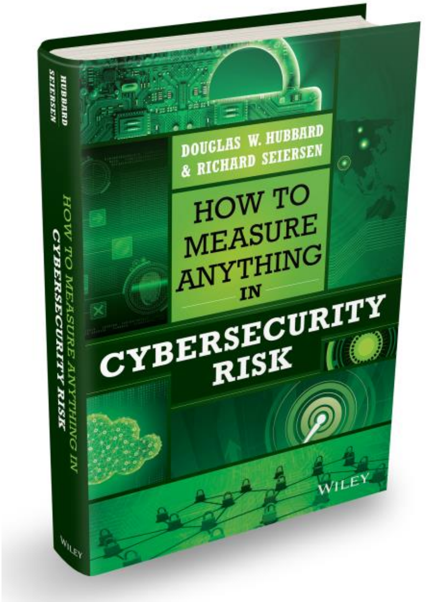
Hubbard
Decision Research

How to Measure Anything in Cybersecurity Risk



Hubbard Decision Research
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Glen Ellyn, Illinois 60137
www.hubbardresearch.com

Introduction

My Co-Author and I

Richard Seiersen

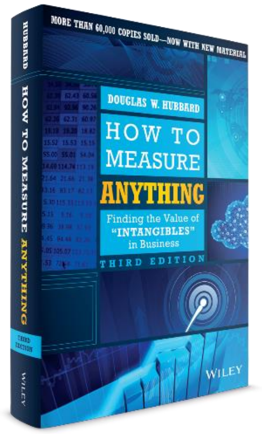
Currently the General Manager of Cybersecurity and Privacy at GE Health Care. Data driven executive with ~20 years experience spanning subject matters in Cyber Security, Quantitative Risk Management, Predictive Analytics, Big Data and Data Science, Enterprise Integrations and Governance Risk and Compliance (GRC). Led large enterprise teams, provided leadership in multinational organizations and tier one venture capital backed start-ups.

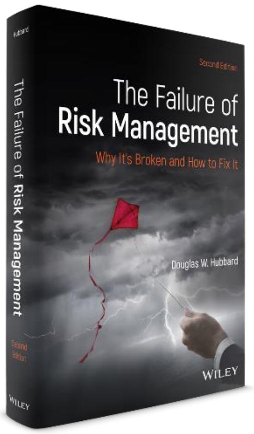
Douglas Hubbard

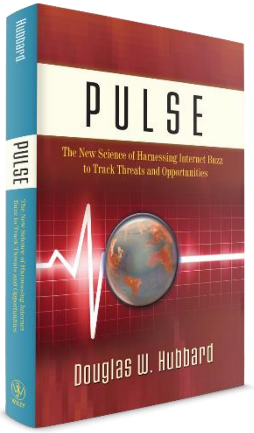
Mr. Hubbard is the inventor of the powerful Applied Information Economics (AIE) method. He is the author of the #1 bestseller in Amazon's math for business category for his book titled ***How to Measure Anything: Finding the Value of Intangibles in Business*** (Wiley, 2007; 3rd edition 2014). His other two books are titled ***The Failure of Risk Management: Why It's Broken and How to Fix It*** (Wiley, 2009; 2nd edition 2020) and ***Pulse: The New Science of Harnessing Internet Buzz to Track Threats and Opportunities*** (Wiley, 2011).

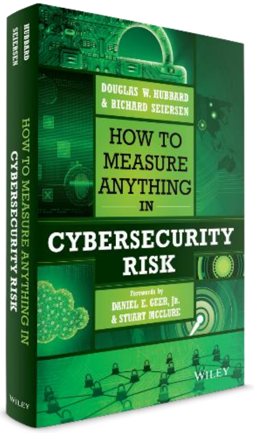
Introduction

My Books



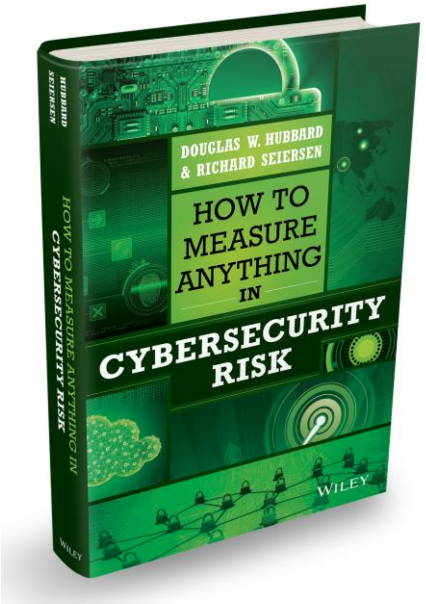






Introduction

How to Measure Anything in Cybersecurity Risk



"For thorough and practical guidance on using probability analysis for cybersecurity decision making, consult the book, How to Measure Anything in Cybersecurity"

Cite: CIS RAM Version 1.0 Center for Internet Security, Risk Assessment Method For Reasonable Implementation and Evaluation of CIS Controls

Introduction

Applied Information Economics

Applied Information Economics (AIE)

Information Technology

- Prioritizing IT portfolios
- Risk of software development
- Value of better information
- Value of better security
- Risk of obsolescence and optimal technology upgrades
- Value of network infrastructure
- Performance metrics for the business value of applications

Business Investments

- Prioritizing R&D in aerospace, biotech, pharma, medical devices and more
- Publishing
- Real estate
- Movie/film project selection

Engineering

- Power and road infrastructure upgrades
- Mining Risks

Government & Non-Profit

- Environmental policy
- Sustainable agriculture
- Procurement methods
- Grants management
- Public schools

Military

- Forecasting battlefield fuel consumption
- Effectiveness of combat training to reduce roadside bomb/IED casualties
- Methods for testing equipment

Introduction

The Biggest Cybersecurity Risk

Question: What is your single biggest risk in cybersecurity?

Answer: How you measure cybersecurity risk.

(This also applies to risk in general.)

Introduction

Topics for Today

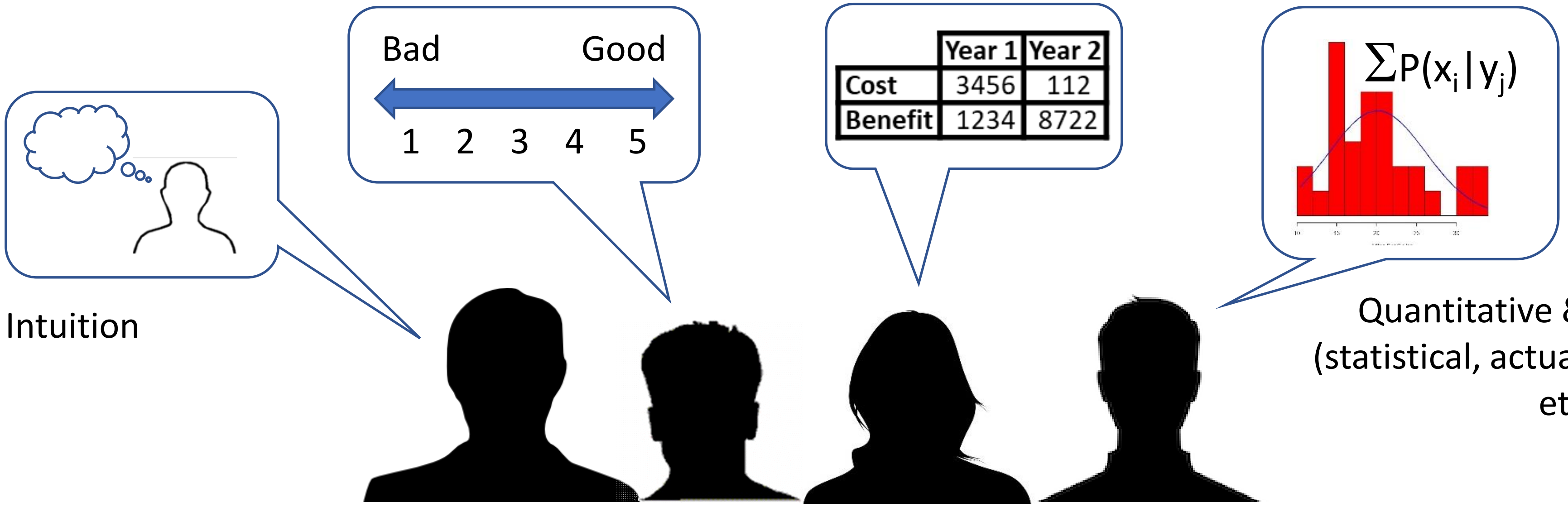
- What is wrong with current methods
- Why there are no immeasurables
- Improving the performance of experts
- Improving models with empirical data
- “Takeaway” and aspirational issues
- Common objections to quantitative methods

Introduction

Types of Measurement Methods

Qualitative
(soft scores or “high/medium/low”)

Accounting-style
Cost estimate analysis
(point estimates, deterministic)



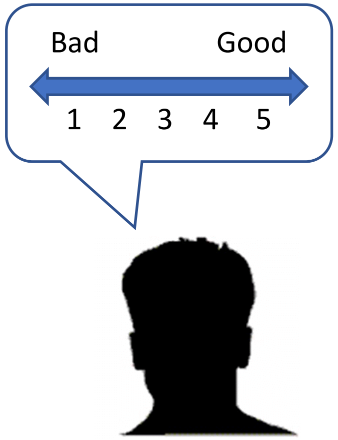
	Year 1	Year 2
Cost	3456	112
Benefit	1234	8722

Expert Intuition

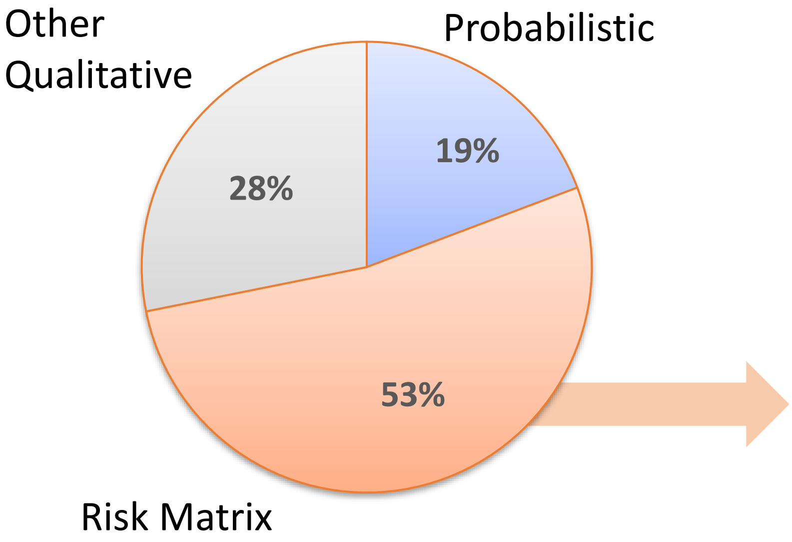
Quantitative & Probabilistic
(statistical, actuarial, simulations, etc.)

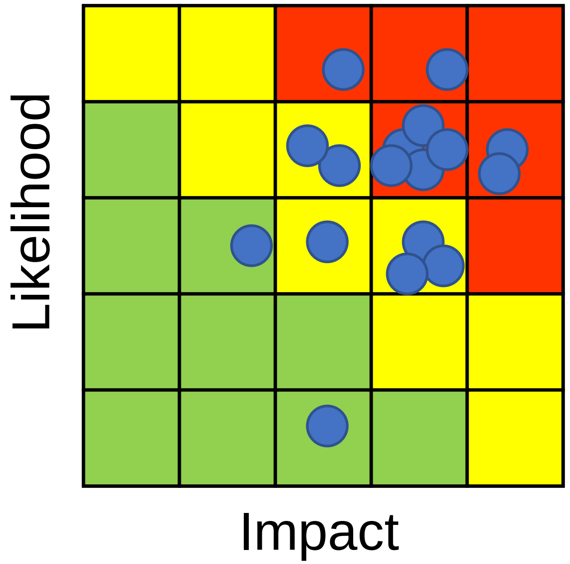
Do “Scores” and “Scales” Work?

The Current Most Popular Method



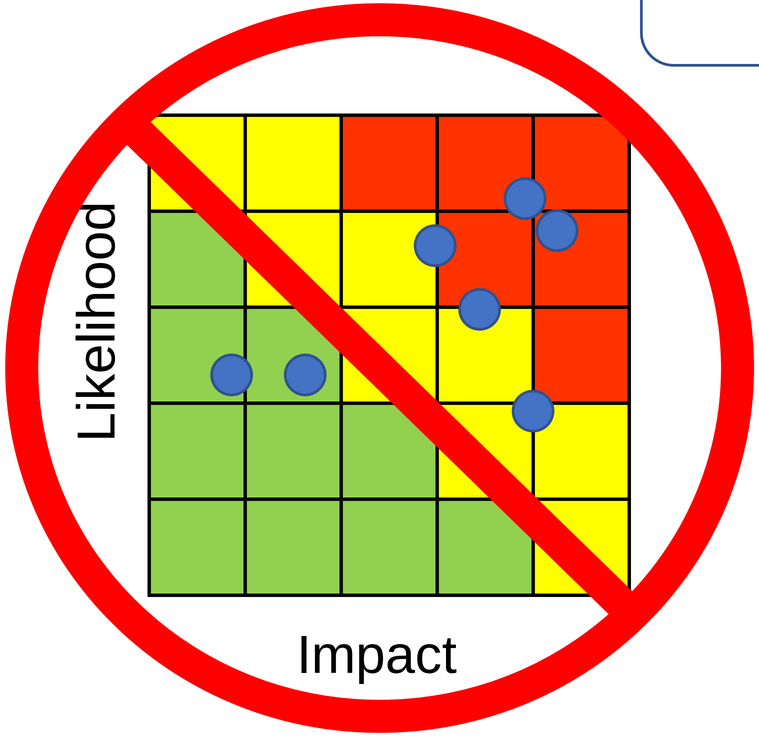
Share of Methods Used in Cybersecurity Risk Assessment





Do “Scores” and “Scales” Work?

The Ubiquitous Risk Matrix



“[Risk Matrices] can be worse than useless”

Risk Analysis 28, no. 2 (2008).

What’s Wrong with Risk Matrices?

L. A. Cox, Jr.

“Risk Matrices should not be used for decisions of any consequence”

Society of Petroleum Engineers Economics &Management 6, no. 2 (April

The Risk of Using Risk Matrices

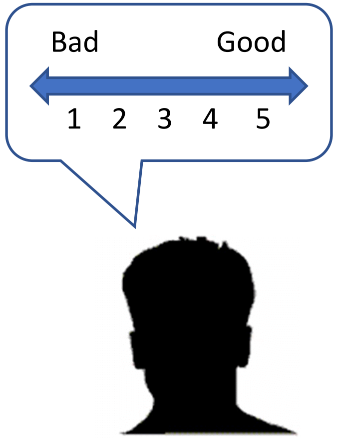
P. Thomas, R. Bratvold, and J. E. Bickel

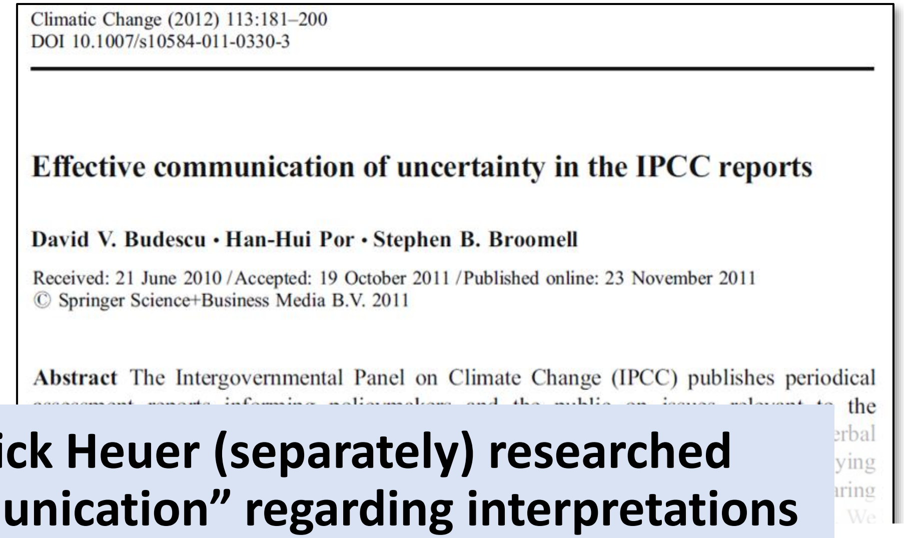
Abstract

The risk matrix (RM) is a widely espoused approach to assess and analyze risks in the oil & gas (O&G) industry. RMs have been implemented throughout that industry and are extensively used in risk-management contexts. This is evidenced by numerous SPE papers documenting RMs as the primary risk management tool. Yet, despite this extensive use, the key question remains to be addressed: Does the use of RMs guide us to make optimal (or even better) risk-management decisions?

Do "Scores" and "Scales" Work?

Unintended consequences of simple scoring methods





Climatic Change (2012) 113:181–200
DOI 10.1007/s10584-011-0330-3

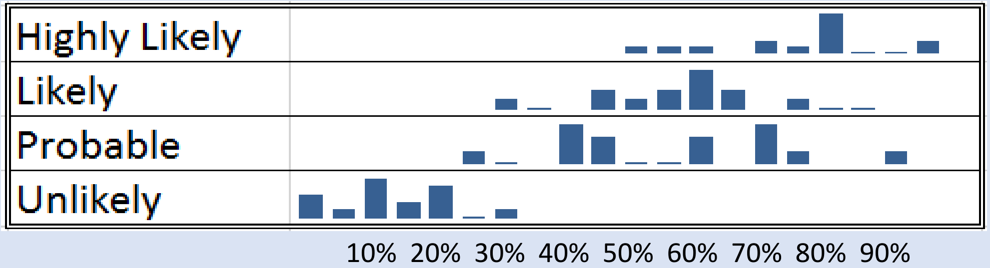
Effective communication of uncertainty in the IPCC reports

David V. Budescu · Han-Hui Por · Stephen B. Broomell

Received: 21 June 2010 / Accepted: 19 October 2011 / Published online: 23 November 2011

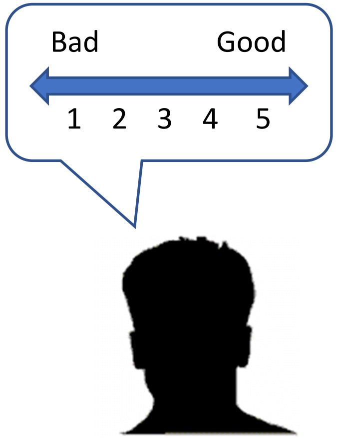
Abstract The Intergovernmental Panel on Climate Change (IPCC) publishes periodical ... the

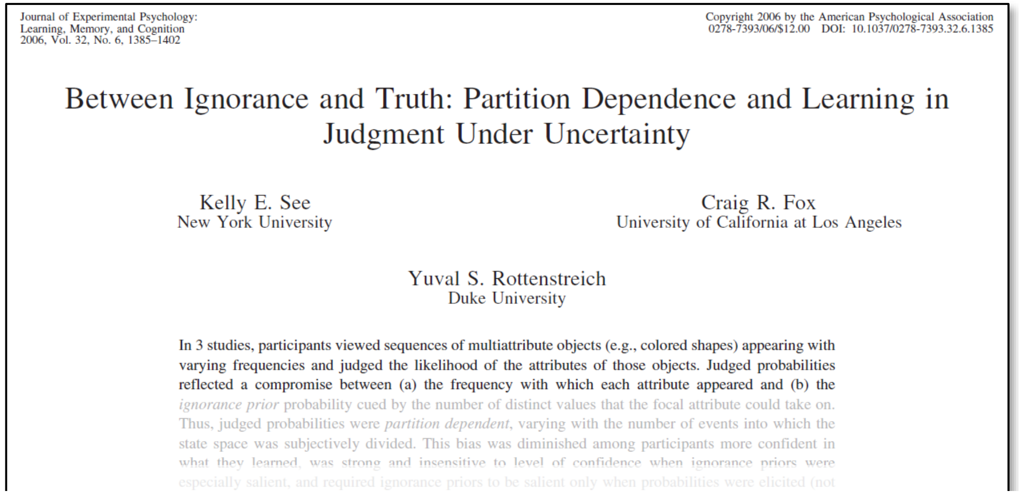
David Budescu and Dick Heuer (separately) researched the "illusion of communication" regarding interpretations of verbal labels for probabilities.



Do “Scores” and “Scales” Work?

Unintended consequences of simple scoring methods





Journal of Experimental Psychology:
Learning, Memory, and Cognition
2006, Vol. 32, No. 6, 1385–1402

0278-7393/06/$12.00 DOI: 10.1037/0278-7393.32.6.1385

Between Ignorance and Truth: Partition Dependence and Learning in Judgment Under Uncertainty

Kelly E. See
New York University

Craig R. Fox
University of California at Los Angeles

Yuval S. Rottenstreich
Duke University

In 3 studies, participants viewed sequences of multiattribute objects (e.g., colored shapes) appearing with varying frequencies and judged the likelihood of the attributes of those objects. Judged probabilities reflected a compromise between (a) the frequency with which each attribute appeared and (b) the *ignorance prior* probability cued by the number of distinct values that the focal attribute could take on. Thus, judged probabilities were *partition dependent*, varying with the number of events into which the state space was subjectively divided. This bias was diminished among participants more confident in what they learned, was strong and insensitive to level of confidence when ignorance priors were especially salient, and required ignorance priors to be salient only when probabilities were elicited (not

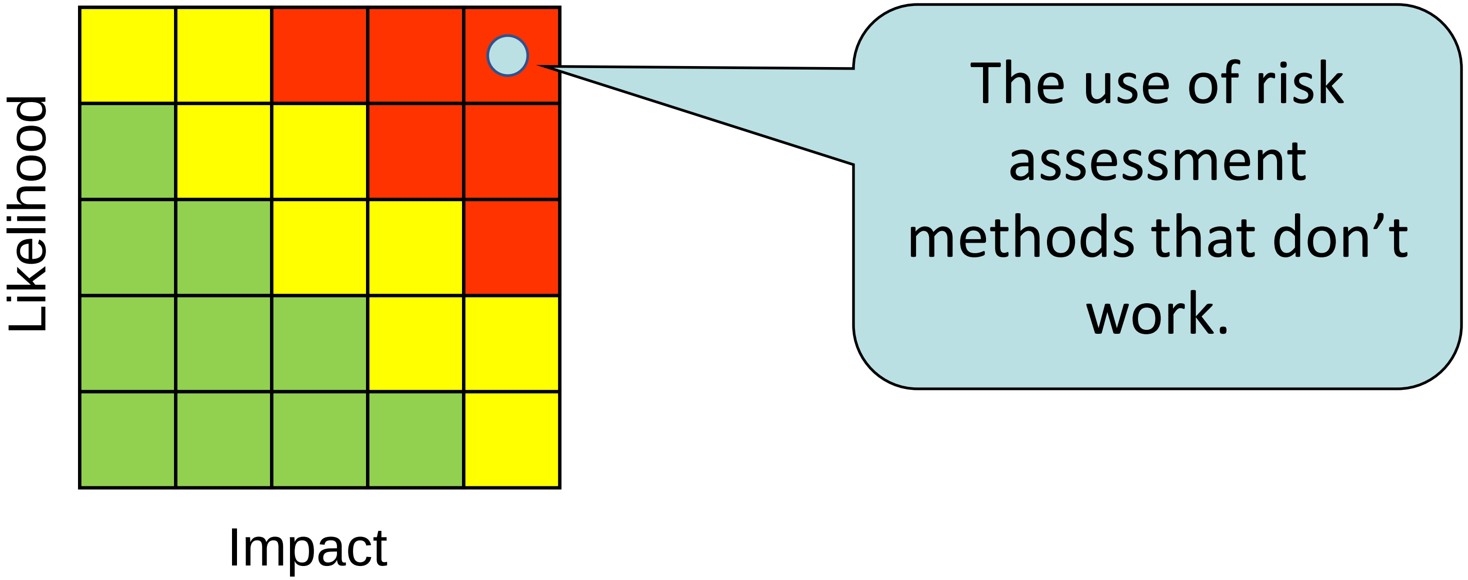
Craig R. Fox showed how arbitrary features of how scales are partitioned effects responses.

Example:

If “1” on a 5-point impact scale means “less than $1 million loss”, the share of that response is affected by the partition of *other* choices.

Do “Scores” and “Scales” Work?

The Only Risk Matrix You Need



The Analysis Placebo

Confidence in decision making methods is detached from performance

Organizational Behavior and Human Decision Processes 107, no. 2 (2008): 97– 105

Journal of Behavioral Decision Making 3, no. 3 (July/ September 1990): 153– 174

Law and Human Behavior 23 (1999): 499– 516.

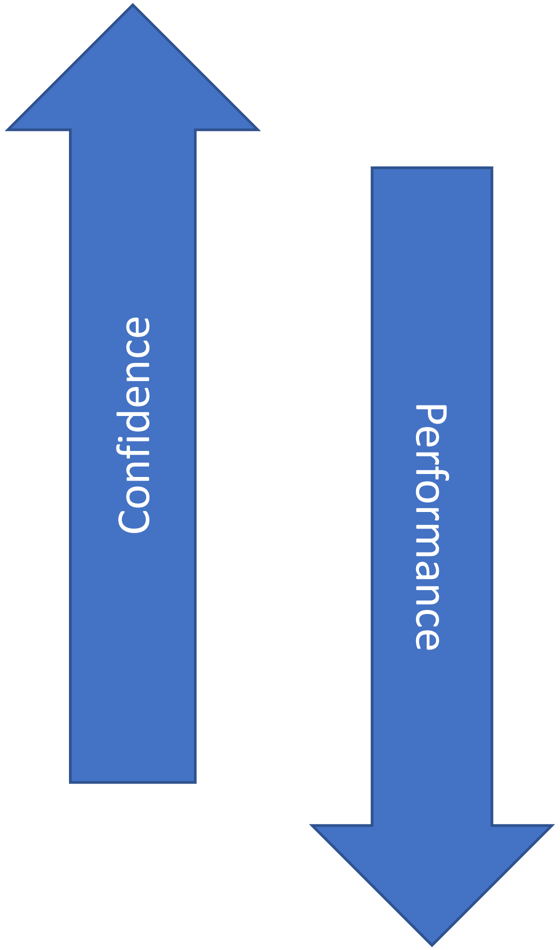
Organizational Behavior and Human Decision Processes 61, no. 3 (1995): 305– 326.

Interaction with Others Increases Decision Confidence but Not Decision Quality: Evidence against Information Collection Views of Interactive Decision Making

Heath and Gonzalez

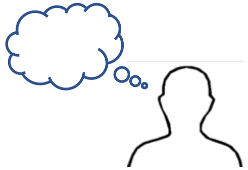
Abstract

We present three studies of *interactive decision making,* where decision makers interact with others before making a final decision alone. Because the theories of lay observers and social psychologists emphasize the role of information collection in interaction, we developed a series of tests of information collection. Two studies



Deciding How to Decide

- Why experience alone may not be enough to make the meta-decision



To learn from experience, you need feedback.

And that feedback has to be *CONSISTENT…*

…IMMEDIATE…

…and UNAMBIGUOUS.

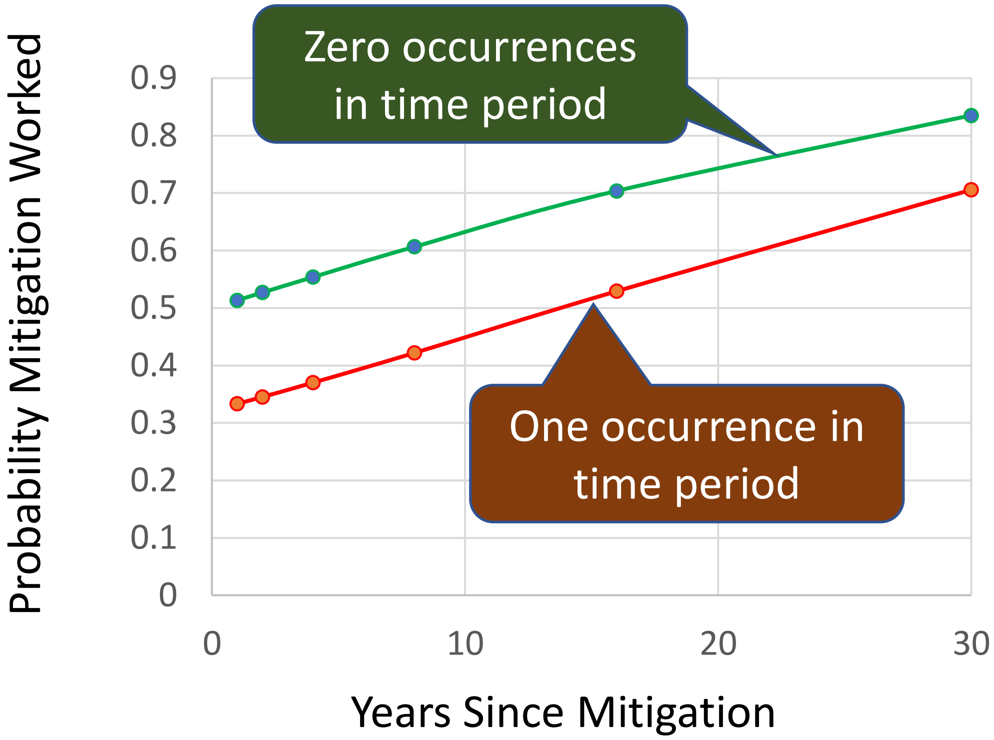
Daniel Kahneman

Gary Klein

Limitations of Direct Experience in Control Effectiveness

A Bayesian Look at Mitigation Assessment Over Time

- Suppose we have an event we assess as having a 10% chance/yr of occurrence.
- We implement a mitigation that we think may reduce that chance to 5%.
- Uncertain of whether the risk will actually be reduced, we give a prior probability that there is a 50% the mitigation works as stated.
- How long do we have to watch our environment to see if the annualized probability went from 10% to 5%?



Solving for the probability a mitigation reduced event likelihood from 10% to 5% per year given number of occurrences in time period.

The Meta Decision

How to Build a Method That Works

- Start with components that work.
- Don't rely on anecdotes, testimonials or claims of "best practices" as evidence of working.
- If you can't answer "What is the probability of losing more than X in the next 12 months due to event Y?" then you aren't doing risk analysis.

A Cybersecurity Survey

2015 Survey: Interesting Connection

Those who said they could "compute the probability of various levels of losses" had about *half the rate of data breaches* as those who could not.

Does your organization compute the probability of various levels of losses?	Average Annual Data Breach Rate
Yes	4.5%
No	9%

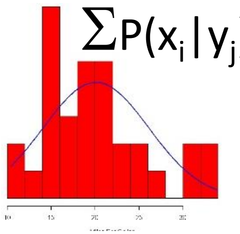
173 responses total

A single survey might still be inconclusive – but it is consistent with other research about the improvement from using quantitative methods.

Experts vs. Algorithms

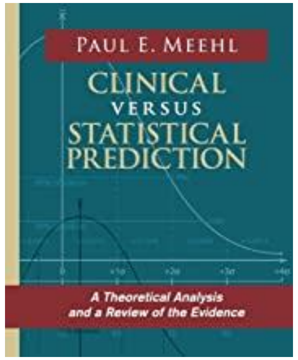
What the research says about statistical methods vs. Subject Matter Experts

$\sum P(x_i|y_j)$

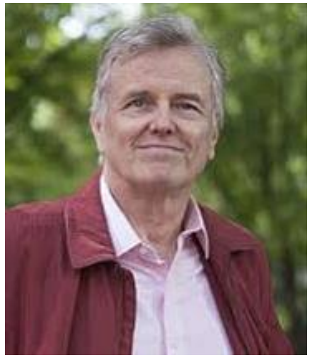


Paul Meehl assessed 150 studies comparing experts to statistical models in many fields (sports, prognosis of liver disease, etc.).

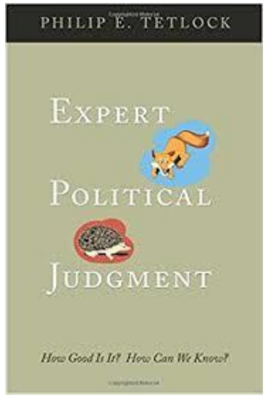
"There is no controversy in social science which shows such a large body of qualitatively diverse studies coming out so uniformly in the same direction as this one."



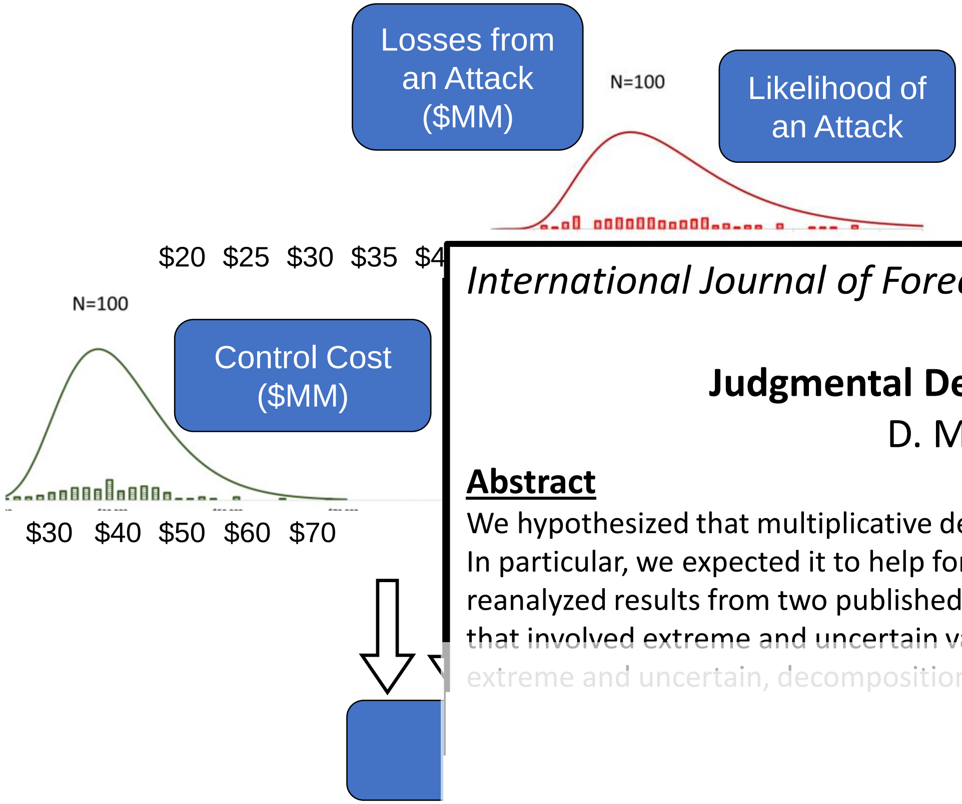
Philip Tetlock tracked a total of over 82,000 forecasts from 284 experts in a 20-year study covering politics, economics, war, technology trends and more.



"It is impossible to find any domain in which humans clearly outperformed crude extrapolation algorithms, less still sophisticated statistical ones."



Monte Carlo: The Decomposition of Uncertainty



Society of Petroleum Engineers (2000)

The Application of Probabilistic and Qualitative Methods to Asset Management Decision Making

G. S. Simpson, F. E. Lamb, J. H. Finch, and N. C. Dinnie

International Journal of Forecasting (1994)

Judgmental Decomposition: When Does It Work?

D. MacGregor, J. S. Armstrong

Abstract

We hypothesized that multiplicative decompositions would improve accuracy only in certain conditions. In particular, we expected it to help for problems involving extreme and uncertain values. We first reanalyzed results from two published studies. Decomposition improved accuracy for nine problems that involved extreme and uncertain values, but for six problems with target values that would not extreme and uncertain, decomposition was not more accurate. Next, we conducted experiments

Conference (2008)

imism in Early Conceptual
nd Schedule Growth

r, R. Bitten, and D. Emmons

nators are often criticized for
conceptual design stage. The final
t launch, however, can be

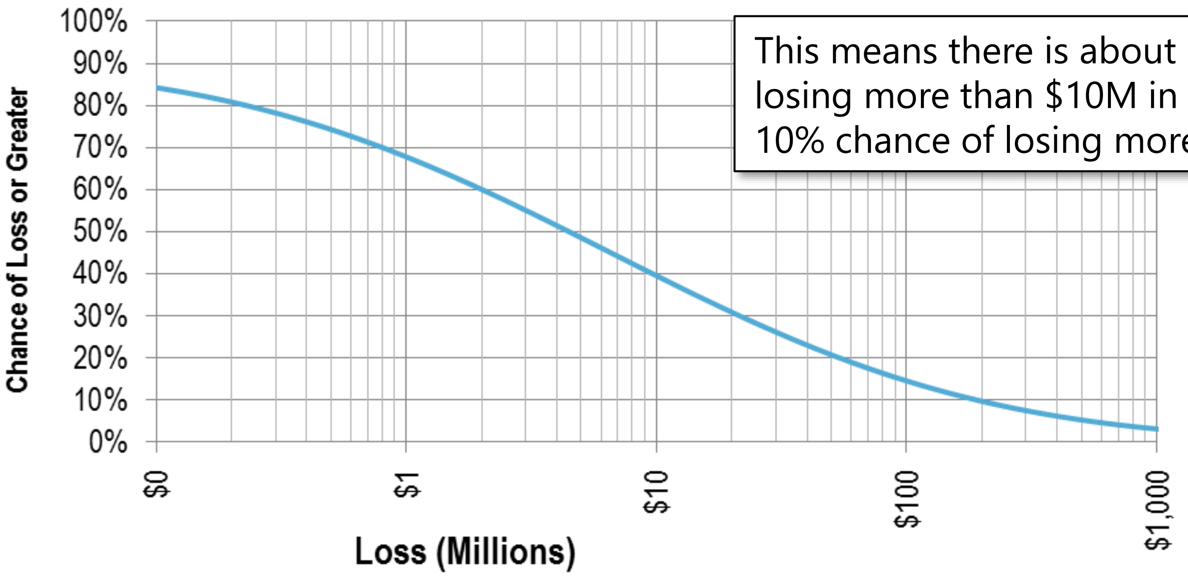
What Measuring Risk Looks Like

The Loss Exceedance Curve

What if we could measure risk more like an actuary? For example, "The probability of losing more than $10 million due to security incidents in 2016 is 16%."

What if we could prioritize security investments based on a "Return on Mitigation"?

	Expected Loss/Yr	Cost of Control	Control Effectiveness	Return on Control	Action
DB Access	$24.7M	$800K	95%	2,832%	Mitigate
Physical Access	$2.5M	$300K	99%	727%	Mitigate
Data in Transit	$2.3M	$600K	95%	267%	Mitigate
Network Access Control	$2.3M	$400K	30%	74%	Mitigate
File Access	$969K	$600K	90%	45%	Monitor
Web Vulnerabilities	$409K	$800K	95%	-51%	Track
System Configuration	$113K	$500K	100%	-77%	Track

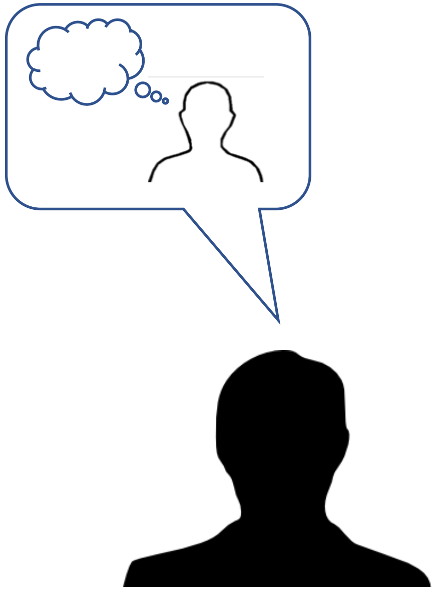


This means there is about a 40% chance of losing more than $10M in a year and about a 10% chance of losing more than $200M.

The Method of Measurement

Why Does Our Risk Tolerance Change?

Decision makers are also inconsistent regarding their own aversion to risk.



Neuron Vol. 47, (2005): 763–770

The Neural Basis of Financial Risk Taking

Camelia M. Kuhnen and Brian Knutson

Journal of Personality and Social Psychology
2001, Vol. 81, No. 1, 146–159

0022-3514/01/$5.00 DOI: 10.1037//0022-3514.81.1.146

Fear, Anger, and Risk

Jennifer S. Lerner
Carnegie Mellon University

Dacher Keltner
University of California, Berkeley

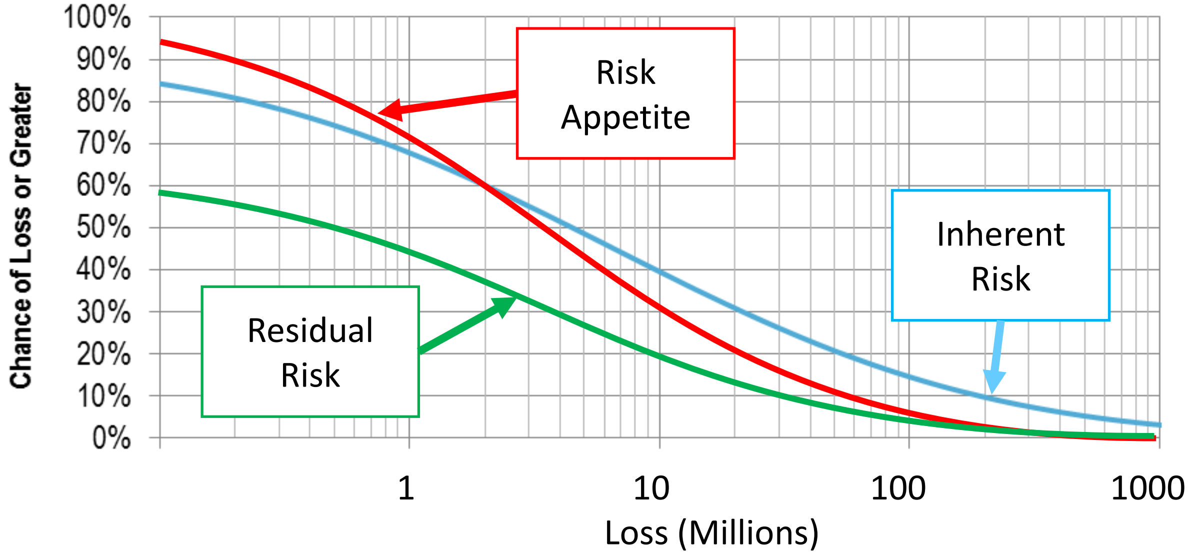
ner & D. Keltner, 2000), the authors predicted
k perception. Whereas fearful people expressed
people expressed optimistic risk estimates and
for naturally occurring and experimentally
eople more closely resembled those of happy

Factor	Risk Aversion
Being around smiling people	↓
Recalling an event causing fear	↑
Recalling an event causing anger	↓
A recent win in an unrelated decision	↓
A recent loss in an unrelated decision	↑

A Version of Risk Tolerance

The Loss Exceedance Curve

Unambiguous risk lets us have unambiguous risk tolerance.

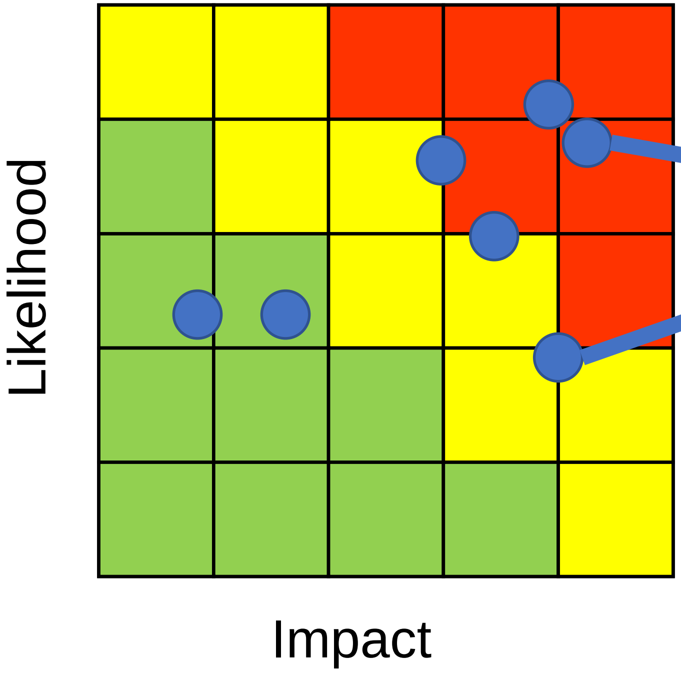


What Measuring Risk Looks Like

A Simple "One-For-One Substitution"

Each of these examples can be found on

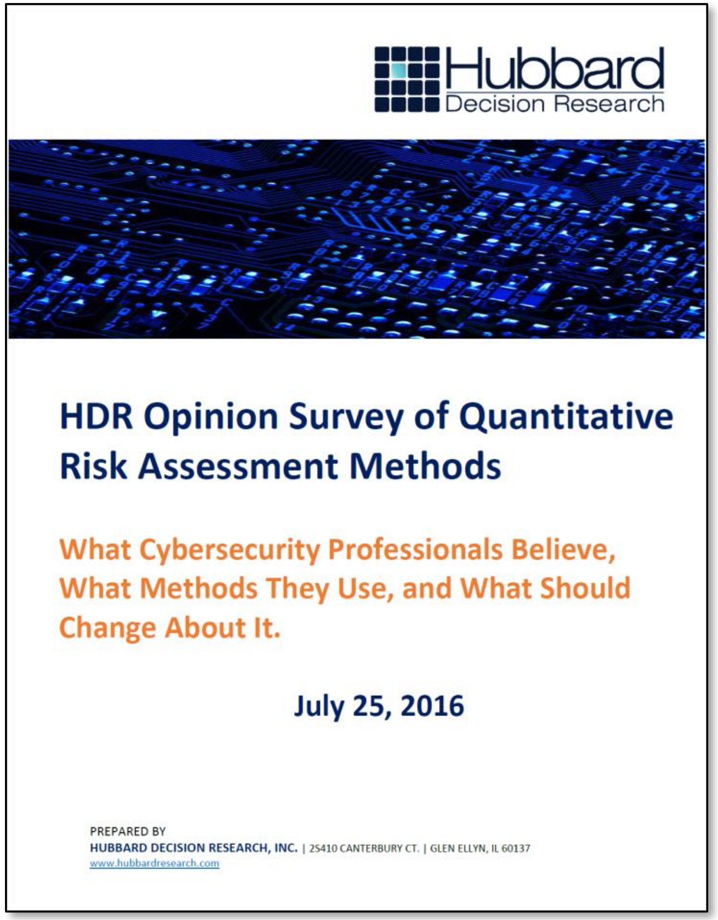
www.howtomeasureanything.com/cybersecurity



Event	Event Probability (per Year)	Impact (90% Confidence Interval)		Random Result (zero when the event did not occur)
		Lower Bound	Upper Bound	
AA	.1	$50,000	$500,000	0
AB	.05	$100,000	$10,000,000	$8,456,193
AC	.01	$200,000	$25,000,000	0
AD	.03	$100,000	$15,000,000	0
AE	.05	$250,000	$30,000,000	0
AF	.1	$200,000	$2,000,000	0
AG	.07	$1,000,000	$10,000,000	$2,110,284
AH	.02	$100,000	$15,000,000	0
⇩	⇩	⇩	⇩	⇩
ZM	.05	$250,000	$30,000,000	0
ZN	.01	$1,500,000	$40,000,000	0
			Total:	$23,345,193

Obstacles to Better Decisions

Acceptance of quantitative methods vs. statistical literacy: survey results


Hubbard
Decision Research

HDR Opinion Survey of Quantitative Risk Assessment Methods

What Cybersecurity Professionals Believe, What Methods They Use, and What Should Change About It.

July 25, 2016

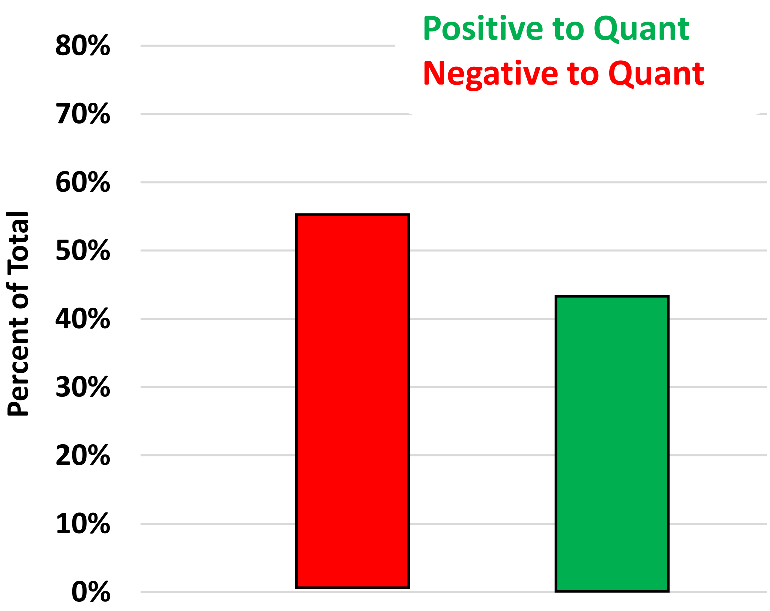
PREPARED BY
HUBBARD DECISION RESEARCH, INC. | 25410 CANTERBURY CT. | GLEN ELLYN, IL 60137
www.hubbardresearch.com

- 173 cybersecurity were surveyed regarding opinions about quantitative risk analysis methods in their fields.
- There was a bit more resistance to quantitative methods than acceptance.
- They also took a quiz on basic statistical literacy.
- When we looked only at those responses that scored above the median on statistical literacy, there was a lot more acceptance.
- When we look at those that did not score above the median, resistance was much higher.
- Those who answered “I don’t know” on stats literacy questions were not the most resistant to quantitative methods – it was those who thought they did know and were wrong.

So Why Don’t We Use More Quantitative Methods?

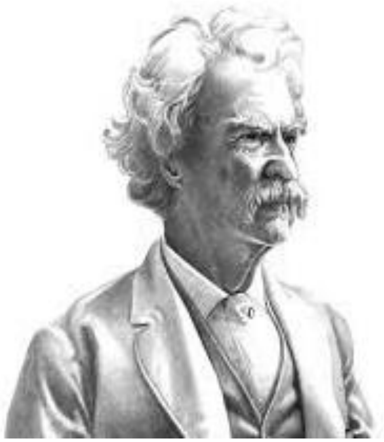
The Main Obstacle to Quantitative Methods

Another finding in the same survey: Strong opinions against “quant” are associated with poor stats understanding.



“It’s not what you don’t know that will hurt you, it’s what you know that ain’t so.”

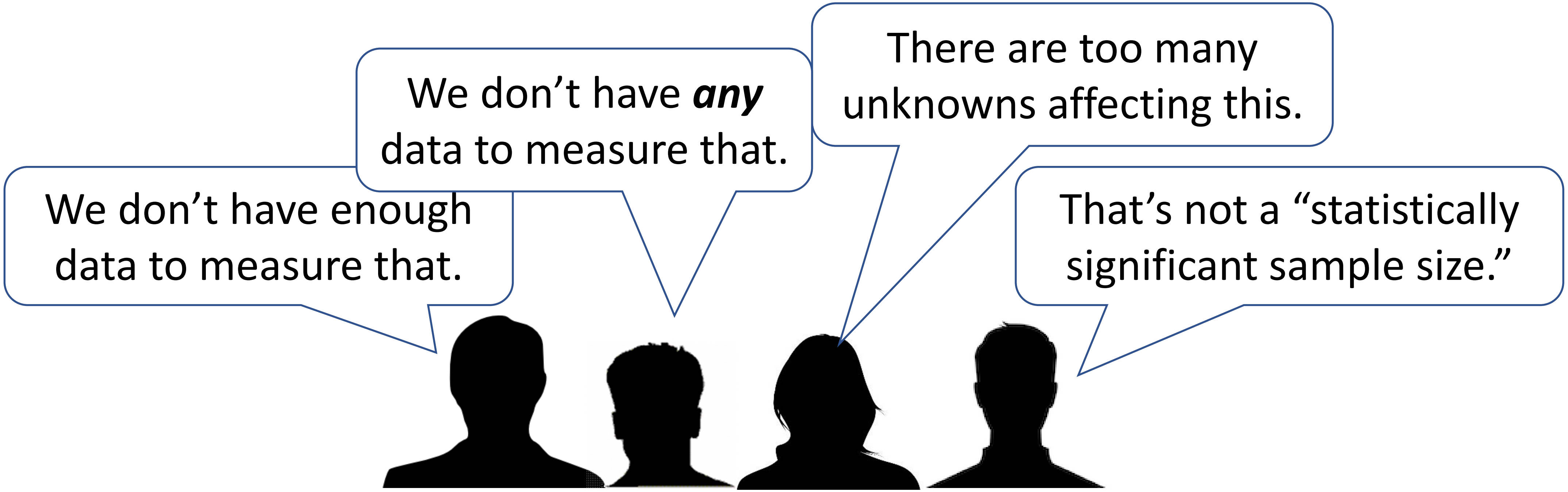
Mark Twain



So Why Don’t We Use More Quantitative Methods?

Commonly stated reasons for not using quantitative methods

Have you heard (or said) any of these?



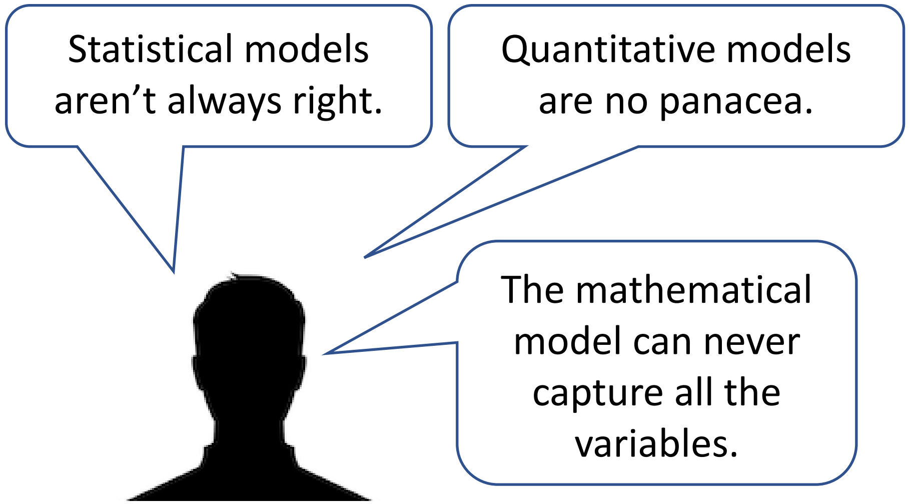
So Why Don’t We Use More Quantitative Methods?

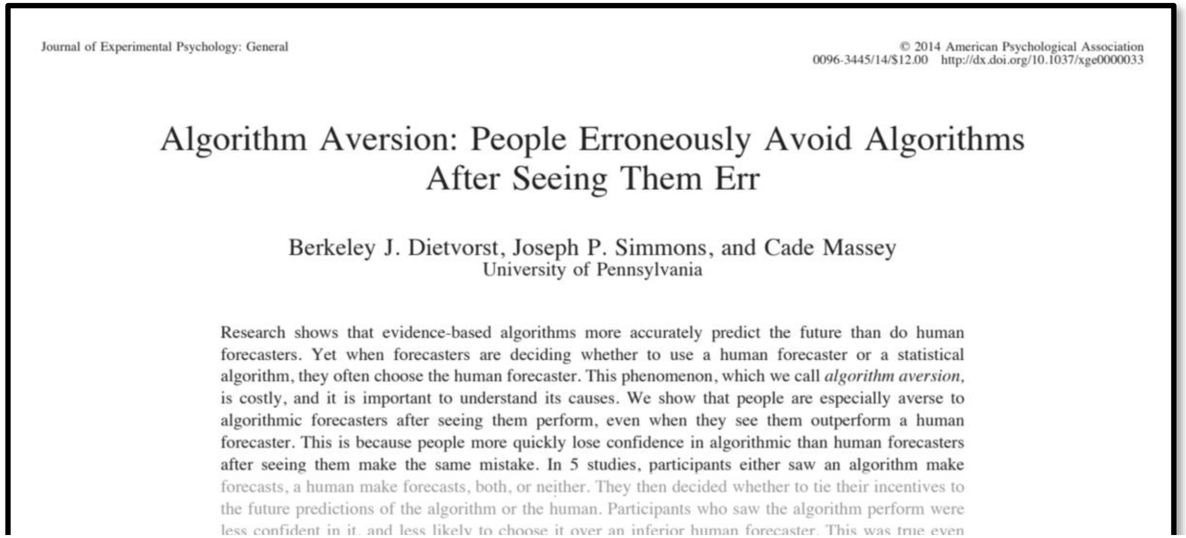
Commonly stated reasons for not using quantitative methods

The implied (and unjustified) conclusion from each of these is….

Irrational Bias Against Algorithms

A Double Standard





Journal of Experimental Psychology: General

0096-3445/14/$12.00 http://dx.doi.org/10.1037/xge0000033

Algorithm Aversion: People Erroneously Avoid Algorithms After Seeing Them Err

Berkeley J. Dietvorst, Joseph P. Simmons, and Cade Massey
University of Pennsylvania

Research shows that evidence-based algorithms more accurately predict the future than do human forecasters. Yet when forecasters are deciding whether to use a human forecaster or a statistical algorithm, they often choose the human forecaster. This phenomenon, which we call *algorithm aversion*, is costly, and it is important to understand its causes. We show that people are especially averse to algorithmic forecasters after seeing them perform, even when they see them outperform a human forecaster. This is because people more quickly lose confidence in algorithmic than human forecasters after seeing them make the same mistake. In 5 studies, participants either saw an algorithm make forecasts, a human make forecasts, both, or neither. They then decided whether to tie their incentives to the future predictions of the algorithm or the human. Participants who saw the algorithm perform were less confident in it, and less likely to choose it over an inferior human forecaster. This was true even

Don't commit the classic

"Beat the Bear" fallacy.

Exsupero Ursus

The Three Misconceptions Behind Any Perceived "Immeasurable"

The Illusions of Immeasurability

CONCEPT of Measurement	The definition of measurement itself is widely misunderstood.
OBJECT of Measurement	The thing being measured is not well defined.
METHOD of Measurement	Many procedures of empirical observation are misunderstood.

The Three Misconceptions Behind Any Perceived "Immeasurable"

The Concept of Measurement

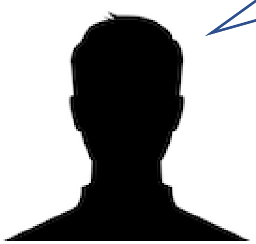
CONCEPT of Measurement	The definition of measurement itself is widely misunderstood.
OBJECT of Measurement	The thing being measured is not well defined.
METHOD of Measurement	Many procedures of empirical observation are misunderstood.

The Concept of Measurement

What Measurement Really Means

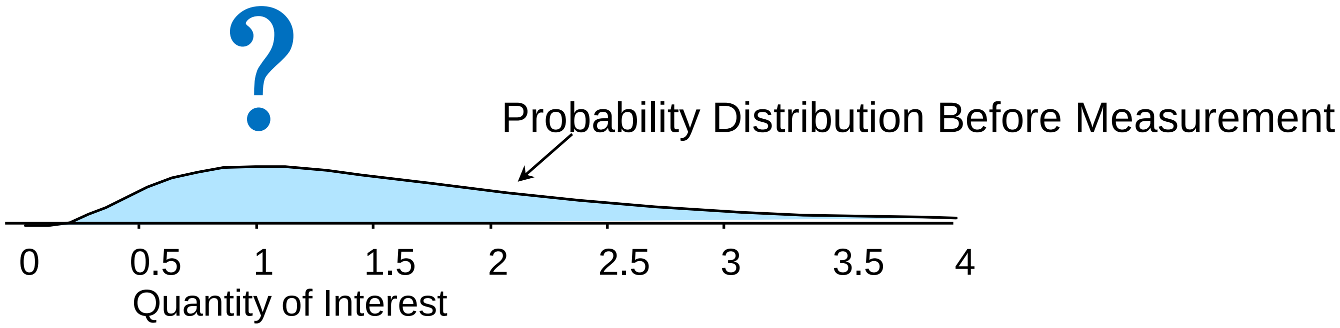
There is no way to put an exact value on this.

There are too many unknowns to measure this.



It's not a point value.

Measurement: a quantitatively expressed reduction in uncertainty based on observation.

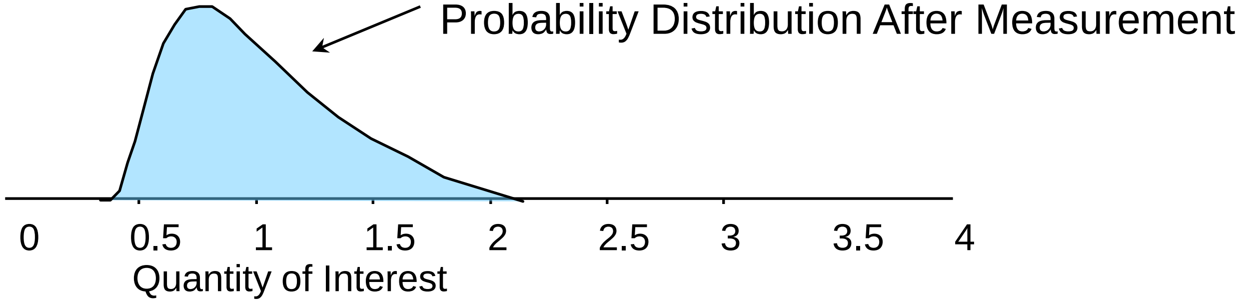


The Concept of Measurement

What Measurement Really Means

It’s not a point value.

Measurement: a quantitatively expressed reduction in uncertainty based on observation.



The Concept of Measurement

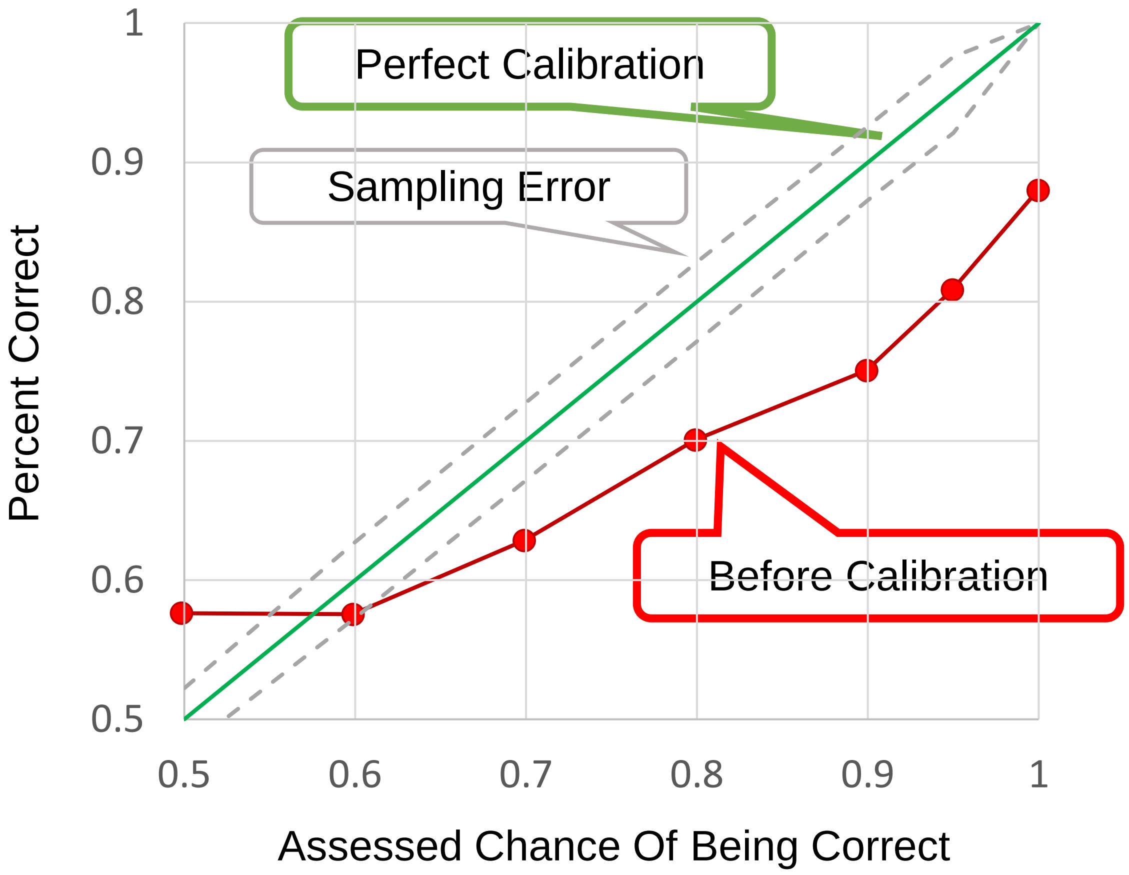
What the research says about Subject Matter Experts

"Overconfident professionals sincerely believe they have expertise, act as experts and look like experts. You will have to struggle to remind yourself that they may be in the grip of an illusion."

Daniel Kahneman, Psychologist, Economics Nobel

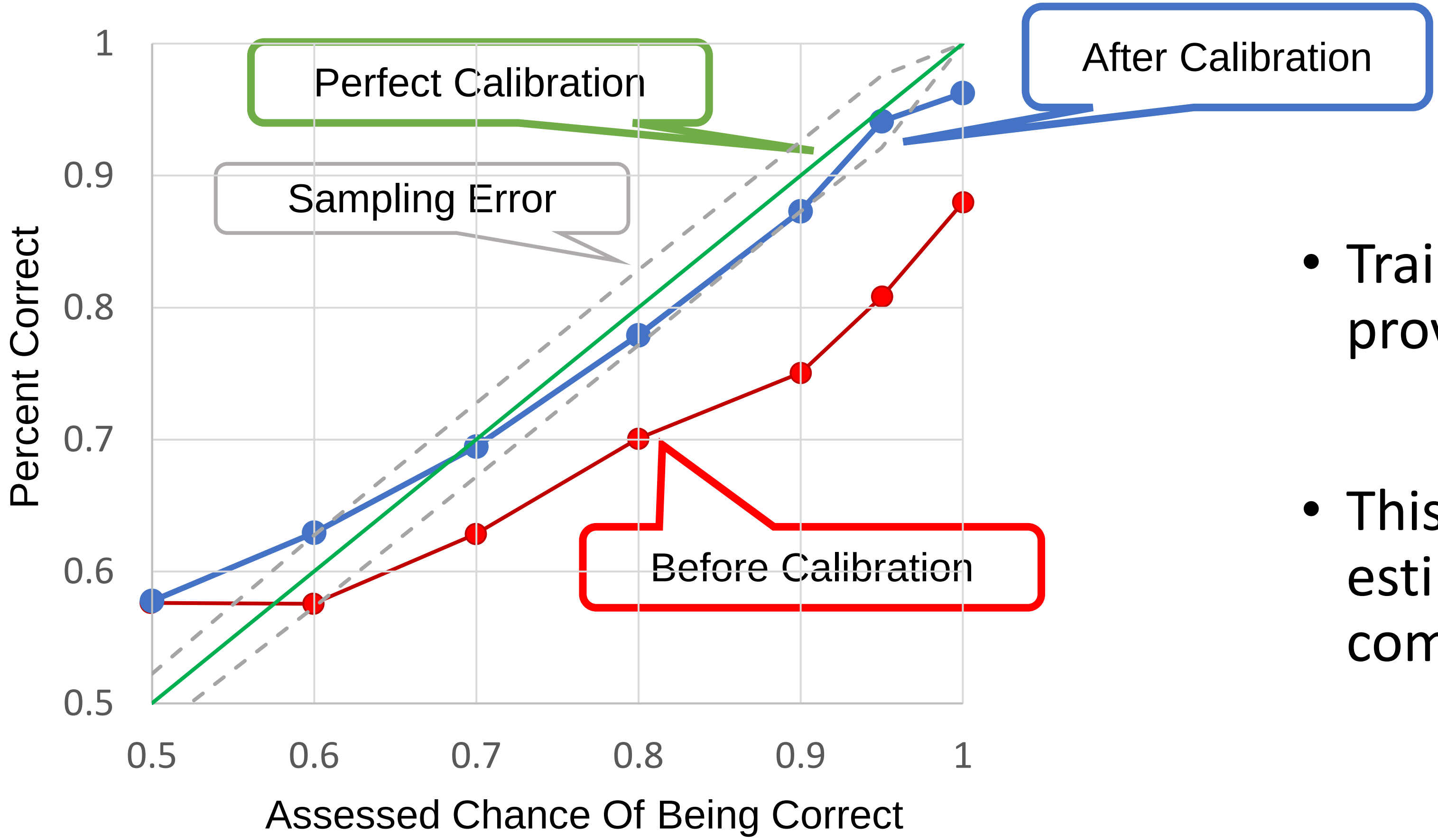
- Decades of studies show that most managers are statistically "overconfident" when assessing their own uncertainty.
- Studies also show that measuring *your own* uncertainty about a quantity is a general skill that <u>can be taught</u> with a ***measurable*** improvement.

Measuring Overconfidence



- We've trained over 2,000 individuals in subjective estimation of probabilities.
- Almost everyone is overconfident on the first benchmark test.

Measuring Calibration Training

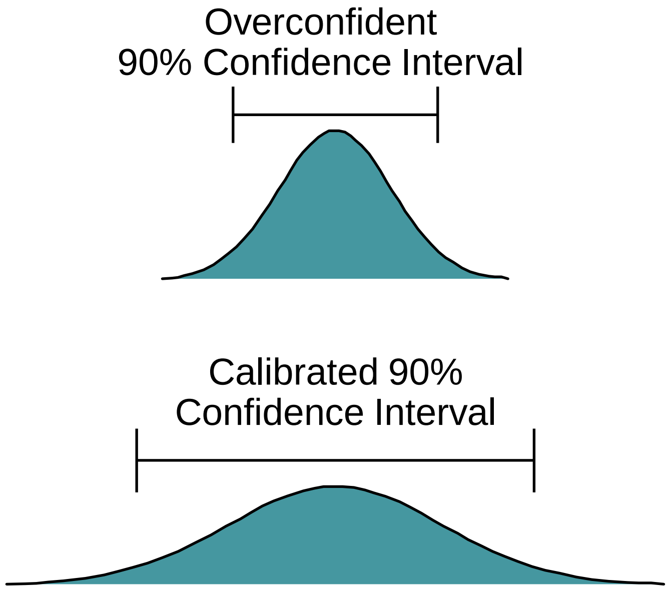


- Training improves the ability to provide calibrated estimates.
- This improves real-world estimates after training is complete.

Overconfidence in Ranges

The same training methods apply to the assessment of uncertain ranges for quantities like the duration of project, the impact of a major data breach, etc.

Group	Subject	% Correct (target 90%)
Harvard MBAs	General Trivia	40%
Chemical Co. Employees	General Industry	50%
Chemical Co. Employees	Company-Specific	48%
Computer Co. Managers	General Business	17%
Computer Co. Managers	Company-Specific	36%
AIE Seminar (before training)	General Trivia & IT	35%-50%
AIE Seminar (after training)	General Trivia & IT	~90%



The "Equivalent Bet"

If you say something is 80% likely, which game would you rather play?

- **Game A**: Win $1,000 if the event happens.
- **Game B**: Spin a dial with a chance to win $1,000 equal to your stated confidence.

(Assume no difference in time of payments)

Calibration Exercise: Ranges

For the following questions, provide a range (an upper and lower bound) that you are 90% certain contains the correct answer:

Questions	Lower Bound	Upper Bound
Napoleon Bonaparte was born what year?		
What is the average weight of an adult male African elephant (tons)?		
The Coliseum in Rome held how many spectators?		
How many countries were in NATO in 2010?		
In what year did Newton publish the Laws of Gravitation?		

The Concept of Measurement

Calibration Exercise: True/False

For each statement below, answer whether you believe it is true or false and provide a percentage confidence that your answer is correct. Confidence is any value between 50% ("no idea") to 100% (certainty).

Questions	True or False?	% Confidence
Brazil has a larger population than Spain.		
A hockey puck will fit in a golf hole.		
The Yangtze River is the longest river in Asia.		
Mars is always further away from Earth than Venus is from Earth.		
The movie *Titanic* still holds the record for box office receipts in the first six weeks.		

The Concept of Measurement

Calibration Answers

	Lower Bound
Napoleon Bonaparte was born what year?	1769
What is the average weight of an adult male African elephant (tons)?	3.5 tons
The Coliseum in Rome held how many spectators?	50,000
How many countries were in NATO in 2010?	28
In what year did Newton publish the Laws of Gravitation?	1687

	True or False?
Brazil has a larger population than Spain.	True
A hockey puck will fit in a golf hole.	True
The Yangtze River is the longest river in Asia.	True
Mars is always further away from Earth than Venus is from Earth.	False
The movie Titanic still holds the record for box office receipts in the first six weeks.	False

The Three Misconceptions Behind Any Perceived "Immeasurable"

The Object of Measurement

CONCEPT of Measurement	The definition of measurement itself is widely misunderstood.
OBJECT of Measurement	The thing being measured is not well defined.
METHOD of Measurement	Many procedures of empirical observation are misunderstood.

The Object of Measurement

The Importance of Defining a Measurement

- If a thing seems like an immeasurable “intangible” it may just be ill-defined.
- Often, if we can define what we mean by a certain “intangible” we find ways to measure it.
- Examples: Brand image, Security, Safety, etc.

The Object of Measurement

Clarifying the Problem

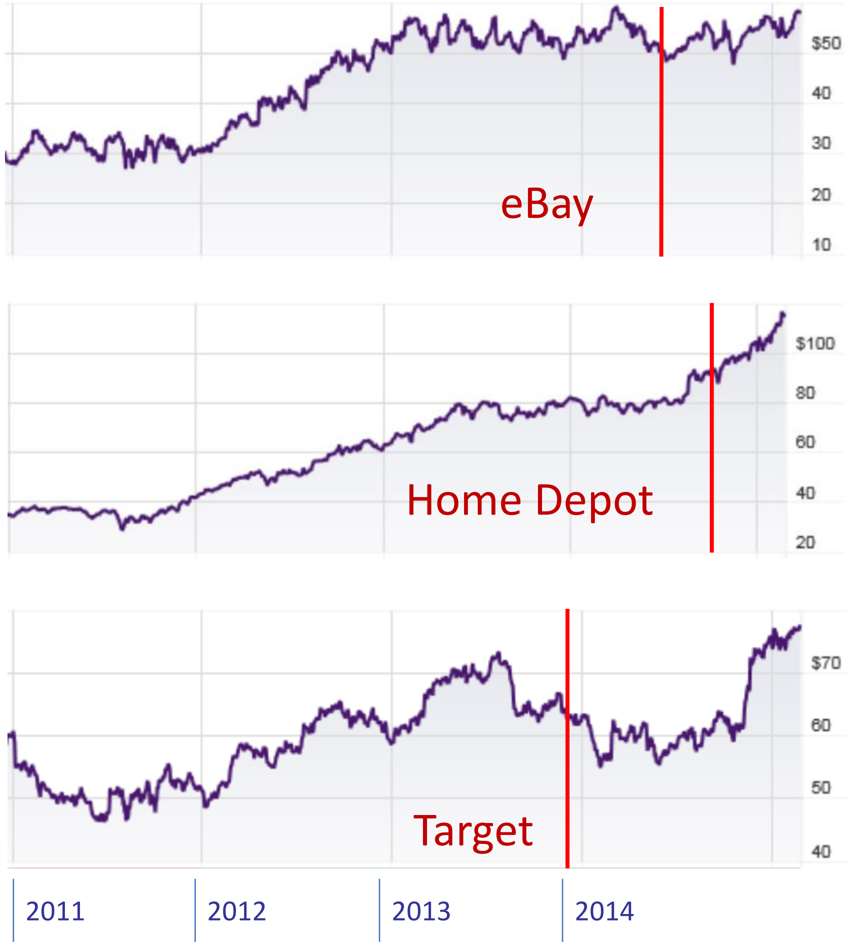
1. Why do you care? (What decision could depend on the outcome of this measurement?)
2. What do you see when you see more of it? (Describe it in terms of observable consequences, then units of measure.)
3. How much do you know about it now?
4. At what point will the value make a difference?
5. How much is additional information worth?

If you can answer the first three, you can usually compute the last two.

The Object of Measurement

Measurement Challenge: Reputation Damage

- One of the perceived most difficult measurements in cybersecurity is damage to reputation.
- Trick: *There is no such thing as a “secret” damage to reputation!*
- How about comparing stock prices after incidents? (That’s all public!)
- So what is the *REAL* damage?
    - Legal liabilities,
    - Customer outreach
    - “Penance” projects (security overkill)
- The upshot, damage to reputation actually has available information and easily observable measured costs incurred to *avoid* the bigger damages!



The Three Misconceptions Behind Any Perceived "Immeasurable"

The Method of Measurement

CONCEPT of Measurement	The definition of measurement itself is widely misunderstood.
OBJECT of Measurement	The thing being measured is not well defined.
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Another Small Sample Example

THE *URN OF MYSTERY* PROBLEM

There is a warehouse full of thousands of urns.

Each urn is filled with over a million marbles, each of which are red or green.

The proportion of red marbles in each urn is unknown – it could be anything between 0% and 100% and all possibilities are equally likely.

Questions:
If you randomly select a single marble from a randomly selected urn, what is the chance it is red?
If the marble you draw is red, what is the chance the majority of marbles are red?
If you draw 8 marbles and all are green, what is the chance that the next one you draw will be red?

The Method of Measurement

Intuitions About Samples Are Wrong

- There are widely held misconceptions about probabilities and statistics – especially if they vaguely remember some college stats.
- These misconceptions lead many experts to believe they lack data for assessing uncertainties or they need some ideal amount before anything can be inferred.

"Our thesis is that people have strong intuitions about random sampling…these intuitions are wrong in fundamental respects...[and] are shared by naive subjects and by trained scientists"
Amos Tversky and Daniel Kahneman, Psychological Bulletin, 1971

Summary

Final Thoughts

It's Been Measured Before	• Important topics have often been measured already..
You Have More Data Than You Think	• Define a reference class – don't commit the reference class fallacy.
You Need Less Data Than You Think	• Question your intuition about how and whether messy and incomplete data is.

Example Spreadsheets for many of the calculations mentioned can be found at www.howtomeasureanything.com.

The Method of Measurement

Improving Expert Judgement

- Calibration of experts for overconfidence and inconsistency is a start.
- Decomposition tends to further improve expert estimates.
- We can leverage these facts for making improved models even without other recorded, empirical data (adding that comes next).

The Method of Measurement

Informative Decompositions

Informative decompositions use what you know or data you can get to improve estimates in models.

Informative Decompositions:

- **Systems**: You have fairly detailed knowledge of your applications, what data they have and the hardware it runs on. Some of the parameters of these systems would change your estimate of a risk.
- **Types of Impacts**: You separate confidentiality, integrity and availability events. You have an idea of business volumes like sales and other processes. If a breach or outage occurred, you can describe something about the consequences.
- **Staff**: You have knowledge of the number of employees, device loss rates, and some knowledge of what data they may have.
- **Vendors & Customers**: You know who the parties you interact with and you have some knowledge about them.
- **Insurance:** Any cyber-insurance will have detailed language regarding limitations, exclusions, etc.

The Method of Measurement

Bayesian Methods

- "Bayesian" methods in statistics use new information to update prior knowledge.

Bayes Theorem: $$P(X|Y) = \frac{P(X)P(Y|X)}{P(Y)} = \frac{P(X)P(Y|X)}{\sum_i P(Y|X_i)\,P(X_i)}$$

P(X) = the probability of X

P(X|Y) = the probability of X given the condition Y

Σ $P(Y \mid X_i)\,P(X_i)$ = the sum of the probability of Y under each possible condition

- The Simplest Measurement Method — It turns out that calibrated people are already mostly "instinctively Bayesian".
  - Assess your initial subjective uncertainty with a calibrated probability
  - Gather and study new information
  - Give another subjective calibrated probability assessment

The Method of Measurement

The Rule of Succession

Danny Kahneman

A reference class is a population from which you draw observations of events to determine their frequency. Your "reference class" is much larger than you.

You can start by making as few assumptions as possible – your "baseline" uses only your reference class.

Pierre-Simon Laplace
1749-1827

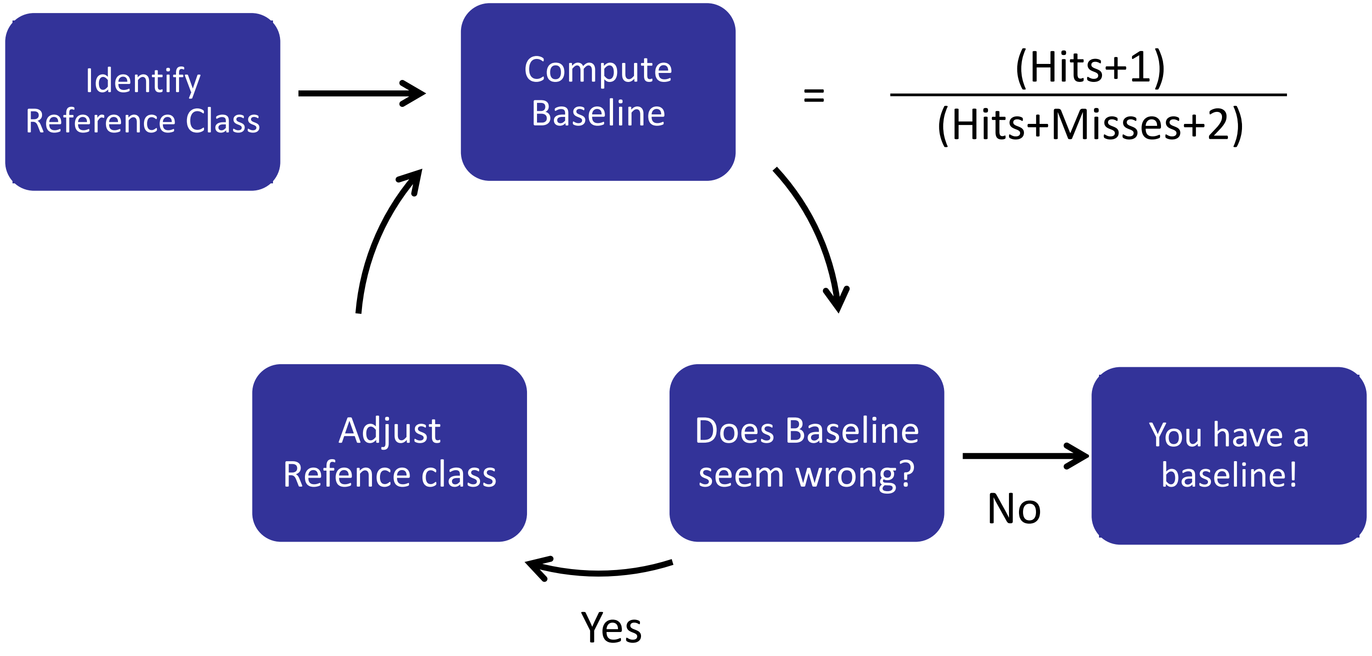
- Laplace's "rule of succession": Given a population of reference class, like company-years, where some number of events occurred:

  - Chance of X (per year, per draw, etc.) =(1+hits)/(2+hits+misses)

The Method of Measurement

Computing Baseline Probabilities

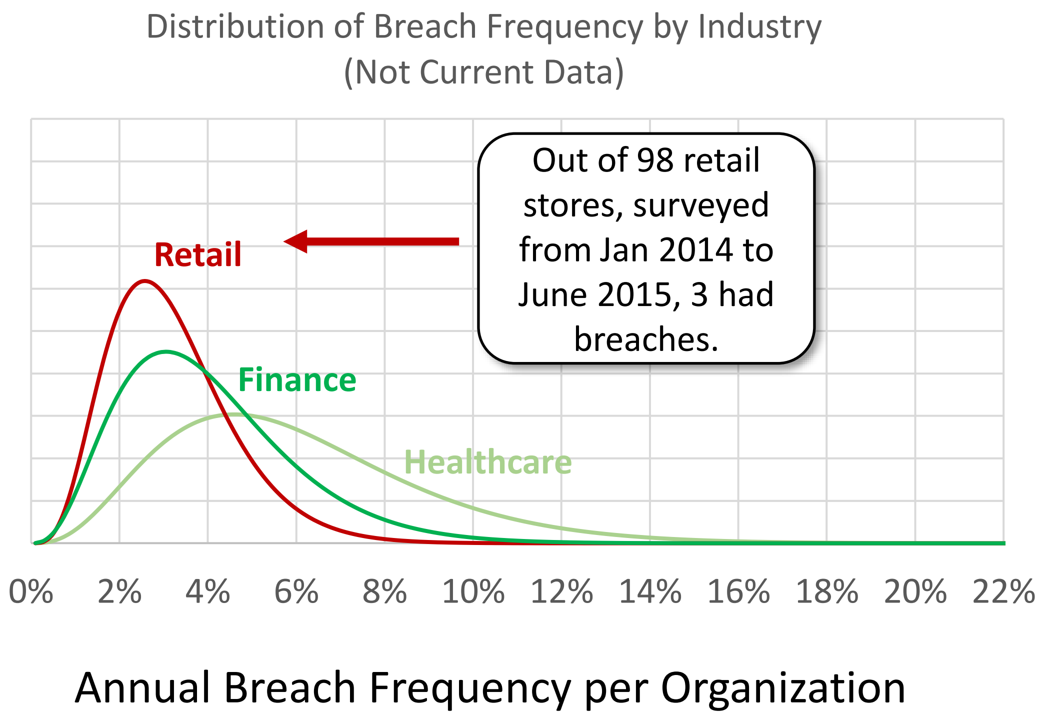
If the baseline seems too low or too high, it is probably because your reference class is larger than you first thought or because you believe a subset of it is more relevant.



The Method of Measurement

Estimating Breach Rate w/History

- You have relatively few examples of major, reported breaches in each industry.
- There is a statistical method for estimating the frequency of breaches based on small samples.
- Spreadsheet for this at www.howtomeasureanything.com/cybersecurity.



The Method of Measurement

Other Handy “Naïve Estimators”

Mean of a beta distribution is alpha/(alpha+beta).

alpha=observed hits +1, beta=observed misses+1

These are all the means of beta distributions to different questions. The alpha and beta are “hits and misses” but with one “free” hit and miss.

The chance of seeing an event that happened x times in y years in z organizations

=(1+x)/(2+yz)

The chance that the next event will be worse than previous events:

=1/(1+n)

Making Use of Publicly Available Data (and Subscriptions)

With a few adjustments, free reports can offer a baseline for the probability of breaches, types of attacks, the cost of attacks and vulnerabilities being exploited.

Your Real Job in Risk Management

You are a creator and manager of models – not just a "down in the weeds" estimator/forecaster.

Published Research
- General: Measured Performance of Methods
- Specific: Frequency and Impact of Specific Risks

First Model
- Initial Team Calibration
- Reference Classes & Baselines
- Simple Quantitative Models

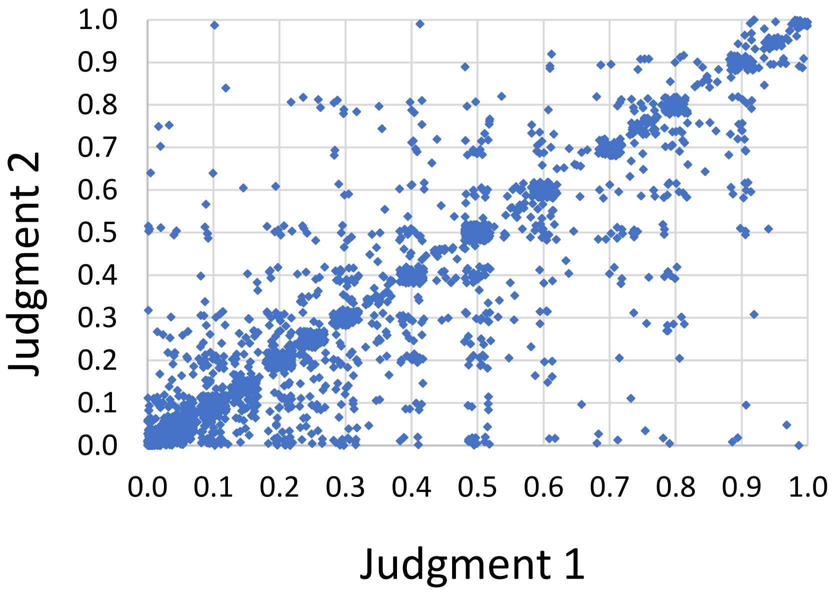
Continuous Improvement
- Monitoring Performance of Subject Matter Experts & Models
- Bayesian Updates with Internal and External Observations
- Adding Model Complexity Where Value is High and as Skills are Developed

The Method of Measurement

Calibrating Expert Consistency

- We have gathered estimates of probabilities of various security events from:
  - 48 experts from 4 different industries.
  - Each expert was given descriptive data for over 100 systems.
  - For each system each expert estimated probabilities of six or more different types of security events.
- Total: Over 30,000 individual estimates of probabilities
- These estimates included over 2,000 duplicate scenarios pairs.

Comparison of 1st to 2nd Estimates of Cyber risk judgements by same SME



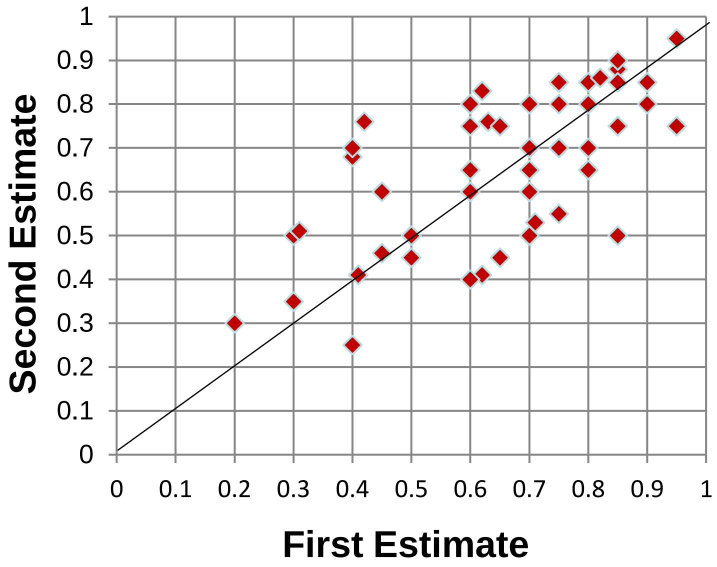
21% of variation in expert responses are explained by *inconsistency.*

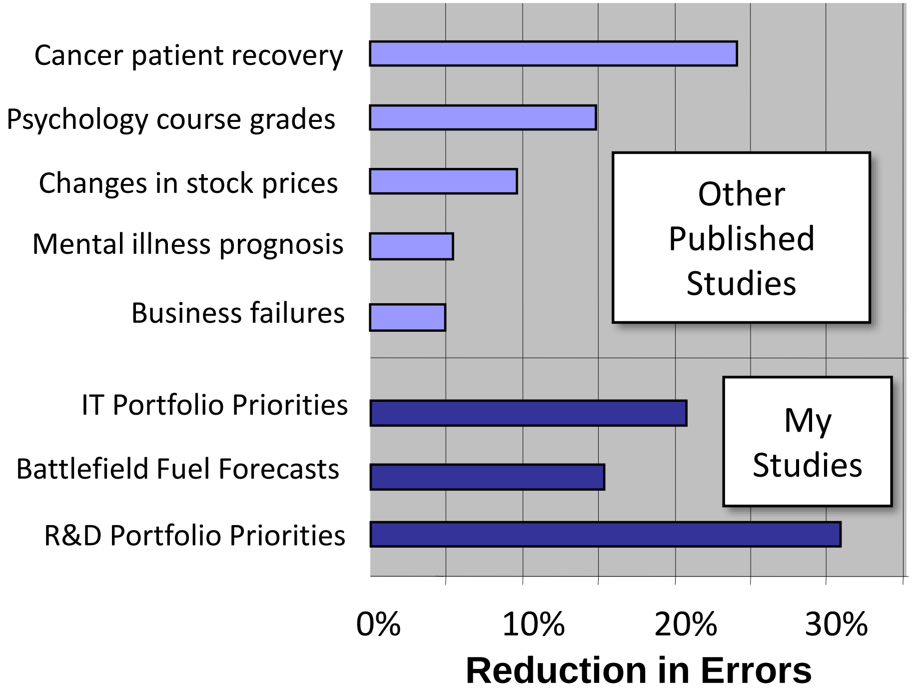
(79% are explained by the actual information they were given)

The Method of Measurement

Measuring and Removing Inconsistency

Methods that statistically “smooth” estimates of experts show reduced error in several studies for many different kinds of problems.





Do’s and Don’ts

- Stop using risk matrices and “high, medium, low” as assessments of risk.

- Start using previously proven components:
    - probabilistic methods including Monte Carlo
    - calibrated experts
    - historical observations
    - quantified risk tolerance

Questions?

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Supplementary Material

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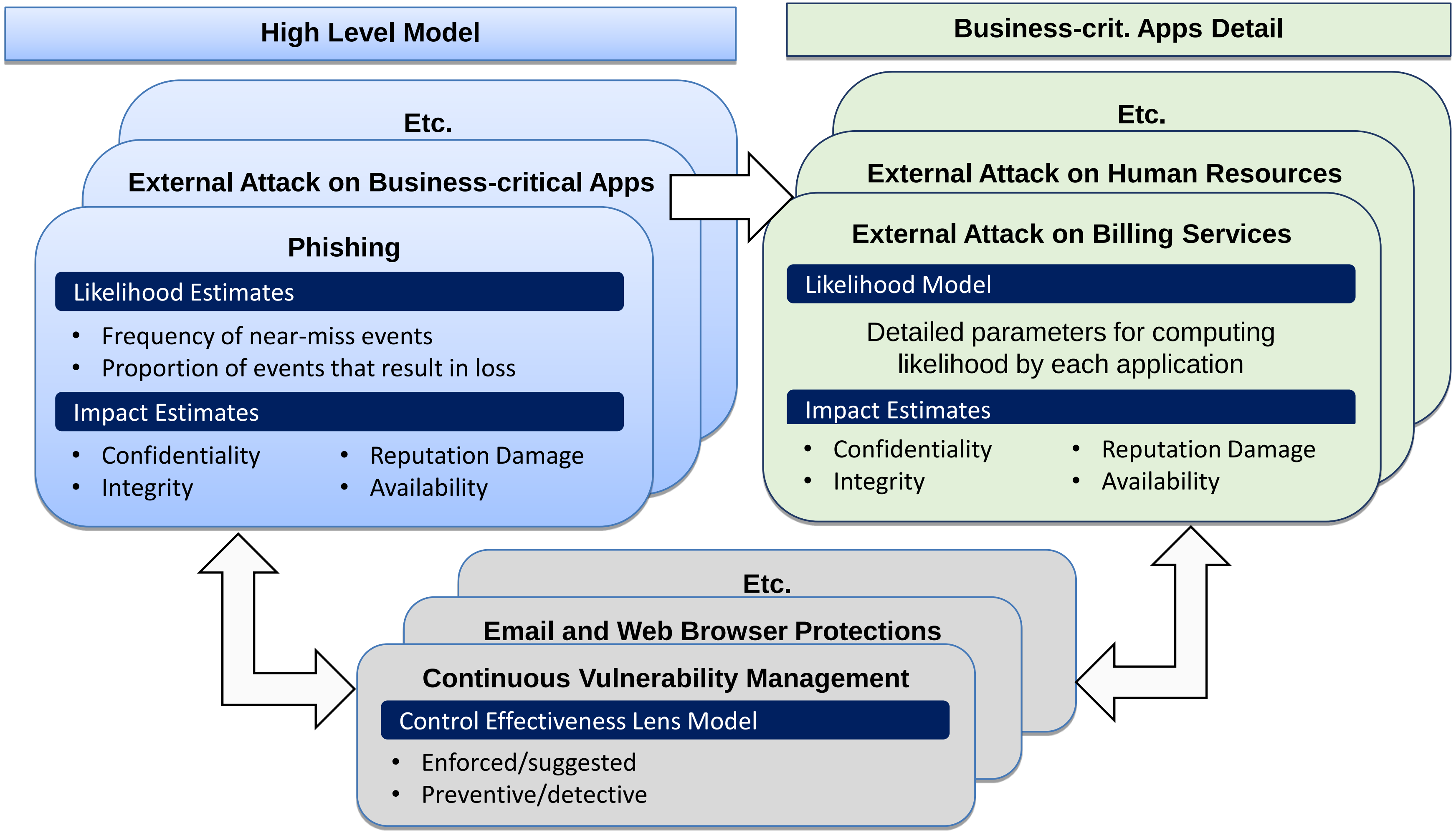
The Method of Measurement

Cybersecurity Risk Model Structure

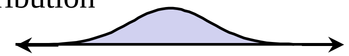
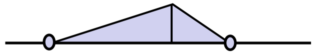
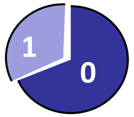
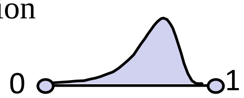


The Method of Measurement

Basic Distributions

Each of these examples can be found on

www.howtomeasureanything.com/cybersecurity

Distributions*	Upper & Lower Bound	Best Estimate
Normal distribution 	Represents the "90% confidence interval"	Always half-way between upper and lower bound
Lognormal distribution 	Represents the "90% confidence interval"; the absolute lower bound of a lognormal is always 0	Always a function of the upper and lower bound
Uniform distribution 	Represents the absolute (100% certain) upper and lower bounds	NA
Triangular distribution 	Represents the absolute (100% certain) upper and lower bounds	Represents the mode; the most likely value
Binary distribution 	NA	Represents the % chance of the event occurring
Beta distribution 	Generates a value between 0 and 1 based on “hits” and “misses”	The mode of a beta is (hits-1)/(hits+misses-2)

*A “●” means a “hard” stop, an “➔” arrow means unbounded

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Heath C., Gonzalez R. “Interaction with Others Increases Decision Confidence but Not Decision Quality: Evidence against Information Collection Views of Interactive Decision Making” *Organizational Behavior and Human Decision Processes,* Vol. 61, No. 3, 1995, pp 305-326.

Andreassen, P.” Judgmental extrapolation and market overreaction: On the use and disuse of news” *Journal of Behavioral Decision Making*, vol. 3 iss. 3, pp 153-174, Jul/Sep 1990.

Williams M. Dennis A., Stam A., Aronson J. “The impact of DSS use and information load on errors and decision quality” *European Journal of Operational Research,* Vol. 176, No. 1, 2007, pp 468-81.

Knutson et. al. “Nucleus accumbens activation mediates the influence of reward cues on financial risk taking” *NeuroRepor*t, 26 March 2008 - Volume 19 - Issue 5 - pp 509-513.

A small study presented at Cognitive Neuroscience Society meeting in 2009 by a grad student at U. of Michigan showed that simply being briefly exposed to smiling faces makes people more risk tolerant in betting games.

Risk preferences show a strong correlation to testosterone levels – which change daily (Sapienza, Zingales, Maestripieri, 2009).

Recalling past events that involved fear and anger change the perception of risk (Lerner, Keltner, 2001).