

WEBINAR SERIES

The ACLI logo features the letters 'ACLI' in a bold, white, sans-serif font. To the left of the letters are three parallel, slanted white lines of increasing length, creating a stylized graphic element.

# Future of Predictive Analytics and Innovation

Presented by

**Willis Towers Watson** The Willis Towers Watson logo consists of a series of vertical bars of varying heights, arranged in a pattern that resembles a stylized bar chart or a series of data points.

October 20, 2021 | 1:00 - 2:00 PM ET

# Willis Towers Watson

## Insurance Consulting and Technology

Our Insurance Consulting and Technology line of business provides advice, solutions and software to the insurance industry. We are an integrated consulting and technology provider.

As well as advising more than three quarters of the world's leading insurers, Insurance Consulting and Technology is the world's largest provider of actuarial software and we have over 1000 colleagues dedicated to technology solutions, including over 350 dedicated to insurance software.



### Our consulting services include:

- Risk based and economic capital
- Actuarial transformation and process improvement
- Enterprise Risk Management
- M&A
- Pension Risk Transfer
- Financial and regulatory reporting
- Actuarial outsourcing
- Experience studies and predictive analytics
- Litigation and reinsurance arbitration support
- Pricing and product development

### Our technology solutions include:

- Financial and capital modeling
- Predictive modeling and analytics
- Process automation and governance

# ACLI Antitrust Statement

The American Council of Life Insurers is committed to adhering strictly to the letter and spirit of the antitrust laws. Meetings conducted under the ACLI's auspices are designated solely to provide a forum for the expression of various points of view on topics described in the agenda. Under no circumstances shall ACLI meetings be used as a means for competing companies to reach any understanding, expressed or implied, which tends to restrict competition, or in any way, to impair the ability of members to exercise independent business judgement regarding matters affecting competition.

Wednesdays with Willis Towers Watson

# Future of Predictive Analytics and Innovation

Kim Steiner and Amber Ruiz




October 20, 2021



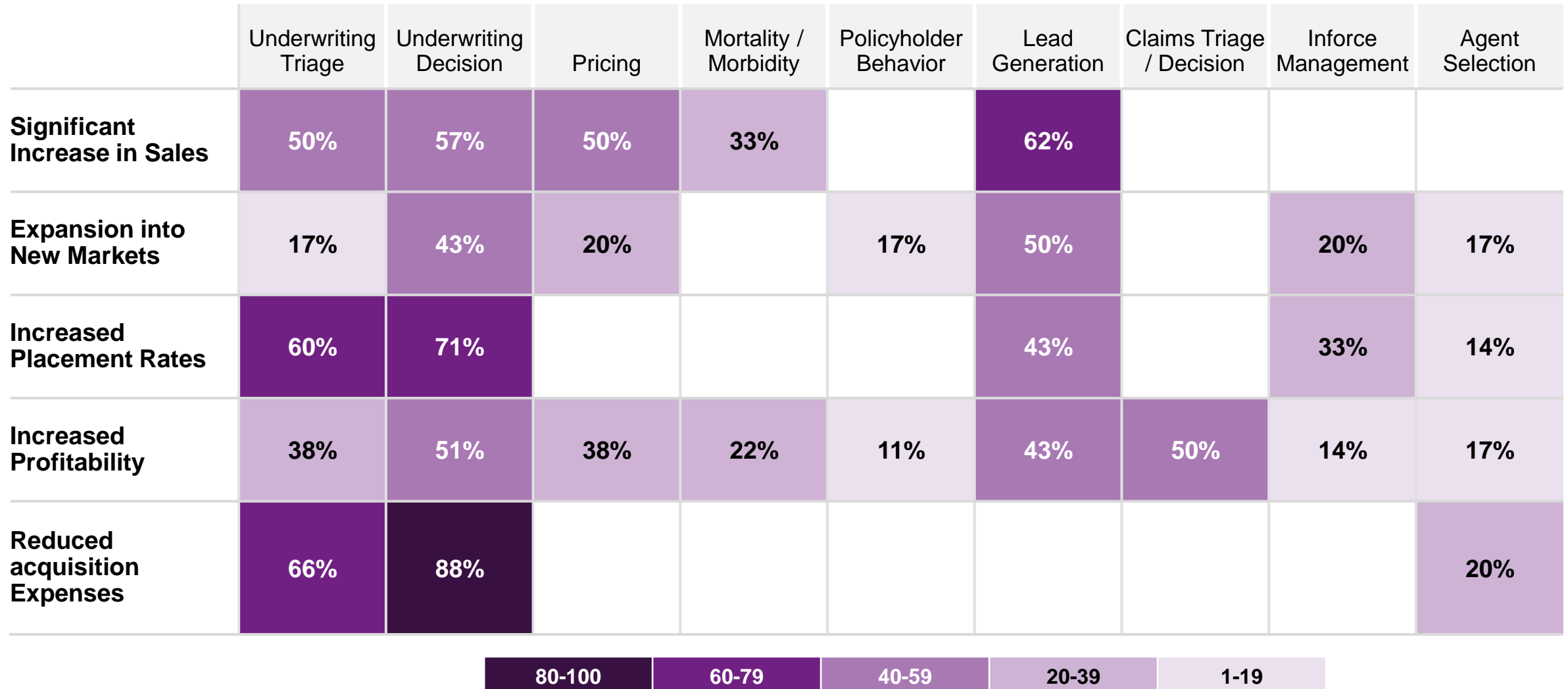


## Life Predictive Analytics Survey

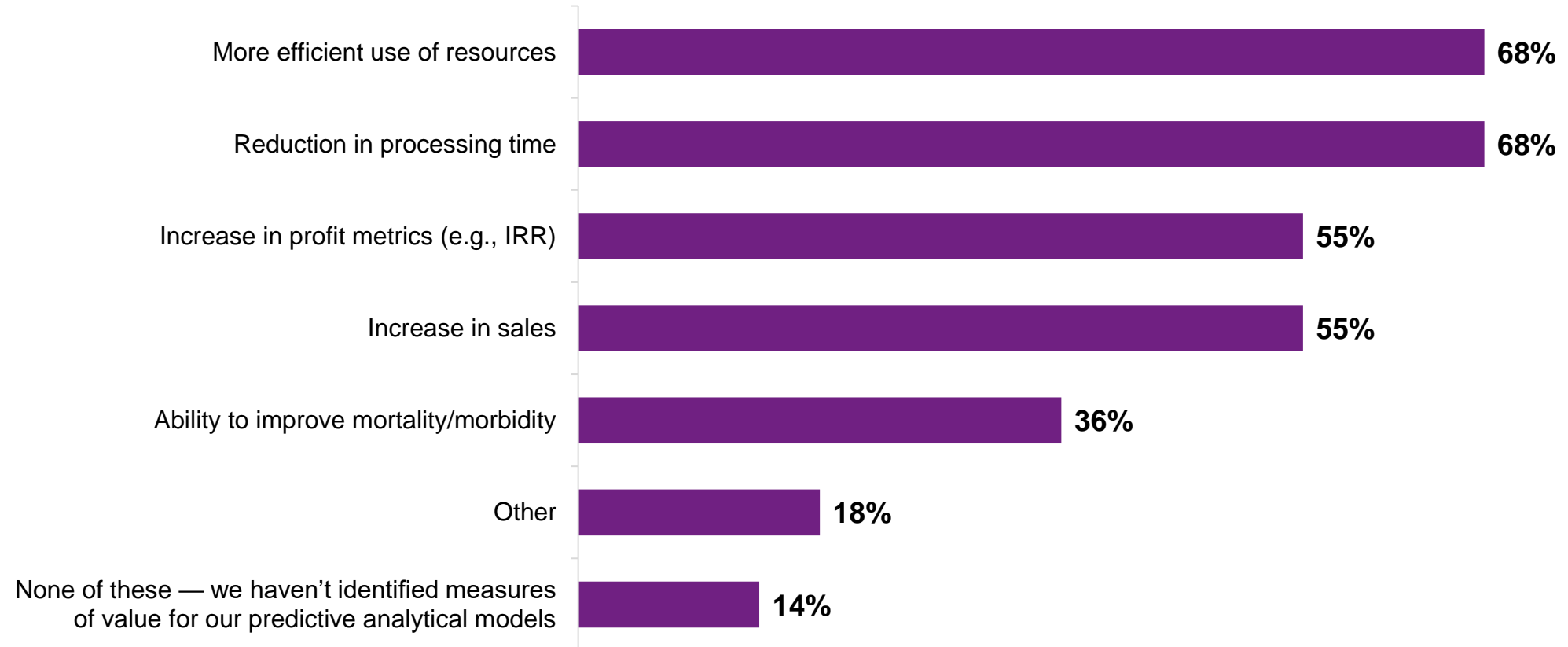
## Multiple drivers make predictive analytics capabilities essential for life insurers hoping to compete

		High importance	Low importance	No importance
	Earnings and profitability pressures	76%	24%	0%
	Customer relationship management	76%	12%	12%
	Technological innovation	56%	40%	4%
	Competitive pressures in product development and pricing pressures	56%	36%	8%

## Life insurers realize significant positive impact from predictive analytics usage



## Value of the predictive analytics initiatives are most often determined by efficient use of resources and reduction in processing time





Not surprisingly, large carriers lead the way in investing in predictive analytics. However, all carriers expect to invest over the next two years.

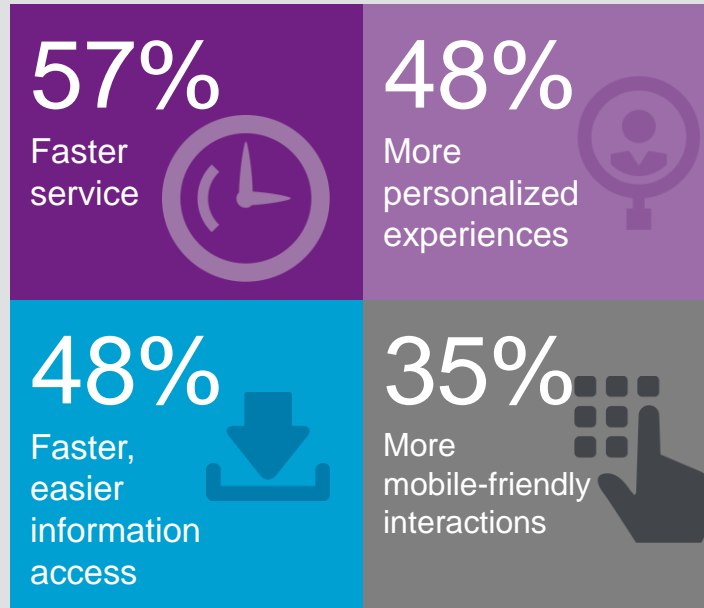


		Now	Two years
Large carriers (over \$1 billion)	Individual life insurance	89%	89%
	Group insurance	57%	71%
	Retail individual annuities	73%	82%
	Institutional annuities	38%	38%
	Individual health	67%	67%
Small and Medium carriers (less than \$1 billion)	Individual life insurance	24%	65%
	Group insurance	8%	38%
	Retail individual annuities	8%	25%
	Institutional annuities	0%	14%
	Individual health	20%	60%

## Creating customer engagement is a strategic focus

Predictive analytics plays a key role now, and even more so in the future.

How life insurers plan to improve customer experiences



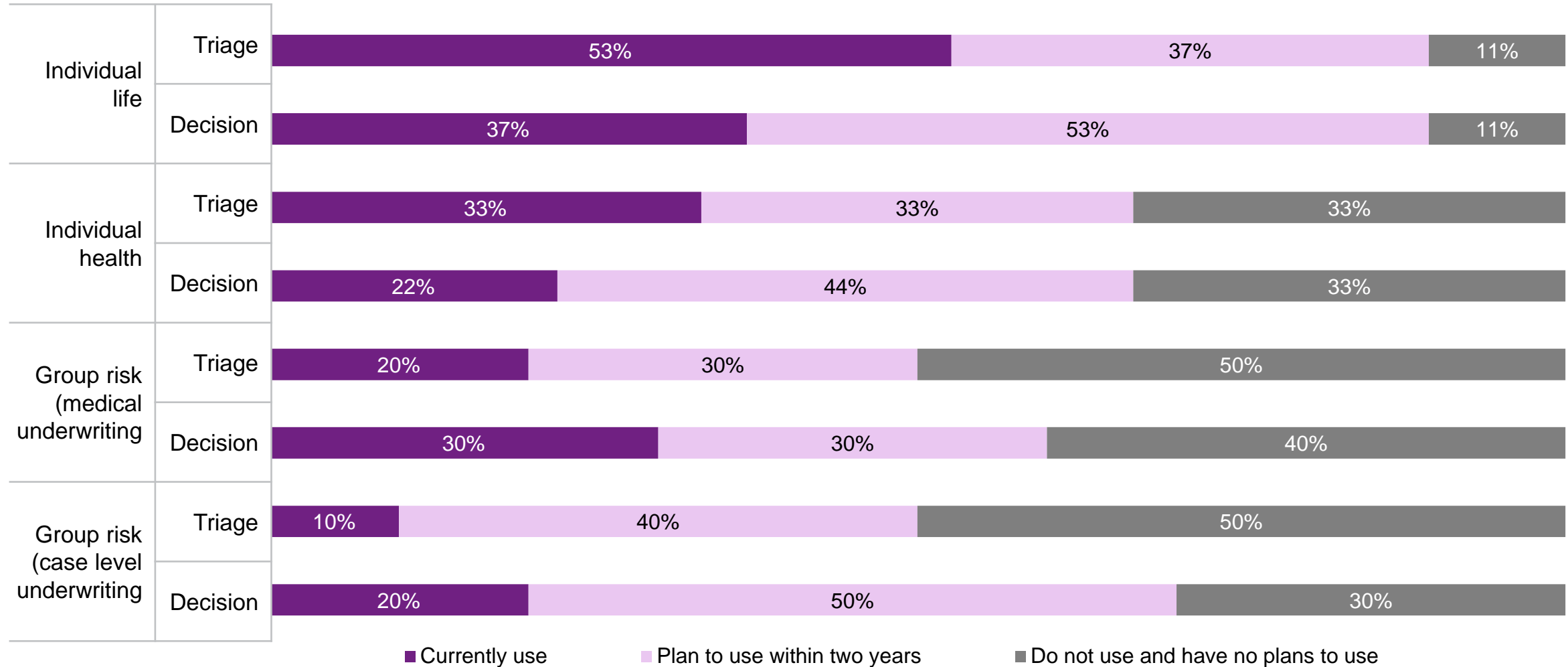
Top data sources life insurers use now and plan to use in two years to improve customer centricity

	Now	Two years
Internal customer data	57%	61%
Customer interactions/Surveys	35%	48%
Web scraping	17%	30%
Clickstream	17%	43%
Social media	13%	22%
	Now	Five years
Wearables	2%	19%

Insurers plan to capitalize on this data with inforce management opportunities such as cross selling

	Individual Life	Individual Health	Group Insurance	Institutional Annuities	Retail Institutional Annuities
Now	32%	20%	33%	25%	22%
2 Years	72%	50%	75%	25%	78%

## Use of predictive analytics in underwriting is becoming table stakes to remain viable.



## Claim management and fraud detection will be far more data-driven

Desired outcomes: better claim management, reduce cost and risk

### Current and planned analytics applications

	Now	Two years
Evaluation of claims for fraud potential	17%	60%
Evaluation of application for misrepresentation	13%	40%
Claim triage	13%	34%
Evaluation of claims for litigation potential	2%	11%

### Use of claims triage in various lines of business

	Now	Two years
Individual Life Insurance	11%	33%
Group Insurance	40%	40%
Individual Health	22%	33%

Companies are looking to identify misrepresentation in their fraud models



21%  
Smoking  
Status



21%  
Customer  
Data



16%  
Medical  
Conditions



11%  
Height &  
Weight







5%  
Family  
History

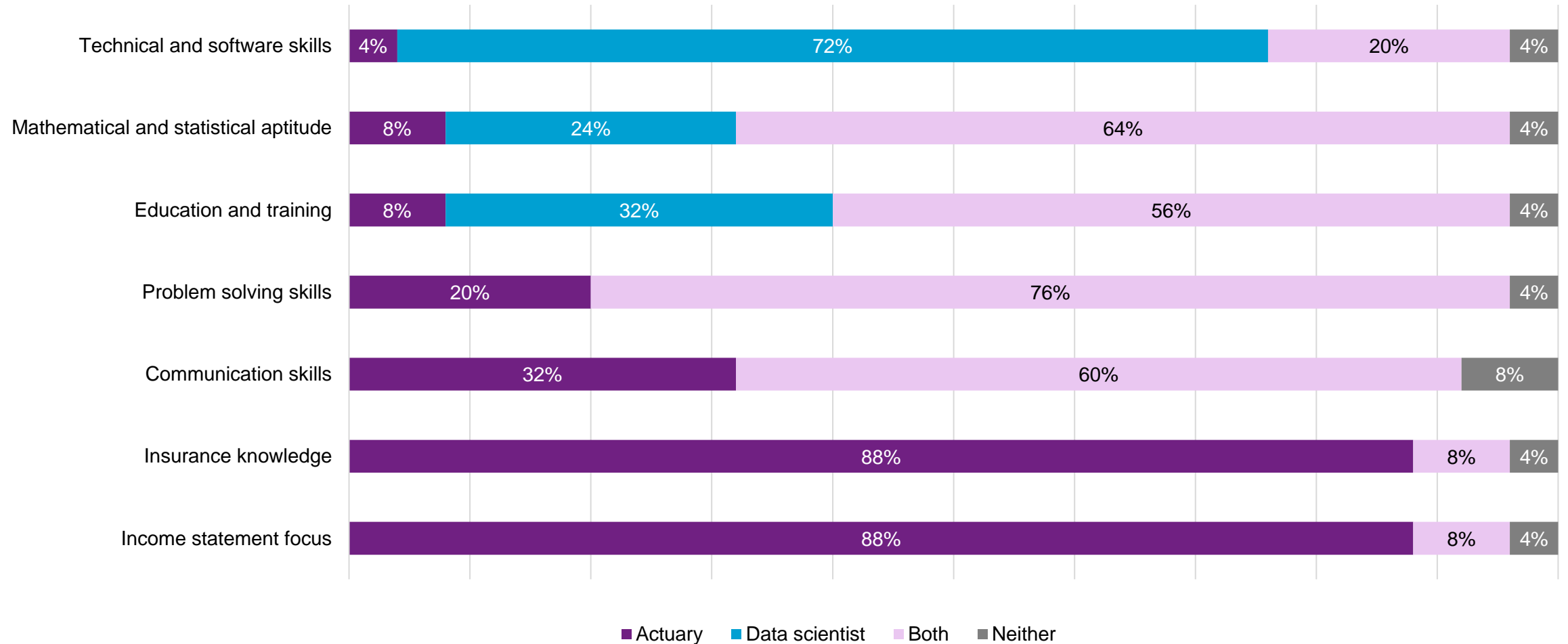


5%  
Customer  
Comments

## Most companies are using a combination of life actuaries and data scientists

	25 <sup>th</sup> Percentile	Median	75 <sup>th</sup> Percentile
 <b>Life actuaries</b>	10%	33%	56%
 <b>Property &amp; casualty actuaries</b>	0%	0%	0%
 <b>Data scientists with insurance backgrounds</b>	0%	5%	30%
 <b>Data scientists without insurance backgrounds</b>	0%	37%	56%

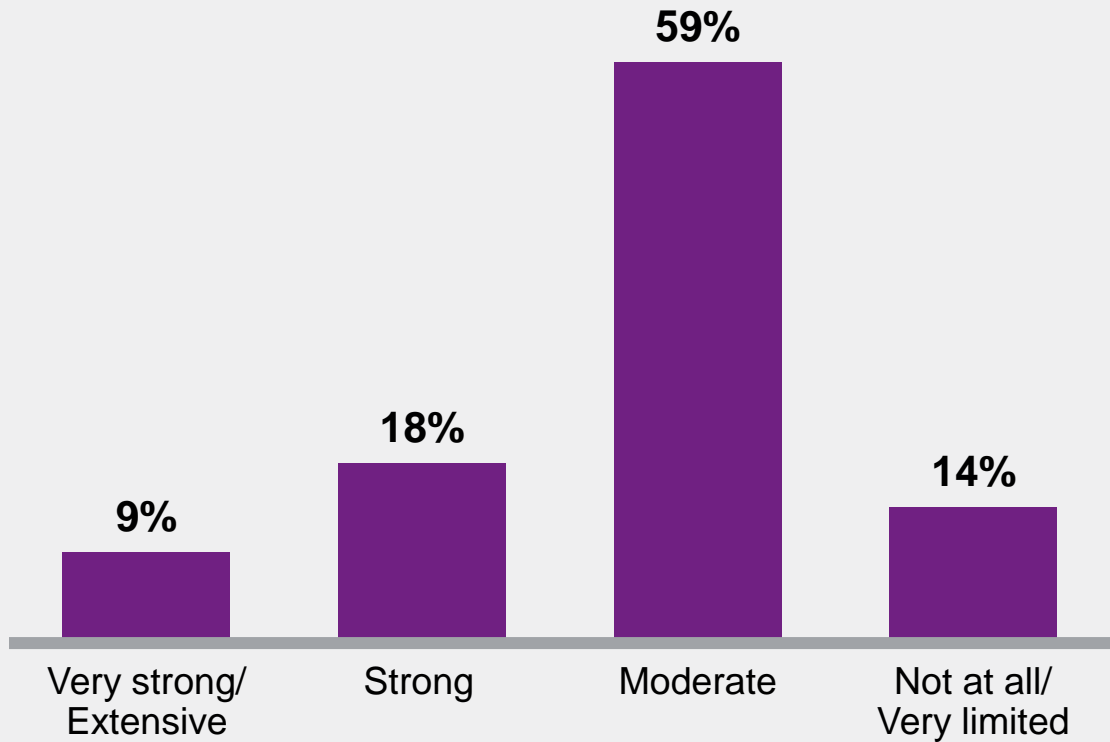
## Most companies believe that actuaries have skills to handle various characteristics of predictive analytics



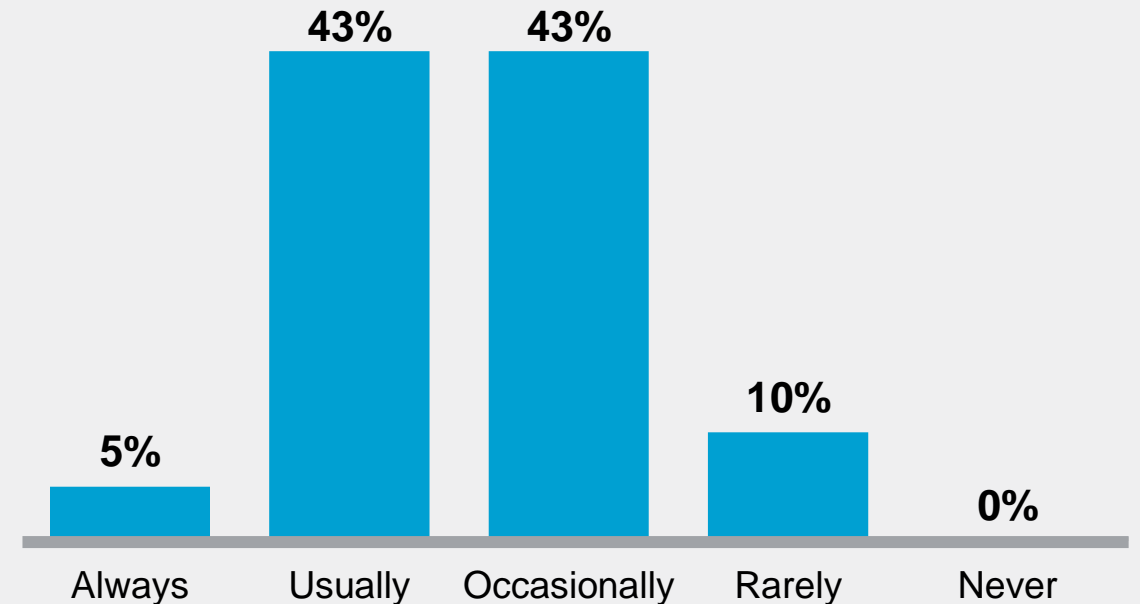


## Data scientists and actuaries must partner to deliver actionable results

### How well model results are understood outside of the modeling team



### Less than half of models usually get implemented



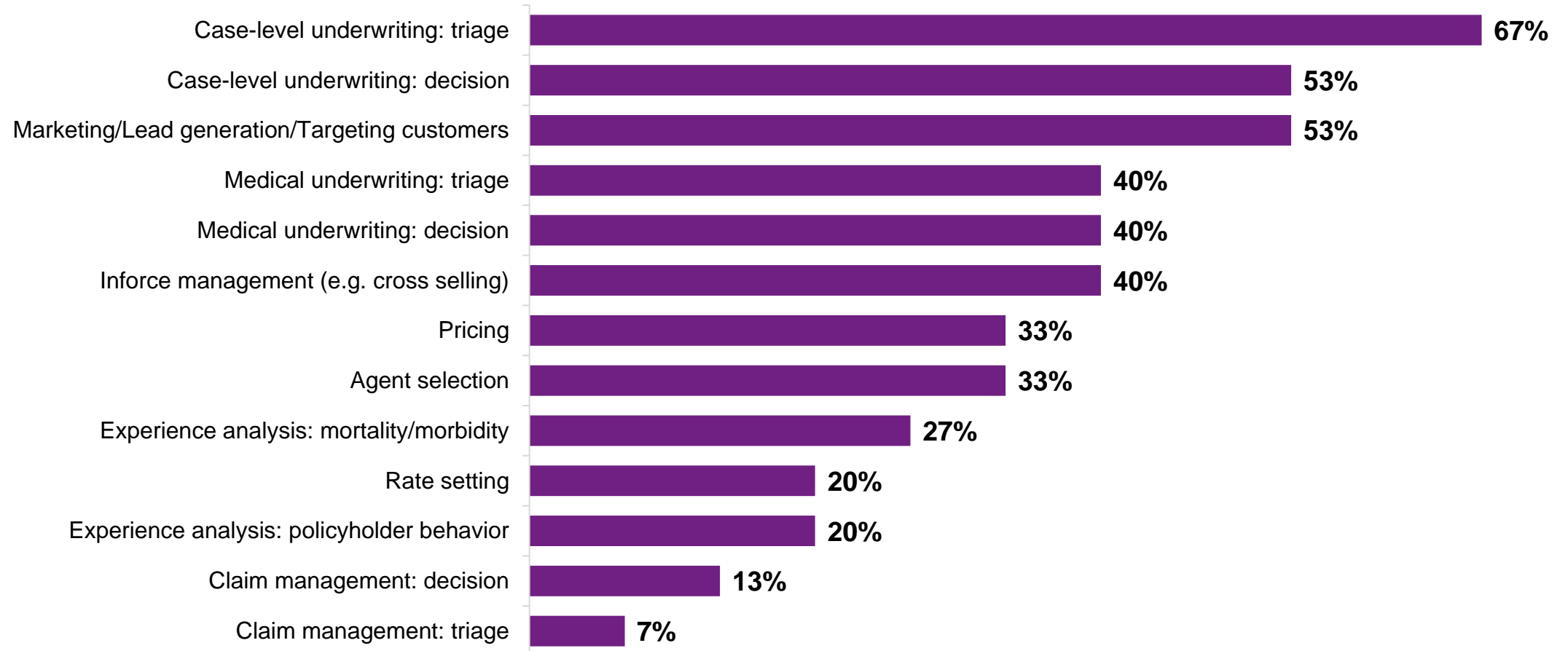
## Use of third-party data assets – a hot topic in the industry

Usage varies significantly by line of business

	Individual life insurance	Group insurance	Retail individual annuities	Individual health
▪ External credit/Financial attributes	69%	40%	40%	38%
▪ Prescription drug history	69%	40%	10%	25%
▪ Account/Household penetration <i>(by the company for other products)</i>	54%	0%	40%	25%
▪ Geo-demographic information <i>(i.e., information, other than crime, about the area in which the risk is located)</i>	54%	80%	40%	38%
▪ Lifestyle data	54%	60%	20%	13%
▪ Sociodemographic information <i>(i.e., information other than credit attributes about an insured)</i>	46%	60%	40%	13%
▪ Electronic medical record	38%	20%	10%	0%
▪ Commercial applications <i>(e.g., LexisNexis)</i>	38%	20%	10%	13%
▪ Consumer buying behavior	31%	20%	30%	0%
▪ Credit reports	31%	40%	10%	13%
▪ Geographic crime information	15%	20%	10%	0%
▪ Social media	15%	20%	20%	0%

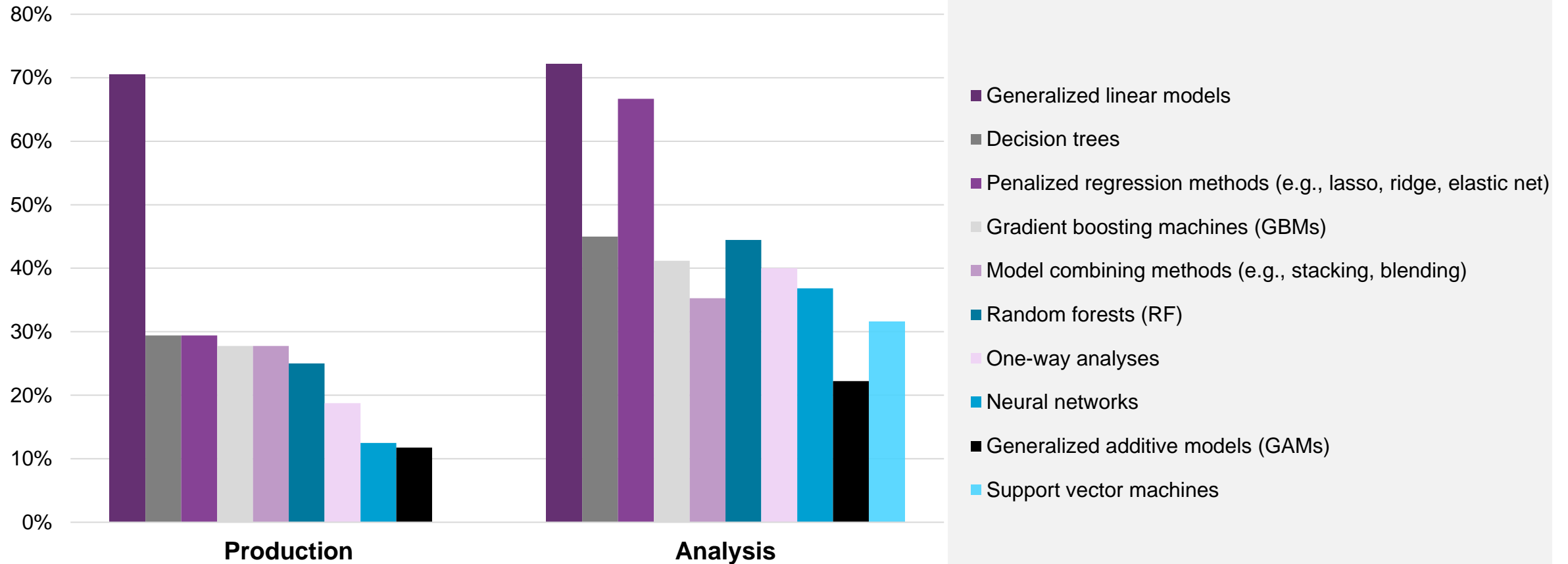


## External data sources are most commonly used as part of predictive analytics for underwriting and lead generation



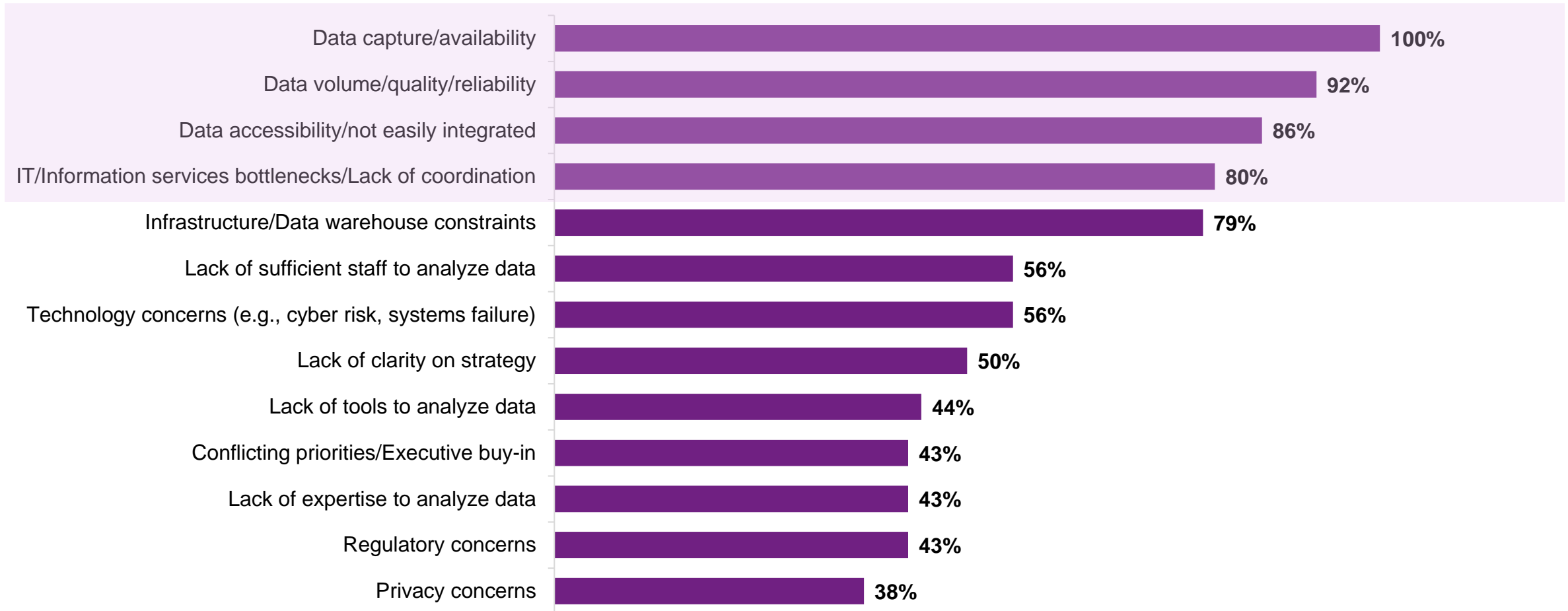
**Generalized linear models (GLMs) are by far the most common modeling technique used in production – suggesting that interpretability is a valued trait**

### Predictive Analytical modeling techniques currently used

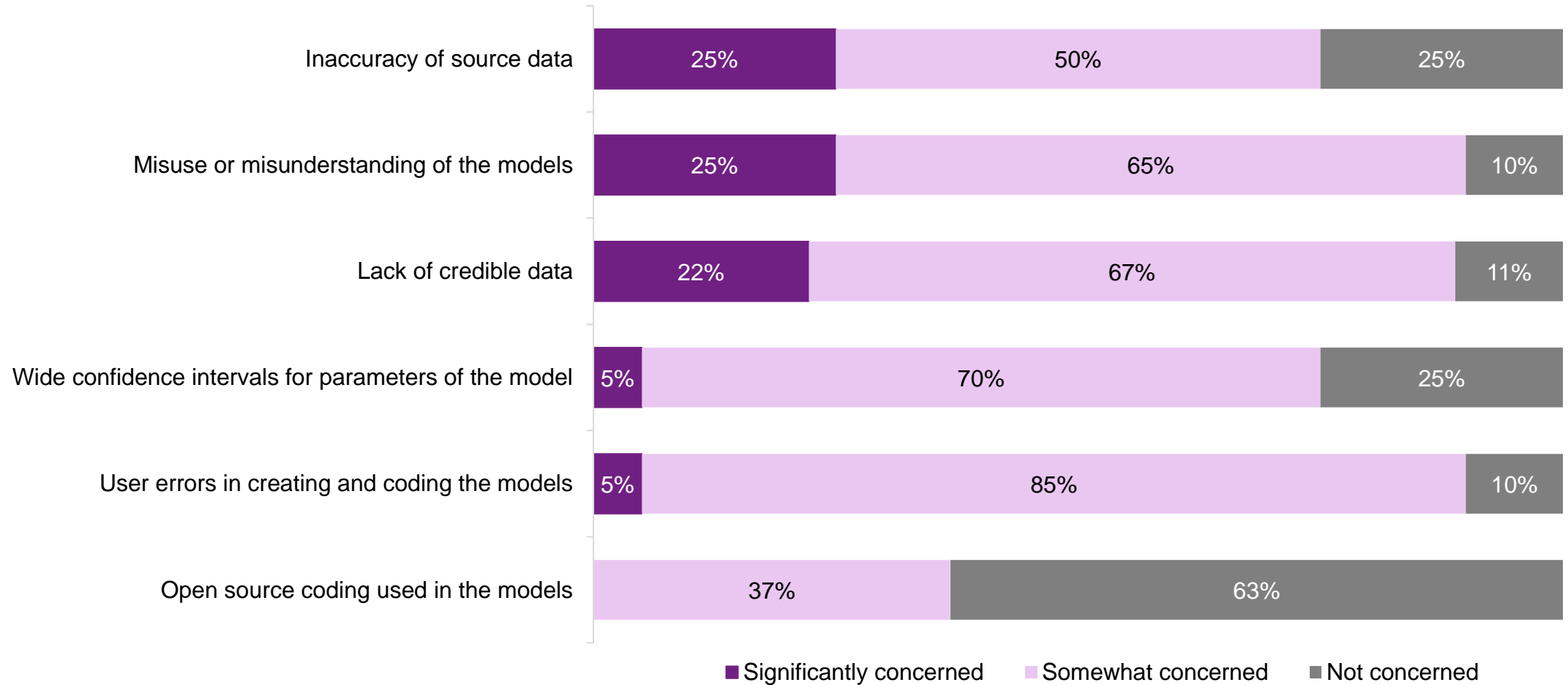


## Significant challenges pose a risk to ability to capitalize on analytics

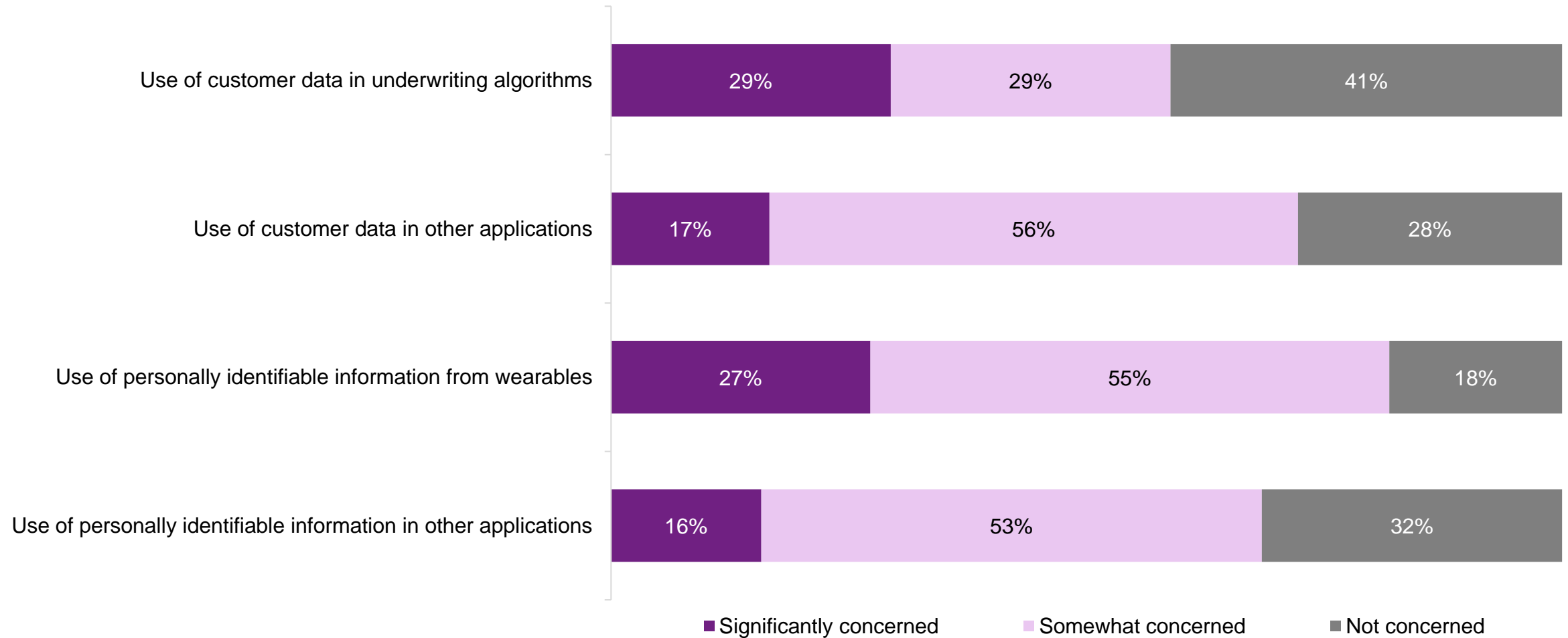
All aspects of data are most cited complications



## Aspects of predictive models are areas of concern in complying with risk management guidelines



## In the current regulatory environment, addressing various concerns regarding data usage and privacy is critical



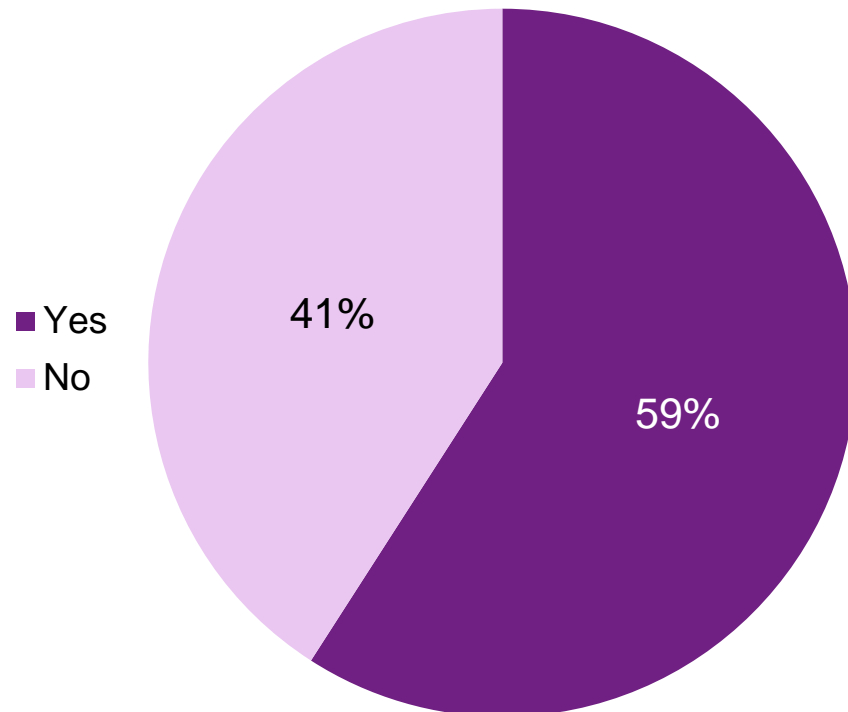
## Key Takeaways

- It is clear from studying the industry that analytics is becoming table stakes – with significant growth on the agenda ahead
- Data scientists and actuaries must partner to deliver actionable solutions – thereby delivering value to stakeholders
- All aspects of data remains a huge challenge – focus needs to remain on improving vast amount of data such that it can be leveraged for predictive analytics

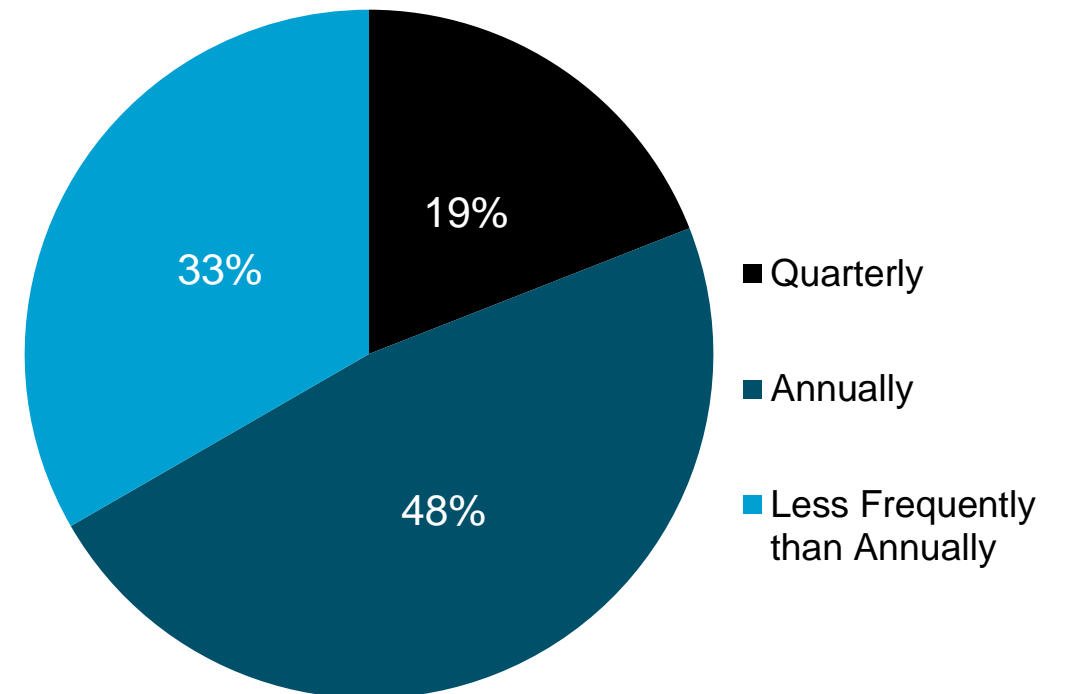
## Over half of companies have their predictive models covered by the governance process

Nearly half have them reviewed annually

### Predictive models review by governance



### Frequency of Review





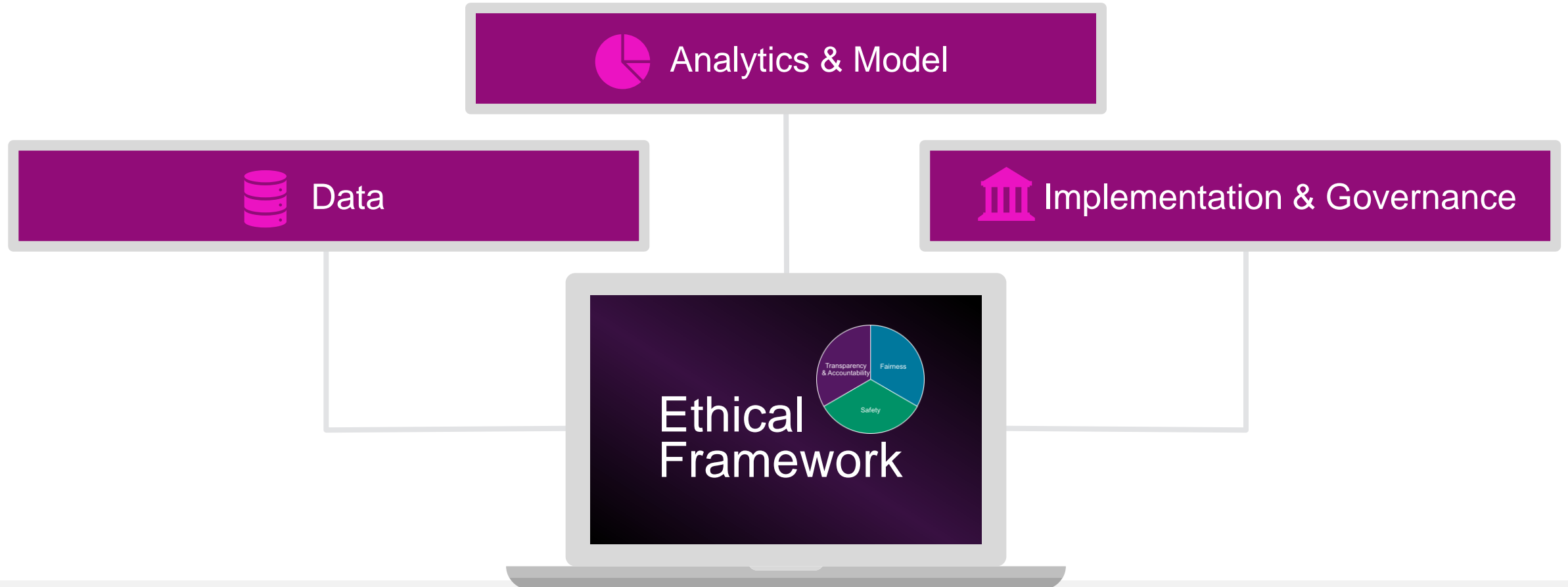
## Ethical Implications of Big Data, Predictive Models and Artificial Intelligence

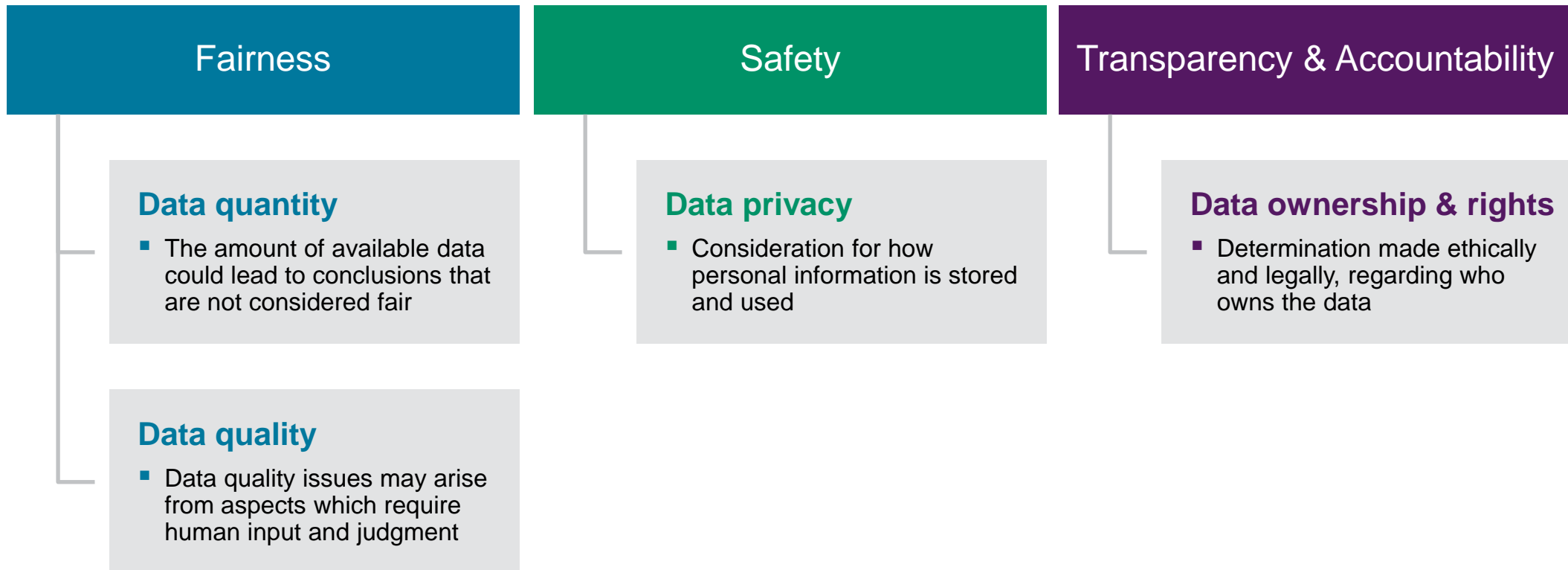


# Ethical framework



# Application of the ethical framework





## Fairness

- The fairness of the resulting predictive model should be considered in the design, to prevent bias. For example, building models that do not discriminate against protected classes of people.
- The model may be assessed by outcome equity, where an outcome may be defined as the average level of prediction or errors for each group.
- Care should be taken to avoid usage of proxy variables that are dependent on or correlated to prohibited variables. For example, a zip code may correlate with race or other prohibited classes.

## Safety

- Causation and association should be distinguished.
- Predictive models strive to maximize the accuracy of the predictive power given the data set. This accuracy is an aspect of safety, as the model aims to minimize any potential prediction error.

## Transparency & Accountability

- Model explain ability is important, as “black box” models may include algorithms that are too complex to be easily comprehended.
- If people do not understand why or how the model works, or the drivers behind the results cannot easily be explained.

## Fairness

- Even if fairness is considered in data collection, data selection, and the modeling stage, biased results may occur during the implementation and governance stages.
- For example, even if the pricing or underwriting predictive models considered the data and model fairness, in ensuring that only actuarially sound factors were used, the marketing and commission strategy may promote or demote certain customer groups, leading to potential discrimination.

## Safety

- New data may cause the model to break down after the deployment.
- It is important to implement a post-deployment monitoring framework to ensure the model is working as intended and blind spots are being guarded against.

## Transparency & Accountability

- Transparency requires that the process and outcomes are clearly documented and communicated, such that it can be repeated and audited.
- Includes the ability to explain and justify the effect of the model in relation to the business context.

# Applicable Actuarial Standards of Practice (ASOPs)

**ASOP 23:**  
Data Quality

**ASOP 56:**  
Modeling

**ASOP 41:**  
Actuarial  
Communications

**ASOP 12:**  
Risk  
Classification

**ASOP 54:**  
Pricing of Life  
Insurance and  
Annuity Products

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