs.
$1000	Baseline $1000 Coefficient of Gain = 125.89 (.80)	$980 Coefficient of Gain =124.12 (.20)	($125.89 * .80) + ($124.12 * .20)) = $125.5 or 5.0 hrs.

Figure 10. Protovalue Denominator—Notional Situational Awareness Application

Calculating the PV ratio is a matter of combining the fitness numerator with the distance denominator. For the innovator fitness numerator, the protovalue for the $100 reference point is 35.7 and for the $1,000 reference points 6.3, per Figure 11.

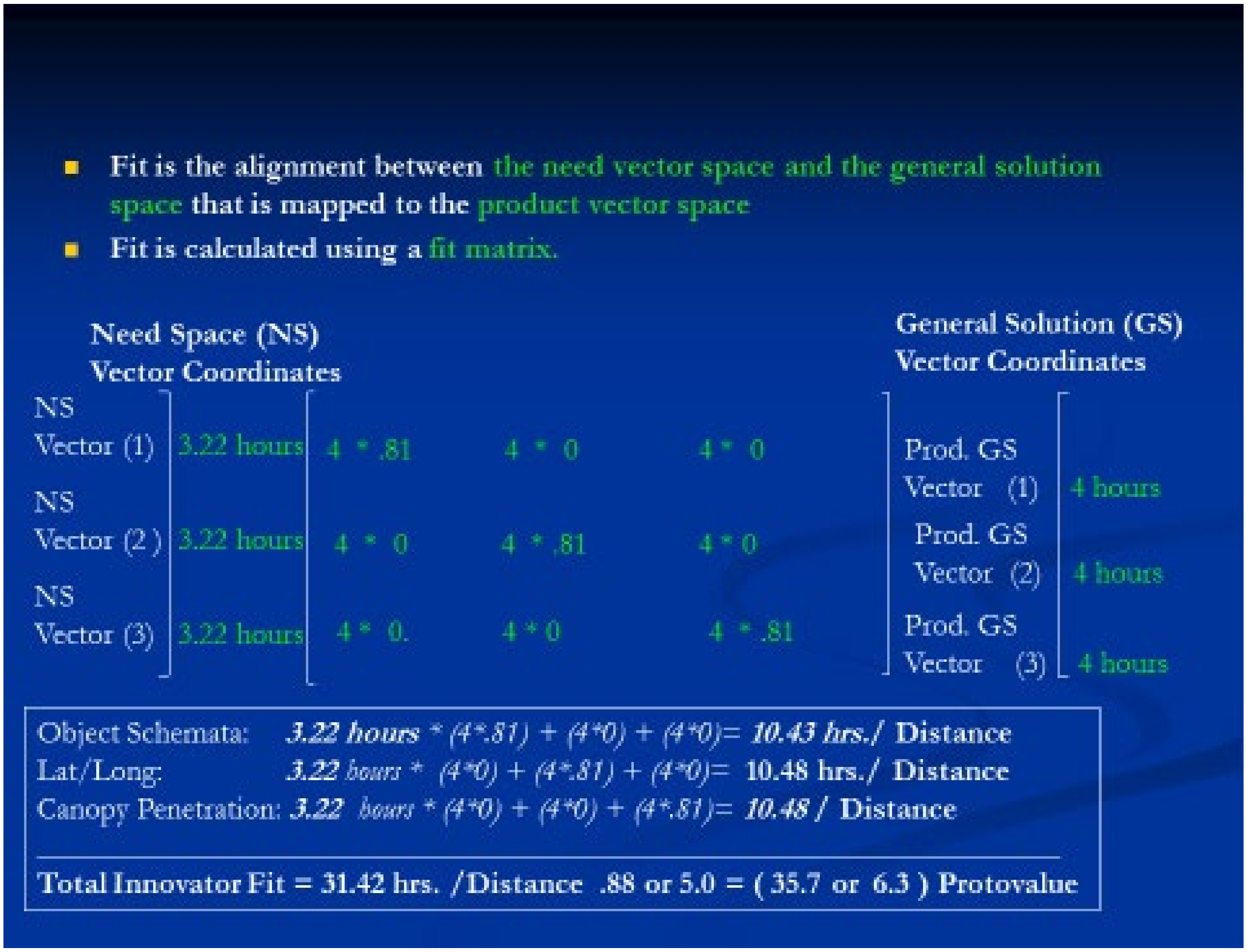

Figure 11. Notional Example: Innovator Fit

Imitator Fit and the resulting PV are calculated, once again, using the satisfaction fit matrix that considers two reference points $100 and $1,000. Imitator Protovalue for the $100 reference point is 54.4 and for the $1,000 reference points 9.6 hours, per Figure 12. Imitator PV is higher than innovator PV for both reference points, due to the imitator user segment having a narrow range of need variability and a higher level of preference bias across that range than the innovator user segment. This presents a counterargument to innovators typically exhibiting expected use patterns that produce higher levels of fit than imitators. When we introduced risk aversion variability into the user need space, imitators rather than innovators exhibited higher levels of fit and resulting higher PV estimates.

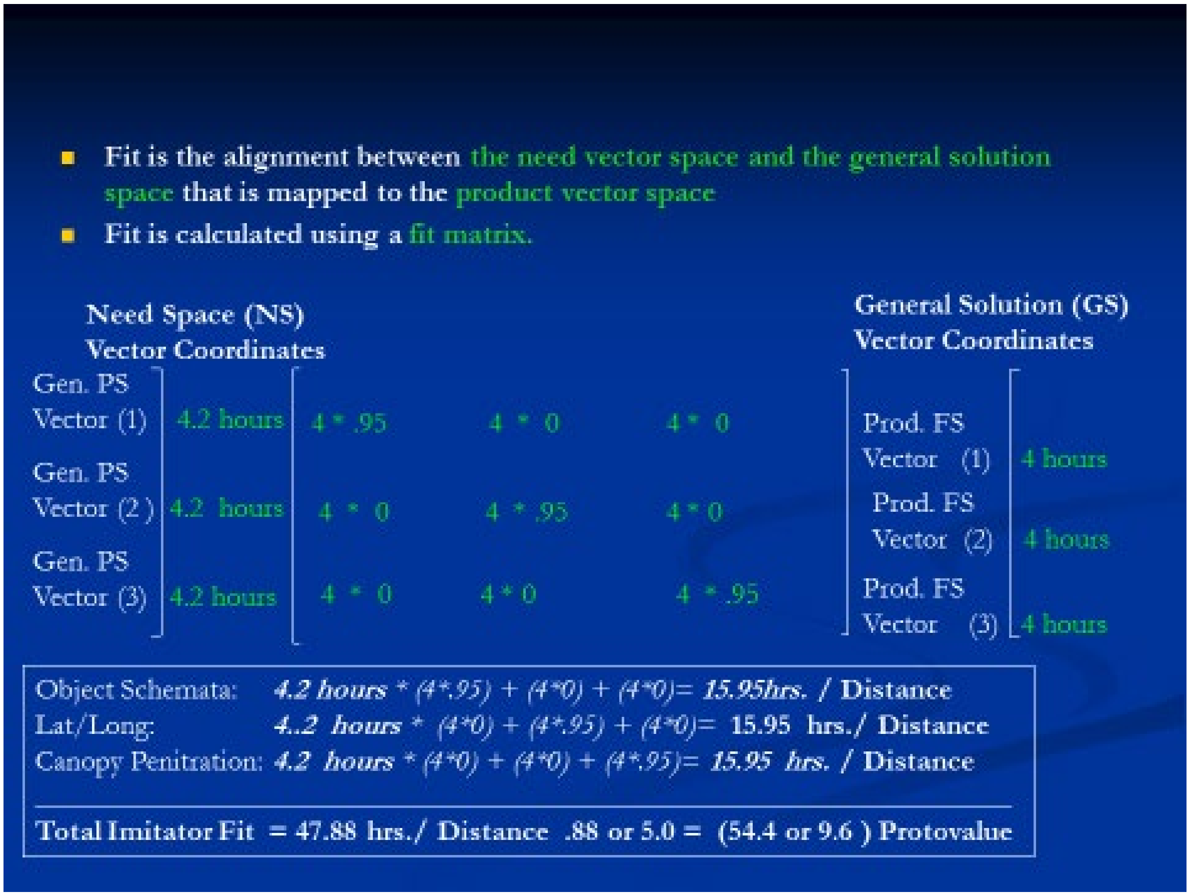

Figure 12. Notional Example: Imitator Fit

Based on the Protovalue estimates for the $100 and $1,000 reference points for innovators, two anticipated adoption curves result per Figure 13. For the $100 reference point, innovator user segment saturation is expected to occur in 16.8 months. For the $1,000 reference point, innovator user segment saturation is expected to occur in 95 months. These adoption curves are supported by prospect theory–based concepts and earlier empirical work on reference point and gain estimates. Given the notional example, the aforementioned adoption curves indicate that, for a reference point of $100 versus $1,000 and a gain of $20, to reduce distance across two reference points produces significantly different adoption curves.

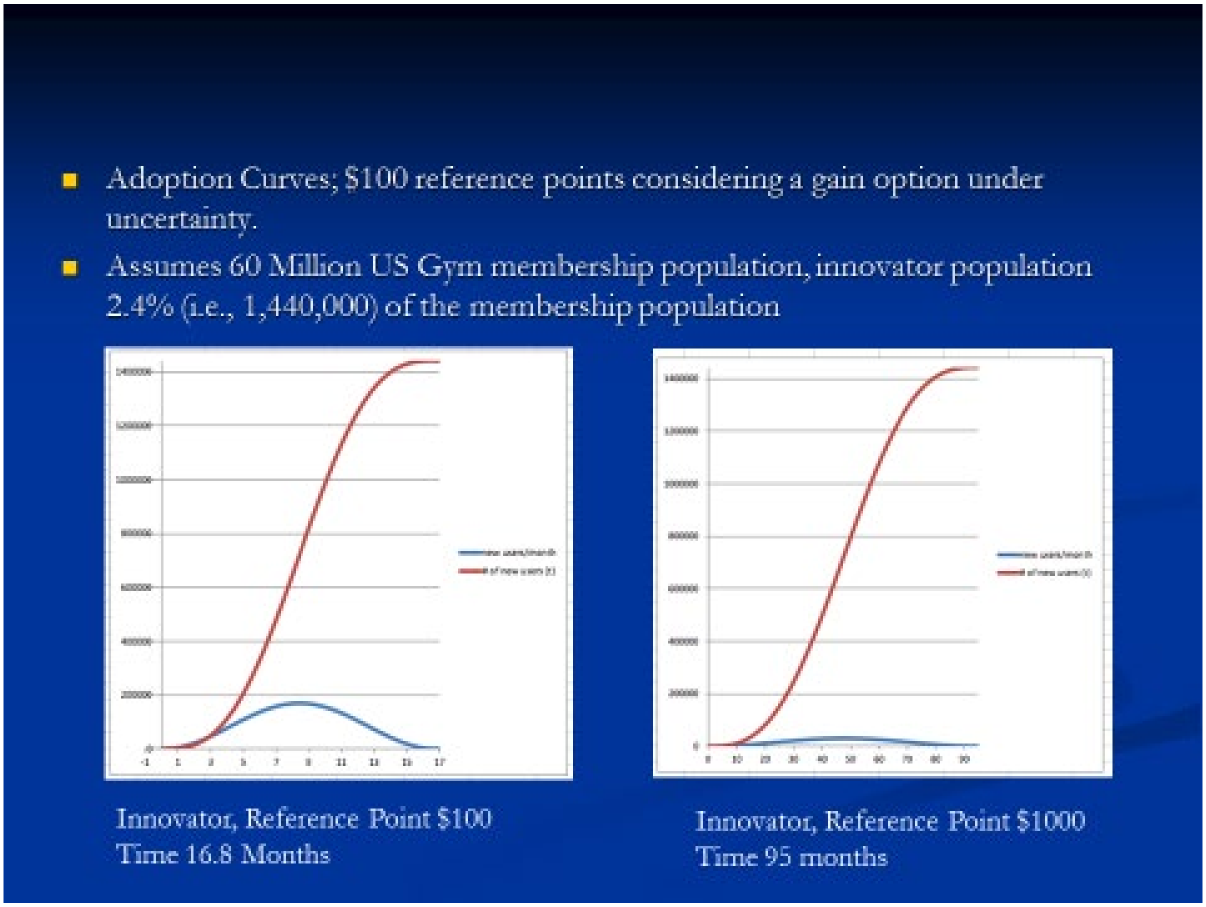

Figure 13. Notional Example: Innovators $100 and $1,000 Reference Points: Distance Under Uncertainty/Gain

Based on the PV estimates for a $100 and $1,000 reference point for imitators, two adoption curves result per Figure 14. For the $100 reference point, imitator user segment saturation is expected to occur in 11 months. For the $1,000 reference point, imitator user segment saturation is expected to occur in 63 months. Again, these adoption curves align with earlier empirical work that considers reference point and a gain versus a loss from Prospect Theory and how such cognitive biases influence decision making behaviors under uncertainty. While the difference in time to market saturation between two reference points for imitators is less than innovators, user groups’ reference point and a gain have an important influence on cognitive bias and resulting PV.

The notional example demonstrated how two reference points derived from prospect theory result in a 10X spread and a gain to provide an example of how reference points and gain versus loss can be used to extend our basic econophysics model to include cognitive bias and uncertainty in better explaining the distance between a particular user group and a vendor solution space.

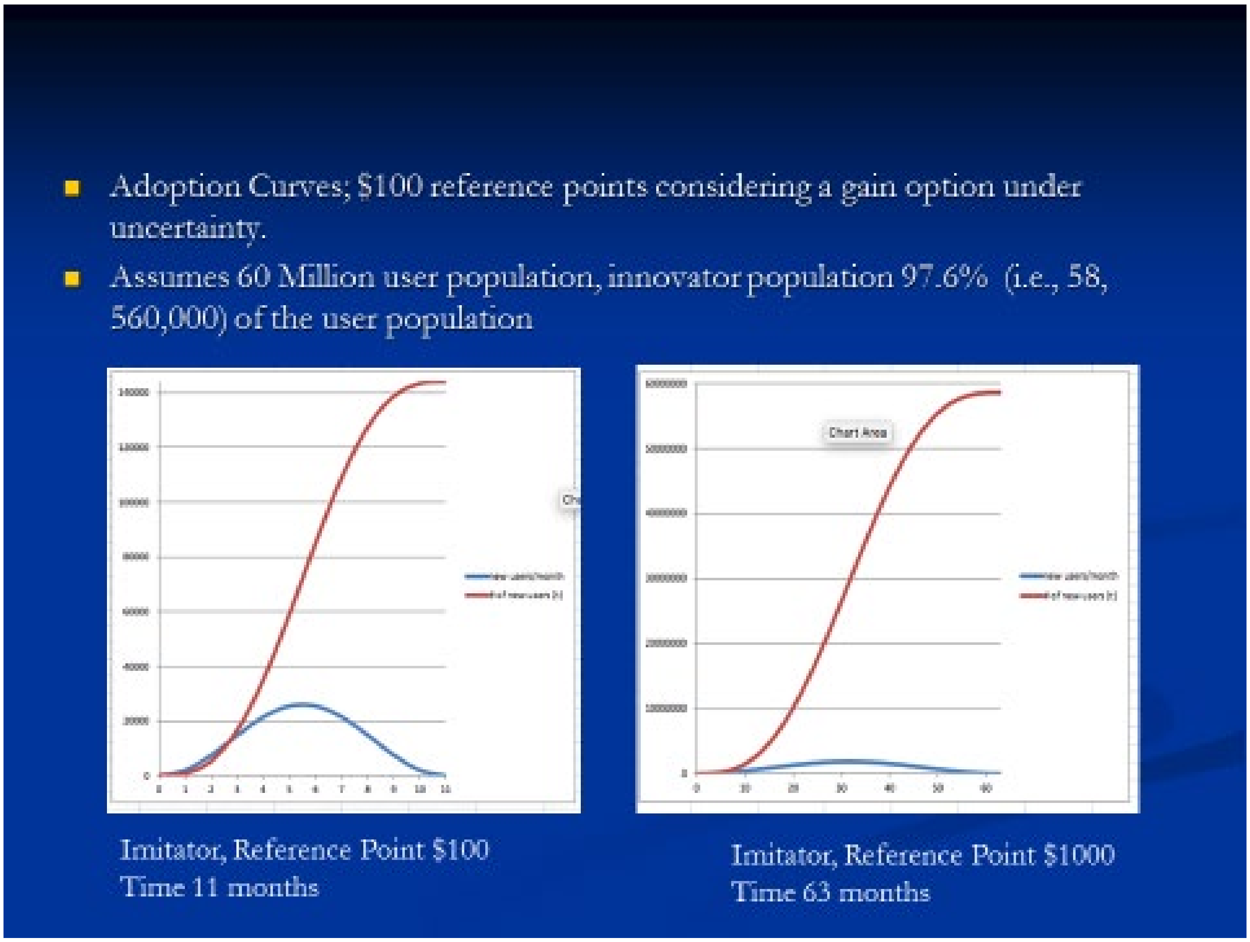

Figure 14. Notional Example: Imitator $100 and $1,000 Reference Points: Distance Under Uncertainty/Gain

Program Development Life Cycle Application

In what follows, we offer an econophysics-based extension to the traditional acquisition program management framework. The focus of this section of the report was to provide a defensible extension of EVM that could be implemented using existing EVM data with a relatively minimal learning curve for acquisition professionals. It thus represents a practical extension of the econophysics conceptual model, while the preceding sections were devoted to a largely theoretical development of the general econophysics value model.

Extensions of the Current EVM Approach

The preceding examples begin to explain the relationships between the econophysics protovalue models with regard to acquisitions of IT applications, which is a critical element in eventually developing more robust, theoretically based predictive methods for acquisition program performance. The econophysics models do not include a parameter for value volatility. Future empirical research will help us determine whether a parameter for value volatility should be included in the evolving econophysics model.

The EVM extension, described in what follows, does include a new value volatility parameter and is consistent with standard practice in investment finance forecasting models. This EVM extension provides a way to use existing archival acquisitions data within a framework that most acquisition professionals are familiar with and should be readily adaptable to their current use of the standard EVM approach. The contribution of a value volatility parameter will strengthen the forecasting capability of the current EVM approach.

Current methods rely exclusively on historical cost information with no real measure for relative value of investment in a program. Additionally, traditional program management techniques do not integrate risk and volatility into the analytical framework as a variable, other than to conduct parallel risk management processes from a qualitative organizational decision-making process. We introduce the concept of risk and probability of success to demonstrate a practical extension of the current acquisitions frameworks can benefit from these concepts in terms of predicting program performance.

Risk in the program management sense is the likelihood and consequence that an event will occur. Within this framework, a risk is also something that a program manager feels is controllable within the program office resources. From a financial perspective, risk is categorized as the chance an outcome or investment's actual return will differ from the expected outcome or return. Risk includes the possibility of losing some or all of the original investment ("Risk," n.d.). A fundamental idea in finance is the relationship between risk and return. The greater the amount of risk an investor is willing to take, the greater the potential return. Considering this view of risk management, a program manager might entertain the impact of risk from an outcomes-based perspective, rather than a zero-sum perspective. Under current management models, risk is considered something to mitigate at all reasonable cost, rather than something to manage from a risk return perspective. If we can provide more insight into the return on investment, informed by analytical risk and probability of success methods, program managers will be able to make more informed decisions based upon performance rather than cost. By introducing protovalue (revenue) and risk, we show how program performance prediction is significantly more reliable than traditional methods using cost as the primary metric.

As in the simplified and more detailed examples of econophysics cited previously, we need to define key variables within the program framework that are logically represented by physical properties. Table 8 relates the behavioral econophysics terms with a more generic defense acquisition program. We are initially using the defense acquisition framework, due to its well-defined process structure and the ability to obtain detailed data from throughout the life cycle. A risk term is introduced with regard to the probability completing requirements defined by the operational user, which are articulated in the Capabilities Development Document (CDD). The CDD is the primary requirements document that defines program performance expectations and is subsequently defined in the contract statement of work. Understanding risk is necessary for determining the probability of success for a particular program and subsequently the protovalue.

Table 8. Framework for Simple Model to Estimate the Protovalue of a Contract Pre-Award Modified for Standard DoD Acquisition Program

mass {**m**} = relative complexity of key performance parameters (KPP) as defined in the Capabilities Development Document (CDD) multiplied by its Technology Readiness Level (TRL) (Scale of 1-9, as defined in diagram 2)
Number of capabilities (**N**) = number of capability solutions in the contract relative to the proposed contractor schedule that support meeting the KPPs
Potential **F**ield (**PF**) = (**m*N**) the number of capabilities of a given complexity (m) offered by the contractor in the contract proposal
Velocity = Change in rate of **PF** over time period of contract performance
Probability of Success (P_s) = (1-%risk) of completing a specified requirement defined in the CDD_
(PP) - Number of potential requirements **(R)** multiplied by the probability of Success – **[R*(P_s)]**
Realized Protovalue (RP) – number of requirements actually accomplished in the contract relative to the CDD and proposed schedule

The realized protovalue (RP) term in Table 8 is the surrogate variable for revenue with which we will establish a definitive ROI value for the program. Before now, true ROI was not achievable in the program management field due to the lack of a sufficient revenue term with which to compare cost information.

While risk is considered in current source selection processes, it is not integrated into a probability of success calculation that reflects potential ROI. Consequently, risk is simply used as a qualitative variable based upon analytical and subjective methods in determining the potential cost and schedule impacts a given contractor might experience throughout the program life cycle. Table 8 defines Probability of Success as

$$(P_s) = (1\text{-}\%\text{risk})$$

For the purpose of this research, we use the traditional risk management framework in defining percentage of risk, as shown in Figure 15.

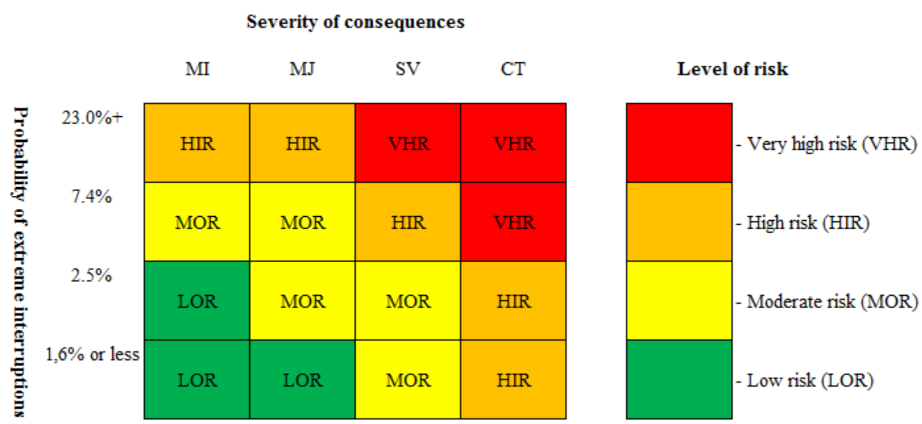

Figure 15. Standard Risk Matrix

While our initial research applies the same level of qualitative rigor to establishing a risk determination, our future research will include a turbulent flow model and Computational Fluid Dynamic (CFD) methods using program derivatives as variables in the calculations. Our intent is to establish a series of curves similar to Reynolds number plots that show a laminar region (low risk), transition region (transition zone), and turbulent region (high risk) that can be traced to the individual variables within the model. These curves will provide the level of risk of a program at any point in time and under specified conditions. By selecting a point on the curve, we are able to calculate the probability of success and subsequent PV (revenue) for the program.

Reynolds number (Re) is an important dimensionless quantity in fluid mechanics used to help predict flow patterns in different fluid flow situations. It is an important analogy to program management and product development in that it represents the level of uncertainty within the fluid region. At low Reynolds numbers, flows tend to be dominated by laminar (sheet-like) flow, while at high Reynolds numbers, turbulence results from differences in the fluid’s speed and direction, which may sometimes intersect or even move counter to the overall direction of the flow or otherwise referred to as eddy currents. These eddy currents begin to churn the flow, using up energy in the process, which, in our context of finance and management, can be translated into inefficiency and increasing cost. The Reynolds number approach has wide applications that deal with uncertainty. If sufficient variables can be defined and measured, the underlying principles of fluid dynamics can apply. The predictions of the onset of turbulence and the ability to calculate scaling effects can be used to help predict fluid behavior on a larger scale. By selecting measurable variables for and collecting data from historical programs, we will be able to generate reliable risk curves that can be used for future program probability of success and ROI prediction.

At this point, we will contain our risk identification methods to traditional methods and apply them to our extended econophysics equations form a probability of success perspective.

Using risk as a basis for understanding the potential for success, we have redefined the traditional risk matrix in terms of the probability of either meeting or not a meeting the specified requirements defined in the user's requirements documents. While these percentages are debatable, they simply reflect the logic of the argument. These values will be refined in subsequent research. Table 9 reflects the likelihood and consequence of not realizing the completion of a particular defined requirement listed in the CDD, which is important in determining the overall value of the program.

Table 9. Percent Risk of Not Completing an Individual Requirement Defined in the CDD and the Relative Consequence of Not Completing the Requirement

High	60	70	80	90	100
High	50	60	70	80	90
Medium	40	50	60	70	80
Medium	30	40	50	60	70
Low	10	20	40	50	60
Low	Low	Medium	Medium	High	High

Return on Investment Performance Index (RPI) Comparison with Earned Value Cost and Schedule Indices (CPI/SPI).

Major defense programs and large commercial programs typically use EVM metrics to measure the performance. These data are generally historical in nature and require the program manager to extrapolate future performance based on program risk and other mitigating factors. While this is a good measure of tracking pre-contract award cost to work relationships, it does not provide an early assessment of program value relative to the potential for program success. Consequently, programs tend to get into trouble earlier than program managers are able to observe through traditional measures, and program managers are unable to ascertain the relative program performance based upon investments. If there were a way to inform the program manager on how a program was performing relative to the investment, decision-makers would be able to make decisions as to the true program net value rather than simply falling victim to making cost and performance trades based upon increasing cost and schedule.

Using the principles of econophysics described above, we are able to show that ROI is a better predictor of program performance than traditional EVM metrics alone. A more detailed explanation can be found in "Extending a Behavioral EconoPhysics Value Model for a Pre-Contract Award DoD Acquisition Investment Decision*"* (Jones & Housel, 2018).

The econophysics framework identified the production of protovalue using analogies to a comprehensive physics conceptual model. By establishing protovalue as a surrogate for allocated revenue, we are able to definitize the required parameters for ROI in an acquisition program over time, leading to an ROI performance measurement baseline (PMB) and subsequent ROI Performance Indicator (RPI) for a particular program under consideration.

The ROI performance measurement baseline is analogous to the EVM PMB in that it will provide a measure of work accomplished over time. However, while the EVM PMB measures the cost of work over time, the ROI PMB measures the value of the investment relative to the level of effort over time. For each increment in time, the ROI PMB will provide the decision-maker a unit of value relative to investment and cost, providing a more informed measure by which the program can be evaluated for relative worth and practicality. With a surrogate value for revenue, the ROI PMB can be operationalized at the work breakdown structure cost center level to which costs are allocated. Similar to the EVM PMB, the ROI will provide indices of performance such as cost performance index (CPI), revenue (protovalue) performance index (RPI), and schedule performance index (SPI). Current EVM indices only provide CPI and SPI, and provide no analytical index for true value of the program. CPI, SPI, and RPI are calculated using the following equations:

CPI = BCWP/ACWP
SPI = BCWP/BCWS
RPI = [PV -ACWP]/ACWP

Where:

BCWP – Budgeted cost of work performed
ACWP – Actual cost of work performed
BCWS – Budgeted cost of work scheduled
PV – Protovalue (surrogate revenue term)

The existing econophysics model described above uses terms from physics to define relationships between the various participants in the defense acquisition community. Terms such as *mass* and *distance* are used to explain product performance and quality as well as the level of consumer attraction toward the product. The consumer attraction toward a product is defined in the DoD requirements documents such as the Capability Development Document (CDD), which specifies the system's requirements and critical attributes. These critical attributes are delineated in Key Performance Parameters (KPP) that specify both threshold and objective values that must be met by the program manager of the system under development. If a system under development is close to the objective for the KPP, then the distance between the operational user (consumer) is very close. However, if the system under development is closer to the threshold, then the distance between the user and the product is further away. If the system is below the threshold, then the distance between the user or customer and the product under development approaches infinity.

Figures 16 and 17 summarize results of a notional program with preliminary data calculated using the aforementioned RPI methodology. The equations defined above for PV and RMI, a plot of PV relative to EVM data is shown in Figure 16. The cumulative PV shows a rate change as early as 11% earlier than the first significant indicator in EVM.

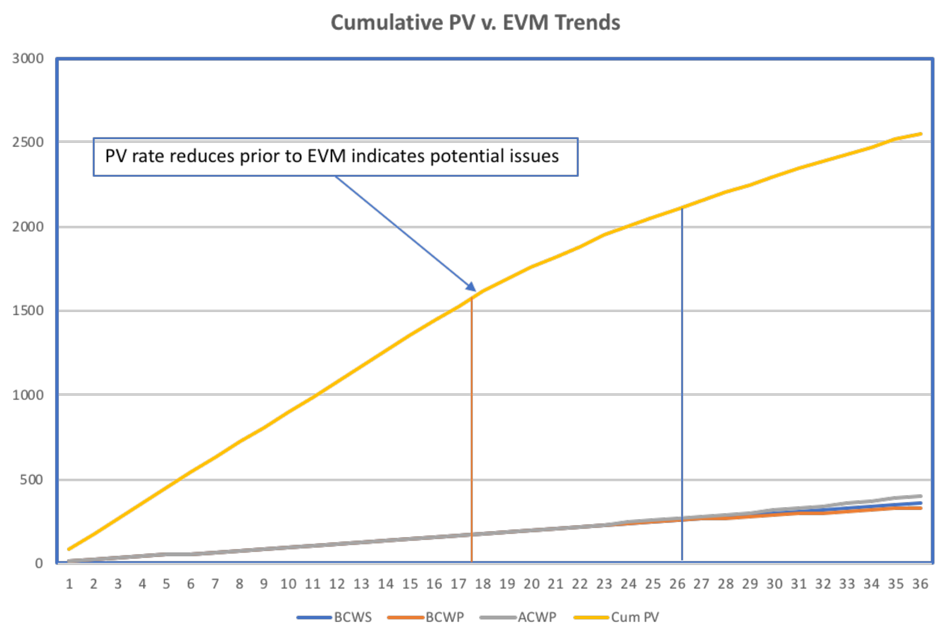

Figure 16. Cumulative PV versus EVM Trends

Figure 17 is another view of the same information. RMI begins to fall off earlier than CPI and SPI. This is explained by the fact that risk and probability of success are incorporated into the PV calculation, as well as in determining the PF for the program.

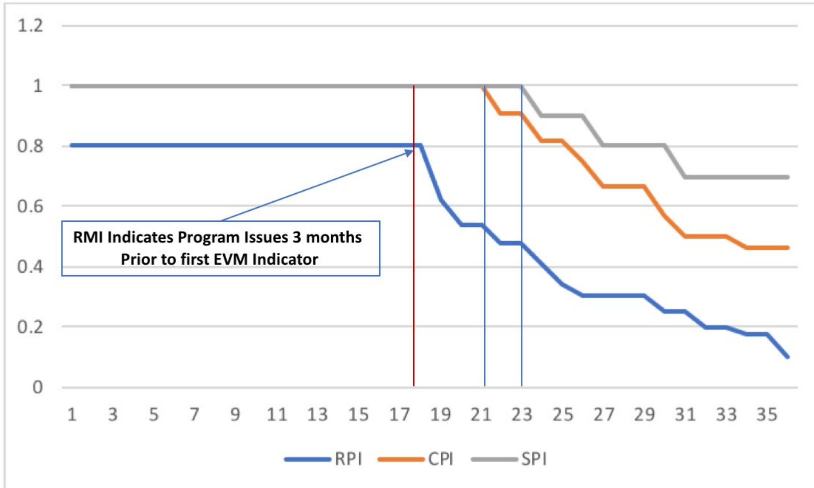

Figure 17. RMI versus EVM CPI/SPI Indices

The data shows that establishing a measure for value based upon revenue will inform the decision-maker about the relative nature of program ROI. This decrease in ROI, as reflected in the RPI, can be an early indicator of program issues. While this first pass analysis is based upon rudimentary risk and revenue calculations, as we refine our risk prediction methods using CFD modeling, we will more definitively describe the relationship between RPI, CPI, and SPI. Additionally, validation of these techniques will provide an enhanced and complimentary tool for program managers in any business domain to improve their decision-making through better prediction methods based upon risk and surrogate measures of performance. Knowing that a program is attaining less value for its investment is a powerful measure by which leaders can make informed decisions regarding the viability of a program.

Future Extensions of the Acquisition Framework: Turbulent Flow Models

Much like the turbulent nature of fluids, the random particles within the fluid are not precisely predictable at any moment in time. While they seemingly follow fundamental laws of nature, our ability to observe these patterns in real time for every possible variable and permutation of the variable is still elusive. Similarly, the actions of humans within a defined frame of reference such as the standard acquisition program development life-cycle model is not possible. With that said, however, we are able to define quantitative variables that impact a program and subsequently observe these variables and their effect within the greater acquisition framework. Much like turbulent flow models, the relevant variables within the frame of reference are defined and their relationship to the outputs are constructed in a way that allows the researcher to manipulate them in search of a causal relationship. The use of turbulent modeling is an appropriate analogy in that it is a physics-based approach that will allow us to derive a dynamic term for risk and volatility within our econophysics-based return on program investment calculations for instantaneous program performance.

Turbulence modeling is fundamentally the construction and use of a model to predict the effects of turbulence. Turbulent flows are commonplace in most real-life scenarios, including the flow of blood through the cardiovascular system, the airflow over an aircraft wing, the re-entry of space vehicles, or similar frameworks that have a complex interrelationship between variables such a program management life-cycle model. The equations governing turbulent flows, however, can only be solved directly for simple cases of flow. For most real life turbulent flows, CFD simulations use turbulent models to predict the evolution of turbulence. These turbulence models are simplified constitutive equations that predict the statistical evolution of turbulent flow (Pope, 2000).

The extension of the general acquisition framework to include turbulent flow models will serve as the basis for a PhD dissertation (i.e., Raymond Jones's dissertation) as well as the foundation for future research for the Acquisition Research Program. Much fundamental theoretical and empirical research remains to be completed to test the viability of this extension of the econophysics model.

Conclusions

The driving assumption of econophysics research is that standard economics and physics models are focused on predicting the future. For example, in economics literature, predicting the adoption rate of new products and services such as IT applications is critical to predicting the success of a start-up organization. Physics models have been focused on predicting the effects of various energy models on the movements of particles or nuclear entities. While physics theories have been very successful in predicting extremely complex phenomena, such as tropical cyclones, economics theories have been much less successful in predicting changes in highly volatile markets and adoption rates for new products and services. The success of physics models makes them an attractive option for developing new theories of economic value by providing a plausible quantitative structure to conceptualize economic phenomena (e.g., value accretion, decision risk, black swan events).

A major difference between physics models and economic prediction models is that physics models do not require historical volatility to make predictions but economic theories do. However, neither model provides clear guidelines for ways to include human biases in investment decision-making or adoption rate predictions. Using econophysics and adoption rate methodologies allows us to construct a more analytical approach to predicting program value performance that is highly influenced by decision-maker biases.

One of the problems with the current economic-based adoption rate theories is that there is no general explanatory theory of quantitative value that is agnostic to monetization or historical price volatility. This gap in the current adoption rate theories is addressed in our extended econophysics value model that measures value in common units and does not require historical volatility parameters to predict adoption rate. The fact that our model addresses these two gaps in the prior literature makes it an effective potential approach to predicting the potential quantitative non-monetized value of new IT systems and applications, as well as the adoption rate of these new IT acquisitions in the DoD. This is primarily because our approach is agnostic value monetization that is the case in the DoD. This capability allows us to provide an estimate of quantitative value volatility in standard acquisition approaches such as in EVM.

Future Research

Adoption rate predictions are important for the acquisitions of new IT systems and applications in the DoD. The implicit assumption about the acquisition of truly new IT systems in the DoD is that it will be imposed, from the top, followed by automatic adoption regardless of potential users' expressed needs or risk aversion biases. Given the failure of users to quickly and successfully adopt numerous DoD IT systems, it is surprising that there is not more research on predicting adoption rate in the DoD. Because the proposed econophysics model is agnostic to monetization of value and also incorporates user biases, such as risk aversion, it is well designed for the task of forecasting the adoption rate of new IT systems in the DoD. Also, the proposed model does not require historical volatility estimates to make adoption rate predictions.

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