International Association for Food Protection

Applying Behavioral Economics to Model the Threat of Food Fraud

Presented By: Brian Hawkins

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Webinar Housekeeping

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- This webinar is being recorded and will be available for access by IAFP members at www.foodprotection.org within one week.

About the Speaker (Brian Hawkins)

- From Bristolville, Ohio (population ~3,000)
- Graduated from The Ohio State University and the University of Wisconsin-Madison with degrees in Chemical Engineering
  - Thesis focused on semiconductor growth
- 20 years at Battelle Memorial Institute researching Chemical, Biological, Radiological, Nuclear, and Explosive Defense, mostly focused on probabilistic modeling simulation to quantify and predict the Threat, Vulnerability, and Risk of uncertain events, such as terrorism attacks, food safety, and food defense

Applying Behavioral Economics to Model the Threat of Food Fraud

Brian Hawkins[1], Kevin Wegman[1], and Ashley Kubatko[2]

1- Battelle Memorial Institute (Columbus, OH USA)
2 – Nationwide Children's Hospital (Columbus, OH USA)

Mathematical Modeling & Risk Assessment PDG Webinar **April, 2019**

Overview

- Presentation Objectives
- Brief Background on The Science of Modeling Decisions
- Modeling the Threat of Food Fraud Using Utility Theory
- Validation of Concept Using Historical Data

Objectives of this Presentation

- Entertain while providing information on an interesting topic

- Broaden the context mathematical modeling in the IAFP MMRPG beyond microbial growth and dose-response by introducing behavioral modeling and discussing an example relevant to food industry

- Generate interesting discussions about other types of mathematical models and/or applications of behavioral modeling

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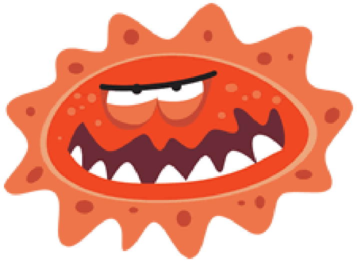
Food Fraud

- Food Fraud is a term used encompass the deliberate and intentional substitution, addition, tampering, or misrepresentation of food, food ingredients, or food packaging; or false or misleading statements made about a product, for economic gain[1]
- Unlike the majority of food safety modeling efforts, the cause is a ***Person*** instead of a ***Pathogen***

instead of



- This can be modeled, but requires a different approach because a decision is being modeled instead of growth or dose-response

1 – Defining the Public Health Threat of Food Fraud, Michigan State University http://foodfraud.msu.edu/wp-content/uploads/2014/07/food-fraud-ffg-backgrounder-v11-Final.pdf

The Science of Modeling Decisions

April, 2019

Behavior Economics and Utility Theory

- Behavioral Economics is a field that studies the various effects that drive decisions, typically to understand and/or influence those decisions
- Utility Theory is a concept within Behavioral Economics that posits decision makers weigh the perceived value of their options and tend to select the option with the highest value
  - Note: Value can be defined and subsequently quantified in many ways, but is generally correlated to the pleasure or satisfaction derived from the option
  - Based on Utilitarianism, which was proposed by Jeremy Bentham, a moral philosopher from England in the late 1700s-early 1800s
  - Foundational component of neoclassical economics, which is often used to explain and/or predict consumer behavior
  - Key assumptions are that the decision maker is rational and that the utility can be sufficiently approximated

Multi-Attribute Utility Theory Basics

- A common implementation of Utility Theory is a Multi-Attribute Utility Model, which posits that the likely behavior can be approximated based on multiple attributes that represent

$$P \propto U = f(attributes, weights)$$

- Attributes typically need to be transformed or scaled to avoid artifacts (e.g., comparing 0-60 acceleration times to sticker prices in $s to expert reviews of 0-4 stars)

The specific choice of mathematical form of the utility equation (there are many), as well as the specific transforms and scales applied to the attributes are typically the ‘trade secret sauce’ of a threat model

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Marginal Utility Example: Thirst in the Desert

- Marginal utility is a concept that focuses on how much additional satisfaction an additional unit of something will provide the decision maker.

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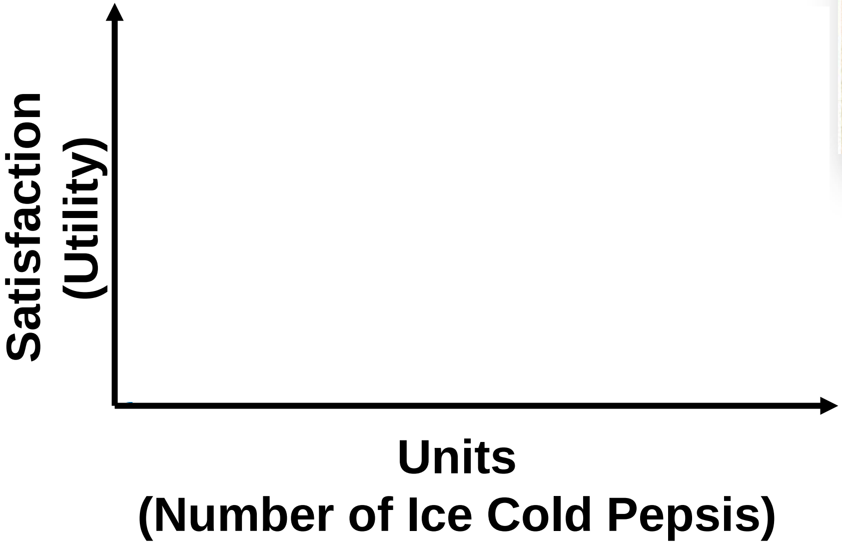

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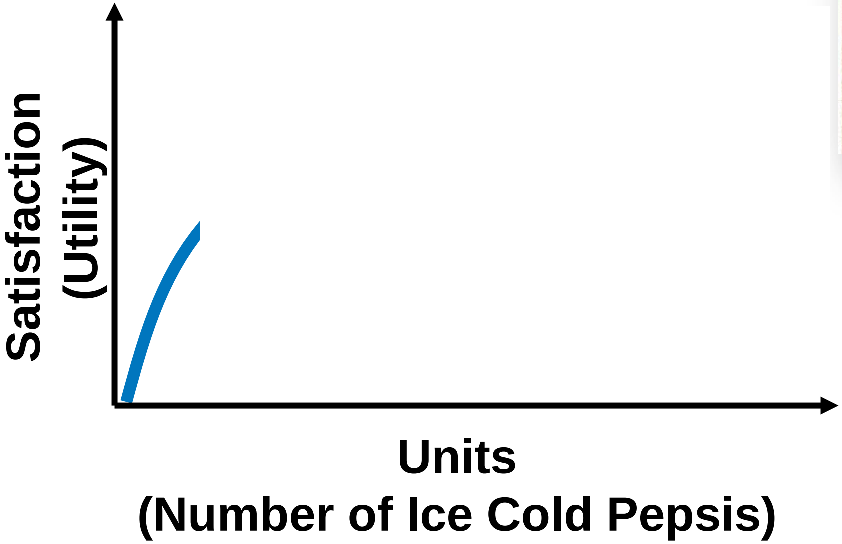

Under the blazing hot sun in the middle of the desert, that first drink (e.g., bottle of Pepsi) is tremendously satisfying

Marginal Utility Example: Thirst in the Desert

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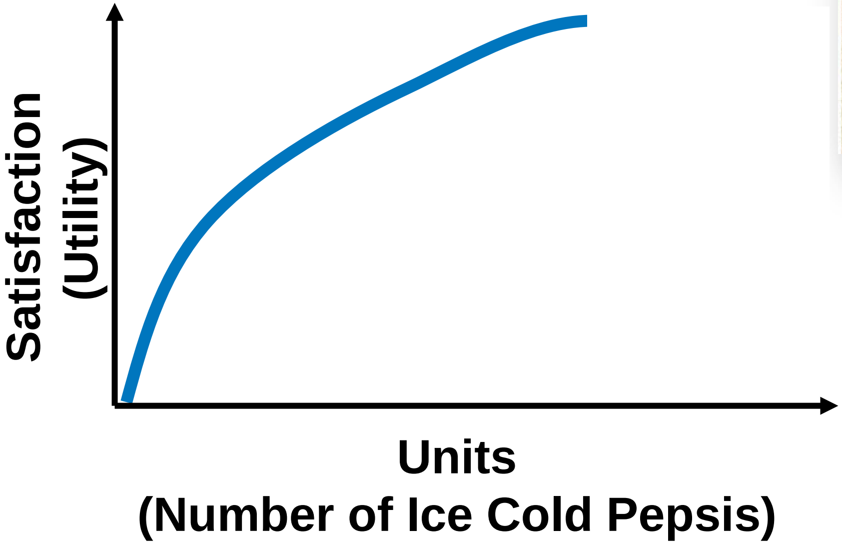

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The next three drinks (e.g., bottle of Pepsi) are satisfying, but not nearly as satisfying (on a per drink basis) as the first drink

Marginal Utility Example: Thirst in the Desert

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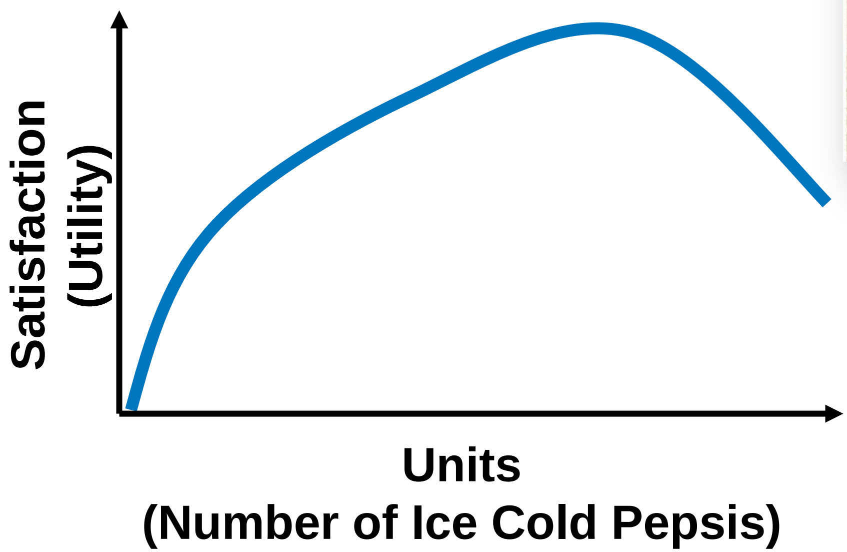

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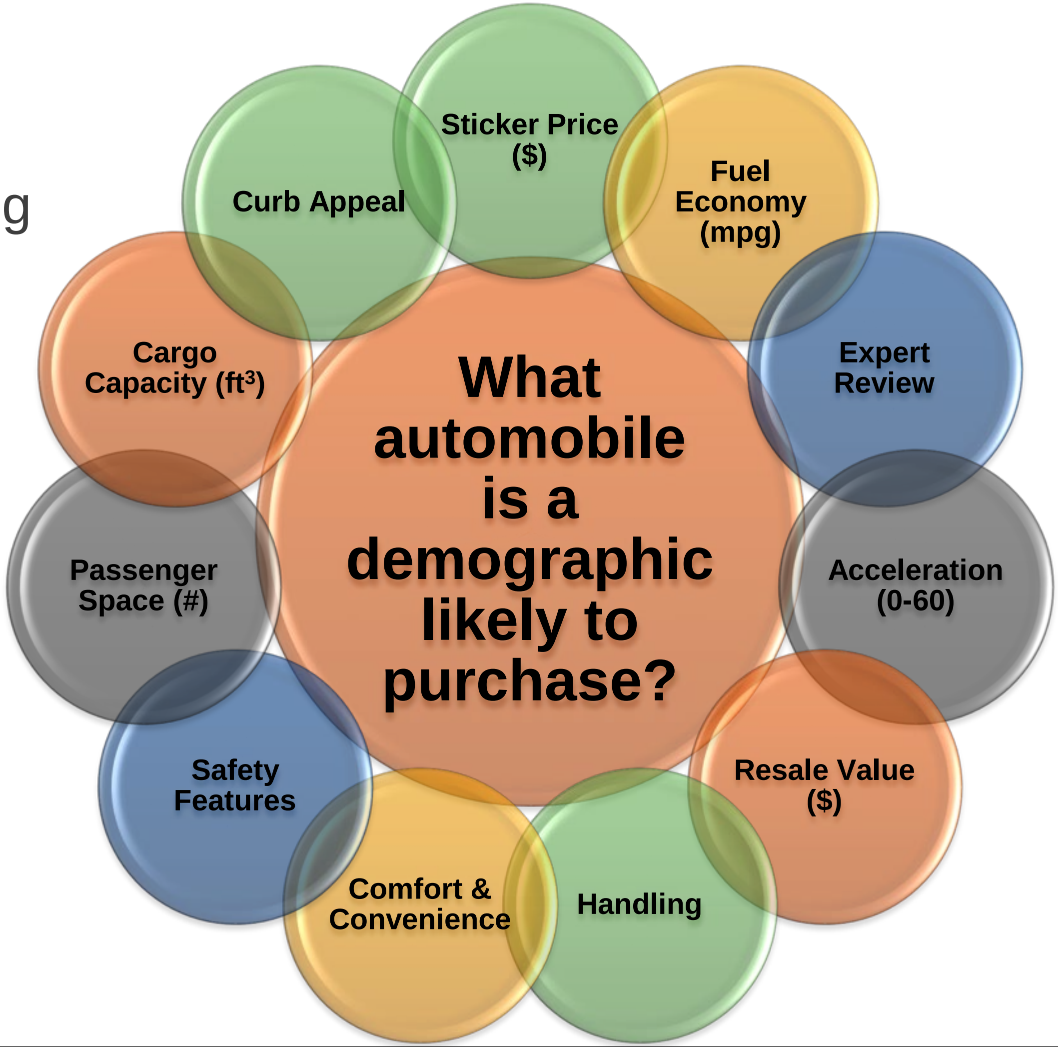
Eventually, once your thirst is sated, more drinks are not desirable – perhaps due to feeling full or bloated

Utility Example: Predicting Car Purchase Trends

- Utility is also commonly used to predict or explain purchasing trends, such as which automobile is likely to be purchased by a subpopulation or demographic



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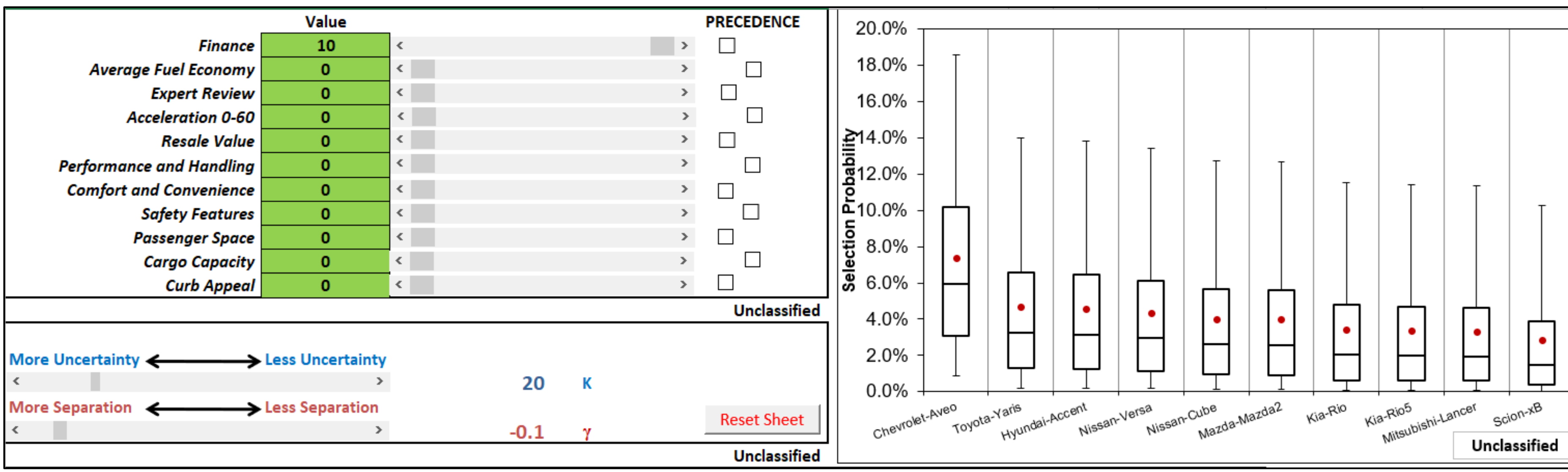
Utility Example: Predicting Car Purchase Trends

- As part of illustrating application of utility modeling for Intelligence Community (IC) Subject Matter Experts (SMEs), an simple Excel® sheet containing a utility model applied to 2013 model automobile data was developed

If the only factor was ***Sticker Price***, low-cost compact models such as a Chevrolet Aveo were likely purchases



Utility Example: Predicting Car Purchase Trends

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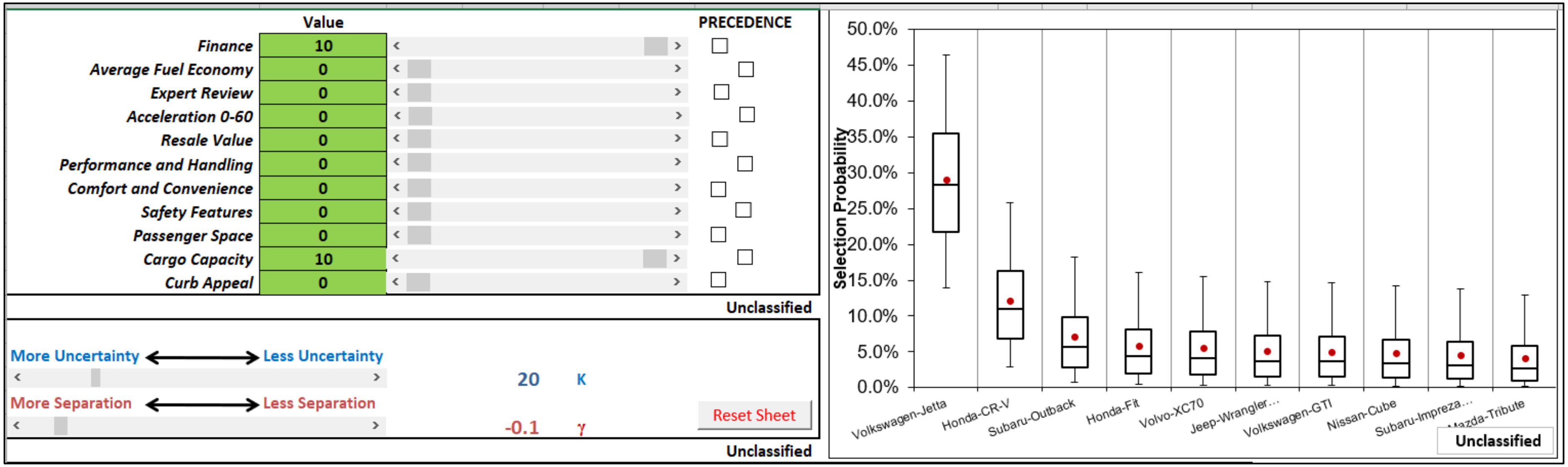
If ***Sticker Price*** and ***Cargo Capacity*** were equal factors, smaller hatchbacks such as a Honda CRV were likely purchases



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Utility Example: Predicting Car Purchase Trends

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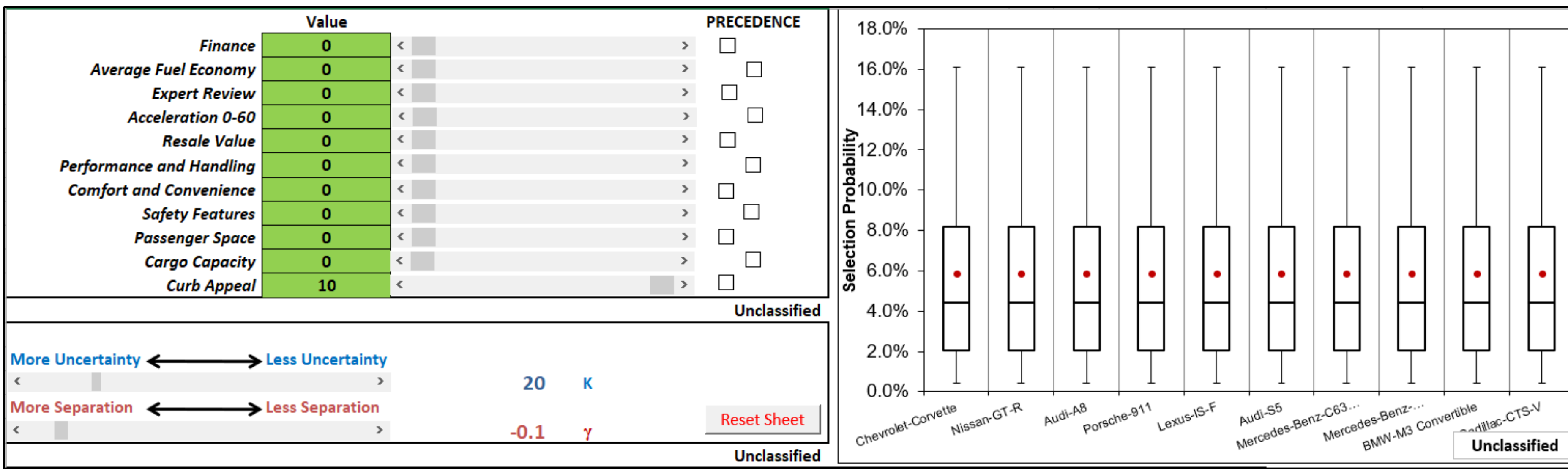
If *Curb Appeal* was the driving factor, sports cars and luxury cars, such as a Chevrolet Corvette or Porsche 911 were likely purchases



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Utility Example: Predicting Car Purchase Trends

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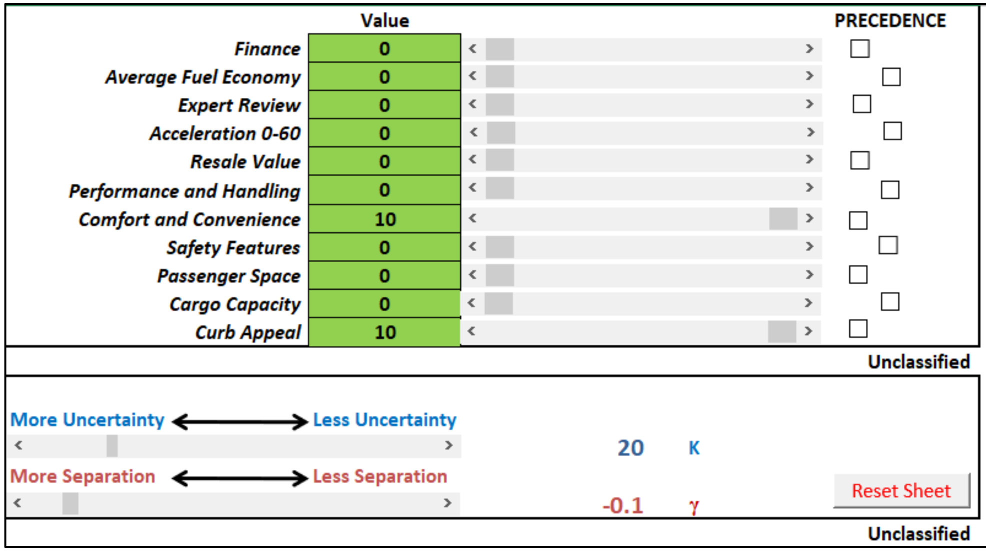
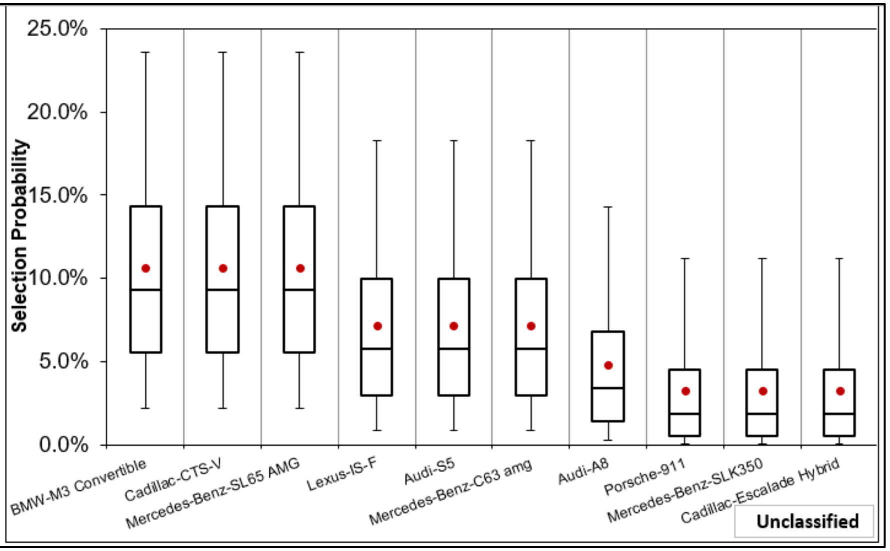
If *Curb Appeal* and Comfort and Convenience were equally weighted factors, different sports cars and luxury cars from the segment become likely

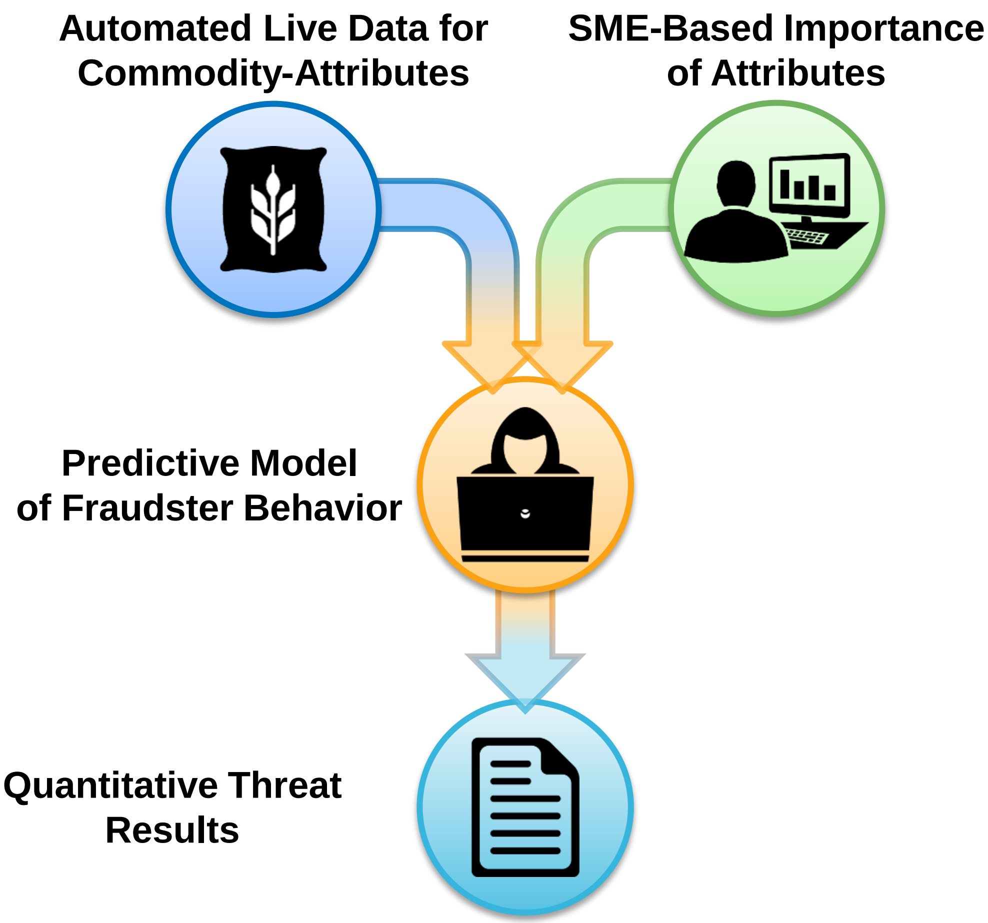




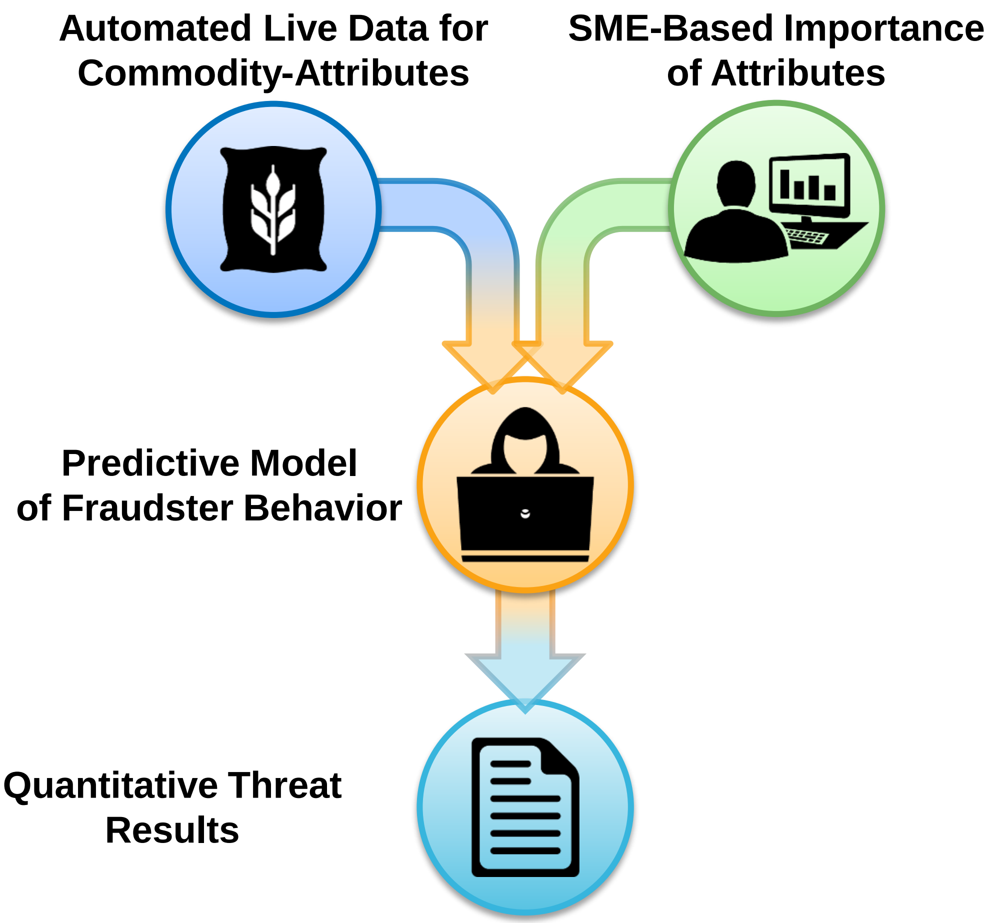
Modeling the Threat of Food Fraud Using Behavioral Modeling

April, 2019

Modeling the Threat of Food Fraud



Modeling the Threat of Food Fraud



Automated Live Data for Commodity-Attributes

Numerous attributes (e.g., value, volume, historic occurrence, and supplier reliability) representing key characteristics that drive a fraudster's decision to adulterate a commodity are continuously updated at defined intervals for each commodity through numerous online websites and databases to support the best possible assessment of threat

- Automated updating of attribute data for each commodity supports live vulnerability updates without requiring effort from users

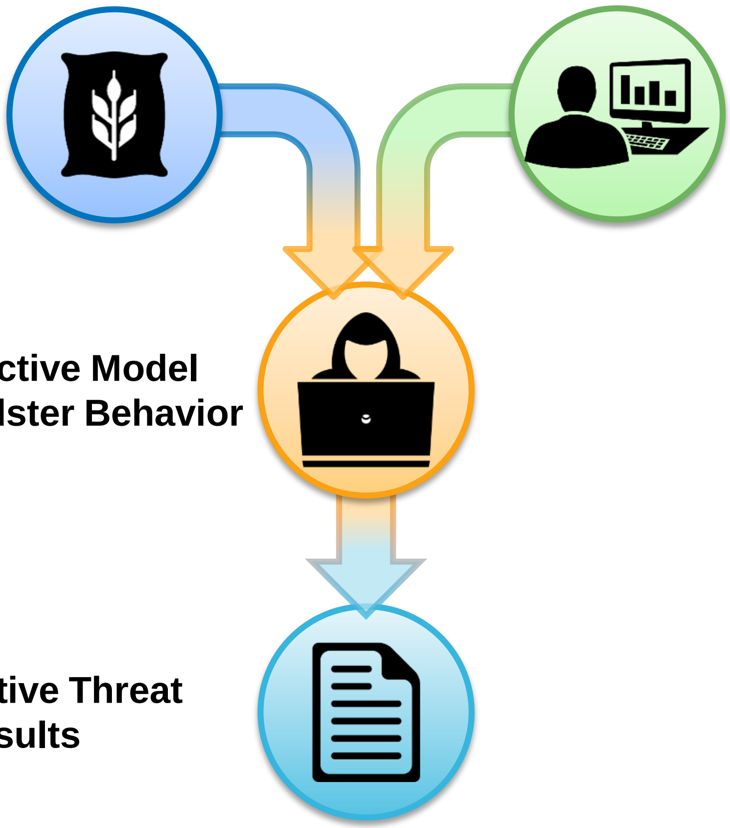
Modeling the Threat of Food Fraud

Automated Live Data for Commodity-Attributes

SME-Based Importance of Attributes

Predictive Model of Fraudster Behavior

Quantitative Threat Results

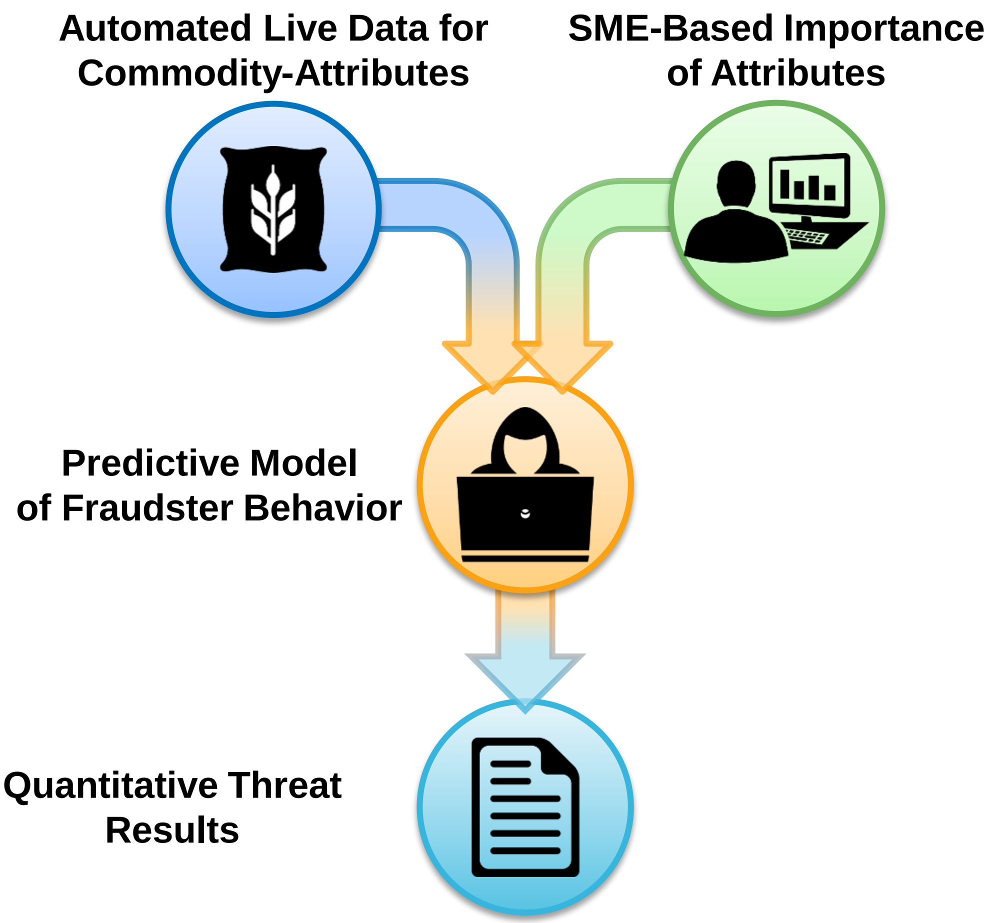


SME-Based Importance of Attributes

Users (SMEs) weight the attributes based on their expert opinion as to how important each attribute is to a fraudster when deciding which commodities to adultery for economic reasons

- Providing attribute weights better aligns with SME intuition, captures the driving forces behind food fraud, and reduces the number of inputs required from a user

Modeling the Threat of Food Fraud

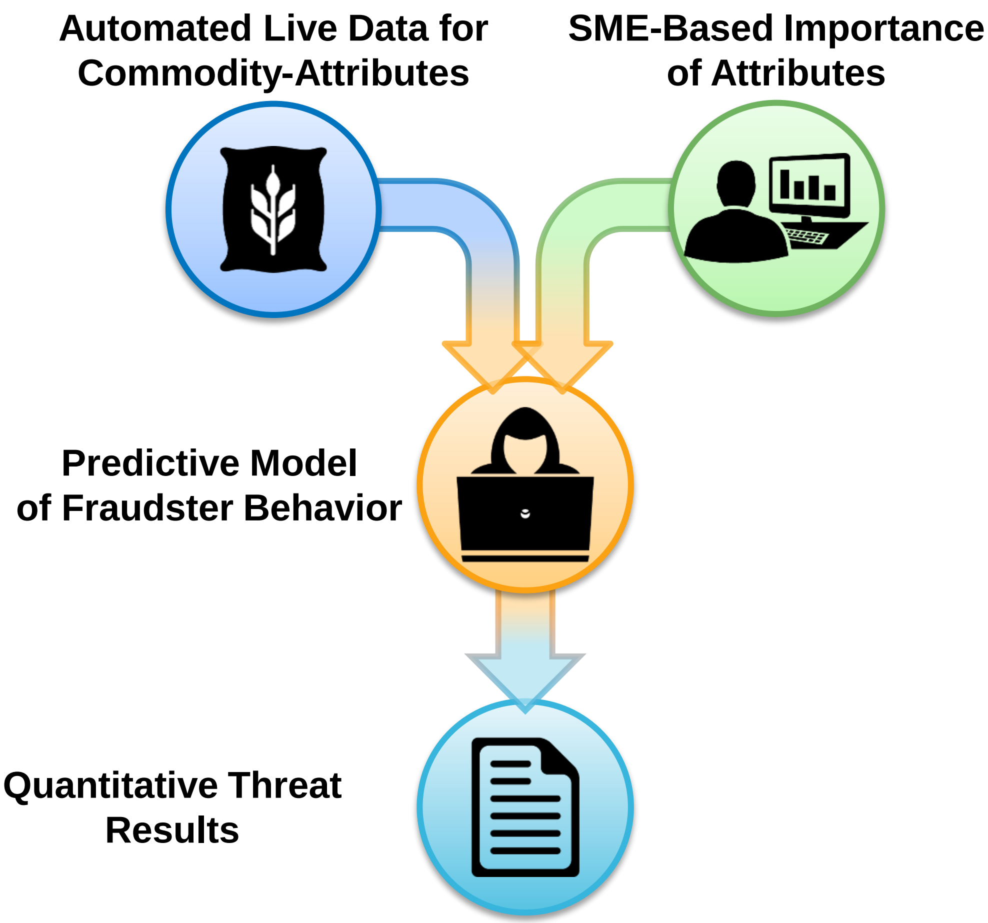


Predictive Model of Fraudster Behavior

The behavioral model translates the factors involved in fraudster decision making (characteristic attributes and their importance) into meaningful mathematical structures for calculation, analysis, and incorporation into decision making

- Understanding the behavior of fraudsters is an important part of assessing and mitigating food fraud
- Behavioral modeling approach is based on approaches relied upon by the Department of Homeland Security to predict terrorist behavior

Modeling the Threat of Food Fraud



Quantitative Threat Results

Quantitative threat results help users effectively rank and prioritize mitigation efforts associated with food fraud in a forward-looking (predictive) manner

- Analysis of results and driving factors provides improved understanding of threats and potential mitigation
- Comparative analysis offers insight into whether changes in threat is based on differences in SME opinion, supplier-driven differences, or trends in global markets

Predictive Modeling Approach

- Multi-attribute utility model
  - Allows for quantitative estimation of fraudster tendencies based on a combination of characteristic attributes and SME-based weightings
  - Similar to approaches used by the U.S. Department of Homeland Security and Domestic Nuclear Detection Office to model CBRNE terrorist tendencies

Economic Drivers

Ease Drivers

Historical Drivers

Driving Attribute Categories

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Automated Live Data for Commodity-Attributes

Automated Data Mining from Web-Based Sources

UN comtrade

Quandl

Transparency International

USP

FDA

Economic Drivers

- Value
- Volume
- Scarcity/Surplus

Historical Drivers

- Historic Occurrence
- Geopolitical Stability

Ease Drivers

- Frequency of Identity Tests
- Government Regulations
- Ownership
- Repackaging
- Trade Association
- Supplier Reliability

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Validation Study using Historical Data

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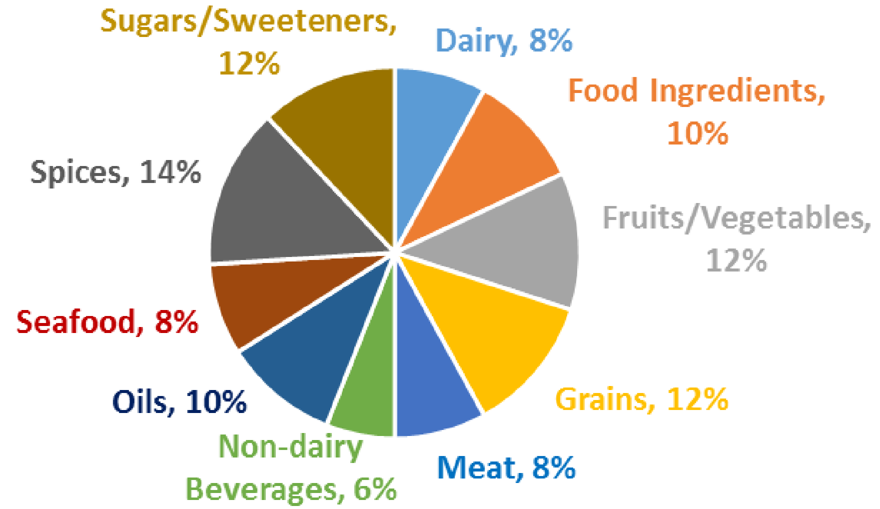
Validation Study Commodities

Spices	Grains	Dairy	Seafood	Meat
Cumin	Wheat flour	Butter	Shrimp, fresh	Ground Beef
Basil	Corn flour	Whey	Cod, Frozen	Pork
Black Pepper	Rice	Milk	Tilapia, Frozen	Chicken, breast
Cocoa beans	Quiona	Cheese	Canned Tuna	Turkey
Cocoa powder	Durum wheat pasta	**Non-dairy Beverages**	**Sweeteners**	
Saffron	Wheat gluten	Apple juice	Maple Syrup	
Vanilla	**Fruits and Vegetables**	Orange juice	Honey	
Oils	Tomatoes	Coffee	Glycerol	
Palm oil	Onions	**Food Ingredients**	Stevia	
Sesame oil	Apples	Corn starch	Beet Sugar	
Bergamot oil	Peas	Xanthan gum	High fructose corn syrup	
Olive Oil, extra virgin	Avocado	Guar gum		
Vegetable oil	Strawberry Puree	Beeswax		

- 48% (24 of 50) in one of USP's Top 25 Lists
- 76% (38 of 50) have a history of food fraud based on occurring in the Decernis Food Fraud Database
- Comprised of commodities from many categories of foods



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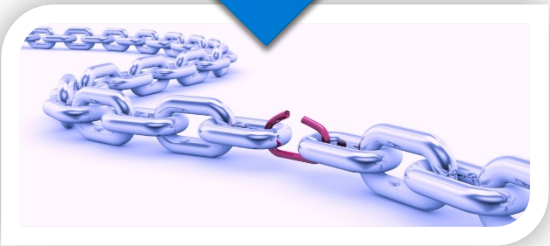
Validation Study Concept

Attribute Data (Historical)

Attribute Weights (SME-Based)

EMAlert™
Vulnerability Assessment Tool
GMA + Battelle Partnership



Threat Estimates (Historical)

versus

Top 25 Lists
and
Incident Databases

Validation Study: Inputs

Attribute Data (Historical)

- Mined from electronic resources (e.g., comtrade) or estimated (e.g., existence of trade associations) for December 31, 2009
- Note: No customization for supplier reliability was incorporated in the validation study data

Attribute Weights (SME-Based)

- Inferred from SME rankings of attributes from interim survey-based research by ***Lindsay Murphy*** at the University of Tennessee

EMAlert™
Vulnerability Assessment Tool
GMA + Battelle Partnership

EMAlert^{TM} Algorithms

- Vulnerability to EMA (food fraud) estimated quantitatively using EMAlert^{TM} algorithms that predict fraudster preferences

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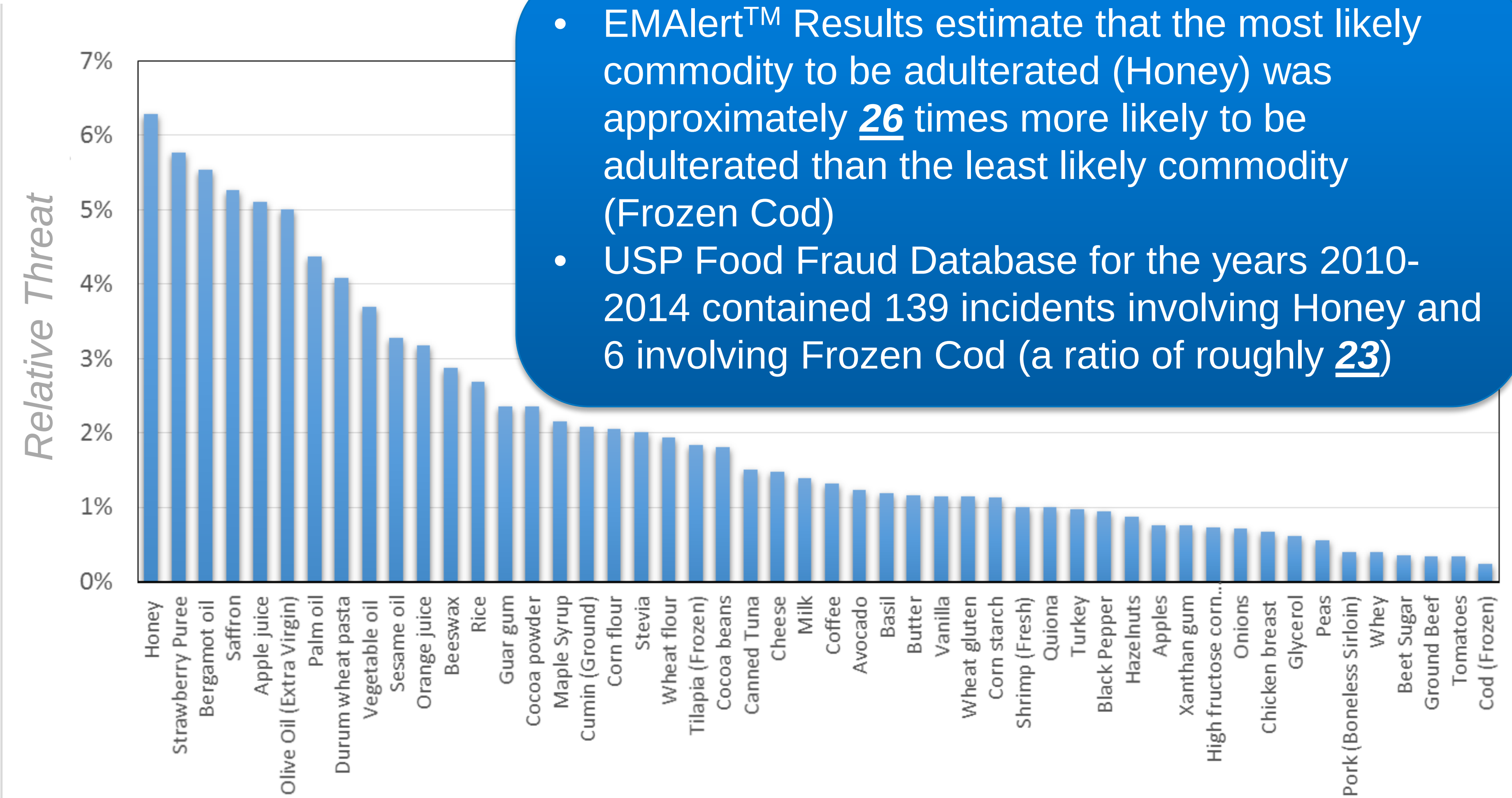
Validation Study: Comparison Sources

- EMAlert™ quantitatively predicts relative threats
  - Those threats should be observable as incidents over a period of time (or volume of incidents)
- However, direct comparisons are complicated slightly because:
  - Perpetrators of food fraud do not want to be caught
  - Our knowledge of food fraud incidents is imperfect (we don't know what we don't know of)
- Comparison metrics selected for this validation study:
  - USP Top 25 List (Scholarly and Media)
  - USP Food Fraud Database
  - FPDI EMA Database

Validation Study: Results



- EMAlert™ Results estimate that the most likely commodity to be adulterated (Honey) was approximately ***26*** times more likely to be adulterated than the least likely commodity (Frozen Cod)
- USP Food Fraud Database for the years 2010-2014 contained 139 incidents involving Honey and 6 involving Frozen Cod (a ratio of roughly ***23***)

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Validation Study: Comparison Metrics

- Commodities categorized as ***High***, ***Medium***, or ***Low*** vulnerability based on the following criteria:

Vulnerability Category	USP Top 25 Lists[1]	USP Food Fraud Database[2]	FPDI EMA Database[3]
High	Appears on **both** the Scholarly and Media Top 25 List	Constitutes 10% or more of known incidents for next 5 years	
Medium	Appears on either the Scholarly **or** Media Top 25 List	Constitutes less than 10% of known incidents for next 5 years	
Low	Does **not** appears on the Scholarly or Media Top 25 List	No historical incidents contained in the database for next 5 years	

1 - USP Top 25 List: Moore, J.C., Spink, J., and Lipp, M. 2012. Development and Application of a Database on Food Ingredient Fraud and Economically Motivated Adulteration from 1980-2010. Journal of Food Science 77(4): R118-126.
2 - USP Food Fraud Database: http://www.usp.org/food-ingredients/food-fraud-database
3 - FPDI Food Fraud / EMA Database: https://foodprotection.umn.edu/innovations/food-fraudema/incidents-database

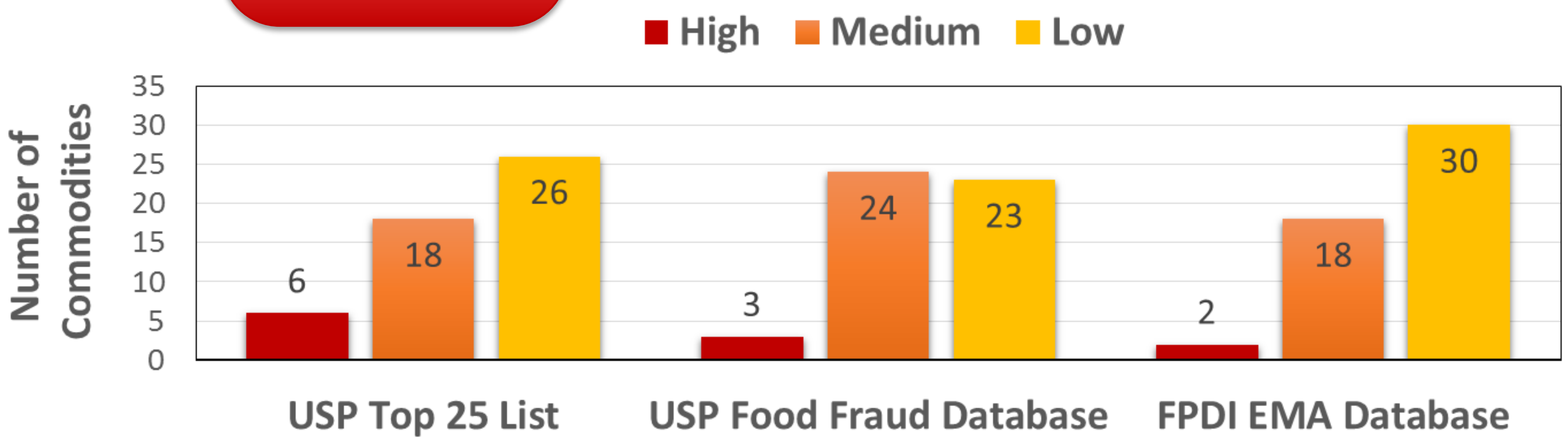
Validation Study: Comparison Metrics

High Threat Category Commodities

USP Top 25
Honey
Saffron
Olive Oil
Apple Juice
Rice
Milk

USP Food Fraud DB
Honey
Olive Oil
Milk

FPDI EMA DB
Olive Oil
Milk



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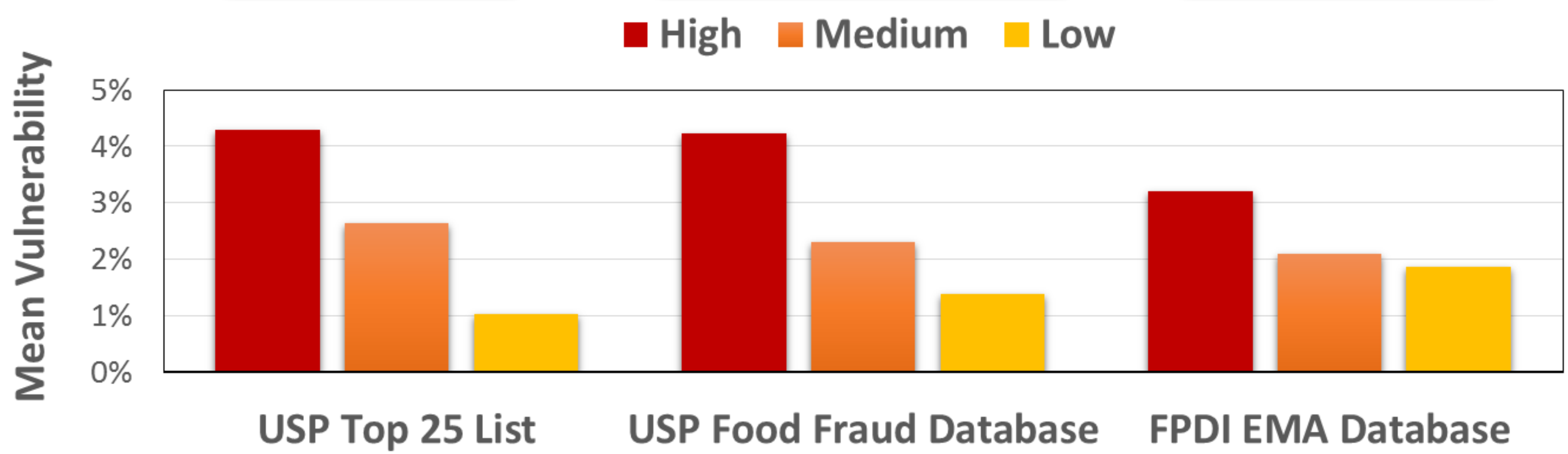
Validation Study: Comparison Results

Mean Threat Scores by Category

USP Top 25	USP Food Fraud DB	FPDI EMA DB
High: 4.3%	High: 4.2%	High: 3.1%
Med: 2.6%	Med: 2.3%	Med: 2.1%
Low: 1.0%	Low: 1.4%	Low: 1.9%



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Validation Study: Milk Analysis

- ***Non-intuitive Result***: At first glance, EMAlert^{TM} estimates a lower vulnerability for Milk (vulnerability of 1.4%) than would be expected based on historic incidents between 2010-2014
  - ***Note: The vast majority of incidents were in international locations that do not trade milk globally (e.g., adulteration with melamine in China)***
- ***Customized Input Adjustments***: If the Supplier Reliability attribute for milk is lowered from 5 (default) to 0 (low reliability), reflecting a the potentially reduced reliability of an Asian milk supplier
- ***Customized Threat Result***: ***The threat to Milk increases significantly to 4.8%***

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Validation Study: Milk Analysis

- ***Non-intuitive Result***: At first glance, EMAlert™ estimates a lower vulnerability for Milk (vulnerability of 1.4%) than would be expected based on historic incidents between 2010-2014
  - ***Note: The vast majority of incidents were in international locations that do not trade milk globally (e.g., adulteration with melamine in China)***
- ***Customized Input Adjustments***: If the Supplier Reliability attribute for milk is lowered from 5 (default) to 0 (low reliability) and the Geopolitical Stability attribute is changed from the global weighted average (0.70) to that of China (0.36)
- ***Customized Threat Result***: ***Milk is then the highest threat commodity with a mean threat of 9.8%***

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Acknowledgements

- ***Many thanks to***:
  - Battelle team of researchers who developed and support EMAlert™, especially *Ashley Kubatko, Michael Ma*, *Regina Gallagher*, *Joseph Casciano*, *Lucas Rodriguez*, and *Kevin Wegman*
  - *Lindsay Murphy* at the University of Tennessee for the interim survey results used for generating attribute weights in the validation study
  - GMA staff who supported the development of EMAlert™, especially *Warren Stone*, *Sam Cooper*, and *Shana Cooksey*
  - EMAlert™ Steering Group members for providing feedback and perspective during development and beta testing, especially *Joseph Scimeca* who served as chairperson of the Steering Group and has been involved throughout the entire EMAlert™ effort

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Questions and Subsequent Discussion

International Association for Food Protection.

Slides and a recording of this webinar will be available for access by IAFP members at www.foodprotection.org within one week.

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