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Submitted to the Program of Organizational Dynamics, College of Liberal and Professional Studies in the School of Arts and Sciences in Partial Fulfillment of the Requirements for the Degree of Master of Science in Organizational Dynamics at the University of Pennsylvania

Advisor: Dana Kaminstein

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The Cognitive and Emotional Reactions of Commercial Casualty Insurance Underwriters to the Use of Predictive Analytics

Abstract

The rise of big data and predictive analytics continues to proliferate throughout many industries across the globe and the commercial insurance industry is no exception. One of the core operations of any insurance company is underwriting, where underwriters make important decisions about which risks the insurance company accepts (or rejects), at what price and what terms. These decisions have traditionally been made through a balance of human intuition, judgment and actuarial science but now, with the ability to capture large bodies of data and the application of sophisticated algorithms, insurance companies are developing new decision-making tools that may change the traditional underwriting process and methodology. This exploratory study examines the cognitive and emotional reactions of underwriters to these new tools.

Although a limited amount of research exists dealing with human reactions to computer-based decision making, a near complete gap exists examining the interaction of commercial casualty underwriters and predictive analytics. A quantitative research methodology was used as the framework for an online survey was completed by 46 commercial casualty underwriters from various insurance companies. Purposeful sampling was used to select participants for the study and a simple statistical analysis was used to develop inferences about the population.

The prominent finding showed that underwriters often acquiesced to the output produced by algorithmic based tools when they did not agree with the result. This in turn caused frustration and ambivalence toward the model. In addition, the majority of underwriters did not always agree with the model setting the stage for more frustration. Interestingly the data showed a notable split in how underwriters do their job now in the face of predictive analytics. The majority are still underwriting the same and considered predictive analytics as a complementary piece, rather than an exclusive one, signaling that underwriters still had meaningful influence in the decision making process while a sizable portion spent less time underwriting knowing the model would ultimately trump their decision.

Keywords

casualty insurance, underwriting, predictive analytics

Comments

Submitted to the Program of Organizational Dynamics, College of Liberal and Professional Studies in the School of Arts and Sciences in Partial Fulfillment of the Requirements for the Degree of Master of Science in Organizational Dynamics at the University of Pennsylvania

Advisor: Dana Kaminstein

THE COGNITIVE AND EMOTIONAL REACTIONS OF COMMERCIAL
CASUALTY INSURANCE UNDERWRITERS TO THE USE OF PREDICTIVE
ANALYTICS

By

Steven P. Larzelere

Submitted to the Program of Organizational Dynamics,
College of Liberal and Professional Studies
in the School of Arts and Sciences
in Partial Fulfillment of the Requirements for the Degree of
Master of Science in Organizational Dynamics at the
University of Pennsylvania

Philadelphia, Pennsylvania

2021

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ANALYTICS

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ABSTRACT

The rise of big data and predictive analytics continues to proliferate throughout many industries across the globe and the commercial insurance industry is no exception. One of the core operations of any insurance company is underwriting, where underwriters make important decisions about which risks the insurance company accepts (or rejects), at what price and what terms. These decisions have traditionally been made through a balance of human intuition, judgment and actuarial science but now, with the ability to capture large bodies of data and the application of sophisticated algorithms, insurance companies are developing new decision-making tools that may change the traditional underwriting process and methodology. This exploratory study examines the cognitive and emotional reactions of underwriters to these new tools.

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CHAPTER 1

INTRODUCTION

“It’s tough to make predictions, especially about the future.” - Yogi Berra

This capstone is an exploratory study of the cognitive and emotional reactions of commercial casualty insurance underwriters to the introduction of predictive analytics designed to assist, or possibly replace, portions of the underwriters’ role that traditionally required the use of human judgment.

The chapter begins with some background and context by briefly describing what a commercial casualty insurance underwriter does and where predictive analytics fit into the underwriting process. Next, I discuss the importance of this topic for not only the underwriters but, also the companies they work for. The chapter continues with an overview of the literature review I conducted. It follows with a description of the research methodology and method I employed. Last, I explain my personal interest and experience that led me to this topic including certain assumptions that I made as I embarked on this journey.

Background / Context

Beattie (2019) describes one of the earliest examples of underwriting, and thus the creation of the underwriter, that dates back to the 1600’s when the coffeehouse owned by Edward Lloyd, later of Lloyd’s of London, was used as a meeting place for merchants, ship owners and others seeking insurance for exotic goods being shipped back and forth between the British Empire and colonies that were forming in North America. These voyages were funded by venture capitalists who would help find people who wanted to be colonists, usually those from the more desperate areas of London, and would purchase

provisions for the voyage (2019). In return, they would be guaranteed some of the goods the colonists would produce or find in America. Once the voyage was funded and ready to sail, the merchants and ship owners would meet at Lloyd's where a list of the ship's cargo was read to the investors and underwriters who gathered there (2019). "Those who were interested in taking on the risk for a set premium would sign at the bottom of the manifest beneath the figure indicating what share of the cargo they were taking responsibility for (hence, underwriting)" (2019, para 11).

Fast forward hundreds of years and the basic concept of insurance really hasn't changed much. Generally, insurance companies are in the business of assuming the risk of others with the hope of collecting more premium dollars than they pay out in the form of claim payments thereby generating a profit. In insurance parlance this is known as underwriting income and is a major component that leads to either the success or failure of an insurance company; and in turn, the underwriters play a vital role in this outcome. They decide, on behalf of the insurance company, which risks they should accept or reject, how much premium should be charged and what terms should be included or excluded in the contract (i.e. insurance policy). These three elements: risk selection, pricing and contract structuring are the three integral tenets of underwriting.

Of course, most underwriters do not have free reign to make complete arbitrary decisions and so, guardrails are typically placed on them in a couple of ways. Companies restrict underwriters by implementing written underwriting guidelines and issuing formal underwriting authority letters to individual underwriters. These two mechanisms typically work together to control the underwriters' actions. Underwriting guidelines typically apply to a broader group (e.g. an underwriting department or division) within

the Company while underwriting authority are normally written letters tailored to individual underwriters. Underwriting authority letters normally are reflective of the amount of experience or expertise that the underwriter has and are dictated by an underwriting manager.

Within the boundaries noted above, underwriters use a combination of tools and judgment to analyze and make decisions relative to risk selection, pricing and contract structure. Just as the Lloyd's underwriters of the 1600's relied on instinct and later Pascal and Fermat's actuarial tables, today's underwriters use a combination of data gathering and analysis, interviewing and professional knowledge to evaluate whether a given risk meets the insurer's standards and, if so, under what terms. As stated in A.M. Best (2019), perhaps the most significant responsibility of underwriters is to determine premium that recognizes the likelihood of a claim and enables the insurer to earn a profit (p. 9).

How an underwriter prices the risk is generally done using a combination of actuarial based models coupled with underwriting judgment. There are various types of models based on various scientific approaches, the details of which fall well beyond the scope of this capstone. However, an essential principle of these models is their reliance on data to predict future outcomes. As noted in A.M. Best (2019), insurance is based on probability and statistics. Actuaries are skilled in both areas and use their training to help insurers set rates, develop and price policies and coverage, determine reserves for anticipated claims and develop new products that provide coverage at a profit (p. 9). Although scientifically based, underwriters are still expected to interpret and adjust the outcomes of the model based on the parameters of the risk and are trusted to do so based

on their level of expertise. To illustrate this, a company's underwriting guidelines may dictate that a maximum premium credit of 10% can be applied to a risk. What this really means is that the underwriter has the permission to grant this credit but, he should do so only if the risk deserves it. Making this determination would be a simple example of where an underwriter uses judgment.

Big Data and Predictive Analytics

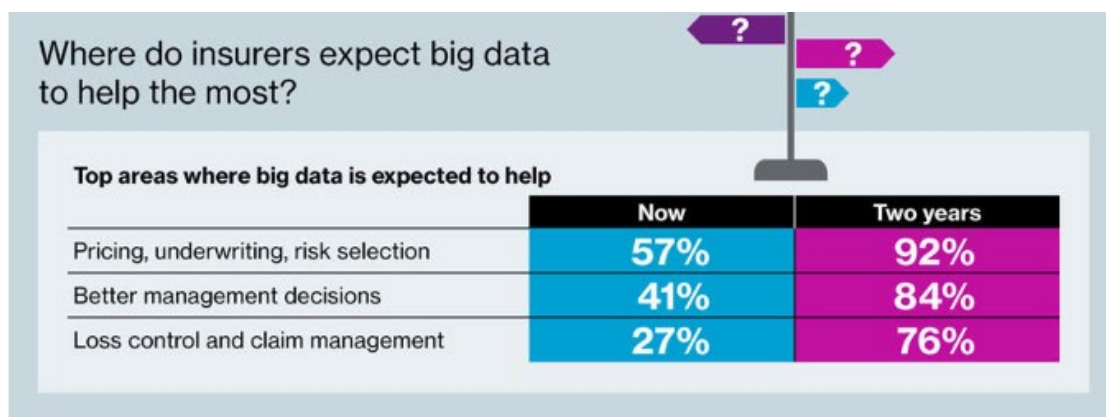
Within the insurance industry, the term "big data" is often used in a colloquial sense to encompass more specific subsets. In a literal sense, "big data refers to the large, diverse sets of information that grow at ever-increasing rates. It encompasses the volume of information, the velocity or speed at which it is created and collected, and the variety or scope of the data points being covered (known as the "three v's" of big data). Big data often comes from data mining and arrives in multiple formats" (Segal, 2019, para. 1).

Large sets of data on their own, no matter how they are acquired are generally not useful until something is done with the data. Predictive analytics describe the use of statistics and modeling to determine future performance based on current and historical data. Predictive analytics look at patterns in data to determine if those patterns are likely to emerge again, which allows businesses and investors to adjust where they use their resources to take advantage of possible future events. Halton (2019) explains that predictive models look at past data to determine the likelihood of certain future outcomes, while descriptive models look at past data to determine how a group may respond to a set of variables.

Big data, and all that this phrase encapsulates, is changing the way the world is doing business and the insurance industry is one business that is certainly trying to

capitalize on this. Since the insurance industry is founded on estimating future events and measuring the risk/value of these events; volume, velocity, veracity and variety of massive datasets has become an essential tool for insurers. With new data sources such as telematics, sensors, government, customer interactions and social media, the opportunity to utilize big data is more appealing across new areas of this industry nowadays (Exastax, 2017). The graphic below depicts a few of the ways that insurance companies are using big data now and where they expect to be in two years.

Figure 1. Where big data is expected to help



(Willis Towers Watson, 2017)

As the chart above depicts, big data is playing a prominent role in the underwriting process for insurers and projects to play a more prominent role in the near future. Though the usage of large amounts of data dates back hundreds of years with the beginnings of actuarial tables that are an integral part of underwriting. In the 1600's, French mathematicians Blaise Pascal and Pierre de Fermat, used an old pyramid of numbers to eventually prove that probabilities could be determined (Swiss Reinsurance Company, Ltd., 2020). This led to more development of probability theory across Europe and eventually Pascal's triangle led to the first actuary tables that were, and still

are, used when calculating insurance rates (Beattie, 2019). Today, insurance underwriting is still deeply rooted in actuarial science and underwriters often rely heavily on models that assist them in forecasting future loss.

Importance of Topic

I view the importance of this topic from two vantage points. First, as organizations invest in this new technology, I believe it is important for them to understand how underwriters are responding cognitively to the results produced by these new tools and models. Resistance to the results, or even complete acceptance without questioning the result, may have unintended consequences for the organization.

As noted earlier, the pricing element of underwriting has always been predicated in part on a scientific approach utilizing data and underwriters have been accustomed to incorporating this into their decision making. But clearly the ability to capture large swaths of data in record time has the potential to improve certainty in predicting outcomes in pricing as well as, risk selection. As Yohn (n.d.) notes, “this isn’t exactly a new use for predictive analytics in insurance, but pricing and risk selection will see improvement thanks to better data insights in 2021. Given the increased variety and sophistication of data sources, information collected by insurers will be more actionable” (para. 6).

While big data and the resulting insights seem likely to proliferate, the way in which these tools are integrated and implemented into the underwriting process is less clear. One could imagine a wide range rigidity and/or leeway in how insurance companies see their underwriters using these tools. This is something I will explore further in the literature as well as in my own research. What is clear, however, is that

underwriters and underwriting decisions will be affected in some measure by these new tools.

The second vantage point is how underwriters react cognitively to these tools. Do they accept them at face value or look to challenge the result within the confines of organizational boundaries? Another question is how are underwriters reacting emotionally? How does it make them feel when the model produces a result that they don't agree with but, they use the result anyway? The range of emotional response could vary greatly and, the underlying reasons are explored in this capstone. This is an important question to consider relative to job satisfaction and all that may entail.

Literature Review

My research seeks to answer the question of how commercial casualty underwriters are responding both cognitively and emotionally to predictive analytics. I begin the literature review chapter with a working definition of just what a commercial casualty insurance underwriter does and the challenges they face in making smart underwriting decisions.

The literature revealed five major themes relative to humans, not just underwriters, interacting with algorithmic based decision making tools. First, there is a need for literacy and transparency of algorithms by underwriters (Rainie & Anderson, 2017; Bader & Kaiser, 2019). Second, a proper balance of analytics and human judgment particularly given the myriad variables that underwriters contend with and the basic sophistication that predictive analytics currently offer (Rainie & Anderson, 2017; Chester, Ebert, & McNeill, 2019). Third, that there is an unintended bias present in algorithmically based systems (Rainie & Anderson, 2017; Chester, Ebert, & McNeill,

2019). Fourth, is that an underwriting environment steeped in algorithms will deepen divides between data savvy underwriters and those less informed and may also precipitate changes in the way underwriters collaborate within the organization (Chester, Ebert, & McNeill, 2019; Barbour, Treem, & Kolar, 2017; Rainie & Anderson, 2017). Last, there is a clear indication that algorithmic based tools will continue to proliferate (Rainie & Anderson, 2017).

Unsurprisingly, my search of the literature did not reveal any scholarly articles pertaining to commercial casualty underwriters interacting with predictive analytics so there was a complete gap in the literature. Only one non-scholarly article (Chester, Ebert, & McNeill, 2019) pertained to insurance underwriting specifically. The relative infancy of robust predictive modeling tools and the challenges that data scientists have faced in building these tools is a likely reason for the gap.

Research

The primary research question that this capstone addresses is “How are commercial casualty underwriters reacting to the introduction of predictive analytics in their underwriting process and decision making?” Reactions of underwriters will be examined from both a cognitive perspective and an emotional one. The cognitive responses in the context of this examination refer to the possible actions that the underwriter might take when faced with a data driven output. Did they accept the result at face value, factor it into their overall analysis, reject the result altogether or take some other course of action? Naturally, the companies that these underwriters work for and the guidelines they impose would impact the underwriters’ possible responses. Gaining an understanding of this environment is a secondary objective of my research.

I used a quantitative methodology and the method used to gather information was an online survey consisting of 20 questions (Appendix A). The survey does have one open ended question where respondents were asked to describe how they felt about predictive analytics in general. Also, some of the other questions gave the respondent the option of providing a different response than the choices provided. So, while the survey is primarily thought of as a quantitative method, there is also an element of qualitative data as well.

I utilized purposeful sampling to identify known commercial casualty underwriters with the majority of those underwriters having experience with underwriting tools based on predictive analytics. These potential respondents were recruited from my own network of contacts and included current and former co-workers, customers, competitors and other miscellaneous colleagues. No people or organizations are named throughout this paper in order to protect confidentiality.

Personal Interest and Assumptions

Over the past 30 years, I have worked in various underwriting roles and have handled thousands of insurance applications with varying degrees of authority. My belief in my ability to make good underwriting decisions is strongly rooted in my many years of experience. I believe that I know a good risk or a bad risk when I see one. I believe I know how to adequately price the risk as well and have had comfort with the various tools I have had at my disposal. This all changed for me when predictive analytic tools started making these decisions for me. I typically had a strong reaction, often one of disbelief, to the tool's output. This reaction was exacerbated by the fact that my company's guidelines bound me to use this result. In a practical sense, this meant that I

normally would have to take an action that I did not agree with such as delivering bad news to an otherwise good client. Not only would those tasks be unpleasant, in my opinion they were also costly to the organization. To avoid this, I often responded by pleading my case and voicing my displeasure to my superiors (and anyone else who would listen). It was these reactions that prompted me to explore this topic further. I wanted to know if I was alone in my feelings or did others share my viewpoint.

Before I began this capstone, I held certain assumptions that in some ways guided my own research. First, I assumed that predictive analytics could not be an effective replacement for sound underwriting judgment in the commercial casualty space. I believe that commercial casualty insurance is too complex and subject to too many variables for a computer-based algorithm to be the sole decision maker. I don't dismiss their potential to be a useful and even important contributor to the underwriting equation. I simply don't believe they can exist on their own without the assistance of underwriter judgment and intuition. My other assumption was also that everyone shared my same belief and frustrations in using these results. That assumption, however, was dispelled before I embarked on this capstone yet ironically, influenced my research approach. This occurred one day while speaking with a new trainee that had been assigned to my underwriting team. As his manager, I was complaining about our new underwriting tools when he stopped me in my tracks and said "Steve, I like that the machine tells me what to do. I am new to all of this and don't have much confidence in making a decision." This was my "a-ha" moment. I realized at that point that not everyone saw things the same as me. Until that point, I hadn't stopped to consider other frames and so, that's what this capstone purports to do. This "a-ha" moment altered the direction of the capstone early

on. Without it, I likely would have approached this with the hypothesis that predictive analytics are bad and set out on mission to prove that I was correct. Instead, I began an exploratory mission to see how others acted and felt regardless of my own personal environment and experience.

Conclusion

As you read this capstone, consider these staggering statistics. Studies estimate that 50% of current jobs in Europe and North America will be replaced by automated robots and computers within the next 20 years. As Frey and Osborne report, this disruptive change is hitting the insurance world particularly hard, as 99% of the work of an insurance underwriter could be replaced by a computer (Frey & Osborne, 2013, App. A). “With this in mind, it is not surprising that the Big Data frontline is largely populated by major insurance companies, as the cost of doing nothing is impossible to overcome” (Bossardt, 2015, p. 1). While I recognize that this may not resonate with the non-underwriter, it should still be enough to give pause and would likely be foolish to expect that other fields of work could not be similarly impacted.

In this capstone, I focus on the underwriters emotional and cognitive reactions to working with these tools. I believe that big data offers great promise and can improve the underwriting process but, I also believe the underwriters’ intuition and judgment are equally important particular when assessing complex risks. As you read this, consider whether a balance of science and art would make more sense or would an approach that is heavily weighted toward either end of the spectrum would be better for the organization and/or the underwriter. Also, consider the organizations and the established boundaries

that underwriters work in and how this impacts their actions, feelings and overall job satisfaction and how in turn, this may impact organizations.

CHAPTER 2

LITERATURE REVIEW

Introduction

This capstone is an exploratory study that looks to answer the question, how are commercial casualty insurance underwriters reacting cognitively and emotionally to the introduction of predictive analytics into their underwriting processes? I begin this chapter by utilizing insurance industry literature to provide a working definition of what a commercial casualty insurance is and what an underwriter does. I will also explain the unique nature of this type of insurance and address some of the challenges that underwriters face in making good decisions. I also provide additional clarification on what predictive analytics means for purposes of this review.

Next, I explore the available literature that relates to my research question. My hope, though certainly not my expectation, was that I would find peer reviewed literature that studied the intersection of commercial casualty underwriters and predictive analytics. But given the very specific population of people I was not surprised by the lack of literature. I did broaden my search to look for articles that dealt with the interface of humans in general with predictive analytics and other algorithmic based decision-making tools. I approached these articles cautiously given the populations studied were not commercial casualty underwriters (Bader & Kaiser, 2019; Barbour, Treem, & Kolar, 2017). With some reservation, I present the relevant themes found here. I also reviewed some other relevant but non-peer reviewed studies (Rainie & Anderson, 2017; Chester, Ebert, & McNeill, 2019) commissioned by reputable research organizations. One of these (Chester, Ebert, & McNeill, 2019) deals directly with the property and casualty industry

and so, has more relevance but is not peer-reviewed and detail corresponding to the source of their findings is not disclosed. So, this is also reviewed with some reservation.

There are volumes of literature, both scholarly and non-scholarly, that tout many different aspects of data science and predictive modeling but, very little that studies the dynamics of those models and the practitioners that use them. This capstone hopefully begins to narrow that gap.

Definitions

Commercial Casualty Insurance

To understand what a commercial casualty insurance underwriter does, it is important to understand a few things about commercial casualty insurance in general. The best way to do this is to break things down and offer a definition of each word. First, what is meant by insurance? The International Risk Management Institute (IRMI) defines insurance as “a contractual relationship that exists when one party (the insurer) for a consideration (the premium) agrees to reimburse another party (the insured) for loss to a specified subject (the risk) caused by designated contingencies (hazards or perils)” (2021, sect. I). Commercial insurance is used to cover commercial risks (e.g. buildings, trucks and employees) while personal insurance covers personal risks (e.g. home and autos). Some examples of commercial insurance lines include automobile, general liability, workers compensation, and property insurance. “Put quite simply, commercial insurance consists of one or more types of coverage designed to protect businesses, their owners and their employees” (Nationwide Insurance Company, n.d., para. 4). There are many types and sub-types of commercial casualty insurance and to delve into a deep discussion of these would not only be counterproductive for the

purposes of this capstone, it would run the risk of losing the reader to boredom. The more important distinction I want to make here is describe how casualty insurance works. “Casualty Insurance is insurance that is primarily concerned with the losses caused by injuries to persons and legal liability imposed on the insured for such injury or for damage to property of others” (International Risk Management Institute, Inc., 2021, sect. C). Claims against casualty insurance policies are typically triggered by a lawsuit from the injured party that is also known as the third party.

For example, imagine a snowplow company clearing the streets of the Penn campus when it accidentally sideswipes three vehicles and injures the driver of one of these vehicles who was sitting in the car waiting for his Organizational Diagnosis class to begin. The driver of the snowplow, an employee of Snow White Begone, LLC., was texting his girlfriend while listening to heavy metal music through his air pods. Unfortunately, he never realized he had contacted the vehicles and continued about his business of clearing the streets as if nothing ever happened. A few weeks later, the owner of Snow White received two certified letter in the mail from the law offices of Dewey, Cheatem and Howe advising them of the damages to two of the vehicles that were damaged by the snow plow along with a demand for monetary retribution. The puzzled owner who had no knowledge of the accident, called his insurance agent to tell him about the lawsuit who in turn, advised the claim adjuster at Too Big To Fail Insurance Company (TBTF) who handled the claim from there. The adjuster was able to negotiate a settlement with the lawyer and this the claim was settled out of court. Three years later another certified letter arrived at Snow White, this time from the law offices of Payne and Fears, LLP who was representing Erasmus Dragon, the student who was injured while

waiting in his car. Apparently, Erasmus was seriously injured and has constant pain and suffering and so, after three years enlisted the office of Payne and Fears to represent him in a lawsuit against Snow White. He is seeking retribution of \$500,000. Once again, Snow White notifies his agent who again advises the TBTF claims adjuster. Given the severity of this claim, the adjuster hires a defense council to represent them. Six years have passed since the date of the accident and the final amount of the injury claim remains outstanding as the two sides cannot come to an agreement. The case is scheduled to be heard in the Philadelphia Court of Common Pleas in the near future.

What an underwriter does?

Sometime before the accident in the example above occurred, a commercial casualty underwriter was tasked with reviewing the application for commercial automobile liability insurance for Snow White Begone, LLC. “An underwriter is any individual in insurance who has the responsibility of making decisions regarding the acceptability of a particular submission and of determining the amount, price, and conditions under which the submission is acceptable” (International Risk Management Institute, Inc., 2021, sect. U).

The U.S. Bureau of Labor Statistics (2021) describes what an underwriter does as follows:

- Analyze information stated on insurance applications
- Determine the risk involved in insuring a client
- Screen applicants on the basis of set criteria
- Evaluate recommendations from underwriting software
- Contact field representatives, medical personnel, and others to obtain further information
- Decide whether to offer insurance
- Determine appropriate premiums and amounts of coverage
- Review and update the rules that govern automation software

For auto insurance, which is a form of property and casualty insurance, underwriters look at driving record, age, and, sometimes, type of vehicle. In everything they do, insurance underwriters must strike a balance between risk and caution. “Too much risk means the insurance company will pay out too many claims. Too much caution and the carrier will not make enough money from premiums” (Kaplan Financial Education, 2019, para. 4).

Insurance underwriters enter specific information about a client or applicant into a software program. The program recommends coverage and premiums based on the data, and it’s up to the underwriter to decide to approve or reject the application after an evaluation of the software results. For simple and common types of policies, such as those for automobile or homeowners’ insurance, the automated recommendations are usually sufficient. For more complicated types of insurance, such as workers’ compensation or business income—or even for complexities in a simpler type, like auto insurance—they will have to rely on analytical insight (Bureau of Labor Statistics, U.S. Department of Labor, 2021).

Underwriter Challenges

In some ways, underwriters are asked to be prognosticators and underwriting decisions could be thought of as predictions. When an underwriter makes an offer of insurance at a certain price and with certain conditions, it reflects how the underwriter feels about the ultimately profitability of that risk. For instance, if she offers generous terms at a discounted price, it suggests that she feels there is a good chance that this policy will result in an underwriting profit for the insurance company. Consistently, making smart underwriting decisions is a difficult task at best as there are many unknowns and many variables that make it hard to predict the future. Some of the most impactful and difficult factors to assess include claim uncertainty, legal environments, emerging liability exposures and the current market environment more commonly known

as the insurance cycle. Also, a unique feature of most casualty policies known as the occurrence form, contributes to the uncertainty.

Claims uncertainty

In the example given above, had the underwriter known that one of the snow plows would be driven by a distracted and reckless driver on a snowy night in Philadelphia, would she have offered a proposal for insurance at the same premium or even offered a proposal at all? Or consider the renewal of that policy. Shortly after the accident occurred, the claim for the vehicle damages were settled so the underwriter was aware of the amount and factored it into her proposed renewal premium. However, the claim for the bodily injury is still outstanding with a claim reserve currently estimated at \$500,000 and this will also factor into the underwriter's renewal decisions but with less certainty as the reserve is only an estimate. "A claim reserve is an amount of money set aside to meet future payments associated with claims incurred but not yet settled at the time of a given date" (International Risk Management Institute, Inc., 2021, sect. C). The claims reserve is adjusted over time as each case develops and new information is retrieved during the claim settlement process. "The total amount of funds set aside for a claim is the sum of the expected settlement amount and any expenses incurred by the insurer during the settlement process, such as fees for claims adjusters, investigators, and legal assistance" (Liberto, 2020, para. 13).

Legal environment

The legal environment of a particular venue also contributes to an underwriter's uncertainty about a risk. The worst venues, from an insurer's standpoint, are affectionately known as judicial hellholes which stems from an annual report published

by the American Tort Reform Foundation that ranks the worst venues in the U.S. The current rankings list the Philadelphia Court of Common Pleas and the Supreme Court of Pennsylvania as the number one judicial hellhole. Since 2002, the American Tort Reform Foundation's (ATRF) Judicial Hellholes® program has identified and documented places where judges in civil cases systematically apply laws and court procedures in an unfair and unbalanced manner, generally to the disadvantage of defendants (American Tort Reform Foundation, 2020).

From the underwriters' point of view, it is difficult enough to predict if a claim will happen but even more difficult to assess where the claim will happen. Underwriters typically have a general idea of where a company's vehicles normally operate but of course, drivers are free to travel wherever they want. An unforeseen accident on the streets of Philadelphia could ultimately result in a very unfavorable result for the insurance company.

Emerging liability exposures

Emerging liability exposures are always a concern for casualty underwriters and once again predicting unforeseen exposures can be challenging at best. The purpose of this section is not to provide an encompassing list of these exposures. That would be well beyond the scope of this capstone. But rather, to offer an example to illustrate how changes in the world can impact the underwriters' view and decision making. Without a doubt, the most topical and current exposure of our time is the Covid-19 pandemic. "The grim impact of COVID-19—extensive financial dislocations across asset classes and potentially large increases in morbidity and mortality—could be challenging for insurers" (Kirti & Shin, 2020, p. 1). Few people, let alone underwriters, could foresee the

destruction caused by this devastating disease and yet, here we are. “Two large global reinsurers, Swiss Re and Munich Re, disclosed expected losses in a “1-in-200-year” pandemic scenario (typically associated with the standard 1.5 excess deaths per 1,000 scenario) in annual reports covering 2019” (Kirti & Shin, 2020, p. 9).

Other examples of emerging exposures that impact casualty underwriters include distracted driving, cyber risks, social inflation, the gig economy, and autonomous driving just to name a few.

Insurance Cycle

The insurance cycle refers to the current pricing environment of the industry and is influenced by a variety of factors.

A cycle usually starts with many competitors with plenty of capacity and low premiums. Eventually, a surge in claims drives lesser-capitalized insurers out of business and competition declines. Less competition and insurance capacity improve underwriting conditions for the remaining insurers, enabling higher premium and more stringent underwriting standards. Such an environment usually helps strengthening insurers’ financial results. The prospect of higher profitability attracts fresh capital and new entrants to the market offering lower premium and looser requirements. The increased competition leads to a reduction in premium as incumbents are forced to follow suit and the cycle begins again (Meakin, 2020, para. 3).

Other factors affecting the cycle include market pressures exerted by members of the distribution network including brokers, agents and even the insureds themselves. All will use whatever available leverage they have at times, to persuade the underwriter to lower the premium or relax policy terms.

Long tail liability / Occurrence Form

Many, if not most, casualty insurance policies written today are “occurrence” based. An occurrence policy is “a policy covering claims that arise out of damage or injury that took place during the policy period, regardless of when claims are made”

(International Risk Management Institute, Inc., 2021, sect. O). Referring back to the Snow White example, you may recall that the lawsuit for the bodily injury to the passenger did not show until three years after the accident occurred. Because of the occurrence feature of the policy, this accident will be covered by policy that was in place when the accident “occurred”. This illustrates what is known as long tail liability which IRMI defines as “the liability for claims that do not proceed to final settlement until a length of time beyond the policy year. High incurred but not reported (IBNR) claims contribute to this "tail" effect, since these losses are usually not settled until several years after the expiration of the policy in question” (International Risk Management Institute, Inc., 2021) (2021, sect. L). This policy feature creates a great unknown for insurers and underwriters. “Some claims, such as property losses due to fire, are easily estimated and quickly settled. Others, such as product liability, are more complex and may be settled long after the policy has expired” (Liberto, 2020, para. 6).

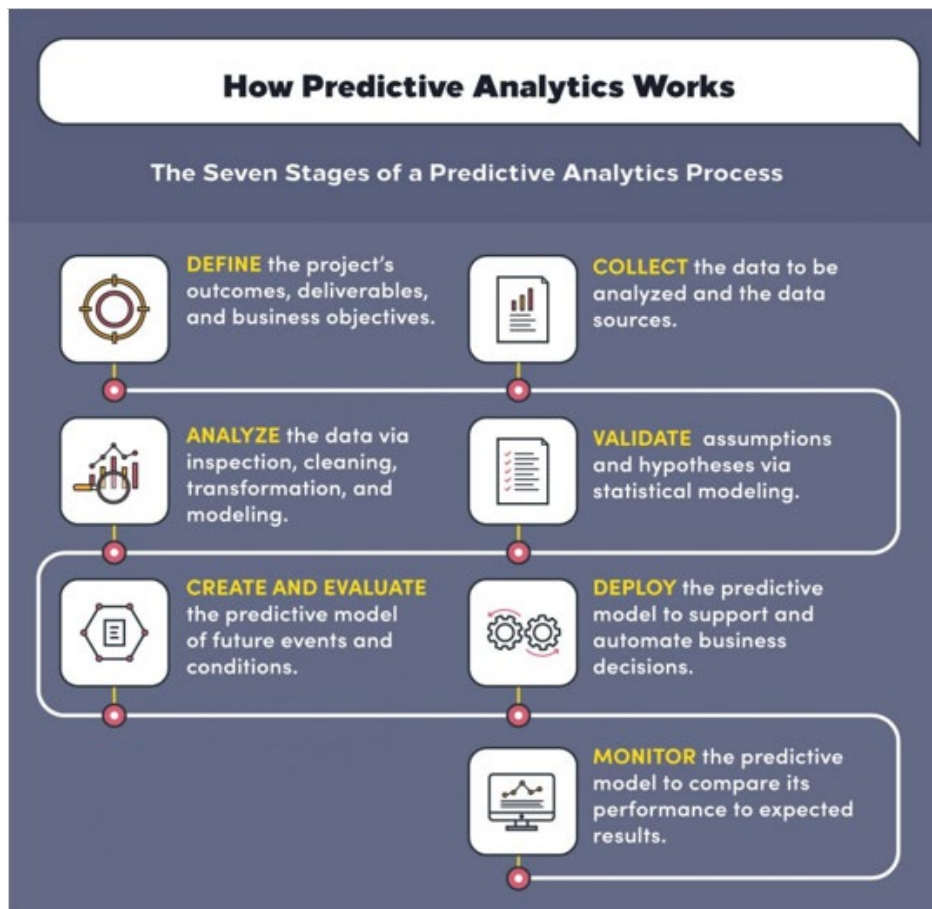
Conclusion

Hopefully, the preceding sections provided some clarity around some of the unique challenges and unknown variables that commercial casualty underwriters have to consider in trying to make wise underwriting decisions. The goal of this capstone was not to dispel the capabilities of predictive analytics or even suggest that humans can make better decisions than computers. Instead, I wanted to paint this picture so that reader has a better idea of the uncertainty that commercial casualty underwriters have to consider in making their decisions and perhaps consider how this might affect an underwriter’s opinion about predictive analytics. “Compared with retail personal lines, commercial exposures are heterogenous, intermediated, and often qualitative” (Chester, Ebert, &

McNeill, 2019, p. 3). This heterogeneity is even true in the small and medium-size enterprise (SME) category, where thousands of microsegments can each have unique risk profiles and face different hazards (2019, p. 3).

In the next section, I review the relevant literature that examines the underwriter and non-underwriter response to predictive analytics. But first, one final note about the term predictive analytics. For purposes of this literature review and the capstone in general, predictive analytics refers to any term that implies that data is collected and manipulated by a computer based algorithm to produce an output (i.e. prediction) as illustrated in Figure 2 below:

Figure 2: How predictive analytics works



(PAT Research as cited in Maryville University, n.d.)

“The use of algorithms is spreading as massive amounts of data are being created, captured and analyzed by businesses and governments. Some are calling this the Age of Algorithms and predicting that the future of algorithms is tied to machine learning and deep learning that will get better and better at an ever-faster pace” (Rainie & Anderson, 2017, p. 3). “Analytics, metrics, data mining, dashboards, big data, data science: these are just a few of the watchwords of the ‘datafication’ of work” (Davenport and Patil, 2012; Hanusch, 2016; Lycett, 2013 as cited in Barbour, Treem, & Kolar, 2017, p. 257). Data science is a multi-disciplinary field that uses scientific methods, processes, algorithms and systems to extract knowledge and insights from structured and unstructured data (Dhar, 2013).

Whether it is called predictive analytics or something else is unimportant. What’s relevant are the dynamics that occur when a computer generated decision or prediction is pitted against a human one. An examination of the literature relevant to this simple concept and the relevant themes I extracted follows.

Literature Review

I wrestled with the section for quite some time while searching for credible literature relevant to the plight of insurance underwriters working with predictive analytics. I worked closely with my advisors and enlisted the help of the Penn library staff on two separate occasions to help to unearth literature worthy of review. It does not exist. I postulate one reason for this is relative infancy of predictive analytics to the insurance industry and more so, to the commercial casualty segment. Modeling in this area is relatively simplistic given challenges that data scientists have faced in harnessing unstructured data found in the legacy computer systems of insurance companies.

“Despite its immense potential, unstructured data comes with its share of challenges, which makes it very difficult for organisations to properly analyse data and get the most value out of their information” (Dixon, 2019, para. 1). “While current use of predictive analytics by insurers focuses on life, health, and vehicle coverage, other types of underwriting have proven more difficult to adapt to this and other AI-based technologies” (Maryville University, n.d., para. 44). In particular, the work of actuaries is challenging to convert to a machine-learning approach because the data models at the core of the analysis must be tweaked continually to account for variations in data (Chester, Ebert, & McNeill, 2019).

Personally, I have been involved in a number of data analytic projects in my current company and can attest to these challenges.

A few studies of non-underwriters were located but fell short in providing literature that could fully be relied on in projecting these findings to my own study group (i.e. commercial casualty underwriters). Most studies seemed to concentrate on computer experts, academicians or practitioners from areas completely foreign to the commercial casualty underwriter. For instance, to illuminate current attitudes about the potential impacts of algorithms in the next decade, Pew Research Center and Elon University’s Imagining the Internet Center conducted a survey of technology experts, scholars, corporate practitioners and government leaders to assess the net overall effect of algorithms for individuals and society (Rainie & Anderson, 2017). One open-ended question was asked and most participants gave detailed responses that provided insights about hopeful and concerning trends (2017).

The questions were administered online to a purposeful sample of targeted experts that Pew had identified from prior studies, none of which were identified as underwriters or even appeared to have any involvement with insurance. The study even offered the following disclaimer, since the data are based on a non-random sample, “the results are not projectable to any population other than the individuals expressing their points of view in this sample” (Rainie & Anderson, 2017, p. 26). A couple of themes they identified could have relevance to my group and so with reservation, I offer them here with support from other readings as well.

The need for algorithmic literacy and transparency

The study infers that “those who create and evolve algorithms are not held accountable to society and argued there should be some method by which they are” (Rainie & Anderson, 2017, p. 15). They also argued “there is great need for education in algorithm literacy, and that those who design algorithms should be trained in ethics and required to design code that considers societal impacts as it creates efficiencies” (Rainie & Anderson, 2017, p. 74).

When users are confronted with opaque algorithmic decisions, the boundary between human and algorithmic intelligence blurs (Günther et al., 2017 as cited in Bader & Kaiser, 2019), leading to a debate about which of the two should have control over decision-making and which should have power over the other (Cramer & Fuller, 2008 as cited in Bader & Kaiser, 2019). While this understanding suggests that algorithms are taking over decisions in organizations, the actual role of AI in workplace decisions and in the ongoing involvement of humans in decision-making lacks clarity (Bader & Kaiser, 2019, p. 3).

From a personal usage point of view, I can attest that the lack of transparency in scoring models (i.e. algorithms) was a major reason for my skepticism. Eventually, more transparency was provided and ironically, when the factors impacting the algorithms were revealed, my skepticism was confirmed, and my emotions changed to frustration as I knew what was behind the score and I had no avenue of appeal. There are cognitive implications to this as well. “When human and algorithmic intelligence become unbalanced in regard to humans’ attachment to decision-making, three performative effects result: deferred decisions, workarounds, and (data) manipulations” (Bader & Kaiser, 2019, p. 1).

Need for a balance between human judgment and predictive modeling

Sophisticated improvements in algorithms and the ability to acquire large sets of data continues to develop. But human judgment and humanity itself could get lost if too much emphasis is placed on science.

Advances in algorithms are allowing technology corporations and governments to gather, store, sort and analyze massive data sets. Experts in this canvassing noted that these algorithms are primarily written to optimize efficiency and profitability without much thought about the possible societal impacts of the data modeling and analysis. These respondents argued that humans are considered to be an “input” to the process, and they are not seen as real, thinking, feeling, changing beings. They say this is creating a flawed, logic-driven society and that as the process evolves – that is, as algorithms begin to write the algorithms – humans may get left out of the loop, letting “the robots decide.” (Rainie & Anderson, 2017, p. 9).

A McKinsey study focused on property and casualty underwriters cements this theme.

We observed that the highest-performing underwriters are those with a structured, intentional approach to analyzing exposures. In some cases, this approach is explicit and can be articulated. In others, it is implicit and reflects intuition based on hard-learned experience. We have also observed that data-driven tools can greatly supplement human judgment, enabling many successful underwriting teams to outperform peers, especially by employing superior risk selection in overcapitalized markets in which pricing is barely adequate. These tools have

proved successful across all segments of risk, spanning SME to midmarket to large to specialty accounts. In some cases, however, we observed companies putting the cart before the horse—enamored with the promise of artificial intelligence and advanced analytics, they mandated that the black box–modeled output prevail over subjective underwriting judgment. Despite good intentions, this overemphasis on analytics led to a vicious cycle in which imprecisely modeled guidance did not accurately anticipate future risk experience. As a result, underwriting performance deteriorated, staff lost faith in the models, and (since judgment and creativity were discouraged) underwriting skills diminished” (Chester, Ebert, & McNeill, 2019, p. 5-6).

Biases exist in algorithmically-organized systems

Algorithm creators (code writers), build their own perspectives and values into their code even if they strive for inclusiveness, objectivity and neutrality; and, the datasets to which algorithms are applied have their own limits and deficiencies (Rainie & Anderson, 2017).

“Even datasets with billions of pieces of information do not capture the fullness of people’s lives and the diversity of their experiences.” (Rainie & Anderson, 2017, p. 57).

“Moreover, the datasets themselves are imperfect because they do not contain inputs from everyone or a representative sample of everyone” (Rainie & Anderson, 2017, p. 57).

In addition, “the separate view of humans and AI in these considerations is based on the idea that AI is a reflection of human intelligence” (Goffey, 2008 as cited in Bader & Kaiser, 2019, p. 3).

The McKinsey study draws an interesting parallel in the pricing algorithms that some insurers are using to score their risks.

Since the early 2000s, many companies have more systematically introduced technical pricing as a core part of underwriting governance. The notion of a model-driven price for any risk is now commonplace in the industry. Technical pricing has its limitations: it sometimes results in prices that are overly biased by input factors, creating under- or overpriced guidance” (Chester, Ebert, & McNeill, 2019, p. 5). “Successful companies mandate technical pricing as guidance but make allowances for deviation” (Chester, Ebert, & McNeill, 2019, p. 5). Debate

about divergence from technical becomes a regular part of performance discussions. They recognize that technical pricing is a critical input to ensure price adequacy but also that it cannot be the sole basis for pricing risks (Chester, Ebert, & McNeill, 2019).

Algorithmic categorizations deepen divides

Rainie and Anderson reported that “two connected ideas about societal divisions were evident in many responses” (p. 13). First, they predicted that an algorithm-assisted future would widen the gap between the digitally savvy and those who are not nearly as connected or able to participate (2017). Second, they said social and political divisions will be abetted by algorithms, as algorithm-driven categorizations and classifications steer people into echo chambers of repeated and reinforced media and political content (2017). From an underwriter’s point of view, I translate this as those who lack knowledge and familiarity with predictive analytics and those who do. Further, it is conceivable that the role of the underwriter could change toward one that is more data centric. “The underwriter and translator roles will increasingly become synonymous with underwriters and data scientists working together in agile teams” (Chester, Ebert, & McNeill, 2019, p. 12). Further,

The Internet of Things is also beginning to have more widespread adoption and may increasingly be directly incorporated into the underwriting process. Considering all these factors together, commercial underwriting may experience disruption similar to the airline industry, in which artificial intelligence is responsible for most of the navigation outside of takeoff and landing. In the future, underwriters will become more like pilots, with mundane activities increasingly automated. Additionally, technology, operations, and underwriting functions will sit side by side, with the underwriter serving as agile coach and translator to actively guide ongoing platform development (Chester, Ebert, & McNeill, 2019, p. 12-13).

This divide in knowledge may also precipitate a need for underwriters to change the way they collaborate within the organization.

A key difference between traditional forms of data-driven decision making in organizations and analytics may be its suffusion throughout the organization, not just in traditionally data-savvy areas. This diffusion can involve problems of collaboration among people in different organizational units (Hanusch, 2016 as cited in Barbour, Treem, & Kolar, 2017). The increasing size and complexity of data available to organizations can make communicating about data sets and developing shared understandings of them more difficult (Tanweer et al., 2016 as cited in Barbour, Treem, & Kolar, 2017). Analytics may also change how organizations work together, or may require contact between units that do not typically work together at all (Barbour, Treem, & Kolar, 2017, p. 259).

Algorithms will continue to spread everywhere

“There is fairly uniform agreement among these respondents that algorithms are generally invisible to the public and there will be an exponential rise in their influence in the next decade” (Rainie & Anderson, 2017. p. 5). This tracks relative to earlier information provided in Chapter 1 that predictive analytics are expected to grow within the insurance industry.

Conclusion

Several themes arose from this literature review although a significant, if not complete, gap exists in literature pertaining to commercial casualty underwriters and the unique challenges or variables and uncertainty they face in making decisions. The relative infancy of sophisticated predictive analytics is one potential reason for the gap. Given that, a review of literature involving other industries and practitioners was performed and a cautious attempt at relating these findings to underwriters was performed. The themes centered around the need for literacy and transparency of algorithms by underwriters; the need for a proper balance of analytics and human judgment; a recognition of bias in algorithmically based systems; and, an underwriting environment steeped in algorithms will deepen divides between data savvy underwriters

and those less informed and may also precipitate changes in the way underwriters collaborate within the organization.

The next chapter presents the methodology and methods used in performing my own research in this area and will serve as a potential source to narrow the gap found in the literature.

CHAPTER 3

METHODOLOGY

Introduction

This chapter describes the methodology and method used to collect data in support of this capstone. The participant recruitment, sampling technique and method design are also described in this chapter. The chapter concludes with a discussion on measures taken to control bias in the research.

The capstone seeks to answer the research question, “How are commercial casualty underwriters reacting, both cognitively and emotionally, to the introduction of predictive analytics in their underwriting process and decision making?” From a cognitive standpoint, I wanted to explore the underwriters’ range of procedural response to the model’s output. Did they accept the result at face value and move on in the process or, perhaps challenge the result in some manner? From an emotional standpoint, I wanted to explore how underwriters “felt” about certain action they were directed to take by the model. For example, if they were forced to accept a result that they didn’t necessarily agree with, how did this make them feel?

Methodology

Quantitative Research

To answer the research question noted above, I utilized a quantitative methodology that employed a single quantitative method, an online survey. The survey was designed to collect a range of multiple choice responses relative to the cognitive and emotional responses of underwriters. In addition, some questions offered the respondent a chance to deviate from the multiple choice options by answering the question as

“Other” and then were given the opportunity to provide a free-form qualitative response. Also, there was a final open ended question that gave the respondent an opportunity to provide any additional comments that they wanted to add concerning their thoughts or experience with predictive analytics. So, while this method did gather some useful qualitative responses, the volume of the data is not sufficient to do a meaningful qualitative analysis. This data instead is used to provide additional context to the quantitative analysis performed on the multiple choice responses.

Rationale

For the aforementioned reasons, I consider the approach to be a quantitative methodology and while the dominant literature suggests that qualitative methods are better for researching human phenomena or in this case, cognitive and emotional reactions to predictive analytics, Sukamolson (2010, p. 9) states that, “quantitative research is also useful to quantify opinions, attitudes and behaviors and find out how the whole population feels about a certain issue.”

Admittedly, I wrestled with using a qualitative methodology over a quantitative one and also considered a mixed method approach where I would conduct interviews with selected survey respondents who were willing to participate. Ultimately, I chose not to do this due to something I learned after conducting the survey. Question six poses the question, “Do you have the authority to override or deviate from the model’s output?” I subsequently realized that this question spoke to organizational boundaries (i.e. underwriting guidelines / rules) that are in place at that particular insurance company. I harkened back to my own experience and what prompted me to delve into this exploration in the first place. I worked for an insurance company that had established

very rigid rules around the usage of predictive analytics. I was essentially hamstrung in my ability to make decisions and had to follow what the machine instructed me to. The appeal process was essentially futile as well and so, because of this environment I became frustrated. Thus, the boundaries in place at my company and my cognitive and emotional reactions to predictive analytics were very much correlated. Since organizations are relatively unique, the established boundaries relative to the implementation and usage of predictive analytics would undoubtedly vary from one organization to another. For a variety of practical reasons, I would not be able to gain access to enough underwriters from a wide sampling of insurance companies without incurring a great deal of time, expense and probable persuasion of insurance executives willing to let me prod their underwriters. The loss of anonymity in a qualitative approach could also become problematic. As Miller (2020, sect. 6) states, “the anonymous nature of quantitative research makes it useful for data collection because people are more likely to share an honest perspective when there are guarantees that their feedback won’t come back to haunt them.” Ultimately, I concluded that a handful of interviews ran the risk of introducing too much bias into my research whereas with a quantitative methodology, I was able to get an ample cross section of underwriters and companies in an efficient and anonymous manner thereby mitigating bias.

Institutional Review Board

The research protocol for this capstone was submitted to the Institutional Review Board (IRB) at Penn and was accepted and determined that the proposal met eligibility criteria for IRB review exemption authorized by 45 CFR 46.104, category 2 (see Appendix A).

Method

Participant Sample and Recruitment

Because of the specific nature and scope of my research that is focused on the reactions of commercial casualty underwriters, I utilized a non-probability sampling method known as purposive sampling or also referred to as judgment sampling.

“Judgment sampling is most effective in situations where there are only a restricted number of people in a population who have qualities that a researcher expects from the target population” (Fleetwood, 2020, para. 3). Accordingly, the participant sample for this research consists of underwriters working for commercial insurance and reinsurance companies in the casualty insurance segment who have or had direct decision making responsibility relative to the acceptance or rejection of requests for insurance proposals.

My sample population of 47 participants was homogenous in that they were all commercial casualty underwriters. However, I also sought to find diversity in this group and collected certain demographic information via the survey. These demographics included gender, years of underwriting experience and type of casualty underwriter (i.e. insurance or reinsurance). I focused on these three attributes with the goal of identifying discernible trends in the data. Most, if not all of the population work for insurance companies in the Mid-Atlantic regional area. As a point of reference, the overall number of insurance underwriters in the U.S. was 114,700 in 2019 (Bureau of Labor Statistics, U.S. Department of Labor, 2021). This number, however, is not representative of commercial casualty underwriters but rather includes insurance underwriters of all types from both the personal and commercial segment. The number of commercial casualty

underwriters would be a much smaller number but unfortunately, even an estimate would be difficult to surmise.

Participant Recruitment

Participants for the survey were recruited from my personal network of 77 commercial casualty contacts. This network is comprised of underwriters who were either co-workers, competitors, clients, or other professional acquaintances who I knew had commercial casualty underwriting experience. These individuals were people working (or had worked) for commercial insurance and reinsurance companies in the commercial casualty insurance segment who have or had direct decision making responsibility relative to the acceptance or rejection of requests for insurance proposals. I emailed the survey link to these people directly and given my personal relationship with these individuals had a high expectation of receiving a 50% response rate (38 respondents). My expectations were exceeded with a 61% response rate (47 respondents). This strong response rate served as a way to somewhat mitigate the sampling bias that is often associated with non-probability sampling. “Online purposive samples have unknown biases and may not strictly be used to make inferences about wider populations, yet such inferences continue to occur” (Barratt, Ferris, & Lenton, 2015, p. 1).

To further mitigate this, I attempted to increase the sample size by offering the survey link to my entire LinkedIn network of over 1,100 individuals. However, my LinkedIn network is filled with many individuals that I have never met with little knowledge of their work backgrounds though I am aware that while many are not underwriters, some are and were not part of my initial recruitment. A copy of the post is

shown in Appendix B, but unfortunately, this second attempt did not yield any additional responses.

Survey

I utilized an online survey (see Appendix A) containing 19 multiple choice questions plus one open ended question that was administered using the online website SurveyPlanet.com. The questions were written in a clear and concise manner and carefully crafted to avoid any leading questions. The survey was designed with the assistance of my capstone advisor, Dr. Kaminstein. The survey was piloted on two of my colleagues and their feedback was incorporated along with advice from my capstone advisor before settling on a final version.

Survey Design

The survey was designed in a linear fashion and begins with a series of questions that establish the respondents' familiarity and experience in working with predictive analytics. The next set of questions attempts to gauge the impact of predictive analytics in their decision making and whether or not the underwriter has the ability to override or deviate from the model's output. The next eight questions comprise the core of the survey and focus on the cognitive and emotional responses to predictive analytics. From a cognitive standpoint, I sought to gauge underwriters' procedural responses. For example, if a model directed the underwriter to take a particular action, how did the underwriter respond? Did they simply follow the guidance or challenge it in some way (e.g. seek approval to override the guidance or perhaps, ignore the guidance altogether)? It was also important to gain an understanding of the boundaries in place. In other words, were underwriters constrained by their company's guidelines or rules? The second type

of reaction is the emotional one and, in this regard, I wanted to gauge how underwriters “felt” about certain action they were directed to take by the model. For example, if they were forced to accept a result that they didn’t necessarily agree with, how did this make them feel.

This is followed by four questions that collect demographic information related to gender, years of experience, and underwriter type. The penultimate question asks the respondent to provide any additional comments concerning their thoughts or experience with predictive analytics. The last question asks the respondent if they would be willing to participate in an in depth interview.

Data Collection and Analysis

Survey data was collected and tabulated utilizing two independent variables, gender and years of experience. Years of experience was stratified into five different tiers as follows: 1) less than 5 years, 2) 5 to 10 years, 3) 11 to 15 years, 4) 16 to 20 years and 5) greater than 20 years. The data was then presented in a nominal (i.e. count) tabular format to establish a basis for further analysis. Cross tabulation was then performed to see what, if any, trends or patterns could be identified. This final open ended question provided an element of qualitative data and was used to provide additional context and support for inferences made from the quantitative analysis.

Bias

Earlier in this chapter, I discussed some of the bias and mitigating strategy associated with my research methodology. In chapter one, I recognized my bias toward the influence of predictive analytics on underwriting that stemmed from my experience. To briefly recap, I resented having my judgment and intuition being supplanted by a

computer model. To mitigate this, I employed a few different techniques. First, the mere cognizance of my personal bias was helpful, and I used this as a constant checkpoint throughout my research and which helped me gain a deeper self-awareness of the issues at hand. I was mindful of this in crafting the questions for the survey by wording them in a non-leading and neutral way and, by providing a wide range of possible responses including room for a free form response where appropriate. In addition, I worked closely with my capstone advisor to not only design a well thought out survey but also one that sought to lessen bias. Lastly, I piloted the survey to three of my colleagues and revisited their feedback with my advisor before settling on a final version.

Conclusion

This exploratory study about the cognitive and emotional response of underwriters to predictive analytics used a quantitative research methodology. The method included an online survey administered to a non-probable purposeful sample consisting of commercial casualty underwriters. The survey was sent to 77 known individuals from my personal network of underwriter contacts and 47 of them participated in the survey. The results of the survey are presented in the next chapter.

CHAPTER 4

DATA RESULTS

Introduction

As discussed in Chapter 2, a significant gap exists in the literature dealing specifically with the reactions of underwriters to predictive analytics or even more specifically, commercial casualty insurance underwriters. The results presented in this chapter serve to partially narrow this gap and focus on answering my research question: “How are commercial casualty underwriters reacting to the introduction of predictive analytics in their underwriting process and decision making?”

As described in Chapter 3, I utilized an online survey designed to capture pertinent demographics about the respondents, with the goal of finding commercial casualty underwriters, preferably those who have had some exposure to predictive analytics in their underwriting processes. Fortunately, the survey was able to attract 47 underwriters and more than half of them had exposure to predictive analytics. This latter group is where the majority of my research is focused. As described in the previous chapter, the survey uses a series of multiple choice questions to gather various information relative to the cognitive and emotional reactions to predictive analytics and also touches on the work environment and boundaries that the underwriters are subjected to in working with these models. A final and optional open-ended question was used to collect additional comments concerning the underwriters’ thoughts and/or experience with predictive analytics.

The results are presented either as simple data without being measured against any independent variable or, in some cases I judgmentally presented the data measured

against the underwriters' years of experience (e.g. independent variable) I chose this variable as it seemed plausible that more experienced underwriters might have a different view about predictive analytics than less experienced ones. This thinking stems from the "a-ha" moment I described in chapter 1 when my trainee pointed out that he liked it when the machine made the decision for him. Other demographics such as gender, underwriter type and underwriting specialty though collected, were mostly not found to be useful in identifying any trends in my analysis.

To compile the data, I assigned numerical identifiers to each multiple choice response and compiled them into a master database using Microsoft Excel. Data filters were used to provide a quick analysis in spotting trends where they existed. Excel's charting feature was then used to visualize the data allowing these trends (or non-trends) to be seen in an easier way.

The results of the survey are organized under the following headings which represent subsections of the survey and are presented in various tabular and graphical formats designed to assist with the data analysis that takes place later in the capstone.

1. Demographics
2. Knowledge and Exposure to Predictive Analytics
3. Impact on Decision Making and Authority to Deviate
4. Cognitive Response to Predictive Analytics
5. Emotional Response to Predictive Analytics
6. Attitude Toward Predictive Analytics
7. Qualitative Responses

Demographics

The survey was e-mailed to 77 insurance underwriters and was responded to by 47 individuals which equates to a 61% response rate. The survey was completed between January 22, 2019 and February 3, 2019. The time that respondents took to complete the survey ranged from one minute and 11 seconds to 17 minutes and 51 seconds. The average time per respondent was five minutes and 20 seconds.

The survey collected several different demographic data including gender, underwriter type, underwriting specialty and years of experience. The population is split by roughly 60% male and 40% female and, 83% of all respondents are insurance underwriters with the remaining working as reinsurance underwriters. The majority of the underwriters (39) specialize in commercial casualty insurance with seven identifying as another type of third party liability underwriter. These other types included workers compensation and environmental liability underwriters. One respondent also identified as a property underwriter. Years of experience was the last demographic collected and 80% of the underwriters had more than 20 years of experience with remaining 20% having 10 years or less. All of the demographics collected are presented below in Table 1.

Table 1. Respondent Demographics

	FEMALE	MALE	TOTAL
All Respondents	19	28 (*)	47 (*)
Insurance Underwriter	16	23 (*)	39(*)
Reinsurance Underwriter	3	5	8

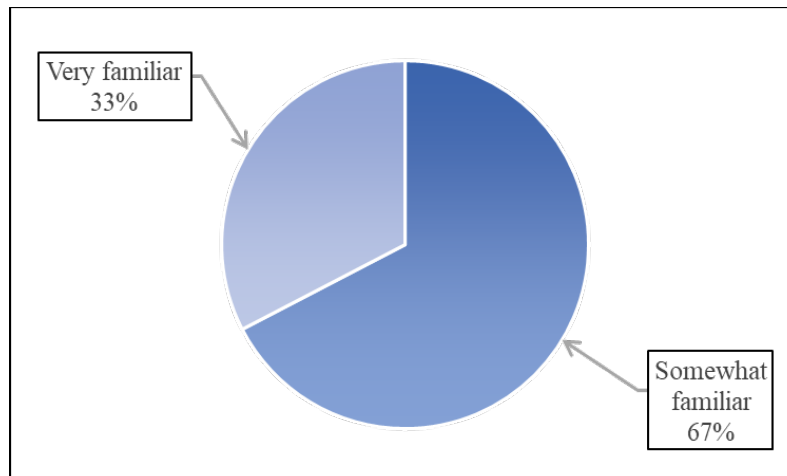
Commercial Casualty Underwriter	15	24	39
Other Third Party Liability Underwriter	4	3	7
Commercial Property Underwriter	0	1 (*)	1 (*)
Years of Underwriting Experience < 5	2	2	4
Years of Underwriting Experience 5 to 10	2	4 (*)	6 (*)
Years of Underwriting Experience 11 to 15	10	7	17
Years of Underwriting Experience 16 to 20	0	7	7
Years of Underwriting Experience > 20	5	8	13

(*) - One of the respondents indicated they were a commercial property underwriter. Since my research was focused on commercial casualty underwriters, I excluded all responses from this individual from the analysis.

Knowledge and exposure to predictive analytics

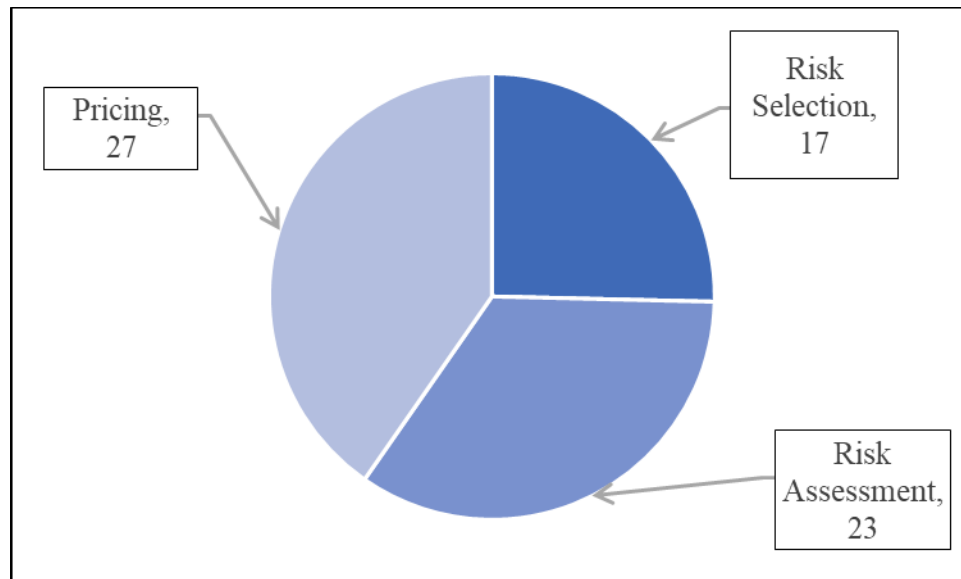
The first question of the survey measures the familiarity of the population with predictive analytics by simply asking the question, “How familiar are you with the concept of predictive analytics?” The possible responses were “Never heard of it”, “Somewhat Familiar” or “Very Familiar”. Figure 3 illustrates that all of the respondents are somewhat familiar with predictive analytics with two thirds of the population reporting they are very familiar.

Figure 3. Familiarity with Predictive Analytics



The next question explores the respondents' exposure to and experience in working with predictive analytics by asking: "Does your underwriting process involve the use of any tools or models that are derived from Predictive Analytics and if so, provide guidance for risk selection, risk assessment and/or pricing?" The possible responses are "Yes", "No", "Maybe", or "I don't know". Twenty-eight of the respondents, roughly 60% of the population, indicated their underwriting processes did utilize models involving the use of predictive analytics while 13 indicated they did not, three responded "Maybe" and two responded "No". If the response was "Yes", then the respondent was asked to indicate the applicable process(es). These processes are summarized in Figure 4 below:

Figure 4. Processes Using Predictive Analytics



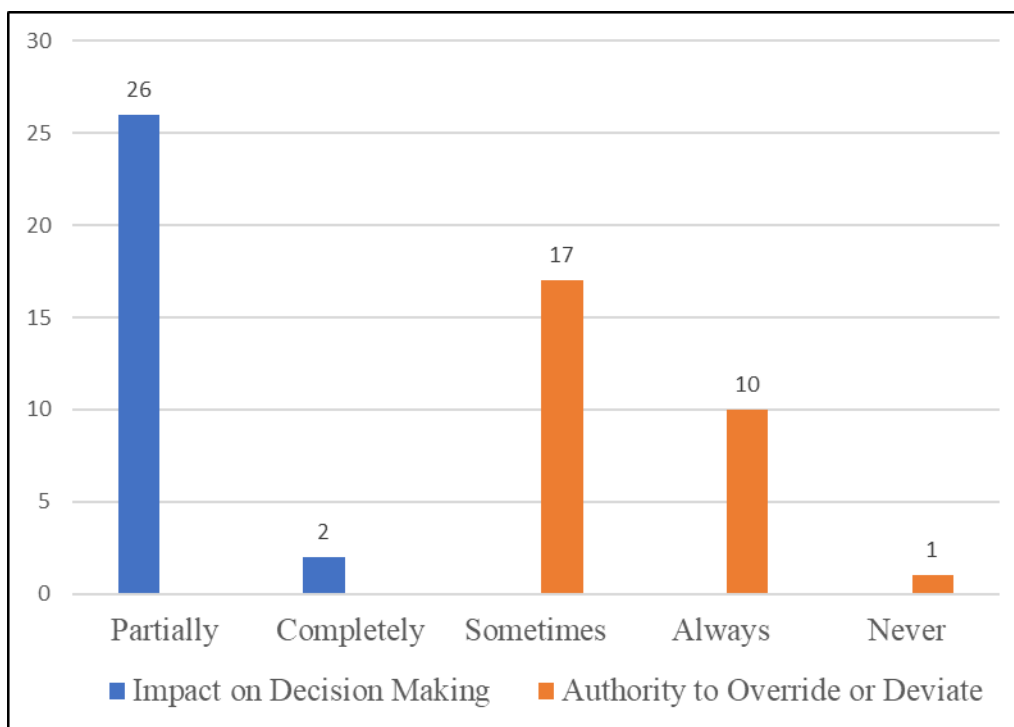
The 18 respondents that did not answer “Yes” were presented with a different question, “Does your company have any plans to introduce a predictive analytic tool into your underwriting process? Twelve responded with a “Yes” while six responded with a “No” or “I don’t know”.

Impact on Decision Making and Authority to Deviate

The next question gauges the importance of predictive analytics in the underwriters’ decision making by asking, “How much do the results of these Predictive Analytics based models impact your decision making?” The possible responses were “Completely”, “Partially”, “Not at All” or “Other”. The follow up question gauges the underwriters’ ability to depart from the model’s output by asking, “Do you have the authority to override or deviate from the model’s output?” The possible responses were, “Always”, “Sometimes” or “Never”.

Only two underwriters indicated that predictive analytics completely impacted their decision making process while the remaining 26 responded “Partially”. As for the ability to deviate or override the result, ten underwriters responded “Always” to this question, 17 responded “Sometimes” and one responded “Never”. These results are illustrated below in Figure 5:

Figure 5. Impact on Decision Making / Authority to Deviate



Cognitive Response to Predictive Analytics

The next two questions on the survey were designed to measure the cognitive response of the underwriter when confronted with predictive analytics result that they did not agree with. Accordingly, the first question asks, “Have you ever had an instance where you disagreed with the output of the model but used the result anyway?” The available responses were simply “Yes” or “No” and, in 24 of 28 (86%) instances the underwriters responded “Yes”. For those that answered “Yes”, a follow up question was,

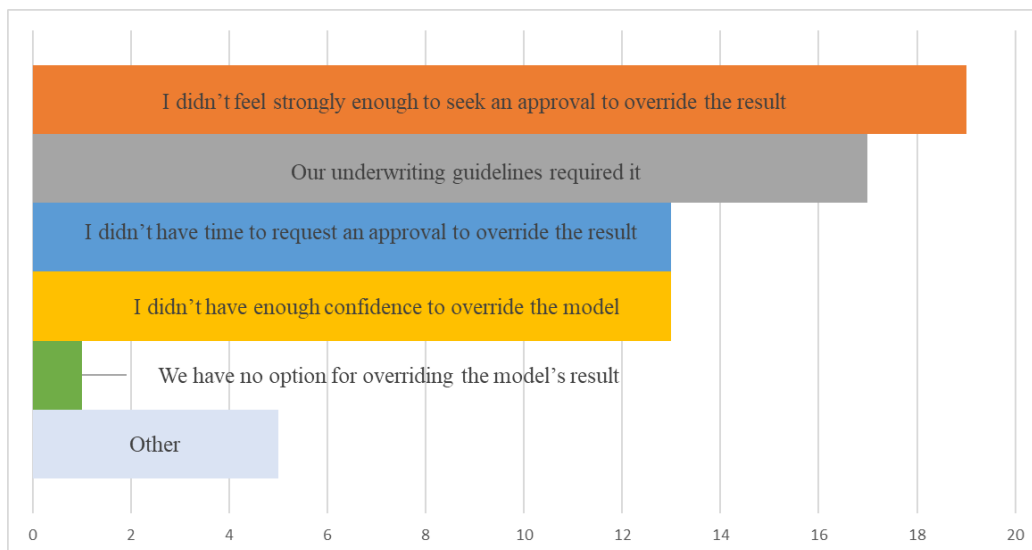
“Why did you use the model result if you didn’t agree with it? (check all that apply)”.

The possible responses are listed below:

1. We have no option for overriding the model’s result
2. Our underwriting guidelines required it
3. I didn’t have enough confidence to override the model
4. I didn’t have time to request an approval to override the result
5. I didn’t feel strongly enough to seek an approval to override the result
6. Other, please specify

The responses were quite varied with a total of 68 provided equating to an average rate of 2.42 reasons per underwriter and are presented below in Figure 6:

Figure 6. Disagreed with model but still used the result



Emotional Response to Predictive Analytics

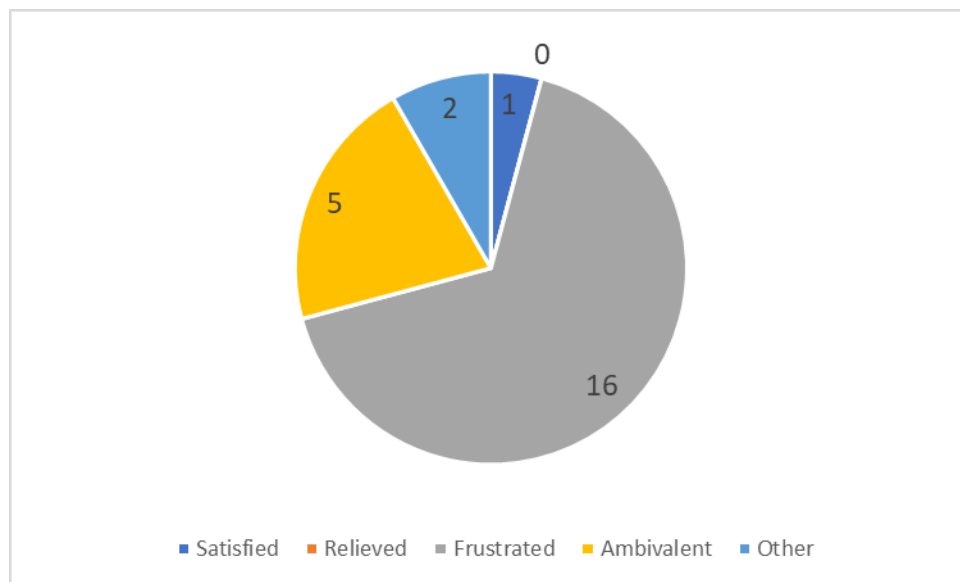
The next question measures the underwriters’ emotional response relative to the previously described cognitive response. When faced with accepting a decision that they

did not agree with, how did this make them feel? The possible responses to this question were “Satisfied”, “Relieved”, “Frustrated”, “No Reaction Good or Bad”, or “Other, please specify”. The results revealed that only one of 24 underwriters felt “Satisfied”, no one responded “Relieved”, 16 answered “Frustrated”, five were ambivalent and two gave another reason. The other reasons are listed below:

1. A 13 year underwriter wrote that she was “frustrated at first, but then after further collaboration - agreed with the plan” and,
2. A 25 year underwriter wrote that she felt “inquisitive and set out to research further”.

These results are depicted below in Figure 7:

Figure 7. Feelings toward accepting a model result they did not agree with



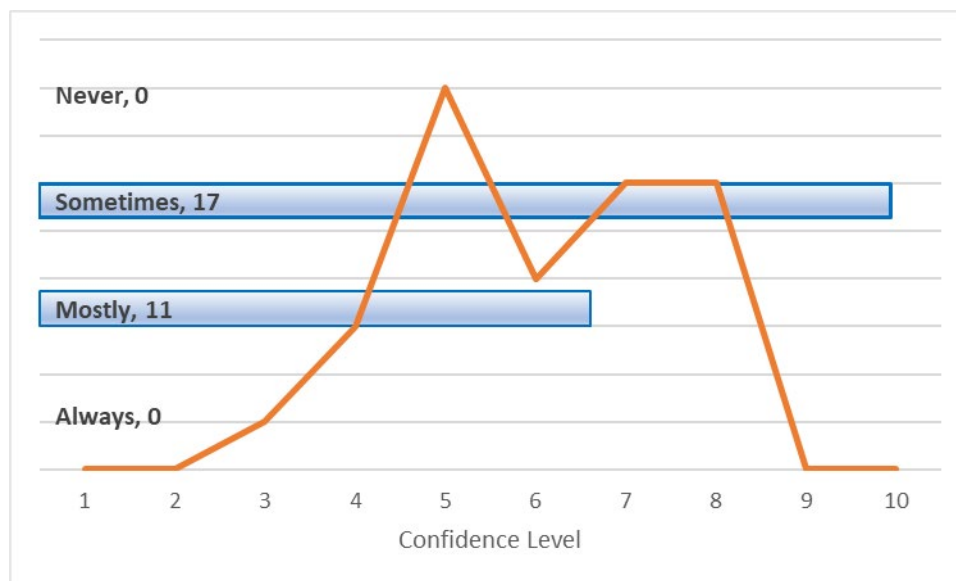
Attitude Toward Predictive Analytics

The next five questions of the survey sought to find additional information about the underwriters’ attitude towards predictive analytics in general. More specifically, I wanted to find out how often they agreed with the model and what their confidence level

was in the model's output. I was also curious to know if they thought their underwriting approach had changed at all since the introduction of predictive analytics into their process(es). Lastly, given the nature of machine made decision making, the survey posed the question, "How much do you feel that your employer values your experience and judgment in making underwriting decisions?"

The first question in the series was "How often do you agree with the results of the model?" The available responses were "Always", "Most of the time", "Some of the time", or "Never". Seventeen underwriters responded, "Some of the time" while the remaining 11 responded "All of the time". The follow up question to this was, "On a scale of 1 to 10, with 10 being the highest, what is your level of confidence in the results produced by these models?" The results show that confidence levels range from a low of three to a high of eight or an average confidence level of 5.5. These responses are depicted below in Figure 8:

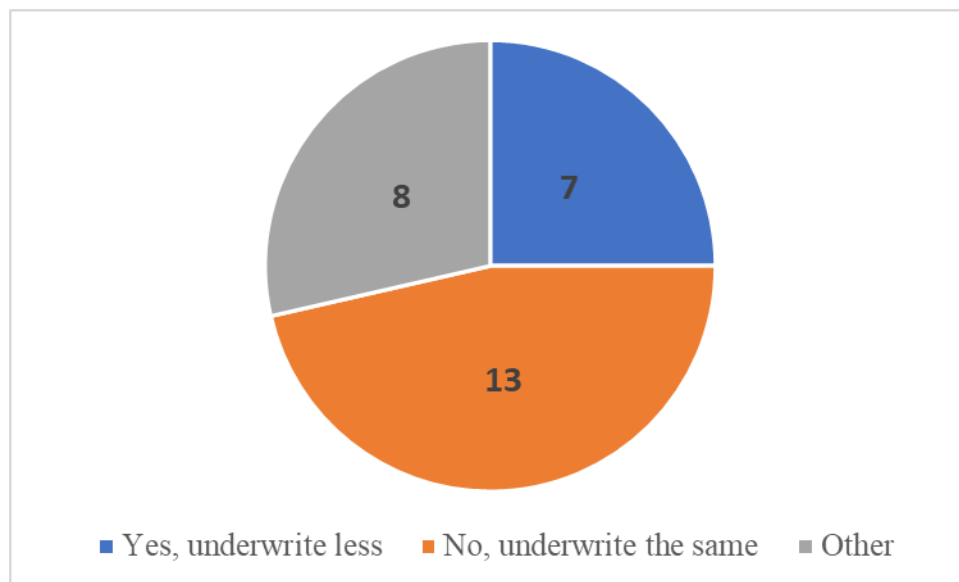
Figure 8. Frequency of agreement with the model and confidence level



The next question asked the underwriters to assess how predictive analytics may have changed their underwriting approach with the question, “Since you've started using predictive analytic models, do you think your underwriting approach has changed at all?”. The response options were: “Yes, I underwrite the risk less because I know I will just have to do what the model says”; “No, I still underwrite the risk the same as if these new models did not exist” or “Other, please specify”.

The results shown below in Figure 9 illustrate that seven underwriters noted that they will underwrite less while 13 indicate they will underwrite the risk the same as if the model did not exist. Eight underwriters responded with “Other” and gave more descriptive responses that will be analyzed in the following chapter.

Figure 9. Changes in underwriting approach

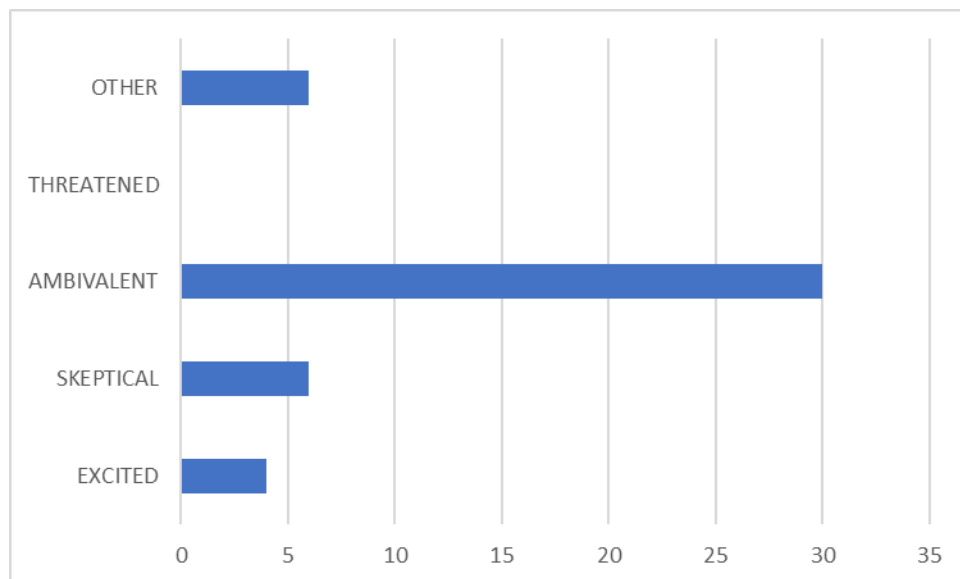


The next question asked the respondent to choose the answer that best describes how you generally feel about predictive analytic models. This question was offered to all respondents regardless of their own experience in using these models. Possible responses were “

1. Excited – I think these tools are awesome and might make better decisions than I can
2. Skeptical – sometimes the result is good but usually I think my decision is better
3. Ambivalent – they are useful but are just another datapoint to consider
4. Threatened – these models scare me as I think eventually, they will eliminate my job
5. Other, please specify

The majority of underwriters, 30 of 46 (65%) answered “Ambivalent” while four were “Excited” and six were “Skeptical”. Six underwriters chose to give more specific responses that will be reviewed in the following chapter. These results are illustrated in Figure 10 below:

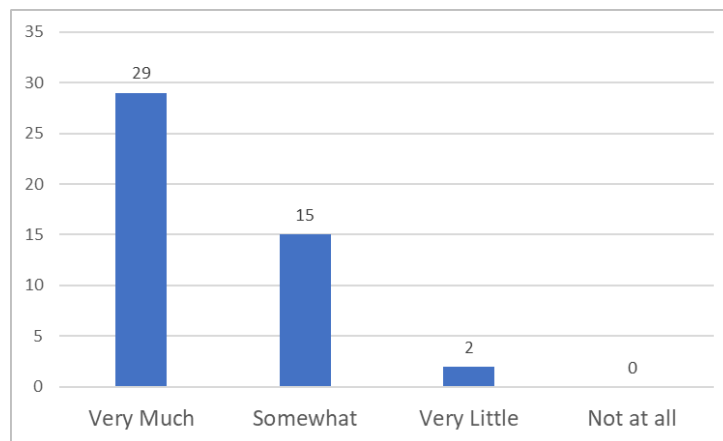
Figure 10: General feelings about predictive analytics



The last question in this section asks the underwriter, “How much do you feel that your employer values your experience and judgment in making underwriting decisions?” The possible responses were, “Very Much”, “Somewhat”, “Very Little” or “Not at All”.

A majority of underwriters (29 of 46) felt that their employers valued them “Very much” while 15 answered “Somewhat”. Only two underwriters thought their employers valued them “Very little”. No one responded, “Not at all”. These results Figure 11 below:

Figure 11. How underwriters feel valued by employer



Qualitative Responses

The final question of the survey was optional and was designed to solicit qualitative feedback by asking the underwriter to, “Please provide any additional comments that you would like to add concerning your thoughts or experience with predictive analytics.” Twelve individuals provided responses which will be analyzed in the next chapter. Primarily, these responses will be used to provide additional color and context to inferences made from the quantitative data.

Conclusion

The purpose of this chapter was to tabulate and present the quantitative results of the survey without much interpretation. In addition, I presented some of the qualitative feedback captured by the survey. A summary of the data revealed a fairly diverse population in terms of gender and underwriting experience though less experienced underwriters are somewhat underrepresented. The population as a whole expressed at least some familiarity with predictive analytics though 40% of the population are not currently using predictive analytic tools. The majority of those that are indicated that these tools partially impact their decision making and most can sometimes deviate from the result. However, at times underwriters have to use a result that they don't agree with for various reasons and, it's generally frustrating for them when this occurs.

Underwriters agreed with model results sometimes or most of the time but, no one expressed complete agreement or disagreement. In addition, underwriters expressed an overall moderate confidence level in predictive analytics and most have not changed their underwriting approach. In general, most underwriters are ambivalent toward predictive analytics and continue to feel that their own judgment and decision making is valued by their employers.

In the next chapter, I interpret the data further to develop inferences and ultimately, propose my findings relative to my research question: "How are commercial casualty underwriters reacting to the introduction of predictive analytics in their underwriting process and decision making?"

CHAPTER 5

DATA INTERPRETATION AND CONCLUSIONS

Introduction

In the previous chapter, I presented the data results of the survey in an aggregate fashion meaning the results were shown across the survey population as whole. Also, the results were presented without any analysis or interpretation. In this chapter, I look for discernible trends or patterns by cross-tabulating the results, using underwriting years of experience as an independent variable and applying critical thought to interpret the data and ultimately, develop findings.

The chapter also includes a discussion on the data findings relative to the literature discussed in chapter 2. This is followed by my thoughts on what surprised me in the data relevant to my own assumption as well as a discussion on the limitations present in the study. The chapter will also review practice implications for insurance companies along with recommendations for future research.

Data Analysis and Findings

Response Rate

The survey was sent to 77 insurance underwriters and 47 of them responded resulting in a 61% response rate. This was an excellent response and I attribute this to my present and past working relationships with these people. A survey response rate of 50% or higher should be considered excellent in most circumstances. “A high response rate is likely driven by high levels of motivation to complete the survey, or a strong personal relationship between business and customer” (Willott, 2019, para. 6).

Demographics

The demographics collected were gender, underwriter type, underwriter specialty and underwriting years of experience. Gender diversification was good with nearly 40% of the underwriters being female and 60% male. Underwriter type was much less diverse with 83% of all respondents being insurance underwriters with the remaining working as reinsurance underwriters. These groups differ by where they sit in the insurance distribution chain but from a functional point of view, both perform underwriting in essentially the same manner. However, given the relatively small number of reinsurance underwriters, this would not be credible to use as an independent variable. The underwriting specialty is also not very diverse but the good news here is that 46 of 47 underwriters identified their specialty as either commercial casualty, environmental liability or workers compensation. All three of these lines of business are very similar for purposes of the study in that these insurance products all have a “third-party” element to them. However, this demographic is also not useful as an independent variable. In truth, this question was really designed to ensure that I captured third-party underwriters as opposed to ones specializing in first party insurance (i.e. property). The survey did capture one property underwriter whose results were not used in the tabulations or analysis.

The final demographic was years of underwriting experience. In Chapter 4, I presented these in a segmented fashion as shown below in Table 2:

Table 2: Years of underwriting experience

Underwriting Experience	Years
Less than 5 years	4
5 to 10 years	5

11 to 15 years	17
16 to 20 years	7
Greater than 20 years	13
Total	46

One glaring item that sticks out here is the lack of survey participation from relatively inexperienced (less than 5 years) underwriters. However, nothing meaningful can really be inferred by this other than probable sampling error. “A sampling error is a statistical error that occurs when an analyst does not select a sample that represents the entire population of data and the results found in the sample do not represent the results that would be obtained from the entire population” (Hayes, 2020, para. 1). More than likely, my own recruitment list of participants was more heavily weighted toward people with more experience

Finding 1: All underwriters are familiar with predictive analytics and many are using them in their current underwriting processes

The entire surveyed population (47) professed to having at least some familiarity with predictive analytics and 61% of the population work with underwriting tools that are derived from predictive analytics. Pricing tools were the most prevalent with all but one underwriter indicating their tools used predictive analytics. However, risk assessment and risk selection tools were also quite prevalent. So, in general, underwriters are knowledgeable about f these tools, but a significant portion of the population are not yet working with these tools. However, a follow up question for the latter group of underwriters inquired about the future plans of their organizations to incorporate such

tools. A third of that group answered affirmatively that new tools were being developed and another third indicated that new tools might be coming. This means that roughly three quarters of the population will likely be using underwriting tools rooted in predictive analytics and thus, these tools appear to have a prominent place in today's underwriting departments.

Finding 2: Predictive analytics partially impact underwriters' decision making

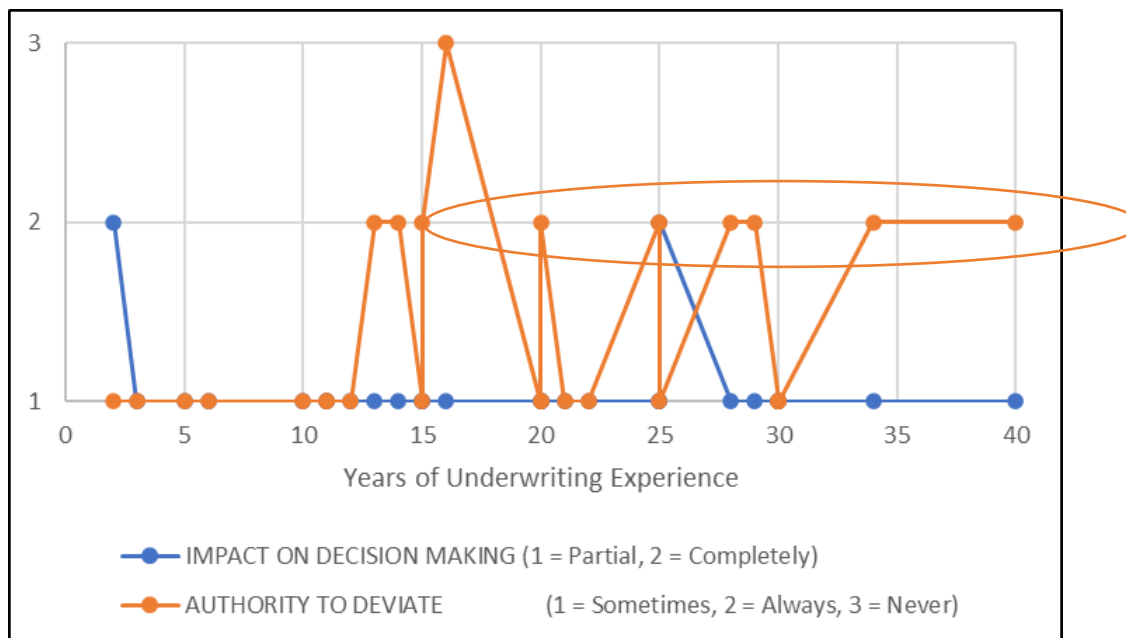
The data indicated that in almost all cases, predictive analytic tools only partially impact the decisions made by underwriters. This is an important finding and reveals that most underwriters are not subject to a strict implementation of the tool's output. Or, in other words the tools are not supplanting the decisions that have traditionally and ultimately been made by underwriters. This finding was supported in other parts of the survey as well when 70% of the full population answered that they were ambivalent toward predictive analytics and though they found them useful they were just another datapoint to consider in their decision making process.

Finding 3: Underwriters generally have the ability to deviate or override the tool's output

An overwhelming majority of the surveyed underwriters indicated that they could deviate or override the tool's output in at least some instances. A deeper look at this question indicated more experienced underwriters are given more latitude in working with these tools as they indicated they always had the ability to deviate or override. Figure 12 below, illustrates that only underwriters who had 13 years or more experience had the most authority when it came to these tools though not every underwriter with this level of experience enjoyed the same amount of authority. In fact, six underwriters who

had 13 or more years of experience appeared to have no more authority than their less experienced counterparts.

Figure 12. Impact on decision making / authority to deviate (by experience)



Why certain experienced underwriters had more authority than other experienced underwriters is difficult to say and one could speculate a myriad of reasons. These could range anywhere from the guidelines or boundaries established by the organization to a lack of trust in a particular underwriter or some other reason altogether. Nonetheless, the data does suggest that when an underwriter is given full authority to deviate from the model, this authority is only granted in certain cases and only to more experienced underwriters.

An interesting outlier on this chart is the 16 year underwriter who responded that predictive analytics partially impacted his decision making and also noted that predictive analytics were being used for risk selection and risk assessment but not pricing. This underwriter was the only one to indicate he could never deviate from the model. I

highlight these responses as these would be similar to my own responses had I taken the survey. I worked in an environment where these models were implemented in a very rigid manner with no ability to deviate and in essence, this was the catalyst for this capstone.

Finding 4: Underwriter confidence and intuition is impacted by predictive analytics

When questioned why the underwriter used the model's output even when they disagreed with it, a few different reasons were provided but a significant number of reasons were noted that indicated that either underwriters didn't have enough confidence to override or didn't feel strongly enough to seek approval for an override. Also, a significant number of people indicated that their underwriting guidelines required the result be used. Collectively, these results speak to an emotional response that underwriters are having to predictive analytics and perhaps even a change in thinking in the underwriting process. Absent of predictive analytics, underwriters would presumably have made a decision based on a traditional blend of their own analysis and intuition. Now that predictive analytics have been introduced and are frequently required to be used, underwriters appear to be less inclined to exercise their own judgment or perhaps, simply feel less sure about their own intuition. One underwriter with 15 years of experience noted that "I didn't have strong enough data to support an override" (Respondent 18). A 25 year underwriter wrote "I didn't have the background on the claim environment in a particular state to override the model" (Respondent 14). Figure 6 shown below illustrates all of the reasons given for using the model when they were in disagreement and is measured using years of underwriting experience as an independent variable. Figure 13 illustrates that the reasons tied to confidence (3 and 5) span across all

levels of experience meaning that highly skilled underwriters sometimes do not feel confident enough to deviate from the model.

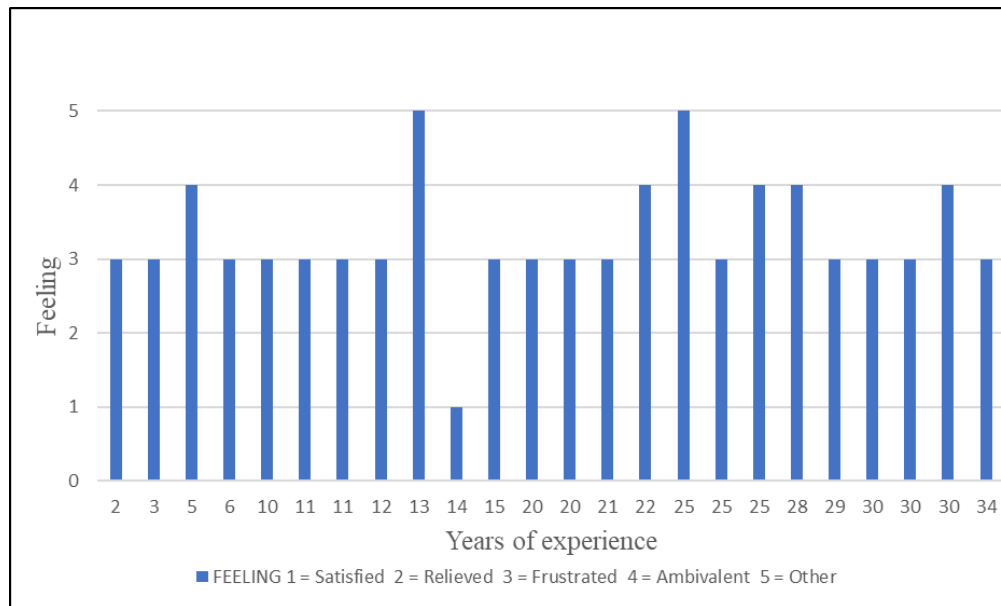
Figure 13. Reasons for using the model result when in disagreement (by experience)



Finding 5: Underwriters feel frustrated when having to use the model when they are in disagreement

Once an underwriter's confidence is compromised and the ability to impart their own judgment in part of the underwriting process, they naturally become frustrated or, at least most do. This is clearly illustrated in Figure 14 which shows that most underwriters became frustrated when forced to use the model. This also shows that this reaction spans across all levels of experience.

Figure 14: Feelings toward predictive analytics when not in agreement (by experience)



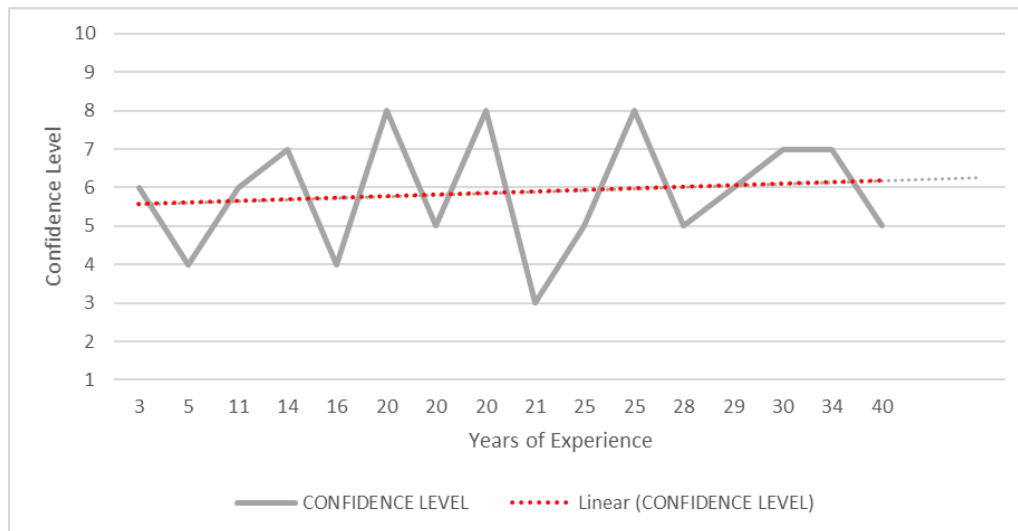
This is concerning and might indicate a decrease in job satisfaction which could have further ramifications for the organization, as well as the underwriter. However, this cannot be fully ascertained as I did not ask about overall job satisfaction. A smaller group of underwriters expressed ambivalence to this occurrence. Ambivalence, while not full blown frustration, still suggests a mixed emotion that could eventually lead to frustration. One interesting outlier wrote that she felt “inquisitive and set out to do more research” (Respondent 14). This illustrates a healthier attitude toward predictive analytics encouraging a blend of science and intuition. Sadly, few seemed to share this view.

Finding 6: In general, underwriters have moderate confidence in predictive analytics

When underwriters were asked what their level of confidence in results produced by predictive analytics on a scale of 1 to 10, with 10 being highest, the results showed only moderate confidence. Figure 15 below illustrates the response by underwriting

experience and doesn't really identify a strong correlation between experience and confidence level.

Figure 15. Confidence in predictive analytics (by experience)



In finding 4, it was noted that at times, underwriters lacked their own confidence to challenge the results of predictive analytics and now this finding reveals they have only moderate confidence in the tools. A lack of confidence in their own decisions as well as only moderate confidence in the tools making the decisions would on the surface seem to be problematic and fosters something less than a good working relationship between man and machine.

Finding 7: The majority of underwriters still approach underwriting in the same way though a sizable portion now underwrite less

Cognitively speaking, the majority of underwriters indicated via the scripted response that that they “still underwrite the risk the same as if these new models did not exist” while some chose to elaborate with custom responses that effectively mean the same thing but provide additional reasoning. For instance, one person stated, “I have always had models to utilize” (Respondent 14). And another wrote, “this is just another

piece of information to use in my decision making” (Respondent 31) and yet another stated “ I use it as a tool and/or data point to combine with other quantitative and qualitative considerations” (Respondent 18). These responses indicate that underwriters don’t see much difference between tools rooted in predictive analytics versus tools rooted in traditional actuarial science and essentially treat them in the same way when making decisions. One underwriter spoke to the simplicity of predictive analytics in their organization as a reason for not changing their underwriting approach, “our predictive analytic modeling is very basic, so I don't feel that we have leveraged the concepts adequately to make it materially drive our decision making process” (Respondent 39).

While the majority of underwriters seems to be going about the job of underwriting in the same way albeit, with the addition of new tools, more than a quarter stated chose the scripted response “I underwrite the risk less because I know I will just have to do what the model says”. This is very reminiscent of the a-ha moment I discussed in chapter 1 when my trainee said something to this effect. However, as Figure 16 below shows, very experienced underwriters espoused this same sentiment.

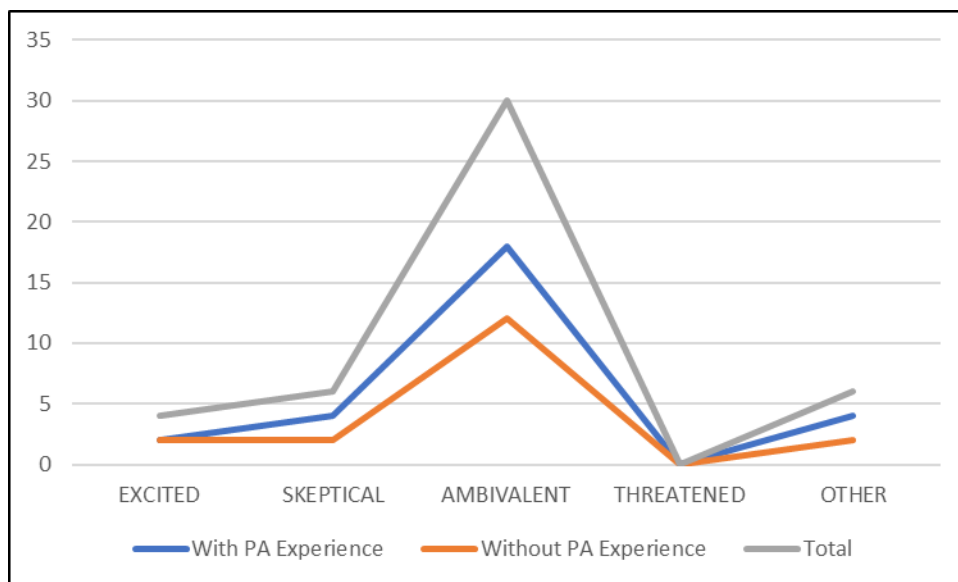
Figure 16. Changes in underwriting approach (by experience)



Finding 8: Most underwriters, regardless of practical experience, feel ambivalent toward predictive analytics

When asked to choose between excitement, skeptical, ambivalent, threatened or other, a large majority of underwriters chose ambivalence to describe their feeling toward predictive analytics. Considering that 40% of the surveyed population did not have any known experience in working with these tools, I wondered if their attitudes might differ from those who had worked with them, but the results were surprisingly similar as Figure 17 illustrates:

Figure 17: General feelings about predictive analytics (by experience)



This suggests that commercial casualty underwriters may have preconceived notions about predictive analytics if a large group is ambivalent before using them and another feels the same way after using them. This was echoed in this comment, “I have heard talk of predictive analytics and big data but have not have first-hand experience with pricing models. I think if/when predictive analytics are incorporated into our models, I would use it more as a guide” (Respondent 1). Another underwriter with no

practical experience with predictive analytics wrote, “I am a little skeptical about PA for casualty as casualty loss amounts are decided by humans” (Respondent 20). This comment also makes a veiled reference to the complexity of casualty insurance and the difficulties in predicting outcomes.

Finding 9: Underwriters feel that employers value their experience and judgment

While one of the major goals of the survey was to find out how underwriters felt about predictive analytics, I thought it would be worthwhile to see how they thought their organizations felt about them. It seemed like a natural question to ask particularly if underwriters thought that predictive analytics were threatening their job or even just supplanting their decision making. While no one expressed complete fear of being replaced by a machine, there was a great deal of ambivalence and isolated frustration when they didn't agree with the model. In spite of those feelings though, over half of the underwriters felt their employer valued their experience and judgment very much in making underwriting decisions and about a third thought their employers valued them at least somewhat. This is good news and contributes to overall job satisfaction and a higher self-esteem. Also, there were no discernible trends by either experience or gender in terms of who felt more or less valued.

How the Findings Relate to the Literature

Relative to the literature reviewed, my findings revealed that underwriters have familiarity with predictive analytics but whether or not they have transparency is an altogether different thing. Unfortunately, I did not pose this question in the survey but wish that I had. Knowing whether or not underwriters have an understanding of what goes into the algorithm(s) that produce their results would have been an interesting point

to explore. The amount of transparency that an underwriter has would undoubtedly impact how they feel about predictive analytics (Rainie & Anderson, 2017; Bader & Kaiser, 2019).

In general, my findings revealed that predictive analytics are playing an important role in their processes but have not become paramount. Many underwriters have the ability to deviate or at least a forum to do so it appears that reasonable balance between human judgment and computer based decisions exist. However, some are still forced to use the computer's result even when they don't agree with it. Sometimes underwriters lacked the time to do so but in other cases they lacked confidence. The latter could indicate a lack of transparency. If underwriters don't know or understand how the result is constructed then it would be difficult to challenge the result.

Algorithmic transparency and literacy could be extended to say, algorithmic fluency. The literature (Rainie & Anderson, 2017) suggests that a divide can occur between underwriters and data scientists and once again, my research did not explore this. But, understanding if underwriters are able to speak the language of data experts, and collaborate with them in meaningful ways would be extremely important. Before there were data scientists, there were actuaries and underwriters often collaborate with them. Personally, I have had many underwriting roles that involved collaboration with actuaries and many conversations where I needed to explain or defend a loss pick (a loss pick is a colloquial term used in insurance that refers to the forecasting of expected losses). Casualty underwriters typically forecast losses with the assistance of tools or models built by actuaries based on standard actuarial principles. It is necessary to have a good working knowledge of these tools and also have an ability to speak in terms that

actuaries relate to in order to have productive collaborations. In addition, actuarial tools are fairly rigid and rarely are capable of understanding nuances about a particular risk that only an underwriter can impart through their own analysis. These insights are typically conveyed in conversations with the actuary who in turn, will consider this additional information in a collaborative session designed to produce a more informed loss forecast. For example, wide fluctuations in the loss history and/or the insured's historical exposure base (e.g. payroll, revenue, etc.) will greatly impact the loss forecast of an actuarial experience model. However, there could be valid reasons for these fluctuations that an underwriter can help the actuary to understand and thus lead to an adjustment to the model's output and ultimately, a more informed and thoughtful decision. I see a distinct parallel with data scientists and the need for underwriters to collaborate with data scientists to make better underwriting decisions.

The literature also indicated that most people expect algorithms and the like to flourish in the coming years (Rainie & Anderson, 2017). This tracks, at least mildly, with what I found specific to underwriters and their companies to introduce more predictive analytic based tools.

Surprises in the Data

As an underwriter who had come from an environment where predictive analytics were being implemented in a very rigid manner, I was pleasantly surprised to see that a majority of underwriters indicated that predictive analytics only partially impacted their processes. Many underwriters also indicated that predictive analytics were essentially treated as just another datapoint to consider in making their ultimate decisions.

Research Limitations

There were a number of limitations in my research. First, the diversity of the sample was lacking in terms of less experienced underwriters (i.e. less than 10 years and less than 5 years). This was likely due to my purposeful sample being chosen from own personal contacts and as a thirty year underwriting veteran, most of my contacts are older. Second, to provide anonymity and encourage more candid responses, I did not ask the underwriters to divulge the name of the company they work for. Because of this, it was not possible to know how diverse the population was in terms of the company. This would have been helpful information to be able to gauge the organizational boundaries, such as underwriting guidelines, in place that may have impacted the underwriters' cognitive responses. Knowing more about the organizational culture at the companies would also have been helpful. For instance, I personally worked in a company where we had a chief science officer and over 200 data scientists that worked closely with the underwriters. Their presence definitely impacted the culture and ultimately, our decision making. Given the obvious financial investment the company had made, I felt that underwriters were less prone to challenge results. Finally, I only got to hear the underwriters' side of the story. It would have been useful to speak with managers, senior executives and even the data scientists themselves to gain a better understanding of the company's expectations relative to predictive analytics and their underwriters' behavior.

Future Research / Practice Implications

The research done in this capstone was exploratory in nature and considered a relatively small sampling of my personal contacts. While I believe this group was fairly representative of commercial casualty underwriters as a whole, I also feel that an industry wide study performed by an independent governing insurance body would be a

worthwhile endeavor. One possible organizations is A.M. Best whose “purpose is to strengthen the overall financial condition and operating performance of the insurance industry in support of economic growth and the well-being of all stakeholders through our work in credit ratings and information services” (A.M. Best Company, Inc., 2021, para. 3). Another good candidate would be the The Institutes Chartered Property Casualty Underwriters (CPCU) Society. “The CPCU Society is a global not-for-profit membership association dedicated to enriching the careers of nearly 18,000 highly motivated risk management and insurance professionals” (The Institutes CPCU Society, 2021, para. 5). These organizations might consider contracting with Pew Research who has already laid the groundwork for how the study might be conducted (Rainie & Anderson, 2017). Alternatively, insurance companies might consider performing their own studies with their own underwriters.

Broadening the scope to incorporate a wider diversity of underwriters to gauge their cognitive and emotional response would be very useful for the organizations they work for. The study should also measure the expectations of managers to ensure that both sides interests are aligned. Afterall, if these companies are making sizable investments in data science, it is natural to assume that they are doing so with the expectation of better underwriting decisions being made and ultimately better underwriting profit. However, if underwriters are not using these tools in the way the companies intended and/or if they are becoming frustrated using them, then these investments could very well have detrimental effects on their workforce and likely will not produce the underwriting returns they are looking for.

Organizations, including the underwriters who work for them, should also strive for full literacy and transparency of the algorithms that produce the results. In other words, they should know how the sausage is made. This is not only helpful for their own understanding and thought process but could also be useful when discussing their underwriting rationale with others. A constructive explanation to an underwriting manager or even a customer is received much better than something like “that’s what the machine said”.

Summary and Conclusion

At the time I embarked on this capstone, I was working for a large insurance company who had made a significant investment into the emerging field of data science. They began by hiring the industry’s first ever Chief Science Officer and, they built an organization below him consisting of roughly 200 data scientists. Soon after, we were presented with new tools whose primary purpose was to assign a score to a risk (i.e. a potential insured). After the underwriter entered some very basic information about the risk, the computer (i.e. an algorithm) generated a score from “A” to “D” with “A” being the best. The score was known as the Account Quality Index and was supposed to be an indication of whether or not the risk was deemed acceptable for the insurance underwriter to offer an insurance proposal to (i.e. risk selection). The score also correlated to pricing guidelines that the underwriter had to adhere to. At first, this score was meant to be a soft guideline for the underwriter and was more advisory than mandated but eventually, this very rudimentary tool became gospel and underwriters were not permitted to deviate nor, were exceptions ever made. This became the source of my frustration and ultimately, the impetus for this capstone.

Fast forward and I am pleased to report that things don't appear to as rigid as they were for me. While predictive analytics and other forms of artificial intelligence continue to develop, underwriting judgment and intuition also seems to be valued and plays an important role in underwriting decisions. It's only when the underwriters' hands are tied and they are forced to use a model result do they become frustrated and unfortunately, they don't always have enough confidence in their own judgment or simply not enough time to appeal the result. And yet, underwriters exhibit general ambivalence and moderate confidence levels when it comes to these tools. This is a curious paradox and further research would help to explain this. Of course, one possible explanation relates to the unfortunate lack of less experienced underwriters participating in my research. This absence is noteworthy, given the inevitable prominence of predictive analytics in underwriting processes. No doubt underwriters in this demographic will have far greater exposure to predictive analytics over the course of their careers than the current older crop of underwriters, present company included. Having a better understanding of their cognitive and emotional reactions to these tools would be useful, if not paramount, for the organizations that want to successfully integrate them into their processes. A reasonable speculation, might be that ambivalence toward these tools will lessen through attrition of older underwriters being replaced by younger ones who are more familiar and experienced with technology and data-based decision making. Further, this reduced ambivalence may also fuel a demand for more transparency.

Just as important as monitoring the future responses of younger underwriters is the need for older more experienced underwriters to continue to mentor and share their perspectives with their younger counterparts. Organizations should foster environments

that allow for coaching, mentoring and collaboration of these demographics. Without this, organizations will risk developing a crop of underwriters that could become overly reliant on predictive analytics. From the organizations' standpoint this may work out but only if, the algorithms are smart enough to predict the future without any human intervention. Ultimately, that risk may be too large, even for insurance companies, to take. A healthy blend of art and science, where man and woman can coexist with machines, will likely prove to be the best path forward. At this point, it seems appropriate to close with a popular quote found on the internet. Often attributed to Einstein though no real evidence of that seems to exist. And so, the irony of this false attribution coupled with the message it conveys is too good to resist, "I fear the day that technology will surpass our human interaction. The world will have a generation of idiots" – Anonymous.

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APPENDIX A

SURVEY

Welcome Message

My name is Steve Larzelere and I am a student at the University Of Pennsylvania pursuing a graduate degree in Organizational Dynamics. This questionnaire will be used to assist me in writing a paper that examines the question of how underwriters are reacting cognitively and emotionally to the introduction of Predictive Analytics tools or models into traditional underwriting processes. As a 25+ year underwriter myself, I am interested in knowing how you feel about this and would greatly appreciate you participating in this brief (about 5 to 10 minutes) survey.

Predictive Analytics are being used in many areas of insurance including claims, accounting, marketing, fraud detection, underwriting and possibly others. This survey, however, focuses on underwriting specifically as it relates to risk selection, risk assessment and pricing. Please keep that context in mind when answering the survey.

All of your responses will remain confidential and no individuals or individual responses will be identified. Only themes will be reported on. If quotes are used to support a theme they will not be attributed to a particular person.

Of course, this is voluntary but by participating you will not only be helping me, but also will be helping all underwriters and the companies they work for to gain a greater understanding of how these tools are affecting their underwriters and organizations as a whole.

Thank you very much for participating!!

Questions

Question 1

How familiar are you with the concept of Predictive Analytics?

- Very Familiar
- Somewhat Familiar
- Never Heard of it

Question 2

Does your underwriting process involve the use of any tools or models that are derived from Predictive Analytics and if so, provide guidance for risk selection, risk assessment and/or pricing?

- Yes
- No
- Maybe
- I don't know

(Question Branching: if the answer is “No”, “Maybe” or “I don't know”, then the respondent is directed to Question 4, otherwise to Question 3)

Question 3

Check all that apply

- Risk Selection
- Risk Assessment
- Pricing
- Other, please specify

(Question Branching: if the answer is “Risk Selection” or “Risk Assessment” or “Pricing” then the respondent is directed to Question 5, otherwise to Question 4)

Question 4

Does your company have any plans to introduce a predictive analytic tool into your underwriting process?

- Yes
- No
- Maybe
- I don't know

(Question branching: any response here directs the respondent to Question 13)

Question 5

How much do the results of these Predictive Analytics based models impact your decision making?

- Completely
- Partially
- Not at all
- Other

Question 6

Do you have the authority to override or deviate from the model's output?

- Always
- Sometimes
- Never

Question 7

Have you ever had an instance where you disagreed with the output of the model but used the result anyway?

- Yes
- No

(Question Branching: if the answer is “No” then the respondent is directed to Question 10)

Question 8

Why did you use the model result if you didn't agree with it? (check all that apply)

- We have no option for overriding the model's result
- Our underwriting guidelines required it
- I didn't have enough confidence to override the model
- I didn't have time to request an approval to override the result
- I didn't feel strongly enough to seek an approval to override the result
- Other, please specify

Question 9

How did this make you feel?

- Satisfied
- Relieved
- Frustrated
- No reaction good or bad
- Other, please specify

Question 10

How often do you agree with the results of the model?

- Always
- Most of the time

- Some of the time
- Never

Question 11

On a scale of 1 to 10. With 10 being the highest, what is your level of confidence in the results produced by these models?

Question 12

Since you've started using predictive analytic models, do you think your underwriting approach has changed at all?

- Yes, I underwrite the risk less because I know I will just have to do what the model says
- No, I still underwrite the risk the same as if these new models did not exist

Question 13

Choose the answer that best describes how you generally feel about predictive analytic models.

- Excited – I think these tools are awesome and might make better decisions that I can
- Skeptical – sometimes the result is good but usually I think my decision is better
- Ambivalent – they are useful but just another data point to consider
- Threatened – these models scare me as I think eventually, they will eliminate my job
- Other

Question 14

How much do you feel that your employer values your experience and judgment in making underwriting decisions?

- Very much
- Somewhat
- Very little
- Not at all

Question 15

What is your gender?

- Male
- Female

Question 16

Indicate if you work for an insurance company or reinsurance company.

- Insurance
- Reinsurance

Question 17

What segment best describes your area of expertise?

- Commercial Casualty
- Commercial Property
- Professional Liability
- Environmental Liability
- Personal Lines
- Other

(Question Branching – if answer is “Personal Lines” then respondent is directed to the default success message)

Question 18

How many combined years have you worked in an underwriting role where you had authority to make underwriting decisions?

Question 19

Please provide any additional comments that you would like to add concerning your thoughts or experience with predictive analytics.

Question 20

Please indicate whether you would be willing to participate in a deeper exploration of this topic by allowing me to interview you. This will take approximately one hour, and all responses will remain confidential. If yes, please provide your contact info or reach out to me. Thanks!

- Yes
- No
- Contact Info

Closing Message

Thank you for taking this survey!

APPENDIX B

LINKEDIN RECRUITING POST

Steve Larzelere posted in Underwriting

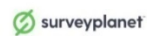
...

**Steve Larzelere**

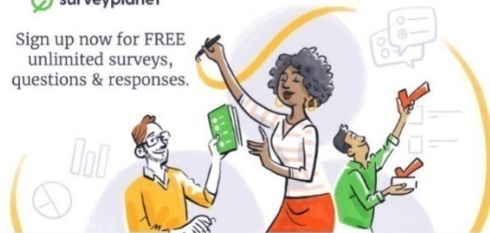
Vice President - Facultative Casualty Underwriter at Munich Reinsurance America

2yr · 🌐

Are you a Commercial Underwriter and does your company use Predictive Analytics? If so, would you be able to take a brief (5 minutes) survey to help me examine the question of "How underwriters are reacting to these models in the course of their day to day underwriting". All responses will be kept confidential. Thanks for your help!! Click this link to take the survey: <https://lnkd.in/eq3TzG3>



Sign up now for FREE unlimited surveys, questions & responses.

**Underwriter Reactions to Predictive Analytics**s.surveyplanet.com