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CLOTHING SIZE AS HEALTH RISK PROXY IN INSURANCE INDUSTRY

Ljubljana, February 2018 GREGA TROBEC

AUTHORSHIP STATEMENT

The undersigned Grega Trobec, a student at the University of Ljubljana, Faculty of Economics, (hereafter: FELU), author of this written final work of studies with the title CLOTHING SIZE AS HEALTH RISK PROXY IN INSURANCE INDUSTRY, prepared under supervision of Prof. Marko Pahor.

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INTRODUCTION

Chronic diseases are the biggest contributor to global health care spending, accounting for 78 percent of healthcare costs, as observed in the 2009 study by Bodenheimer, Chen, and Bennett.

Making the fact that we are on the cusp of a chronic global health epidemic, Mulder (2015) states that obesity is one of the largest drivers of morbidity and thus the main risk factor for chronic diseases such as type 2 diabetes, heart disease and high blood pressure. By no exaggeration, obesity has already reached crisis proportions. More than 2.1 billion people—nearly 30 percent of the global population—are overweight or obese, almost half of the world's adult population will be overweight or obese by 2030 (Dobbs et al., 2014).

Drouin, Hediger, and Henke (2008) state that "if current trends persist to 2050, most member countries of the Organisation for Economic Co-operation and Development (OECD) will spend more than a fifth of gross domestic product (GDP) on health care. By 2080 Switzerland and the United States (US) will devote more than half of their GDP to it—and by 2100 most other OECD countries will reach this level of spending" (Drouin et al., 2008).

If ignored, these unsustainable costs will break the health systems and create destructive financial burdens for countries. This is referred to as a healthcare crisis, which is primarily a financial problem in which countries cannot successfully cope with people's access to healthcare. This happens when supply fails to match demand for treatment and makes healthcare services & health insurance unaffordable, causing devastating health problems for the wide population.

We are conducting this research in close cooperation with Styliff Inc, of which the founder and chief executive officer (CEO) is also the author of this paper. Styliff Inc, a US-based IT company, is specialised in health insurance technology. We have developed a unique data play in one of the largest industries in the world. An industry, where health data is scarce despite it being a central component of their core service—quantifying & pricing health risk, especially in the US.

Styliff developed the first applicable algorithm for recognizing and calculating obesity levels from clothing sizes. Wellners (n.d.) found that around 20 percent of the US workforce wear uniforms or other corporate workwear, which would make it possible for health insurance and wellness industries to finally be able to screen employees in a cost and time-effective fashion.

We soon understood the immense value of this data. Health data is tough to collect in the workplace because of discriminatory laws in the US such as Health Insurance Portability and Accountability Act (HIPPA). Its invasive & resourceful nature even makes it hard for health insurers to collect in the individual market. For the vast majority without conditions and lack of medical history, health insurers use correlations such as age, gender, postcode and even credit score to assign them a community average risk rating. This fails to account for the true health status of those individuals, and employees' lifestyle choices, such as poor diet and lack of exercise that is shown through obesity levels. Obese people are in process of developing chronic conditions and are yet to regularly claim—these are referred to high risk employees. They go undetected and currently insurance carriers cannot distinguish between low risk and high risk employees—this distinction has never been so important with obesity at unprecedented levels. Therefore, the healthcare market, insurers and companies are practically left in the dark awaiting the looming crisis of chronic diseases and unsustainable healthcare costs driven by obesity (Finkle & Humer, 2014).

The introduction of our model won us the Reinsurance Group of America innovation competition with the aim of finding innovative products to improve their offering. If this model is validated, health insurers around the world can turn to Styliff to help quantify and overcome the growing obesity challenge by just using employees' uniform orders.

1 BACKGROUND

1.1 US Healthcare Costs

The United States spent 17.15 percent of its GDP on healthcare in 2013, compared to five percent in 1960 according to data from the OECD. Squires and Anderson (2015) found that this was almost 50 percent more than the next-highest spender despite being the only country without a publicly financed universal health system.

The rise in costs is partly attributed to obesity (i.e. Body Mass Index equal or higher than 30), which has in the last decade reached epidemic levels: 68.8 percent of people are either obese (35.7%) or overweight (33%) (NIDDK, 2012). For comparison, 51.6 percent of adults in the European Union (EU) are overweight or obese, but only 15.7 percent are actually obese (Eurostat, 2014).

1.1.1 Health Care Spending Linked to Obesity

It is common knowledge that having an increased health risk affects health care costs, but what empirical evidence is there? Goetzel et al. (2012) published a study on the economic impacts of ten health risk factors commonly found in a working population that are responsible for a quarter of all health care costs. They assessed their health risk through health risk appraisals (HRAs) and biometric screenings. In the area of biometric risks, 32.2 percent of employees were obese, 9.9 percent had high cholesterol, 9.5 percent had high blood glucose, and 7.6 percent had high blood pressure. A comparison of results from the HERO study (Goetzel et al., 1998) conducted 14 years earlier found that health risk factors worsened: poor nutrition and eating habits (64.1% of population in 2012 study versus 20.2% in 1998) and obesity (32.2% versus 20%).

Total annual per capita medical expenditures for study group members averaged $3,961 in 2009 dollars. The review of results showed obese employees were 27.4 percent costlier than normal or overweight employees (incurring $1,091 in additional costs) after adjusting them for confounders. Other obesity related risk factors also amounted to a substantial difference in total health care spending: high blood glucose (31.8% or $1,653), high blood pressure (31.6% or $1,378), physical inactivity (15.3% or $606).

Of ten health risk factors, seven were found to significantly increase medical expenditures, of which four were associated to obesity. After adjusting figures to the percentage of people at high risk, obesity directly accounted for 8.8 percent of total health care in the study group. All obesity related risk factors represented almost 18 percent of total annual expenditures (Goetzel et al., 2012).

1.2 US Healthcare System

The healthcare system is somewhat different than elsewhere in the developed world, where a single-payer publicly funded system is in place. Primarily, the US shifts the health care cost burden to employers and relies on company-sponsored private health insurance. Collectively providing health coverage to over 170 million Americans. The insurance cost is further in smaller part split with employees, which is referred to as deductibles (Pipes, 2016).

Healthcare cost trends are double the inflation rate, which is weakening the economy. Barbee (2014) states that ninety percent of chief financial officers (CFOs) agree that if their company’s healthcare costs were lower, they could afford to invest more in their businesses. As a result, these ballooning healthcare costs are making them less competitive globally. Therefore, it is of no surprise that four out of five CFOs across all industries are feeling the pressure (Barbee, 2014) and are attempting to reduce this burden.

In 2016, twenty of America's largest corporations—including American Express, Coca-Cola and Verizon—formed a coalition called the *Health Transformation Alliance* (Pipes, 2016). Their plan was to pool their 4 million employees' healthcare data in order to figure out what was working, and what was a waste of money.

1.2.1 Self-Insured Companies

98% of large US corporations reduce the overall cost of insurance by becoming self-insured. Any insurance arranged with a third-party insurer will include components to cover the insurance company’s administrative costs and desired profit margin. Instead, self-insured companies eliminate these costs through directly covering their own healthcare costs through their own insurance trust (Merhar, 2016).

An additional benefit is that they avoid committing a large sum of capital for over one year to fully insured plans. Westover (2014) argues that by self-insuring they commit every two to three months to free up capital which can be reinvested in different areas of the company

However, self-insuring exposes the company to much larger financial risk in the event of unforeseen catastrophic claims. This is becoming a growing risk and an ever increasing reality given the chronic disease crisis.

Self-insured companies source underwriting professionals from the healthcare industry to quantify health risk to forecast & prepare for future healthcare costs. This is an in-house insurance company named as captive insurance that is wholly owned and controlled by its insureds (Westover, 2014). However, while health insurers have extensive experience in underwriting and pricing health-related risk, their risk is based on relatively little health information and rely mainly on demographic characteristics & previous medical claims. These sources fail to detect employees that are 'at-risk' of developing chronic diseases. This reduces their accountability for their forecasting performance that is referred to as administrator’s moral hazard.

More than 80% of CFOs at large self-insured US companies felt powerless when it came to managing their company’s health care spending according to a 2014 Harris Poll (Barbee, 2014).

Therefore, nearly all CFOs (97%) believe that employers must “step-up” to the plate to help fix the broken healthcare system and pioneering the revolution of health insurance (Liu, 2016).

Self-insured companies are pioneering what is referred to as the future of health insurance. This has been widely defined as expanding the role of health insurance companies in “quantifying and pricing risk, but the insurer expands into the business of influencing and lowering risk” according to Mulder (2015). Transforming “insurance companies from a short-term transaction to a longer-term partnership in which the insurer and the insured collaborate to improve long-term behaviours and health outcomes” (Mulder, 2015).

To fulfil this transformation, self-insured companies have strategic partnerships with corporate wellness programs to help quantify health risk and in turn forecast future healthcare costs, as well as to lower health risk of their employees to reduce their associated healthcare costs.

1.3 Corporate Wellness Programs

Corporate wellness was almost an eight-billion-dollar industry in 2016 (IBISWorld, 2016) with the mission to curb the alarming levels of healthcare costs for corporations. In 2013, Kaiser Family Foundation report showed that 99 percent of enterprises with 200 or more workers offered at least one wellness program (Ajunwa, 2017).

The design of wellness programs is aligned with the self-insurance objectives: to aid in quantifying health risk, and to lower the health risk of their employees.

In order to be eligible to participate in the wellness program, employees must undergo a health screening that consists of a biometric screening and/or a health risk assessment. The purpose of this is to collect employee health data that is used to quantify the health risk to forecast healthcare costs. The value of this data is emphasised by on average $100 incentive offered to employees for participating (Ebeling, 2015).

The health screening determines what wellness program the participant enters, either:

- Disease management program
- Lifestyle management program

Disease management programs are designed to help employees with pre-existing diseases, such as diabetes or coronary heart disease, better manage their condition. This can be in the form of providing them with reminders to take their prescribed medications or to attend lab tests according to Mattke et al. (2013).

Lifestyle management programs are designed to help prevent those without a pre-existing disease from developing one. These programs are focused more on promoting health lifestyle choices such as dietary, smoking and physical exercise programs. Both of these programs are driven through the use of incentives, that averaged $878 in 2016, in the form of deductible payments and merchandise (Ajunwa, 2017).

1.3.1 Are Wellness Programs Effective?

Wellness initiatives are the largest trend in the US workplace, however, they have not proven to reduce healthcare costs or create significantly healthier workforces as shown by the RAND Wellness Program study in 2013 (Mattke et al., 2013). As a result, their success in quantifying and lowering the risk has been limited.

Only 46 percent of the workforce undergo the health screening when the program is initiated, more alarmingly, Cawley (2013) found that 68 percent of participants who enrolled in the program had dropped out by the end of the first year. As a result, there will only be 15% of the workforce providing the program with health data in the following year (Cawley, 2013). Sustained engagement is highly correlated with success experienced during the program, therefore, they are quantifying the healthier population, which can give a skewed representation of the workforce. This significantly restricts the performance of underwriters to produce an accurate risk profile of the company.

Wellness Return on Investment (ROI) is the ‘gold standard’ when evaluating the effectiveness of programs of improving health & reducing associated healthcare costs. RAND’s analysis of a decade of PepsiCo data found that “overall, the two component programs reduced the employer’s average healthcare costs by about $30 per member per month (PMPM)” or $360 annually (Mattke et al., 2013).

The disease management program was responsible for 87 percent of those savings with hospital admission reducing by 30 percent, despite only 13 percent of employees participated in the disease management component (Mattke et al., 2013). This translates into achieving the greatest return on investment through the disease management program. On the other side of the coin, disease management is the main source of savings because it also has the largest cost saving opportunity–people with chronic diseases are responsible for 78 percent of healthcare costs (Bodenheimer et al., 2009). Considering that only 13 percent of the workforce participates in disease management, it is the main source of increasing healthcare costs. But the real victory would be in preventing those high costs from ever incurring in the first place.

This stresses the financial impact of each employee that develops a chronic disease, and the important role that lifestyle management plays in preventing this from happening.
However, the ROI based on reducing healthcare costs devalues the importance of the lifestyle management program. It is tough to quantify the effectiveness of lifestyle management participation based on hospital admissions. At-risk employees are yet to develop chronic diseases, and they are yet to regularly go to hospital. Therefore, transforming a high-risk employee into a low-risk employee would result in similar hospital admissions and that prevention of them developing chronic diseases that goes unnoticed in the balance book.

This results in underfunded and ineffective lifestyle management programs. For example, instead of offering expensive one-to-one counselling and coaching, they offer alternative inexpensive interventions, such as "offering healthy food choices and launching educational campaigns to use the stairs" (Mattke et al., 2013). These programs' inability to impact behaviours of their participants is evident in the prevalence of obesity growth trend on an annual basis and 68 percent of the US workforce being overweight or obese (NIDDK, 2017).

As a result, lifestyle management programs are nothing short of a 'ticking time bomb' with growing populations of high-risk individuals and this will severely cost organization in years to come. However, this will go unnoticed using ROI as the sole measurement tool. Companies are searching for alternative measurement tools to evaluate their wellness initiatives.

Eighty-seven percent of companies measure the effectiveness of wellness programs through participation levels according to Connecticut Business & Industry Association (CBIA) (2017). Even though there is no significant correlation between participation and improved health or weight loss. The bottom line is; people can participate in ineffective programs without any health improvements but measured as a success.

61% percent of organizations assess health changes in biometric measures (CBIA, 2017) that would be a direct and superior competitor for measuring effectiveness of wellness programs. However, the participation rates of assessing health changes depend on people not dropping out the wellness program. Less than half of the workforce typically participate in the first biometric screening and of those participants there is an extreme level of drop out of up to 68% (Cawley, 2013). As a result, there is only 15% of the workforce providing the employer with health data in the following year to track the effectiveness of your wellness initiatives.

The major sources of failure of wellness programs are the low levels of participation and sustained engagement. This low participation in wellness screening means companies remain in the dark as to understanding their risk and properly forecast future healthcare costs. It also compromises their ability to measure the effectiveness of their wellness initiatives to make necessary adjustments to lower health risk and reduce healthcare costs over a long period of time.

Considering the looming crisis of chronic diseases, low investment in lifestyle management programs and their limited insight into their increase of high-risk employees. Companies are heading towards an unforeseen health crisis that will cripple them financially.

Styliff’s advantage is that it doesn't require an opt-in for our data analysis, therefore we have a reliable, robust and unbiased source of health data. This dramatically improves company's ability to quantify their level of health risk. Thanks to annual uniform changes, it provides a consistent measure of the health changes of companies’ workforce. This a more accurate metric for measuring the effectiveness of wellness initiatives. This information is vital for companies to maximize the value of their wellness investment and lower the health risk of their workforce.

1.4 Wearables

In terms of emerging technologies to collect health data for health insurance purposes, wearables are the largest trend and indirect competitor to our alternative data source: “According to ABI Research, employers will integrate more than 13 million wearable health and fitness tracking devices into their employee wellness programs by 2018” (Consociate Benefits Administration, 2017).

Large self-insured companies, such as British Petroleum (BP), bought Fitbit wearables in bulk and integrated them into their wellness program: “BP used the step tracking data to develop an incentive for their employees to become more active” (Smart Compliance, 2017). If an employee walked more than one million steps in a year, they received points that go towards a lower insurance premium.

Wearable devices help collect a wide variety of biometric data, including physical activity, stress level, and cardiovascular health.

The attraction for health insurers is simple: The biometric data quantifies health risk & active people are generally healthier, so they likely make lower-risk (and more profitable) customers. A number of health insurers are already offering premium discounts and rewards tied to fitness level to motivate & reinforce positive behaviour and outcomes.

According to Harvard Business Review (Ajunwa, 2017), research has shown that the data from fitness trackers can be irregular and unreliable. Additionally, the study by Case, Burwick, Volpp, and Patel (2015) confirmed that: “Recent comparisons between various wearables for tracking physical activity showed large variations in accuracy between different devices—with error margins of up to 25%” (Case et al., 2015).

This can lead employees to rely on inaccurate assessments of their health and their health risk, and often their recommendations do not match up with rapidly advancing medical and health research. The premise is that physical activity, as measured by wearables, is not directly correlated to health status because of other health factors such as the person's build, diet and smoking. This data alone is not capable of capturing the entire health risk picture of a customer.

Moreover, insurers must rely upon the good faith of a policyholder to generate fitness data personally and not to pass a motion-sensitive wearable device to a friend in marathon training, or simply put it in the tumble-dryer. The largest challenge is that these wearables are integrated into the confinements of a wellness programs, therefore, restricted by the stagnated participation rate of wellness programs.

Lastly, concerns arise when the significant levels of drop off are acknowledged. Recent surveys have shown that 32 percent of users stop wearing these devices after six months, and 50 percent after one year (Ledger & McCaffrey, 2014). Accoding to Piwek (2016) , “Many wearables suffer from being a 'solution in search of a problem'”. This sporadic and incomplete data makes wearables far less valuable to insurance companies when using the data to improve the accuracy of their risk profiles (Piwek, 2016).

It is fair to conclude that a large health data gap and demand for a less invasive data gathering method remains. Wearables require an opt in process, which is the largest barrier to capture the entire health changes of the uniform workforce population.

The high demand to solve the healthcare situation and the scarcity of supply of this data, creates a more collaborative environment for suppliers to work on this mission and reduce healthcare cost.

2 CLOTHING SIZE AS AN INDICATOR OF HEALTH RISK

Anthropometric measures, such as Body Mass Index (BMI) and Waist-to-Height Ratio (WHtR), are considered the first step in identifying people at ‘early health risk’. By combining them with further risk factors such as gender, age, ethnicity, and socioeconomic status, more complex risk scores can be created. Retrieving anthropometric measurements can often be invasive and seen as an additional hassle. Also, self-reported measurements can deviate from true measurements.

To overcome this, we wanted to explore the predictive power of clothing size in obesity levels. There have been few studies covering the topic of using clothing size as a proxy for body size and health risk, such as a 2015 study from United Kngdom (UK) by Han, Gates, Truscott, and Lean, and a Dutch study by Hughes, Schouten, Goldbohm, Van den Brandt, and Weijenberg, (2009).

A study by Han et al. (2015) conducted at Glasgow Royal Infirmary related clothing size to waist circumference and to risks of obesity related diseases. They developed linear regression equations using UK clothing size as a dependent variable and waist circumference as explanatory variable and showed extremely strong correlations: men trouser size (R2 = 0.64)[1] and women dress size (0.80), clothing size correlated ($P < 0.001$) linearly with indices of adiposity (Han et al., 2015). They showed that “odds ratios for the risk of having at least one the major obesity related diseases (ischaemic heart disease, hypertension or diabetes mellitus) were 3.9 (95% CI: 1.8–8.3) in men with trouser size ≥ 38 inches and 7.0 (95% CI: 2.5–19.4) in women who had UK dress size ≥18” (Han et al., 2015).

A Dutch study by Hughes et al. (2009) analysed a sample of 1158 men and 1334 women for a follow-up period of 13.3 years or more than 21,000 person-years. They hypothesized that

[1] R2 represents the proportion of variability in a data set that is accounted for by the statistical model.

clothing size as a proxy for waist circumference can predict risk of endometrial cancer in women and renal cancer in men. In men, self-reported trouser size correlated slightly better with waist circumference (0.64) than hip circumference (0.63). In women, the correlations between self-reported skirt size and hip circumference were 0.71, and 0.78 for waist circumference (Hughes et al., 2009). They concluded that "clothing size appears to predict cancer risk independently of BMI, suggesting that clothing size is a useful measure to consider in epidemiologic studies when waist circumference is not directly available" (Hughes et al., 2009).

The outcome of both studies led us to conclude that clothing size predicts health risk in 60-80% of cases. They claimed that some misclassification could have occurred since people self-reported the clothing sizes they wore – size charts of clothing sizes also vary among different brands.

2.1 Proposed usage of clothing size as a health proxy

2.1.1 Health Risk from Workwear Order Sheets

Clothing-to-Health Risk algorithm that was created by Styliff Inc can calculate health risk proxies, such as BMI and Waist-to-Height Ratio, from clothing sizes. The algorithm works with one-set uniforms and multi-set uniforms (e.g. polo shirt and chino trousers), while accuracy improves with the amount of garments within the uniform set and additional employee information (e.g. age, gender).

Employers needs to deliver the workwear order sheets and garment details. A health snapshot can be done instantaneously by analysing the order sheets. This product can be offered to organisations that want a quick and relatively general health overview.

The health data obtained via this method is not as accurate and is far more limited as when conducting health check-ups, but the need for employee direct involvement and its cost effectiveness make up for its limitations.

2.1.2 Quantifying Risk

On average employers offer $100 to employees to undergo health screenings (Ebeling, 2015). However, the financial stimulation is not able to solve the problem of low participation. Additionally, in high turnover industries—above 50 percent in industries such as retail (Azcentral 2017)—all their wellness programs efforts are further diminished with a constantly changing and incomplete risk profile of the company.

Styliff have found a way to provide reliable data without an opt-in process nor invading employee privacy. Clothing-to-Health Risk model can help with the loss reserve ratio analysis—covering future healthcare costs—that better reflects the company's unique risk & loss characteristics. This in turn can help CFOs determine the right amount of capital to keep on hand at all times.

The effect of the build on predicting future claims in insurance was first analysed by the Milliman study (Milliman, 2009). They used Medical Expenditure Panel Surveys (MEPS), a US government data source covering approximately 100,000 lives, observing two years of data for each person. The data collected was representative of the United States demographically, health-wise, and with regard to several other factors, including income and coverage levels.

The study showed a significant predictive power of the build either to increase accuracy of estimating future claims when medical history is not available (R2 = 20%) or as an addition to it (R2 = 30%). Since clothing size relates closely to human build (i.e. BMI level) we could in turn expect similar underwriting predictive power from clothing size as our third hypothesis suggest.

> »Although a complete medical history adds the greatest power, build information alone is about half as predictive (7% increase vs 14%). Smoking turned out to be the least important, as can be demonstrated by comparing the R2 predictive power for each combination of information:
>
> - R2 using age and gender information only = 13%.
> - R2 using age, gender and build information = 20%.
> - R2 using age, gender, and medical-history = 27%.
> - R2 using age, gender, medical-history, build, and smoking-status information = 30%.
>
> (R2 represents the proportion of variability in a data set that is accounted for by the statistical model.) « (Milliman, 2009).

The average annual premiums for employer-sponsored health insurance in the US were $6,435 for single coverage in 2016. The employer contribution was $5,369 (Kaiser, 2016).

There is the 80/20 Rule in place that "generally requires insurance carriers to spend at least 80 percent of the money they take in from premiums on health care costs and quality improvement activities" (Healthcare, n.d.). Only 20 percent can be used to cover administrative, overhead, and marketing costs. Considering that 80 percent of the premium represents all medical claims that puts average medical costs per employee to $4,295.

In the 2009 study, Milliman estimated that 70 percent of the costs of medical conditions are typically reported to underwriters and can be explained using both demographics and medical-history information. Therefore, the underreported 30 percent of costs can only be explained using demographic data alone:

- Medical-history information and demographics can together explain 27 percent of costs (R2 = 0.27).
- Demographic data (age and gender) can explain 13 percent of costs (R2 = 0.13).

Example:
An average US employer with 100,000 employees with single coverage would be paying $536,900,000 in health insurance premiums in 2016. Medical costs would amount to $429,500,000.

How much of that could be explained using statistical models with medical history and demographics?

$$\begin{aligned} &\$429{,}500{,}000 \times 70\% \times 27\% + \$429{,}500{,}000 \times 30\% \times 13\% = \\ &= \$81{,}175{,}500 + \$16{,}750{,}500 = \$97{,}926{,}000 \end{aligned} \tag{1}$$

Of $429.5 million in medical claims almost $98 million or 22.8 percent can be explained with medical history, age and gender, as obtained in equation (1).

What happens when we add the human build (BMI) into the equation. Milliman (2009) found out that:

- Build information (BMI) and demographic data (age and gender) can explain 20 percent of costs (R2 = 0.20).
- Medical-history information, demographics, build and smoking can together explain 30 percent of costs (R2 = 0.30).

$$\begin{aligned} &\$429{,}500{,}000 \times 70\% \times 30\% + \$429{,}500{,}000 \times 30\% \times 20\% = \\ &= \$90{,}195{,}000 + \$25{,}770{,}000 = \$115{,}965{,}000 \end{aligned} \tag{2}$$

As obtained in equation (2),of $429.5 million in medical claims almost $116 million or 27 percent can be explained with medical history, age and gender, and build and smoking. That is 4.2 percentage points or roughly $18 million ($180 per employee) more than the normal underwriting scenario without using build information.

If we account for the margin for error when human build is calculated using clothing sizes and that smoking is not included, we can expect the increase to be lower, but still in the range of two to three percentage points or $8.5-$13 million ($85-$130 per employee). That amount would be a sufficient reason for group insurance carriers or self-insured employers to start considering clothing size as a viable proxy to improve quantifying risk.

The biggest limitation of our calculation is the lack of information about the impact of the human build alone on those 30 percent that can be explained using medical-history, demographics, smoking and build together.

2.1.3 Self-Insurance

Self-insurance exposes employers to severe financial risk if they experience unforeseen catastrophic claims. Since the crisis of chronic diseases, firms opt to purchase reinsurance/stop-loss coverage to protect them from excessive losses that could damage their business (SIIA, 2017).

The captive insurance underwriters purchase reinsurance at levels determined by the size and risk of the employees. However, the performance is limited with an incomplete health risk profile to be informed of the level of health risk in the employee population.

Clothing data should identify & monitor the growing amount of high risk individuals in workwear to help clearly evaluate the risk level. This is to purchase the right amount of reinsurance based on the risk acceptable to the company to protect them against severe financial risk or financial loss from over purchasing stop-loss insurance.

2.1.4 Lowering Risk

Due to annual workwear changes (or even seasonal), there is the ability to track the health changes of participants in wellness programs and even nonparticipants. These are both much better indicators than what is currently used, such as satisfaction and participation levels, which do not directly correlate with health risk.

Clothing sizes can evaluate the effectiveness of wellness programs on an annual basis. This is a powerful tool to enable adjustments and improvements to wellness programs, and to gradually lower the health risk of the workforce.

3 HYPOTHESIS OF THE STUDY

The aim of our study was to prove four hypotheses:

- H1: Clothing size can be used to identify the human build.
- H2: Human build is associated with health risk levels related to obesity.
- H3: Human build can be used to predict future medical claims.
- H4: Clothing size can be a useful tool in insurance underwriting.

All four hypotheses form the proposed model:

Clothing size —(H1)——> Obesity —(H2)—> Health risk —(H3)—> Medical claims —(H4)—> Insurance underwriting

In order for this model to be valid and confirmed, all hypotheses need to be confirmed. There is a casual relationship between every hypothesis. For the final (H4) hypothesis to be confirmed all previous hypothesis need to be confirmed as well. In order words, clothing size needs to identify obesity, which in turn predicts health risk of the person, and therefore future medical claims that are useful in insurance underwriting.

3.1 H1: Clothing size can be used to identify the human build

Two studies by Han et al. (2015) and Hughes et al. (2009) confirmed this hypothesis. Both tried to explain waist circumference (WC) levels, which is one of the three widely used human build indexes along with Body Mass Index (BMI) and Waist-to-Height Ratio (WHtR), using clothing sizes.

Han et al. (2015) developed linear regression equations using UK clothing size as a dependent variable and waist circumference as explanatory variable of human build and showed extremely strong correlations: men trouser size (R2=0.64) and women dress size (0.80), clothing size correlated ($P < 0.001$) linearly with indices of adiposity (obesity).

Hughes et al. (2009) previously found that self-reported trouser size highly correlated with waist circumference ($R2 = 0.64$). In women, the correlations between self-reported skirt size and WC were even higher at 0.78.

One of the limitations of the previous two studies were the usage of self-reported clothing size and the lack of BMI or WHtR data. Our study will try to collect objective clothing sizes of clothes that are uniformed with the same size chart (workwear). We will also explain the relationship between those clothing sizes and BMI, as well as WHtR.

3.2 H2: Human built is associated with health risk levels related to obesity

The second hypothesis was confirmed by the largest meta-study published in 2012 by Ashwel, Gunn and Gibson who reviewed thirty-one papers involving more than 300,000 adults in different ethnic groups. The objective was to assess the discriminatory power of anthropometric indices (human build indexes) in distinguishing adults with obesity related diseases: hypertension, type-2 diabetes, dyslipidaemia, metabolic syndrome and general cardiovascular outcomes (CVD). WHtR turned out to be the most accurate human build index at predicting obesity related diseases with 70-80% accuracy. Compared with BMI, WHtR improved discrimination by 4–5% ($P < 0.01$) and WC by three percent ($P < 0.05$) over BMI.

Given Waist-to-Height Ratio superiority, they concluded the WHtR should be considered as a screening tool (Ashwell et al., 2012).

3.3 H3: Human build can be used to predict future medical claims

As described in chapter 3.1.2, the effect of human build on predicting future claims was researched and positively confirmed by the Milliman study (2009).

The study showed that the human build together with age and gender had the predictive power of $R2 = 20\%$. Twenty percent of future medical claims were explained using human build. That was second only to previous medical claims (medical history) that together with age and gender scored $R2 = 27\%$.

3.4 H4: Clothing size can be a useful tool in insurance underwriting

The first three hypotheses are building the fundamentals for the fourth, most crucial hypothesis of this study. While hypotheses H1 (Han et al., 2015; Hughes et al., 2009), H2 (Ashwell, Gunn & Gibson, 2012) and H3 (Milliman, 2009) have all been thoroughly researched in the past, the validation of the fourth hypothesis has never been attempted.

Our study will try to examine the usefulness of clothing size in insurance underwriting. The confirmation of previous hypotheses by distinguished institutions should allow us to introduce the paper's model to the insurance industry and study its potential impact.

4 DATA AND METHODOLOGY

4.1 Strategy

The overall aim of this project was to identify the potential of using the clothing size as a health risk proxy within the health and life insurance industry. We needed to examine whether our solution, even with the first three hypotheses confirmed, either by us or previous studies, could be used to improve the work of underwriters, actuaries and the entire insurance landscape. This approach can be considered as the *technology push*, where a new technology is pushed through R&D into the market without being certain the demand exists, as opposed to *market pull* approach where a novelty is designed to respond to an identified market need (Martin, 1994).

4.2 Research Design

Given that this technology has never been used in a real-life context, qualitative methods had to be used over the lack quantitative methods. A case study was chosen as the best research design. The case study is a research strategy that focuses on in-depth analysis of a specific case or setting, such as an organization or an event, according to Bryman and Bell (2011). Case studies can involve either single or multiple cases, and numerous levels of analysis (Yin, 1984). This is exactly how our study was conducted: on both scientific and industry levels.

Case studies typically combine different collection methods (e.g. through interviews, questionnaires, observations). The evidence may be qualitative or quantitative, as well as of either primary or secondary nature (Bryman and Bell 2011). We relied heavily on primary data, collected through working closely with firms, observing their responses and expressed interest, and interviewing them.

4.2.1 Observations

The observation data was collected in an unstructured setting over the course of 18 months, from January 2016 to July 2017. It was conducted in an open and free manner while working with business consulting agencies, insurance carriers and reinsurance companies. Hundreds of emails and calls were exchanged. This led to the observations presented in chapter 5.2. They were conducted on several occasions: during the virtual fitting application test with Lidl in Slovenia and the UK; in-person partnership meetings with Reinsurance Group of America (RGA) in London, UK; online business meetings with Munich Reinsurance Company (Munich Re), Swiss Reinsurance Company (Swiss Re), Aviva and AXA; in-person meetings with Triglav in Slovenia; in-person meetings with BlueBox and Channel Creators in London, UK; online meeting with Milliman.

4.2.2 Interviews

All interviews were conducted with the main purpose of understanding the value of our solution in the market and its applicable use. Questions were not structured, but they followed the flow of the dialogue. Interviewees were not preselected and they were not aware their responses would be used for the purpose of this study. The results should thus resemble real-life situations. Our goal was to talk to people in decision-making positions as well as specialists that would use our product with aim to test our hypothesis. Interviewees gave us industry insights that we unable to collect via secondary sources. The new insights allowed us to shape the solution even more.

Interviews were conducted mostly in person. Some interviews were conducted via online communication software or through telephone to make it easier for interviews to take place, since interviewees were employees at companies with a global presence.

4.2.3 Empirical Study

A sample of 846 women and 309 men was used to conduct the research. They participated in testing of our virtual fitting mobile application in 2016 on behalf of their employer Lidl. The sample includes 1,155 subjects: 459 from the UK and 696 from Slovenia who were aged 20-59 years at baseline.

Participants self-reported and measured their age, height, weight, chest circumference, waist circumference, high hip circumference, low hip circumference, inner leg length and clothing fitting preference. Based on their self-reported height, weight and waist we calculated BMI and Waist-to-Height Ratio (WHtR). The employer provided us with subjects' workwear sizes they ordered: shirt size, trouser size. The workwear models had the same clothing size chart.

We used Random Trees model for our classification analysis to predict the right class (e.g. obese, normal weight etc.) of BMI and Waist-to-Height Ratio from clothing size, adjusted for age and gender. All statistical analyses were performed using Orange, an open-source software package.

4.3 Background

4.3.1 BMI

Body mass index or BMI has long been used as proxy for obesity (adiposity). It assesses the person's build calculated by dividing body weight by square of body height (kg/m2). BMI correctly predicts the increased health risk associated with obesity such as - type-2 diabetes, cardiovascular diseases or CVD (e.g. stroke, heart failure), metabolic syndrome (MS), high blood pressure (HBP) and dyslipidaemia (e.g. high cholesterol) - with an accuracy of 60–70% (Ashwell & Gibson, 2014).

BMI that was calculated by Styliff was based on self-reported height and weight. Self-reported BMI is widely used because of the ease and efficiency in acquiring data. Stommel and Schoenborn (2017) concluded that health risk estimates associated with variations in BMI values were virtually the same, whether based on self-reported or measured BMI values.

4.3.2 Waist-to-Height Ratio

In recent years, Waist-to-Height Ratio (WHtR) has been increasingly associated with achieving higher accuracy at predicting health risk of 70-80% (Ashwell, 2012). Put differently, 70–80% of individuals classified as obese by WHtR will have increased health risk such as increased levels of HBP, diabetes etc.

Two studies by Ashwell and Gibson (2009, 2014) showed that more than 25% of the UK population who were judged to be of ‘healthy’ build “using BMI, are misclassified and might not be alerted to the need to take care or to take action” (Ashwell & Gibson, 2014). The only reason why BMI is still widely used by insurance companies is its ease of use, in comparison, WHtR needs the waist circumference measurement that requires a tape measure.

Anthropometric measures are the first step in identifying people at ‘early health risk’. By combining them with further risk factors such as gender, age, ethnicity, and socioeconomic status, more complex risk scores can be created that is attainable through Styliff.

Backed by findings from studies by Han et al. (2015) and Hughes et al. (2009), we wanted to validate the linear correlation between clothing size (shirt size, trouser size) and adiposity proxies (BMI and Waist-to-Height Ratio), and find out with what accuracy clothing size can predict obesity levels.

5 RESULTS AND FINDINGS

Four classification analyses were conducted, both for BMI and WHtR. They were further split between analyses of three and six obesity classes. Both BMI and WHtR analyses with three obesity classes gave us a more robust understanding with higher classification accuracy. BMI analysis with three obesity classes gave the best results with 73.03 percent of population being correctly classified, followed by WHtR analysis with three obesity classes with 72.07 percent of population correctly classified. WHtR analysis with six obesity classes gave the worst results with 61.75 percent of population being correctly classidied.

5.1 Classification analysis

Classification analysis results for BMI (six classes) are presented in Table 1. A complete uniform size (trousers and a shirt) was able to correctly classify **68.34 percent** of our population into correct obesity levels.

Table 1. Classification into BMI (six classes) using clothing size

Underweight	Normal Weight	Overweight	Obese I	Obese II	Obese III
<= 18.4	18.5 – 24.9	25 – 29.9	30 – 34.9	35 – 39.9	40+

	True Underweight	True Normal Weight	True Overweight	True Obese I	True Obese II	True Obese III
Pred. Underweight	1	2	0	0	0	0
Pred. Nor. Weight	23	486	92	2	1	2
Pred. Overweight	1	122	218	53	5	2
Pred. Obese I	0	2	28	68	15	2
Pred. Obese II	0	0	0	6	10	6
Pred. Obese III	0	0	0	0	1	5

Pred. = Predictive

Source: own calculations.

When the population was classified into three BMI classes the prediction accuracy was **73.03 percent** (Table 2). The percentage of population that was misclassified as High Risk was 0.31 percent and 7.35 percent in Low Risk and Medium Risk group respectively. The percentage of population that was misclassified as Low Risk was 2.22 percent and 27.35 percent in High Risk and Medium Risk group respectively.

Table 2. Classification into BMI (three classes) using clothing size

Low Risk	Medium Risk	High Risk
<= 24.9	25 – 30	30+

	True Low Risk	True Med Risk	True High Risk
Pred. Low Risk	512	93	4
Pred. Med Risk	123	222	64
Pred. High Risk	2	25	108

Source: own calculations.

Classification analysis results for WHtR (six classes) are presented in Table 3. A complete uniform size (trousers and a shirt) was able to correctly classify **61.75 percent** of our population into correct obesity levels.

Table 3. Classification into WHtR (six classes) using clothing size

Extremely Slim	Healthy Slim	Healthy	Overweight	Obese	Morbidly Obese
0.34	0.35 – 0.42	0.43 – 0.52	0.53 – 0.57	0.58 – 0.62	0.63+

	True Extremely Slim	True Healthy Slim	True Healthy	True Overweight	True Obese	True Morbidly Obese
Pred. Extr. Slim	0	0	0	0	0	0
Pred. Healthy Slim	0	6	8	0	0	0
Pred. Healthy	0	45	508	111	21	8
Pred. Overweight	1	1	86	103	46	17
Pred. Obese	0	0	8	20	43	52
Pred. Morbidly Obese	0	0	0	3	14	52

Source: own calculations.

When the population was classified into three WHtR classes the prediction accuracy was **72.07 percent** (Table 4). The percentage of population that was misclassified as High Risk was 1.21 percent and 9.70 percent in Low Risk and Medium Risk group respectively. The percentage of population that was misclassified as Low Risk was 11.46 percent and 46.84 percent in High Risk and Medium Risk group respectively

Table 4. Classification into WHtR (three classes) using clothing size

Low Risk	Medium Risk	High Risk
<= 0.52	0.53 – 0.57	0.57+

	True Low Risk	True Med Risk	True High Risk
Pred. Low Risk	567	111	29
Pred. Med Risk	88	103	63
Pred. High Risk	8	23	161

Source: own calculations.

5.2 Observation and interview results

5.2.1 Triglav

Zavarovalnica Triglav is the largest insurance carrier in Slovenia and in the Adriatic region with a 20 percent market share. In 2015, they had €747,6 million in total equity, health insurance premiums represented 10,7 percent of gross written premium (Triglav, 2017).

In Slovenia, the health insurance market is heavily regulated (Mossialos, Permanand, Baeten, and Hervey, 2010). The health care system is financed from both public funded compulsory insurance and voluntary private insurance. The compulsory insurance plan covers only a certain percentage of total costs that arise in medical treatment. “Voluntary insurance covers the difference between the full price and the percentage covered by compulsory health insurance” (EURAXESS, n.d.). It is offered by private insurance companies and it has to insure everyone at a flat-rate, regardless of their state of health, without any discrimination (e.g. by age, gender).

Due to the lack of underwriting freedom, Triglav’s corporate offering is limited to only a few group health insurance plans where the client’s employees receive above standard medical treatment. Their health insurance arm stated they had a few blue-collar clients, and they expressed an interest to cover the costs of initial tests. There would need to be at least 2 years of positive validated data points in order implement our solution. In follow-up correspondence, their chief innovation officer expressed additional doubts to whether our solution can be used at all and for what purpose.

Since they receive all medical history of lives they insure, along with self-reported body mass index, our solution gives little additional knowledge. Also, based on their lack of interest, we believe the corporate group plans represent a small portion of their business. Nonetheless, they did express a strong interest for replacing weight and height questions in their Life insurance applications, which they find “invasive” and “time consuming” and often lead to a loss of potential new clients.

5.2.2 AXA

AXA is a French multinational insurance firm. It is the world's largest diversified insurance company by revenue ($133.2 billion) and second by assets ($925.9 billion) according to Forbes (2017). Due to their presence in the US market we believed it was important to get their view on our proposed solution.

We approached their investment arm AXA Strategic Ventures, which later stated our solution lacked validation, and was »one step too early for us« (G. Trobec, personal communication, February 23, 2017).

5.2.3 Aviva

Aviva plc is a British multinational insurance company. With more than $500 billion in assets it is the biggest in the UK (Forbes, 2017). It insures more than thirty million lives in sixteen markets (Aviva, n.d.). We approached their health insurance arm Aviva Health.

Our goal was to find out whether our solution would be of any value when underwriting their corporate clients in group life and health insurance. Due to universal healthcare present all across Europe and the UK, Aviva Health mostly offers additional private health insurance to individuals not groups – the only exception is Ireland where employers provide their employees with a healthcare package (note: as of 2017, Aviva’s Health business in Ireland has been sold off).

After several meetings, Alastair Antell, Aviva Health’s Head of Client Management & Propositions issued the following statement:

> »I’ve consulted with various people in the health business on your proposition. At this stage it isn’t something we would want to consider taking forward or incorporating into our market offering.

> Our overriding reason for this is that the majority of our corporate relationships within Health insurance are with professional / white collar organisations, and even those blue collar companies we insure tend to only cover their senior office based staff. This restricts the value of your proposition to us within Health insurance. « (Alastair Antell, personal e-mail message, March 22, 2017)

They considered our value proposition as low. Having little or no clients within our market-fit – large group insurance schemes for employees in uniform – made any use of our solution unnecessary.

5.2.4 Munich Re and Swiss Re

Munich Reinsurance Company (Munich Re) and Swiss Reinsurance Company (Swiss Re) are the largest and second largest reinsurance companies in the industry respectively (Aglionby, 2009). Munich Re is a German reinsurance company with €48.9 billion in revenue and a total equity of €31.8 billion (Munich Re, 2016). Swiss Re is a Swiss reinsurance company with a revenue of $33.2 billion and total equity of $35.7 billion (Swiss Re, 2016).

Both reinsurance companies stressed out the problem concerning privacy. Their response was definite and clear – the legal and privacy concerns outweigh any potential benefits our solution could bring. According to Munich Re our solution »is not applicable to the European market«, mostly due to the strict privacy and data protection laws. They stated they would never jeopardize their public image and risk their good reputation in regards to privacy.

Growth Innovators Group Ltd, a London-based management consulting firm, looked into legal matters concerning our solution:

> »If an employee provides measurement data, which is then subsequently anonymised, it can still only be used for the purpose for which the employee gave the information in the first place. This is deemed *Legitimate Interest.* If the information is passed to another entity then it can only be for a legitimate purpose, passing it to a health insurance provider is most likely deemed not to be in the area of a Legitimate Interest. For Health purposes (or similar) [it] must be made clear when the employee provides the information. « (Peter Curnow-Ford, personal e-mail message, June 1, 2017)

Based on their knowledge, our privacy criteria would be met if employees were aware that their uniform sizes could be used for the purpose of health insurance (e.g. a clause in an employee contract would suffice).

The findings from Munich Re and Swiss Re raised an important issue. The European insurance market and the entire corporate culture are conservative when implementing new solutions, especially those that concern data protection. Based on the outcomes of our interviews with European insurance and reinsurance companies Triglav (Slovenia), Aviva (UK), AXA (France), Munich Re (Germany) and Swiss Re (Switzerland) we can conclude there was no positive enforcement of our solution, nor did they see a viable business use case. In order to fully test our last hypothesis, we continued in the US market.

5.2.5 RGA

Reinsurance Group of America (RGA) is one of the largest reinsurance companies in the world, with more than $3.1 trillion of life reinsurance in force and assets of $53.1 billion as of December 2016. (RGA, 2017). According to their website, they pride themselves for being the most innovative reinsurance company in the health and life insurance industry.

They came to our attention when their innovation-investment arm RGAx launched the 'Big Ideas' competition in the spring of 2017 in London, UK. The competition was organized "to find the best new ideas that could impact or even revolutionize the protection, health insurance and/or retirement markets" (Murphy, 2017).

Styliff won the competition and the prize of GBP £10,000. Winning the competition made it possible to introduce the clothing-to-health risk concept and our hypothesis of using clothing size in health insurance to more than 20 global RGA offices.

Five RGA offices responded to their internal memo about Styliff. Apart from RGA Australia, the feedback was generally considered negative and our concept was seen as not something that was viable in the insurance landscape.

5.2.5.1 VP, Group Products

> »Generally I find Styliff's approach interesting, albeit not something that I think will be a game-changer on its own. I think that they are definitely pointing in the right direction in terms of gather biometric data to then further analyze and act-upon.
>
> It wasn't clear from the promotional video what was going to be the use for the data that Styliff collects, apart from a reference to accelerated underwriting and general risk assessment.
>
> The extension I would build into their current approach is to use the data collected and analytics as a 'lead-generator' to target individuals in the top-tier of risk profiles, get their attention and then gather additional data to analyze to get a fuller picture of the risk profile that the individual poses. BMI and Weight-to-Height-Ratio are very basic measures. This would be to target at not only giving the top-tier risks the best premium rate but also offering them certain benefits or higher amounts of cover.
>
> The additional data would be reflective of what is available in the target country and could include employee health check data, electronic health records, wearables data, credit risk score, motor vehicle driving records, prescription drug information, etc. « (VP Group Products RGA, personal e-mail message, July 5, 2017)

5.2.5.2 Head of Business Development, US

> »Interesting idea. It makes me think of a presentation by a Northwestern Mutual [a US life insurance company] associate who talked about the difference between sedentary thin people and fit fat. Perhaps another data point for Styliff would be the type of work and how physical it is. An equal average BMI for a working population in a physical job versus not should likely score better in terms of both morbidity and mortality.
>
> As I watched I wondered what proportion of the uniform wearing 500 [million] Styliff has managed to capture and what, if anything, they've been able to do to create exclusivity of the data relationship to limit a competitor copycat from swooping in and replicating the idea. I also wondered if Styliff

was able to securely trend weight gain or loss overtime by individual. This would provide a data point for the question – have you gained or lost any weight in the last x years.

From a market perspective, I wonder what proportion of each country wears uniforms. For example, if it's 20% overall, my guess would be some countries might be higher (some may be more formal and traditional in terms of uniforms – thinking about private/public schools, etc.) and others lower. If there is a big enough difference, this could help guide Styliff to which countries to focus on first. « (Head of Business Development RGA US, personal e-mail message, July 5, 2017)

5.2.5.3 Head of US Mortality Market

»I think it's interesting however I don't see a place in the traditional US life market although I may have missed something from the 6-minute video [he couldn't access the video]. And as noted in your email this morning perhaps in the group space. « (Head of US Mortality Market RGA US, personal e-mail message, July 5, 2017)

5.2.5.4 Business Development Director Australia

»Initial thoughts are that this is exactly the type of additional info that would be useful for us to rate group schemes.

As I was watching it I was thinking about Asos etc. so I was really glad to see that they went that step further to integrate some sort of retail offering.

So you could incorporate this as part of some corporate benefit/wellness package that interfaces with the group insurance cover. My personal view is that to get employees to engage it can't be just about health/medical type offerings, you need something sexy that they really *want* to buy, and who doesn't like new clothes? Even if its exercise gear, that would tick the box for me.

Also – you could use their concept to design some sort of proposition for a retailer that has this type of data on file and was considering getting into financial services. Do we know if any of the big ones (Asos etc.) have made inroads into other products (e.g. credit)? « (Business Development Director RGA Australia, personal e-mail message, July 5, 2017)

5.2.5.5 Head of Innovation Management Asia

»I Like the Styliff idea and think it will have some level of adoption.

I also think this will be competing with other proxies for u/w and other approaches to u/w such behavioural u/w, dynamic u/w where other non-traditional data will play a role. Because of this, I have some reservations seeing this as a sustainable proposition before something better comes along.

Also with the Styliff approach, there is room for misclassification given uniform often will misclassify body composition. It would be great if the Styliff platform can be extended with other parameters as well. Wearables are here to stay, they will only be better and less unobtrusive. « (RGA Head of Innovation Management RGA Asia, personal e-mail message, July 5, 2017)

6 CONCLUSION

Clothing size can work as an alternative proxy for human build and identifying obesity related health risk levels. We are confirming the first H1 hypothesis that clothing size can be used to identify the human build (i.e. BMI, WHtR) and health risk levels related to obesity. Our study with Lidl employees generated empirical evidence, and additionally, both prior studies by Hughes et al. (2009) and Han et al. (2015) confirmed the clothing-human build correlation.

Due to simplicity of data collecting the clothing size, we conclude the clothing size can serve as the first-stage screening tool within companies with employees in workwear to identify unhealthy employee population and take appropriate actions.

We were unable to collect the needed primary data (medical records) that would allow us to test both second and third hypotheses. Given that they were confirmed by robust studies by Ashwell & Gibson (2009, 2014), Ashwell, Gibson and Gunn (2012) and Milliman (2009), we are confirming them for now, until we can validate them with our own set of primary data.

Regardless of our concept winning the RGA's 'Big Ideas' competition, in six months after winning the competition, we were unable to start any pilot projects within the insurance industry and conduct further studies on the correlation between clothing sizes and future medical claims. Therefore, the H4 hypothesis and our model of using clothing size in insurance industry is rejected.

It is important that future studies explore the impact of clothing size on underwriting and its usefulness in insurance landscape by gathering long-term empirical evidence.

In self-insured plans and even commercial plans the information about health status of insured is scarce. The insurer can only rely on basic demographic data (age, gender, ZIP code) and medical claims of the previous year. A more reliable, robust and consistent health data is needed. Our study proposes using workwear clothing sizes of employees as the first stage screening, in order to understand the overall obesity levels within the company, and to identify high-risk individuals who need additional care.

6.1 Discussion

Our study confirms previous studies that there is a high correlation between clothing size and obesity and eventually health risk, and that clothing size can function as a strong proxy for estimating obesity. Hughes et al. (2009) concluded that "clothing size offers simplicity for screening applications in clinical settings and perhaps more improbable a tool for health promotion to alert individuals to the risks associated with obesity and central fat accumulation".

The strength of our study lies in having analysed the same model of clothing (i.e. uniforms worn by Lidl employees) with the same size chart. The main weakness includes the size of our sample – Medium and High Risk individuals were heavily underrepresented in our study population. There were 637 and 663 subjects in BMI and WHtR Low Risk groups respectively, 340 in BMI Medium Risk group (237 in WHtR) and only 176 in BMI High Risk group (253 in WHtR). More High and Medium Risk individuals are needed to improve our prediction accuracy. Also, the male subgroup was heavily underrepresented with only 309 male individuals among 1,115 participants.

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APPENDIX

APPENDIX

A.1 Opis področja dela in opredelitev problema

Kronične bolezni predstavljajo kar 78 odstotkov vseh zdravstvenih stroškov (Bodenheimer et al., 2009). Debelost (indeks telesne mase oz. ITM nad 30) zvišuje stopnjo smrtnost (Mulder, 2015) in je glavni faktor tveganja za razvoj kroničnih bolezni, kot so diabetes tipa 2, srčne bolezni in bolezni ožilja. Stopnje debelosti med svetovnim prebivalstvom so že presegle kritične meje – več kot 2,1 milijarde ljudi, skoraj 30 odstotkov svetovnega prebivalstva, ima prekomerno telesno težo. Do leta 2030 naj bi v takem stanju bila že polovica svetovne odrasle populacije (Dobbs et al., 2014).

Pri izvajanju raziskave in pisanju te diplomske naloge sodelujemo z ameriškim podjetje Styliff Inc, katerega ustanovitelj je avtor tega dela. Styliff je tehnološko podjetje, ki je specializirano za digitalne produkte v zdravstvenem zavarovanju. Skupaj smo razvili prvi uporaben algoritem za prepoznavo in računanje debelosti iz velikosti oblačil. Model lahko računa ITM in razmerje pas-višina (angl. Waist-to-height ratio oz. WHtR). ZDA so svojim zasebnim zdravstvenim sistemov zavarovanj naš ciljni trg. Okrog 20 odstotkov ameriških delavcev nosi delovna oblačila oziroma uniforme (Wellers, b.d.). To pomeni, da bi lahko ugotovili stopnjo debelosti za kar petino ameriške delovne sile brez uporabe invazivnih posegov.

Z našim modelom računanja debelosti iz velikosti oblačil smo v letu 2017 zmagali na zavarovalniškem tekmovanju, ki ga je organizirala pozavarovalnica Reinsurance Group of America (RGA) s ciljem, da najde najbolj inovativni zavarovalniški produkt. Če je naš model uspešno validiran, bi lahko zdravstvene zavarovalnice le-tega uporabile za kvantificiranje debelosti v podjetjih med zaposlenimi z uporabo delovnih oblačil.

Goetzel et al. (2012) je objavil študijo o ekonomskih posledicah desetih najbolj razširjenih dejavnikov tveganja za zdravje, ki so odgovorni za kar četrtino vseh zdravstvenih stroškov med zaposlenimi. Na področju biometričnih tveganj je bilo 32,2 odstotkov zaposlenih debelih, 9,9 odstotkov je imelo prekomeren holesterol, 9,5 odstotkov je imelo povišan krvni sladkor in 7,6 odstotkov je imelo povišan krvni tlak. Primerjava rezultatov iz študije HERO (Goetzel et al., 1998), ki je bila opravljena 14 let prej, pokaže, da so se dejavniki tveganja za zdravje poslabšali: slaba hranila in slabe prehranjevalne navade (64.1% populacije leta 2012 proti 20,2 % v letu 1998) in debelost, ki se je povečala za 12,2 odstotnih točk (32,2 % proti 20 %).

Letni *per capita* zdravstveni stroški opazovancev v študiji so znašali povprečno 3.961 ameriških dolarjev (leta 2009). Raziskava je pokazala, da so bili, prilagojeni z motečimi dejavniki, debeli (ITM > 30) kar 27,4 odstotkov dražji (1.091 $ dodatnih stroškov) pri letnih zdravstvenih stroških kot pa tisti zaposleni z običajno (ITM < 25) ali pa prekomerno telesno težo (ITM ≥ 25 > 30). Ostali dejavniki povezani z debelostjo so prav tako povišali zdravstvene stroške: povišan krvni sladkor (31,8 % oz. 1.653 $), visok krvni tlak (31,6 % oz. 1.378 $) in fizična aktivnost (15,3 % oz. 606 $).

Od desetih dejavnikov za zdravje jih je sedem občutno zvišalo zdravstvene stroške, od tega so bili štirje dejavniki povezane z debelostjo. Po prilagoditvi rezultatov na ljudi z visokim tveganjem je bila debelost neposredno odgovorna za 8.8 odstotkov vseh zdravstvenih stroškov v opazovani skupini. Vsi dejavniki povezani z debelostjo so predstavljali skoraj 18 odstotkov vseh letnih zdravstvenih stroškov (Goetzel et al., 2012).

98 odstotkov vseh velikih ameriških korporacij je samo-zavarovanih, saj lahko tako znižajo celostne stroške zavarovanj. Samo-zavarovanje pomeni, da ima korporacija svoj zavarovalniški fond, ki je namenjen zdravstvenim stroškom (Merhar, 2016). Pri tem se eliminirajo administrativni stroški in marža, ki bi jih drugače vsiljevale zavarovalnice.

Kot dodaten način zniževanja stroškov korporacije vpeljujejo korporativne *wellness* programe za zaposlene, kjer morajo ti opraviti sistematske preglede. Cilj programov je v večini pridobivanje zdravstvenih podatkov zaposlenih, ki so v pomoč pri kvantificiranju tveganja celotne skupine in pri napovedovanju prihodnjih zdravstvenih stroškov.
Nadalje se *wellness* programi delijo na tiste, ki so v pomoč zaposlenim s kroničnimi boleznimi in pa tiste, ki učijo zaposlene o zdravem življenjskem stilu ter delujejo preventivno. Kar 87 odstotkov podjetjih meti uspešnost *wellness* programov s participacijo, četudi ne obstaja neposredne povezave med izboljšanjem splošnega zdravja in udeležbo. Če povzamemo, zaposleni se lahko udeležujejo neefektivnih programov, kjer ni izboljšav na področju zdravja, a bodo programi še vedno smatrani kot uspešni.

Prednost našega predlaganega modela je, da se za analizo debelosti ne potrebuje sodelovanja s strani zaposlenih. Zaradi letnih menjav delovnih oblačil se lahko meritve opravljajo na letni ravni, kar prinaša možnost boljšega merjenja uspešnosti *wellness* programov in njihovega ocenjevanja (npr. primerjajo se lahko rezultati zaposlenih, ki so se udeleževali programov, s tistimi, ki se niso). Taka vrsta informacij je vitalnega pomena delodajalcem za maksimiranje vrednosti investicij v *wellness* in zniževanje dejavnikov tveganja za zdravje med zaposlenimi.

Naš algoritem, ki iz velikosti oblačila računa antropološke mere, kot so ITM in WHtR. Model deluje tako z enodelnimi uniformami kot z dvodelnimi (tj. uniforma je sestavljena iz spodnjega in zgornjega dela). Natančnost napovedovanja se izboljša z več kosi oblačil in dodatnimi informacijami o zaposlenih (npr. starost, spol).

Delodajalci morajo hraniti seznam naročil uniform in pa tehnične specifikacije uniform. Model lahko v trenutku analizira in poda sliko stanja debelosti v podjetju. Produkt je v prvi meri namenjen organizacijam, ki si želijo hitre in relativno splošne slike zdravja v podjetju. Naš način pridobivanja podatkov je veliko manj natančen in manj obširen, kot so sistematski pregledi in biometrična skeniranja, toda preprostost uporabe ter nizki stroški bi lahko prepričali delodajalce.

Študija Millimana (2009) je bila prva, ki se je dotaknila vpliva konstitucije telesa na napovedovanje prihodnjih zdravstvenih stroškov. Uporabili so ankete o zdravstvenih stroških (angl. MEPS), ki so uradni podatkovni vir vlade ZDA. Pokrivajo kar 100 tisoč življenj v periodi dveh let za vsako osebo. Izbor podatkov je reprezentativen in predstavlja demografijo, zdravstveno stanje, dohodke in stopnjo zavarovanja prebivalcev ZDA.

Raziskava je pokazala občutno napovedovalno moč telesne konstitucije, ki je izboljšala natančnost ocenjevanja prihodnjih stroškov, ko zdravstvena kartoteka ni bila na voljo ($R2$ = 20 %) ali kot dodaten faktor ($R2$ = 30 %). Ker je velikost oblačila odvisna od telesne konstitucije (tj. ITM stopnja), lahko pričakujemo podobno napovedovalno moč same velikosti oblačila, kar narekuje naša tretja hipoteza.

> »Čeprav popolna zdravstvena kartoteka doda največjo moč, sama informacija o telesne zgradbi napoveduje že polovico (7 % povečanje proti 14%). Kajenje se je pokazalo kot najmanj pomembno, kar se lahko demonstrira s primerjanjem R2 napovedovalne moči za vsako od kombinacij:
>
> - R2 pri uporabi starosti in spola = 13 %.
> - R2 pri uporabi starosti, spola in telesne konstitucije = 20 %.
> - R2 pri uporabi starosti, spola in zdravstveni zgodovine [zdravstvene kartoteke] = 27 %.
> - R2 pri uporabi starosti, spola, zdravstvene zgodovine, telesne konstitucije in kajenja = 30 %.
>
> (R2 predstavlja delež variabilnosti v podatkovnem setu, ki ga lahko obrazloži izbran statistični model.) « (Milliman, 2009).

Povprečne letne premije za zdravstveno zavarovanje posameznega zaposlenega, ki ga v večini financira delodajalec, so bile leta 2016 v ZDA 6435 $. Delodajalčev prispevek je bil 5369 $ (Kaiser, 2016).

Ameriški zavarovalniški zakoni sledijo Paretovemu pravilu in nalagajo zavarovalnicam, da se mora vsaj 80 odstotkov denarja, ki ga dobijo od premij, nameniti za zdravstvene stroške in aktivnosti, ki izboljšujejo kvaliteto zdravljenja (Healthcare, b.d.), Samo 20 odstotkov se lahko uporabi za kritje administrativnih in marketinških stroškov, kar pomeni, da so povprečni zdravstveni stroški 4295 $.

Milliman je v študiji iz leta 2009 razkrival, da je samo 70 odstotkov zdravstvenih stanj običajno tudi poročanih in se jih lahko obrazloži z demografskimi podatki in zdravstvenimi kartotekami. Ostalih 30 odstotkov stroškov, katerih zdravstvenih vzrokov se ne beleži, skušajo zavarovalnice pojasniti z demografskimi podatki.

- Zdravstvene kartoteke lahko skupaj z demografskimi podatki pojasnijo 27 odstotkov stroškov (R2 = 0,27).
- Demografski podatki (starost in spol) lahko samostojno pojasnijo samo 13 odstotkov stroškov (R2 = 0,13).

Primer:
Povprečen ameriški delodajalec s 100 tisoč zaposlenih, ki imajo posamično kritje, bi plačeval 536.900.000 $ v premijah zdravstvenega zavarovanja leta 2016. Zdravstveni stroški bi dosegali 429.500.000 $.

Koliko tega bi se dalo pojasniti s statističnim modelom, ki uporablja zdravstveno zgodovino (kartoteke) in demografskimi podatki?

$$\$429,500,000 \times 70\% \times 27\% + \$429,500,000 \times 30\% \times 13\% = \\ = \$81,175,500 + \$16,750,500 = \$97,926,000 \quad (3)$$

Od 429,5 milijonov dolarjev zdravstvenih stroškov jih skoraj 98 milijonov dolarjev oz. 22,8 odstotkov lahko pojasnimo z zdravstveno kartoteko, starostjo in spolom. Toda kaj se zgodi, ko dodamo še podatek o telesni konstituciji (npr. indeks telesne mase). Milliman (2009) je ugotovil, da:

- Indeks telesne mase in demografski podatki (starost in spol) lahko skupaj pojasnijo 20 odstotkov vseh stroškov (R2 = 0,20)
- Zdravstvene kartoteke, demografski podatki, ITM in kajenje lahko skupaj pojasnijo 30 odstotkov vseh stroškov (R2 = 0,30)

$$\$429,500,000 \times 70\% \times 30\% + \$429,500,000 \times 30\% \times 20\% = \\ = \$90,195,000 + \$25,770,000 = \$115,965,000 \quad (4)$$

Od 429.5 milijonov dolarjev zdravstvenih stroškov jih skoraj 116 milijonov dolarjev oz. 27 odstotkov lahko pojasnimo z zdravstveno zgodovino, spolom, starostjo, telesno konstitucije in kajenjem. To je 4,2 odstotne točke oz. približno 18 milijonov dolarjev (180 $ na zaposlenega) več, kot lahko napoveduje trenutni zavarovalniški scenarij.

Če upoštevamo še dovoljeno odstopanje, ko je telesna konstitucija izračunana preko velikosti oblačila in da se kajenje ne upošteva, lahko pričakujemo manjše zvišanje, toda še vedno v razponu dveh do treh odstotnih točk oz. 8,5–13 milijonov dolarjev (85 $–130 $ na zaposlenega). Taka velikost bi morala biti dovolj velik razlog, da zavarovalnice ali samo-zavarovana podjetja prično razmišljati o velikosti oblačila in uporabi našega modela kot primernemu za izboljševanje računanja tveganja.

A.2 Namen, cilji in teze diplomskega dela

Cilj naše študije je bil dokazati štiri hipoteze:

- H1: Velikost oblačila se lahko uporabi za računanje telesne konstitucije
- H2: Telesna konstitucija je povezana s tveganjem zdravja in debelostjo
- H3: Telesna konstitucija se lahko uporabi za napovedovanje prihodnjih zdravstvenih stroškov
- H4: Velikost oblačila je lahko uporabno orodje v zavarovalniški industriji

Vse štiri hipoteze skupaj tvorijo sledeči hipotezni model:

Velikost oblačila —(H1)——> Debelost —(H2)—> Tveganje zdravja —(H3)—> Zdravstveni stroški —(H4)—> Zavarovanje

Da ta model uspešno prestane validacijo in se potrdi, morajo biti vse štiri hipoteze potrjene. Obstaja vzročna povezava med vsako hipotezo. Zadnja hipoteza (H4) je tako potrjena samo v primeru, da so potrjene tudi vse prejšnje. Povedano drugače, velikost oblačila mora identificirati debelost, ki mora napovedati tveganje zdravja posameznika, ki spreminja zdravstvene stroške, in končno mora velikost oblačila biti potrjena s strani zavarovalniške industrije kot uporabno orodje.

A.3 Podatki in metodologija

A.3.1 Opazovanje in intervjuji

Podatki s pomočjo opazovanja in intervjuji so bila zbrani v nekonstruiranem okolju v časovnem obdobju 18 mesecev – od januarja 2016 do julija 2017. Opazovanja so bila opravljena v odprtem duhu med delom s svetovalnimi agencijami, zavarovalnicami in pozavarovalnicami. Na stotine spletne pošte in klicev je bilo izmenjanih, ki so jim sledili sestanki in intervjuji. Sodelovali smo z naslednjimi podjetji: Lidl Slovenija, Lidl UK, RGA, Swiss Re, Munich Re, Aviva, AXA, Triglav, BlueBox, Channel Creators, Milliman.

A.3.2 Empirična raziskava

V raziskavi smo uporabili vzorec 846 žensk in 309 moških. Vsi so sodelovali pri testiranju naše mobilne aplikacije za virtualno oblačenje leta 2016 v sklopu skupnega projekta z njihovim delodajalcem Lidlom. Celotni vzorec šteje 1155 subjektov, 459 iz Velike Britanije in 696 iz Sloveniji, s starostjo med dvajsetimi in devetinpetdesetimi leti.

Sodelujoči so sami poročali svojo starost in izmerjeno višino, težo, obseg prsi, zgornjega in spodnjega pasu, bokov, dolžino noge ter nazadnje stopnjo oprijetosti oblačila. Na podlagi njihove višine, teže in visokega pasu smo izračunali ITM in razmerje pasu in višine (WHtR). Delodajalec nam je podal seznam velikosti delovnih oblačil, ki so jih subjekti naročili: velikost srajce in hlač.

Uporabili smo model *Random Trees* za ustvarjanje našega analitičnega modela klasifikacije, ki je različne kombinacije velikosti oblačil moral uvrščati v prave razrede telesne konstitucije oz. debelosti po ITM in WHtR. Vse statistične analize so bile opravljene z odprtokodnim programskim orodjem Orange.

A.4 Rezultati raziskave

A.4.1 Rezultati empirične raziskave

Rezultati klasifikacijske analize za ITM (šest razredov) so predstavljeni v Tabeli 1. S celotnim setom velikosti delovne uniforme (hlače in srajca) smo lahko pravilno klasificirali **68,34 odstotkov** naše populacije v debelostne razrede ITM.

Tabela 5. Klasifikacija v ITM (šest razredov) z uporabo velikosti oblačil

Suhost	Normalna telesna masa	Zvečana telesna masa	Debelost st. I	Debelost st. II	Deelost st III
<= 18,4	18,5–24,9	25–29,9	30–34,9	35–39,9	40+

	Res. suhost	Res. normal. tel. masa	Res. zvečana telesna masa	Res. debelost I	Res. debelost II	Res. debelost III
Nap. suhost	1	2	0	0	0	0
Nap. nor. tel. m.	23	486	92	2	1	2
Nap. zveč. tel. m.	1	122	218	53	5	2
Nap. debelost I	0	2	28	68	15	2
Nap. debelost II	0	0	0	6	10	6
Nap. debelost III	0	0	0	0	1	5

Nap. = Napovedano, Res. = Resnično

Vir: lastni izračuni.

Ko je bila populacija klasificirana v tri razrede ITM, je bila natančnost napovedovanja **73,03** odstotkov (Tabela 2). Odstotek populacije, ki je bil nepravilno klasificiran kot visoko tvegan, je prihajal iz nizko tvegane populacije (0,31 odstotkov) in srednje tvegane populacije (7,35 odstotkov). Odstotek populacije, ki je bil nepravilno klasificiran kot nizko tvegan, je prihajal iz visoko tvegane populacije (2,22 odstotkov) in srednje tvegane populacije (27,35 odstotkov).

Tabela 2. Klasifikacija v ITM (trije razredi) z uporabo velikosti oblačil

Nizko tveganje	Srednje tveganje	Visoko tveganje
<= 24,9	25–30	30+

	Res. nizko tveganje	Res. srednje tveganje	Res. visoko tveganje
Nap. nizko tveganje	512	93	4
Nap. sred. tveganje	123	222	64
Nap. visoko tveg.	2	25	108

Vir: lastni izračuni.

Rezultati klasifikacijske analize za WHtR (šest razredov) so predstavljeni v Tabeli 3. S celotnim setom velikosti delovne uniforme (hlače in srajca) smo lahko pravilno klasificirali **61.75 odstotkov** naše populacije v debelostne razrede ITM.

Tabela 3. Klasifikacija v WHtR (šest razredov) z uporabo velikosti oblačil

Ekstremna suhost	Zdrava suhost	Zdrava telesna masa	Zvečana telesna masa	Debelost	Morbidna Debelost
0,34	0,35–0,42	0,43–0,52	0,53–0,57	0,58–0,62	0.63+

	Res. ekstr. suhost	Res. zdrava suhost	Res. zdrava telesna masa	Res. zvečana telesna masa	Res. debelo st	Res. morbidna debelost
Nap. ekst. suhost	0	0	0	0	0	0
Nap. zdrava suhost	0	6	8	0	0	0
Nap. zdrava tel. masa	0	45	508	111	21	8
Nap. zvečana tel. masa	1	1	86	103	46	17
Nap. debelost	0	0	8	20	43	52

Nap. morbidna debelost	0	0	0	3	14	52

Vir: lastni izračuni.

Ko je bila populacija klasificirana v tri razrede WHtR, je bila natančnost napovedovanja **72,07** odstotkov (Tabela 4). Odstotek populacije, ki je bil nepravilno klasificiran kot visoko tvegan, je prihajal iz nizko tvegane populacije (1,21 odstotkov) in srednje tvegane populacije (9,70 odstotkov). Odstotek populacije, ki je bil nepravilno klasificiran kot nizko tvegan, je prihajal iz visoko tvegane populacije (11,46 odstotkov) in srednje tvegane populacije (46,84 odstotkov).

Tabela 4. Klasifikacija v WHtR (trije razredi) z uporabo velikosti oblačil

Nizko tveganje	**Srednje tveganje**	**Visoko tveganje**
<= 0,52	0,53–0,57	0,57+

	Res. nizko tveganje	**Res. srednje tveganje**	**Res. visoko tveganje**
Nap. nizko tveganje	567	111	29
Nap. sred. tveganje	88	103	63
Nap. visoko tveg.	8	23	161

Vir: lastni izračuni.

A.4.2 Rezultati opazovanja in intervjujev

Velika večina predstavnikov podjetij, katerim smo predstavili naš model, je bila do poslovne implementacije zadržana.

V zavarovalnici Triglav, ki je največja v Sloveniji s 747.6 milijoni evrov kapitala, so zaradi slovenskega univerzalnega zdravstvenega zavarovanja videli naš model edino možen pri zasebnih dodatnih skupinskih zdravstvenih zavarovanjih. Toda ker nimajo klientov z veliko uniformiranimi zaposlenimi, implementacija nima potrebe. V kolikor bi do tega prišlo, bi zahtevali dvoletno testno obdobje. Prav tako jim naši podatki ne bi bili v veliko dodatno pomoč, saj že sedaj izbirajo indeks telesne mase zavarovancev.

Pri francoski zavarovalnici AXA, ki je druga na svetu po čistem premoženju (925,9 milijarde dolarjev) so nas odslovili, ker produkt še ni bil validiran. Britanska zavarovalnica Aviva je kot odklonilen razlog podala, da je »večina naših korporativnih partnerstev v sklopu zdravstvenega zavarovanja s pisarniškimi podjetji, tudi pri tistih podjetjih z modrimi ovratniki, ki jih zavarujemo, pa običajno zavarujemo samo menedžerski pisarniški del.« Naša dodana vrednost je bila smatrana kot nizka.

Munich Re in Swiss Re, dve največji pozavarovalnici na svetu, sta izpostavili problem ravnanja z zasebnimi podatki. Njihov odgovor je bil izjemno jasen – pravni zadržki in zadržki glede zasebnosti podatkov pretehtajo kakršnekoli potencialne koristi našega modela.

Zaradi jasnih negativnih odzivov iz evropskega trga lahko sklenemo, da je naš model vsaj v Evropi neuporaben ali celo nepotreben. Ker je bil naš model ustvarjen predvsem z mislimi na uporabo v ZDA, je bil za končno sprejetje hipoteze potreben ameriški odgovor.

A.4.2.1 RGA

Reinsurance Group of America (v nadaljevanju RGA) je ena največjih pozavarovalnic na svetu. Pozavaruje namreč kar 3100 milijard dolarjev v življenjskih in zdravstvenih zavarovanjih (RGA, 2017). Spomladi leta 2017 je v Londonu, VB, naš model zmagal na njihovem natečaju najbolj inovativnih zavarovalniških produktov v Evropi, Bližnjem Vzhodu in Afriki ter si prislužil nagrado v vrednosti 10.000 britanskih funtov in dostop do vseh 20 svetovnih pisarn RGA.

Pet oddelkov RGA se je odzvalo notranjemu pozivu o našem modelu. Razen RGA v Avstraliji, je bil odziv večinoma negativen. Podpredsednik za skupinske produkte, direktor za poslovni razvoj v ZDA in direktor za tveganje umrljivosti v ZDA so vsi podali odklonilen komentar. Kljub zanimivi tezi, se jim model ne zdi praktičen, omejen in neuniverzalen ter ponuja premalo novih podatkov, hkrati pa bi moral biti validiran, preden bi se sploh odločili za njegovo implementacijo.

Zaradi jasnega in skoraj soglasnega negativnega odgovora vseh velikih akterjev v zavarovalniški industriji lahko zavržemo zadnjo hipotezo in s tem celotni model.

A.5 Ugotovitve in zaključek

Velikost oblačila lahko služi kot alternativni nadomestek za telesno konstitucijo in lahko identificira stopnjo debelosti, ki je povezana s tveganjem za zdravje. Potrjujemo prvo H1 hipotezo, da se lahko velikost oblačila uporabi za identifikacijo telesne konstitucije, ki jo predstavljajo antropološke mere (ITM, WHtR). Naša raziskava Lidlov delavcev nam je dala empirične rezultate, prav tako pa so do podobnih rezultatov prišli raziskave Hughes et al. (2009) in Han et al. (2015), ki so potrdile tesno povezanost oblačil in telesne konstitucije.

Zaradi enostavnosti pridobivanja podatkov lahko sklenemo, da bi lahko velikost oblačila služila kot prvostopenjski presejalni test za identificiranje nezdrave zaposlene populacije.
Druge in tretje hipoteze nismo mogli testirati s svojo lastno empirično študiji, ampak smo se zanašali na literaturo. Dve robustni analizi Ashwell (2009, 2012) sta potrdili H2 hipotezo, medtem ko je Milliman (2009) z analizo sto tisočih življenj za obdobje dveh let potrdil H3 hipotezo.

Kljub temu, da je naš koncept zmagal na RGA-jevem 'Big Ideas' tekmovanju, nam v šestih mesecih po zmagi ni uspelo pričeti pilotnih projektov v zavarovalniški industriji in izvajati dodatnih empiričnih raziskav na temo korelacij med velikostjo oblačil in prihodnjimi zdravstvenimi stroški. Zavračamo H4 hipotezo in s tem tudi naš celoten hipotezni model v zavarovalniški industrij.

Pomembno je, da prihodnje raziskave z dolgoročnim zbiranjem empiričnih podatkov podrobneje raziščejo vpliv velikosti oblačila na zavarovalniško analitiko in njeno uporabnost v zavarovalništvu.