ImpACT
SOA ANNUAL CONFERENCE

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Re-presented to ASNY

Impact of New Underwriting Data Sources and Tools

November 17, 2021

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Overview

Predictive Analytics and Machine Learning

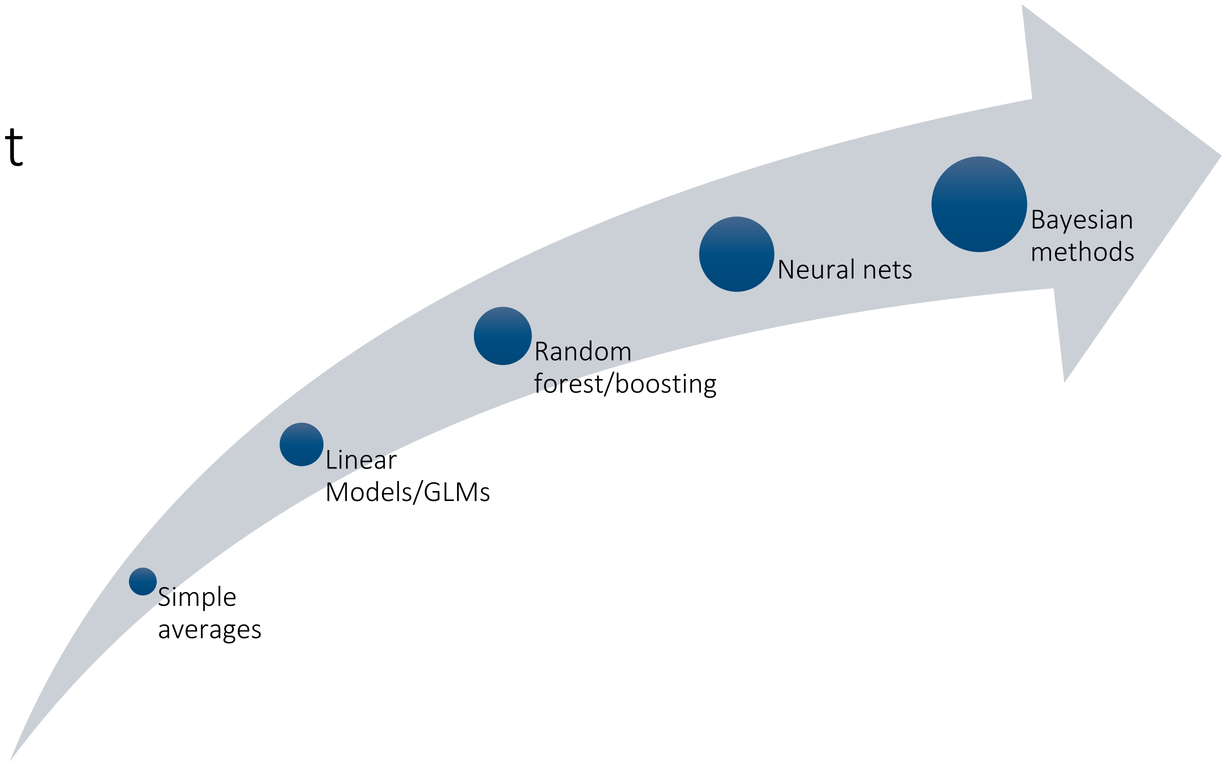
- Applying and understanding methods
- Implementing findings in underwriting and pricing processes

New Underwriting Tools

- Survey of tools and ramifications
- Summary of impacts to underwriting and pricing

Predictive Analytics
In Brief

- What It is
  - "A collection of statistical techniques that analyze current and historical facts to make predictions about future or otherwise unknown events" – Wikipedia
- What It Is Not
  - Cure-all for analysis
  - Data miracle worker
  - Existential threat

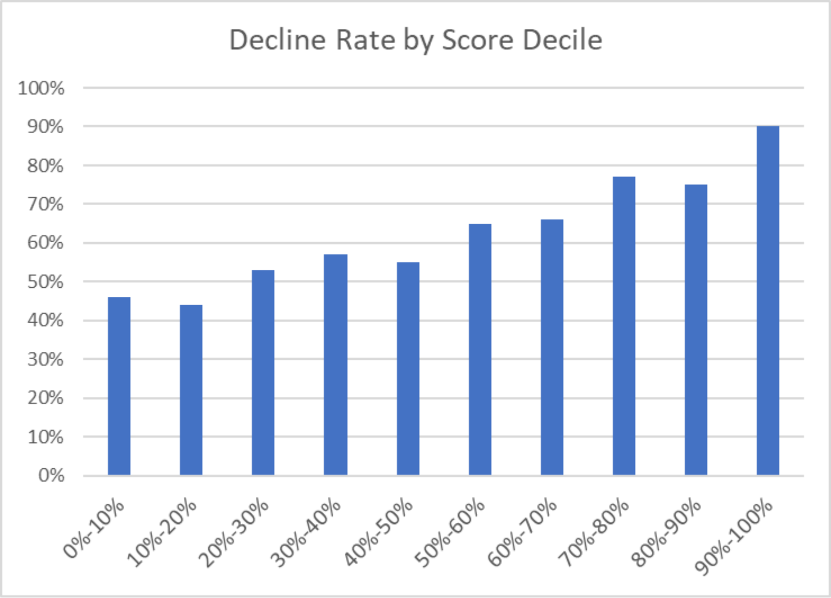


Machine Learning

Use Case: Automated Document Scoring

1) APS or EHR contains useful but unstructured information

2) ML and NLP techniques reveal patterns associated with UW outcomes

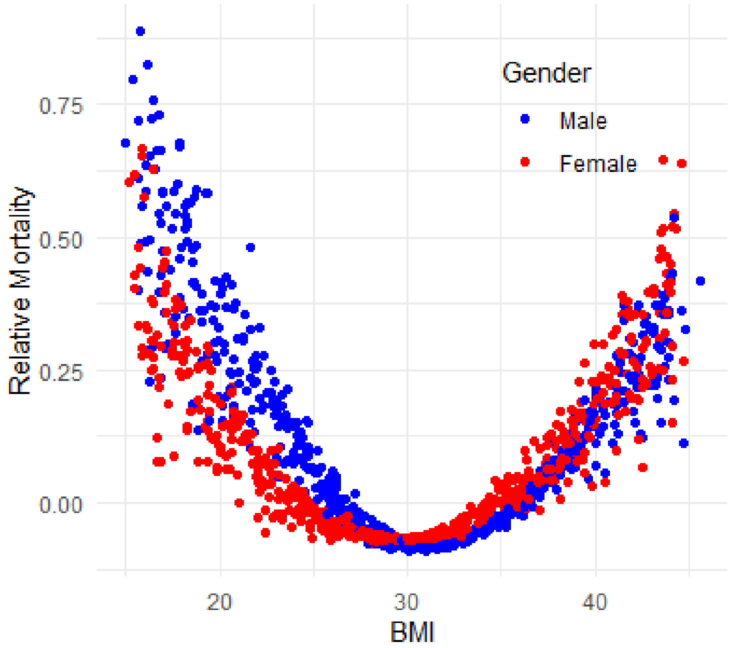


3) Models can highlight where significant information is located

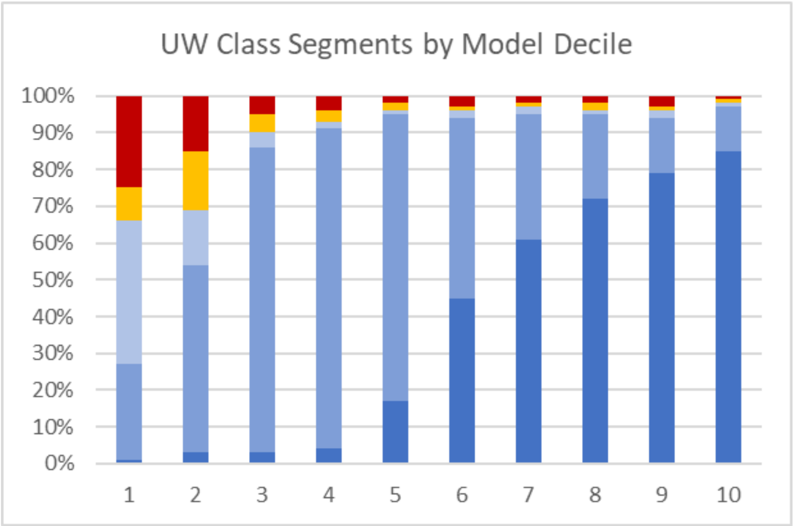
- Axillary: 12, 28, 30
- Prostate: 12, 56, 57
- Svc: 33
- Ancillary: 39, 40, 41, 43
- Jaundice: 59
- Excision: 59, 61, 62

Predictive Modeling

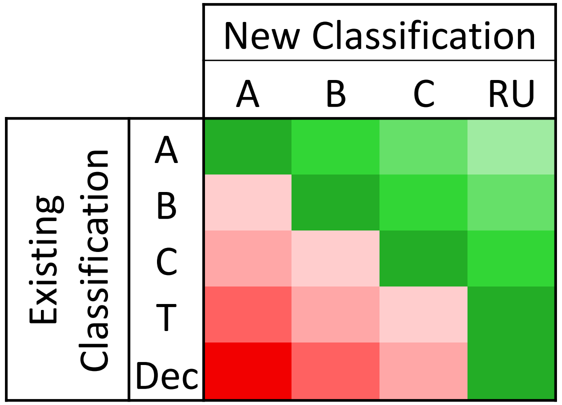
Use Case: Calibration and validation of new risk assessment tool



Build a model



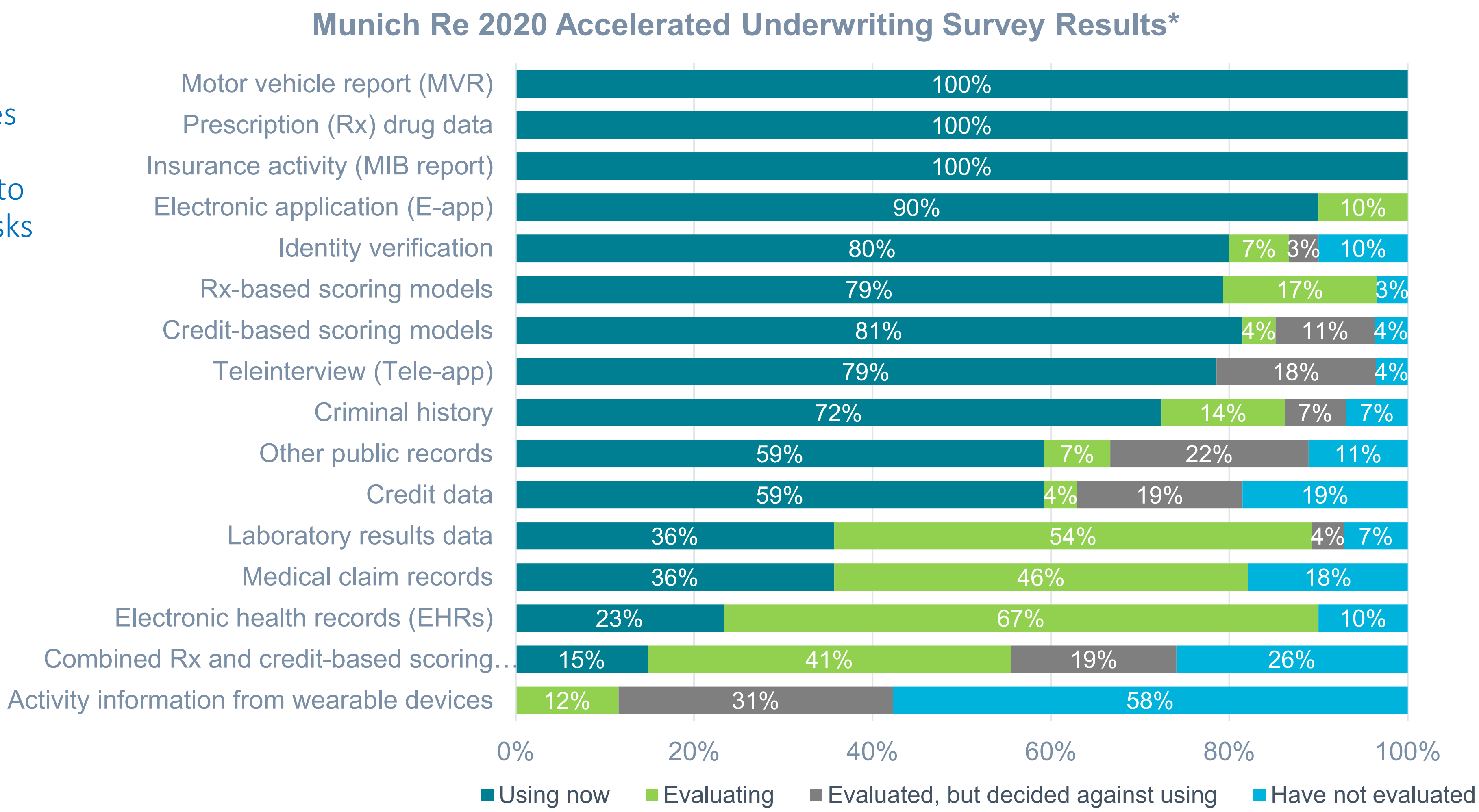
Convert model patterns into decisions



Iterate and tune classifications

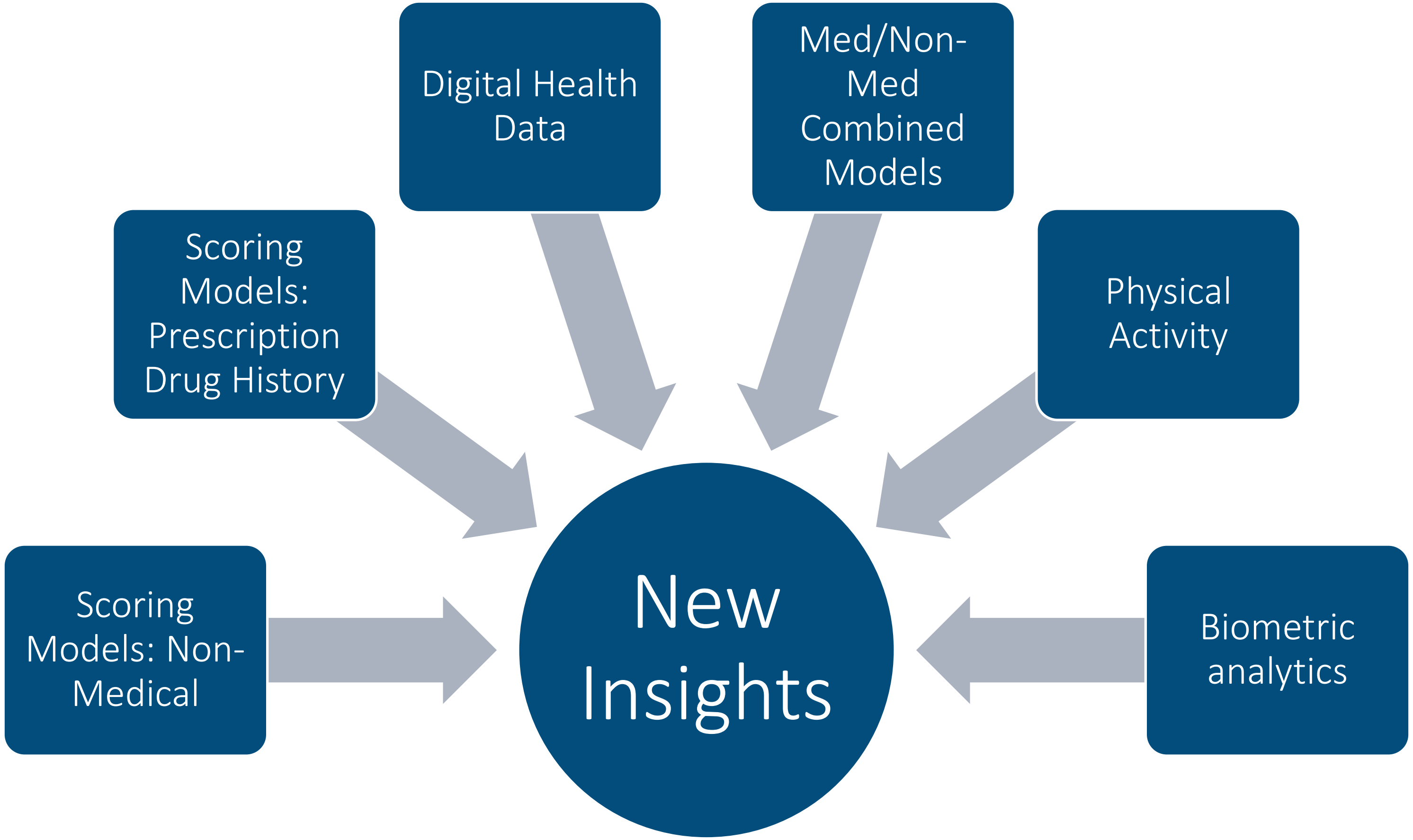
Underwriting Tools and Information Sources

What tools and information sources are used, or being evaluated for use, to triage or classify risks in the accelerated pipeline?

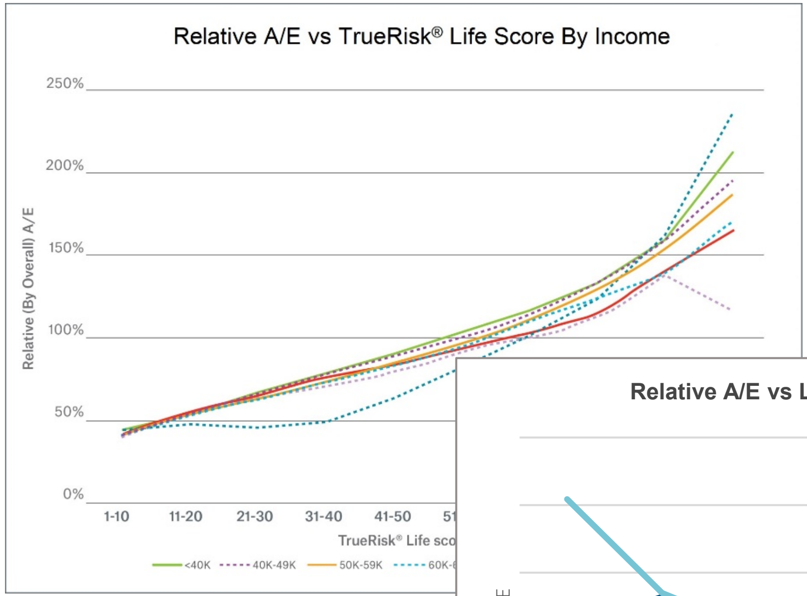


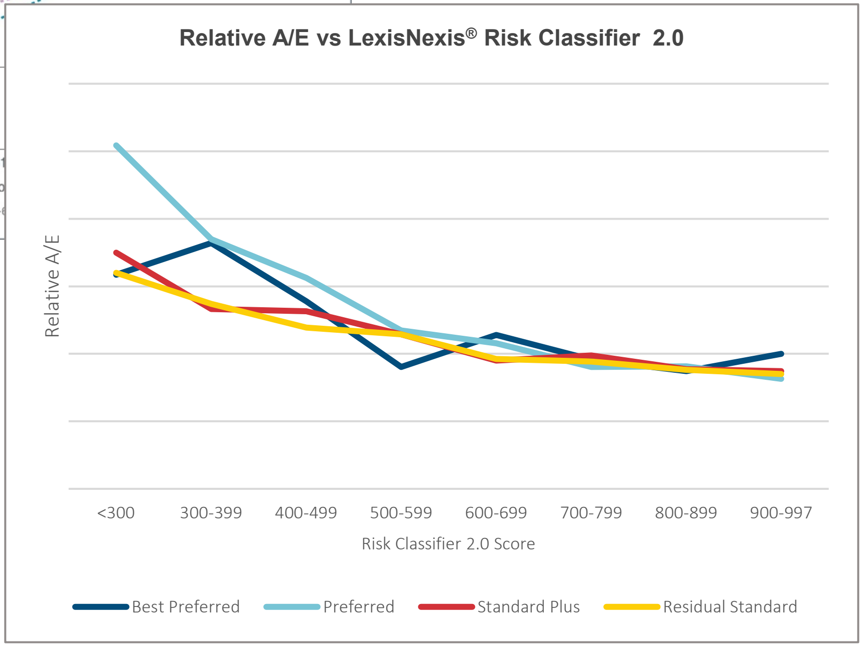
* Survey results represents responses from 30 carriers as of June 30, 2020

Ever More Underwriting Tools



Scoring Models: Non-Medical

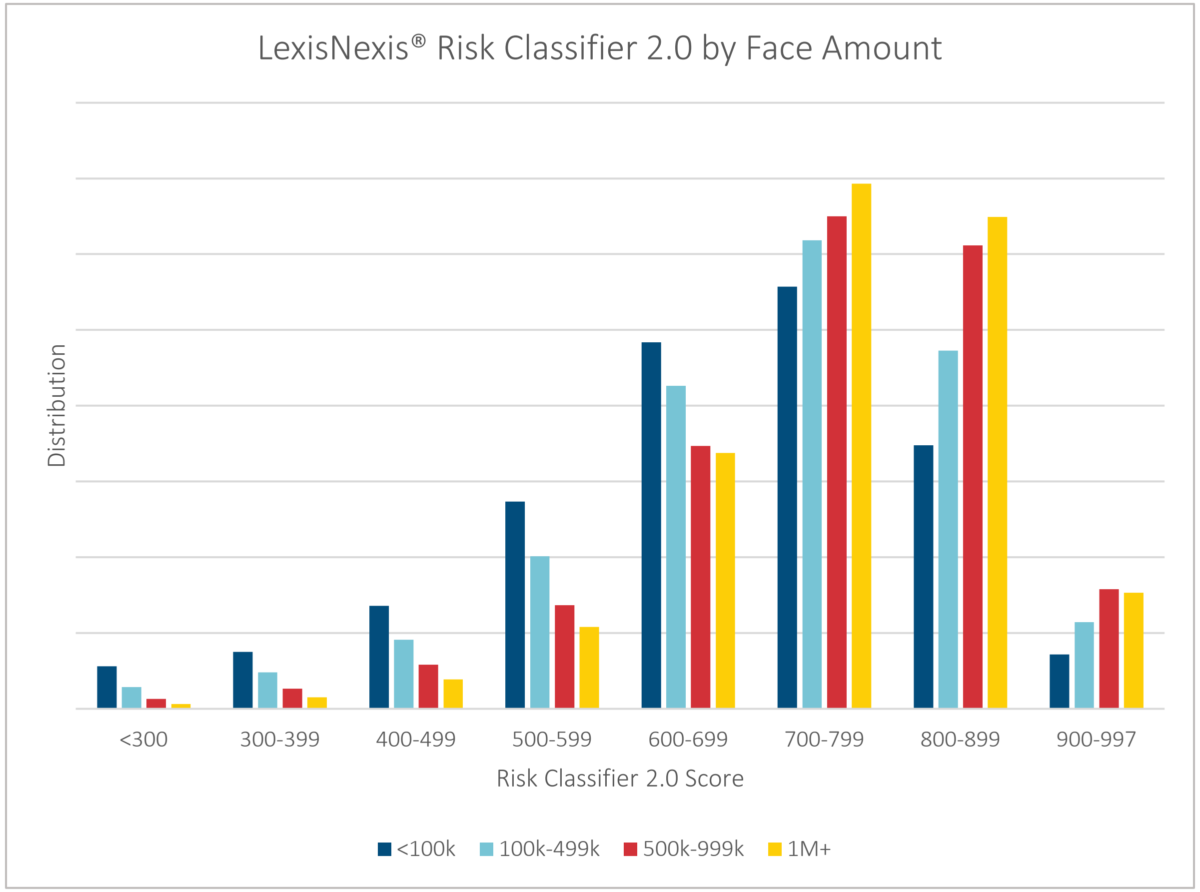




- Reflects behavioral predictors of risk based on attributes such as credit records, MVR and public records
- Little to no overlap with medical risk dimensions
- Improves identification and segmentation
- Useful for triage and classification with or without fluids

Scoring Models: Non-Medical

Impact



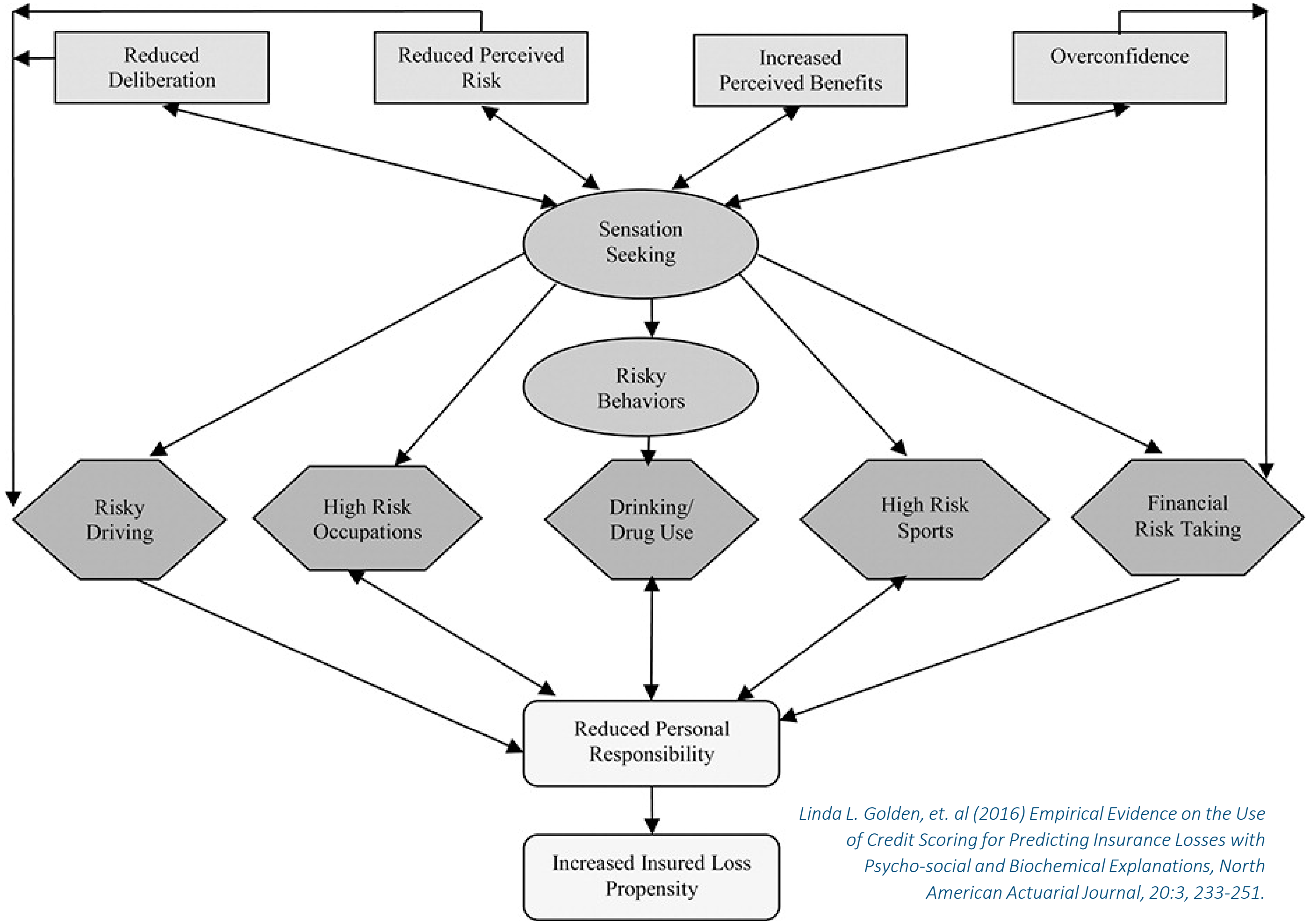
Source: internal reinsured population

- Acceleration triage: non-medical scores can be used as an upfront behavioral screen for accelerated pipeline
- Preferred segmentation: best preferred improves, cascading into other classes
- Overlaps with face amount effects

Face Amount Range	Mean Lexis Risk Classifier Score	Relative Mortality of Face Amount Range – 15VBT	Mortality of Risk Classifier >= 400 relative to FA Range
<100k	677	123%	94%
100k-499k	722	102%	97%
500k-999k	759	89%	98%
1M+	767	86%	99%

Scoring Models: Non-Medical

Why they work: Psychosocial Drivers



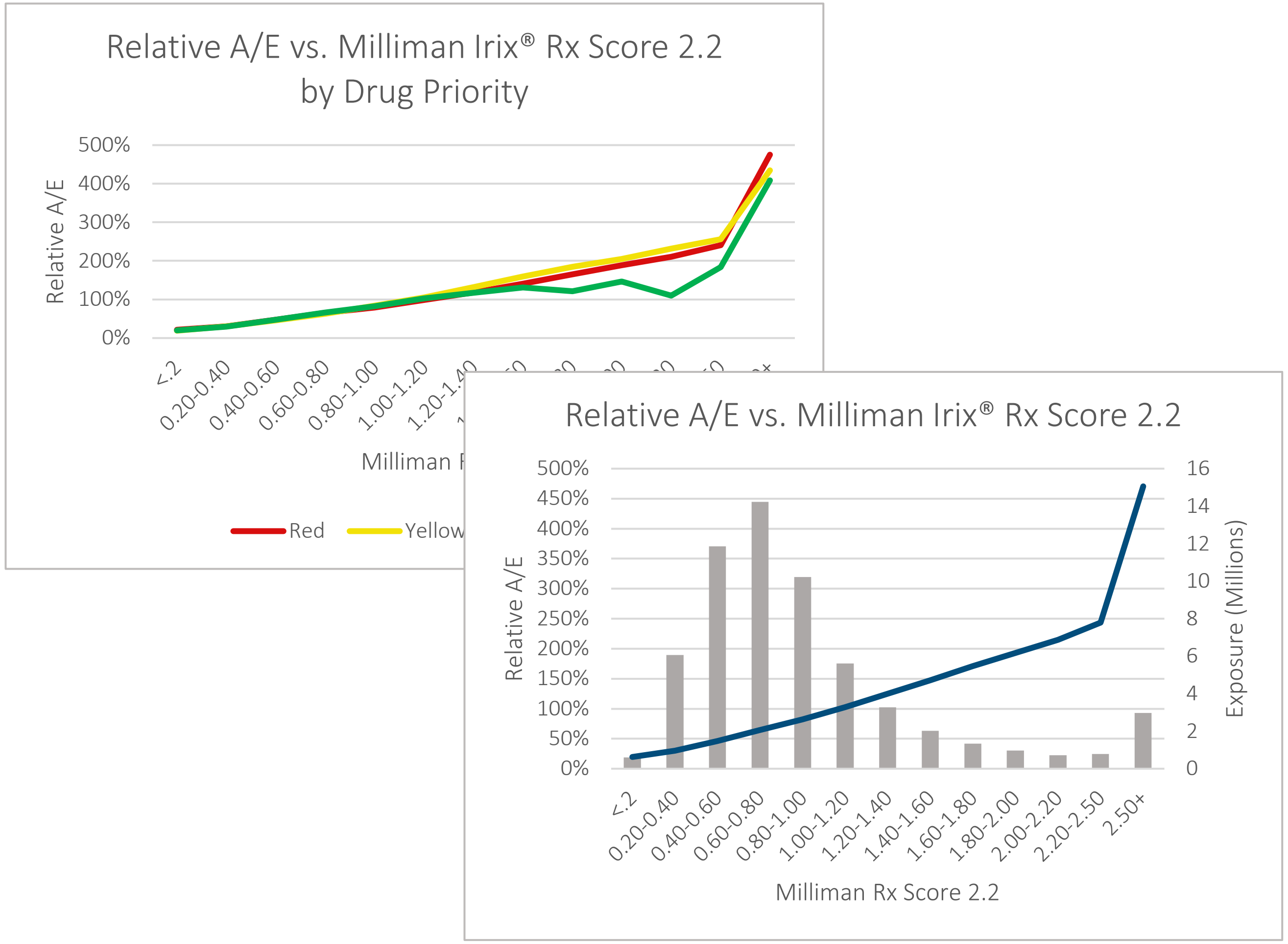
Linda L. Golden, et. al (2016) Empirical Evidence on the Use of Credit Scoring for Predicting Insurance Losses with Psycho-social and Biochemical Explanations, North American Actuarial Journal, 20:3, 233-251.

- Preference for increased sensation levels
- High sensation seekers show increased reduction in perceived risk and increased assurance in ability to avoid negative outcomes
- Deliberation and impulse control moderate sensation seeking behaviors (“think before you leap”)

Scoring Models: Prescription Drug History

- Some major providers include Milliman and ExamOne
- Effectively stratifies risk
- Effective at identifying high risks when little other medical data is available

- Common uses
  - Thresholds
  - Risk class shifting
  - Ingredients in other models



Digital Health Data

Prescription Medication History

Rx's – Dates, Dosages, Number of Fills

Clinical Laboratory Test Results

Complete Blood Count, Urine – Dates, Results

Health Insurance Claims Data

Diagnostic Codes – Dates, Procedural Codes

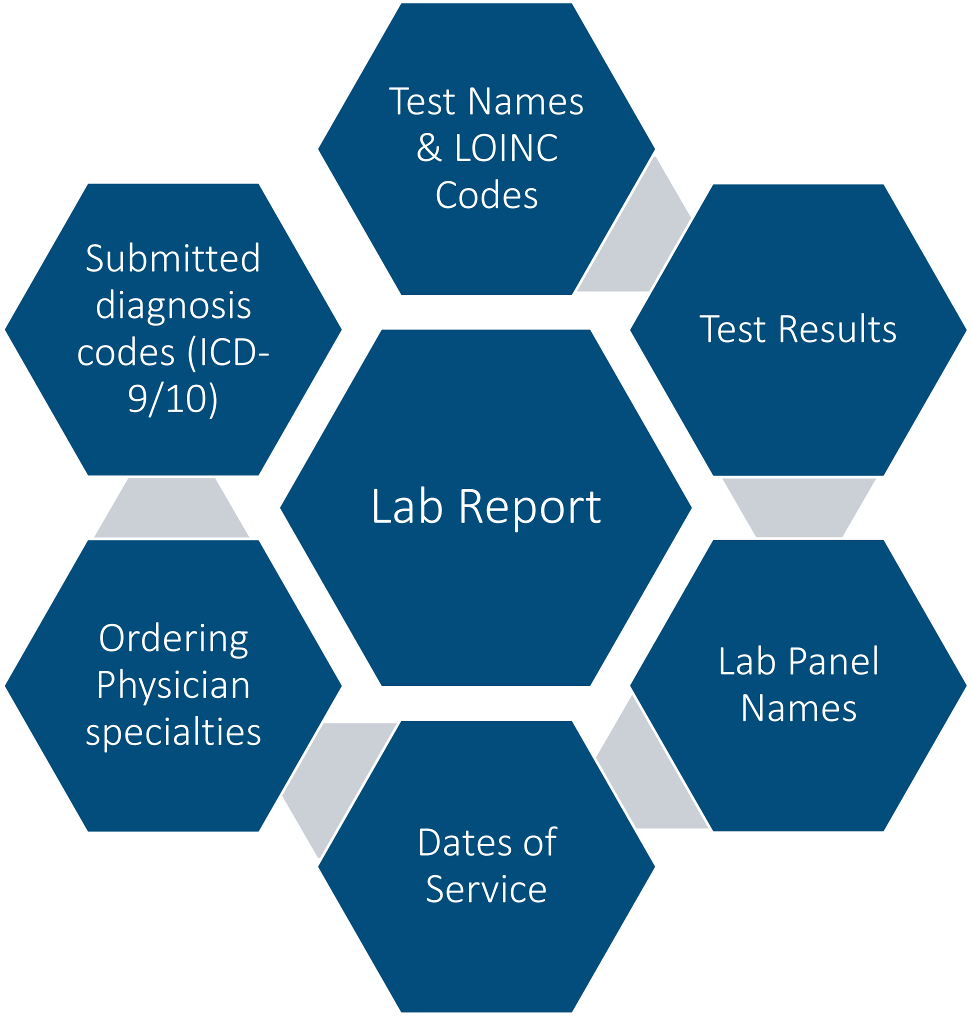
Electronic Health Records (EHRs)

EHR's – Dates, History, Symptoms, Dx, Treatment, Prognosis?

Leading Vendors for the Insurance Industry: Milliman, ExamOne, MIB, Human API, Clareto, Womba, Health Gorilla

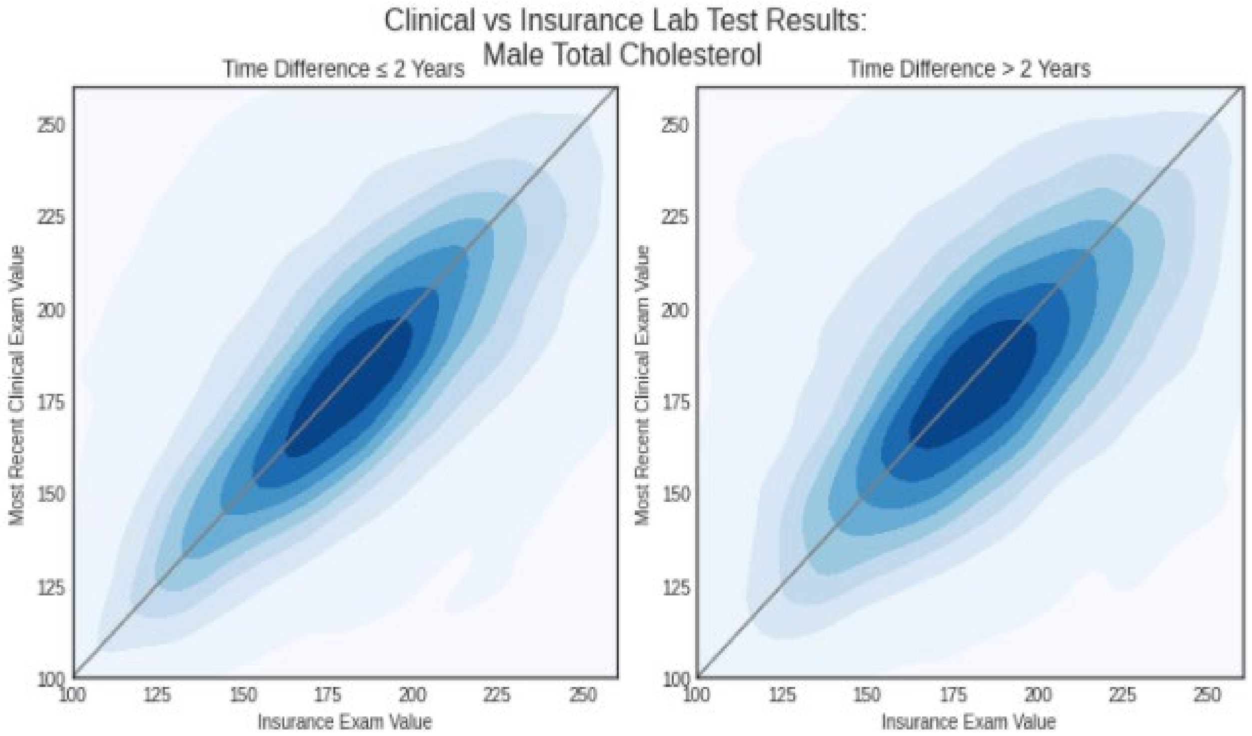
Digital Health Data: Clinical Lab Results

- Some major vendors include ExamOne and CRL
- Underlying data source is network of labs, for example Quest Diagnostics and LabCorp
- Effective at identifying high risks when little other medical data is available
- HIPAA compliant with applicant authorization and meets FCRA requirements.



Clinical vs. Insurance Labs

- **Alignment**: clinical and insurance values largely track with the grey line of equality, where both values are the same.
  - Some differences are expected, possibly related to aging and change in health status over time or different laboratory protocols.
- **Recency**: Better consistency (narrower bands) when clinical labs are within 2 years prior to the insurance exam.



Digital Health Data: Medical Claims Data

What it Provides

- Diagnostic codes used in medical billing
- Allows decision refinements
- Contrast against application disclosures

Issues to Resolve

- Lack of context
- Coding precision
- Lack of history

Digital Health Data: EHRs

An EHR is a real-time patient health record with access to evidence-based decision support tools that can be used to aid clinicians in decision making.

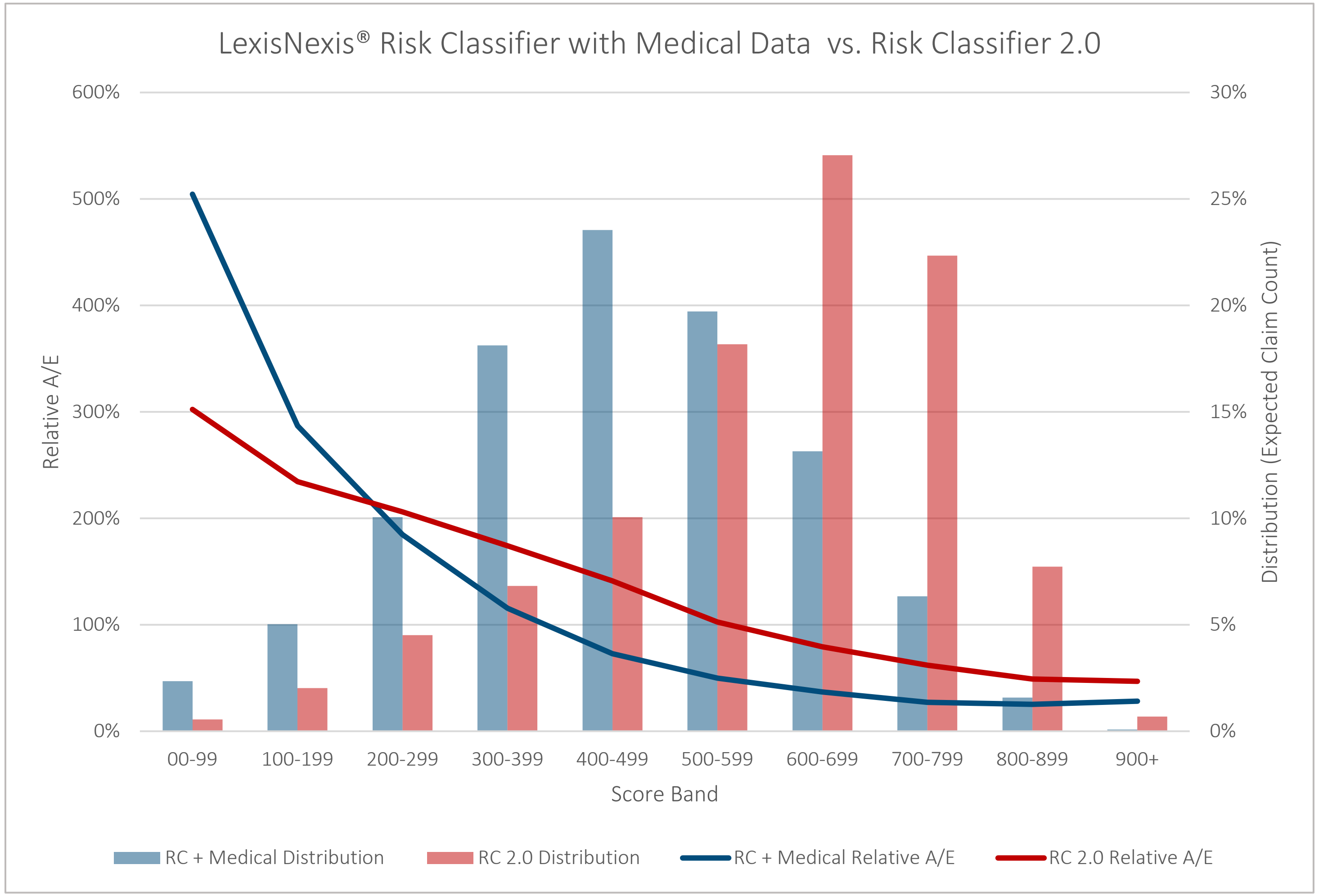
Challenges

- Hit rates are low but steadily increasing
- Hundreds of vendors, many business models, and varying fees
- Legal Requirements for access to medical data must be solved for

Benefits

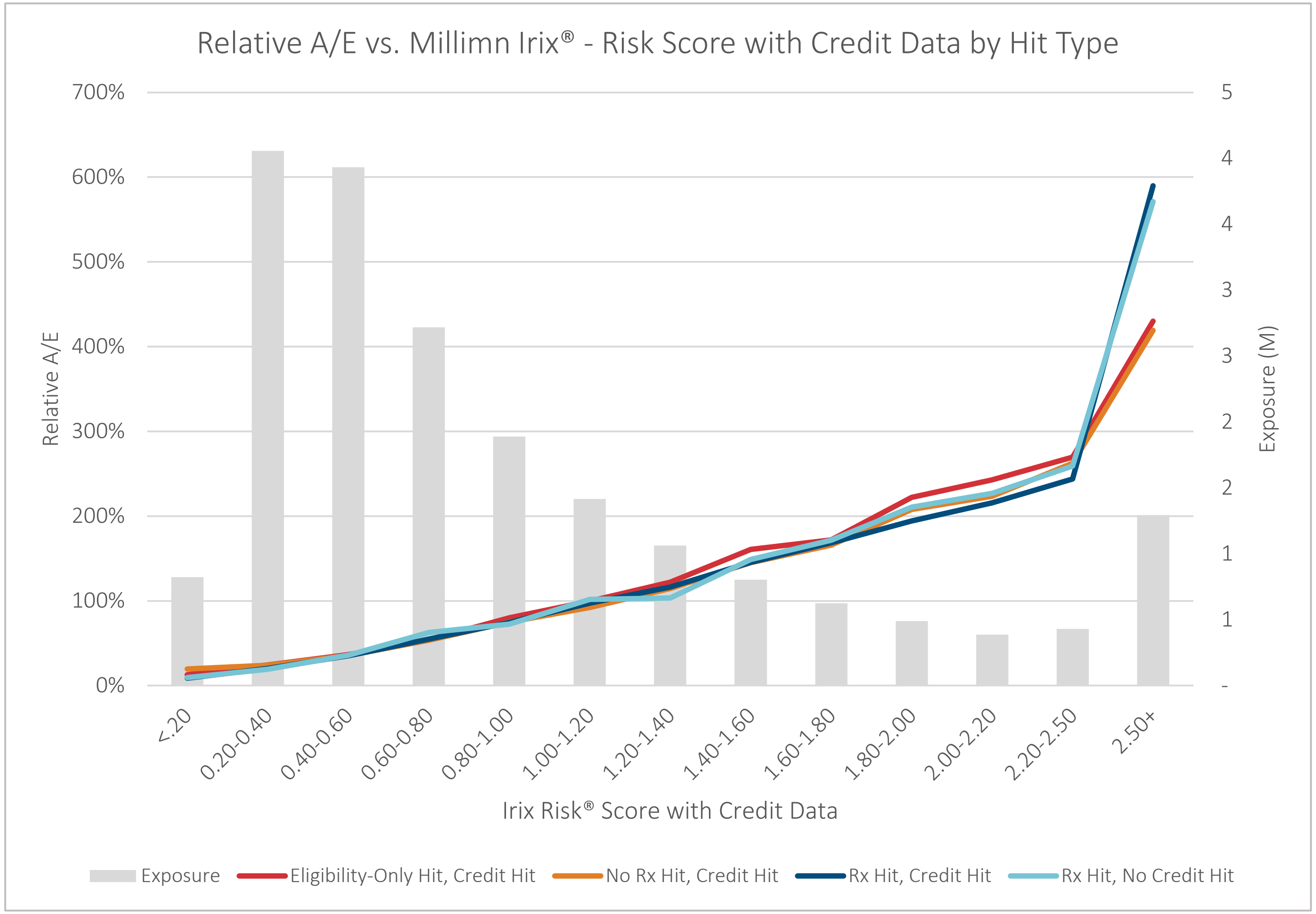
- Realtime access to data – EHR turnaround time is typically a few days vs. weeks for an APS
- Structured data – medical billing and diagnostic codes are labeled
- Possible future state would be to incorporate codes into STP systems

Combined Models: Medical + Credit

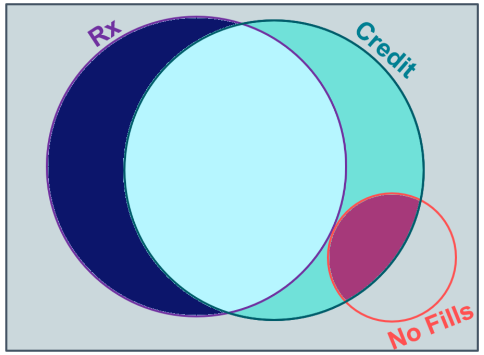


- Risk Classifier with Medical Data incorporates prescription data, labs, and medical claims from ExamOne in addition to behavioral attributes.
- Steeper segmentation: the best scores are reserved for hits with low-risk attributes for both medical and non-medical dimensions
- Bad medical can be offset to an extent with good credit, and vice versa

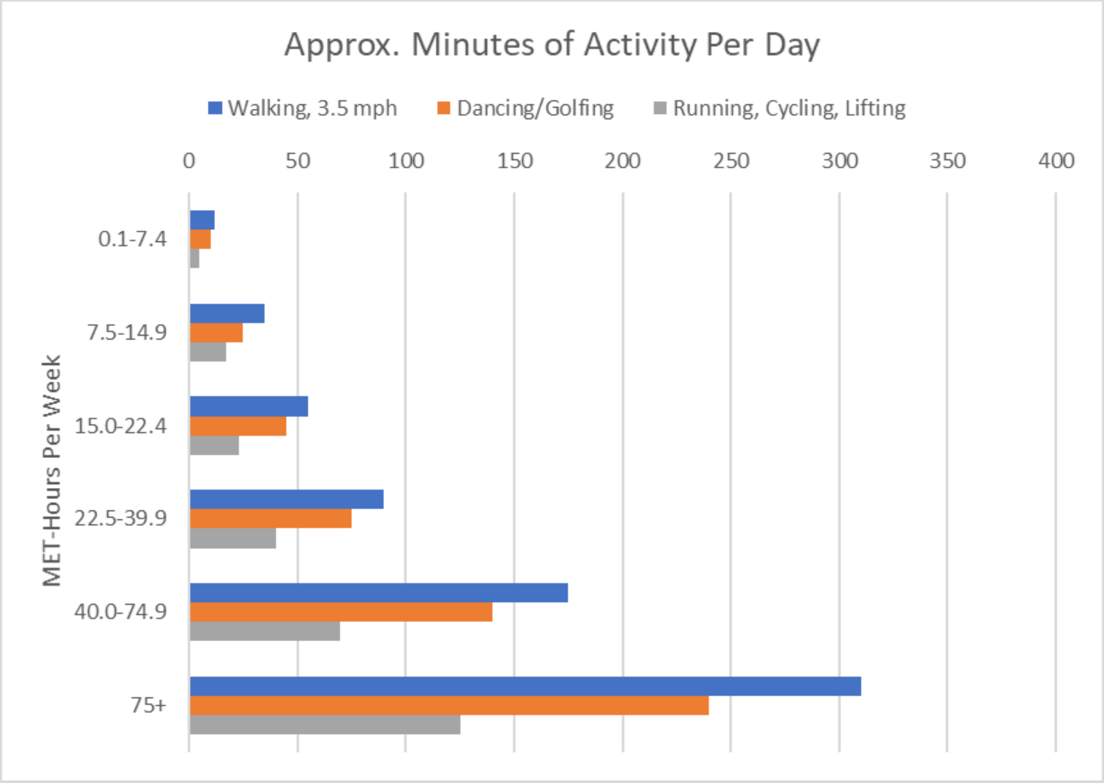
Combined Models: Rx + Credit



- Milliman's Irix risk score with credit data uses both prescription history and credit data
- Score can be produced with Rx-only hit and with credit-only hit, increasing hit rate vs. the Rx-only model.



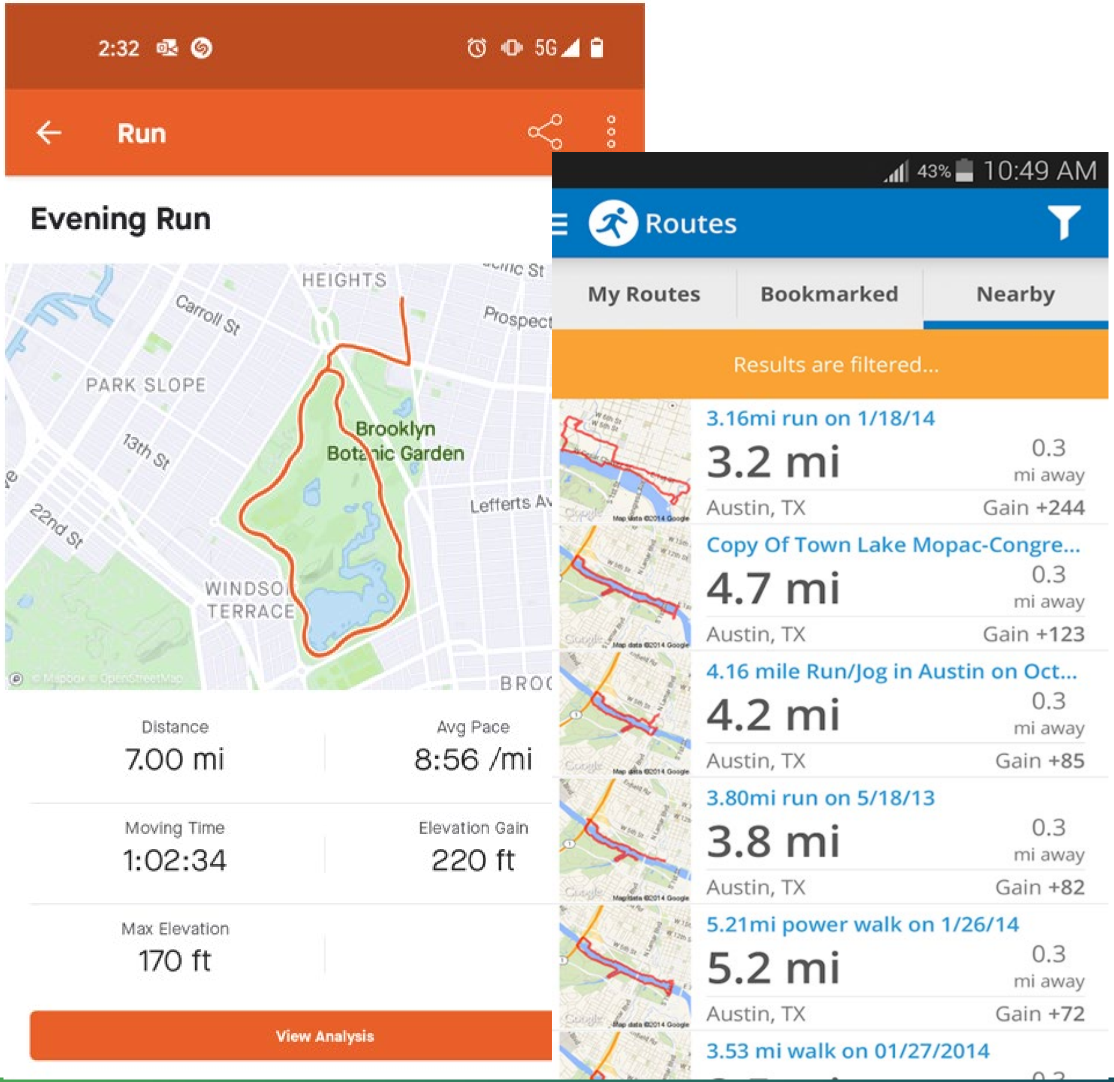
Physical Activity



Hazard Reduction
20%
31%
37%
39%
39%
37%

- Connections to mortality noted in 1953
- Activity level more important than sitting
  - Moderate levels of exercise reverse sitting (standing inadequate)
  - Stop or reduce exercise, and risk increases
- Being sedentary has excess mortality approaching that of tobacco use

Physical Activity



- Wearable devices: phones, watches, bands
- GPS, steps, stairs, pulse, EKG…
- Opportunity for repeated underwriting

The Rest

Biometric Tools

- Facial and voice analytics detect excess “wear and tear”
- Plastic surgery can mislead
- Risk of bias accusations

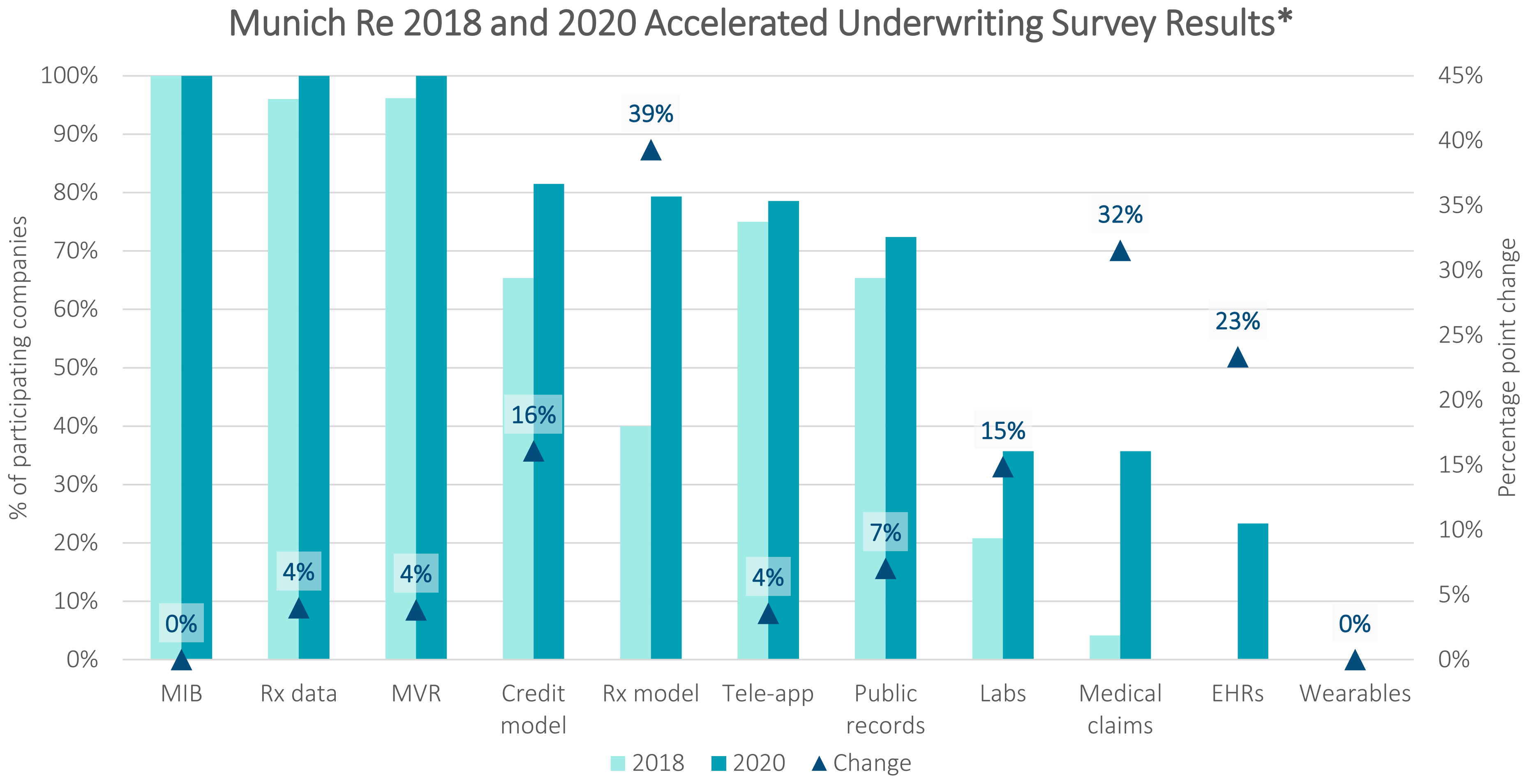
Genomics

- Gene sequencing: indicates future risk
- Epigenetics: signatures of smoking, alcohol use, and so on

Trustworthiness

- Misrepresentation: tobacco use, substance use, build, conditions
- Fraud detection: identity verification

Usage of underwriting data sources over time



* AUW Survey results represents responses from 26 carriers in 2018 survey and 30 carriers in 2020 survey

Impacts to Fluid-Less UW

Tool	Impact to Underwriting
Non-Medical Scoring	Setting thresholds, provides new dimension of risk segmentation
Physical Activity	Setting thresholds
Prescription Scoring	Finer risk classification
EHR, Med Claims, Labs	Better triage, medical Hx proxy
Facial and Vocal Analytics	Improved detection of the unhealthy
Genomics	Personal and family Hx proxy, estimate of future mortality
Truthfulness	Evaluating trust

Many of these tools have use cases outside of fluid-less underwriting, but to-date they've been mostly been evaluated in a fluid-less context

COVID Impacts on UW at Primerica

- Dramatic increase in fluidless sales
- Small reduction in fluid testing

Fluidless and with-fluids products

- Unavailable doctors
- Use LabPiQture to avoid some APS
- EMSI collapse sped up LabPiQture use

APS

- Zoom selling => better disclosures?
- Better Rx hit rates

Better disclosures

Regulatory and Legal Concerns

Privacy and Data Security

- Legal and reputational costs
- Big Data = More Security Risk

Bias and Discrimination

- Disparate impact
- Implicit bias
- Legislative Actions

Ethics

- "We can, but should we?"
- Perils of genomics

The Future

Change is Ever Constant

"New" continues to become "traditional"

Assimilation of InsurTech and data science

Better buyer engagement

Thank you!

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Additional Reading

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