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The Impact of using ALEX on the Efficiency Health Insurance Choices on

Emory Health Plan Enrollees

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An abstract of
a thesis submitted to the Faculty of Emory College of Arts and Sciences
of Emory University in partial fulfillment
of the requirements of the degree of
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Abstract

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With the recent rise of technology and digital transformation, health insurance companies and self-insured employers have been leveraging various technologies to improve the consumer experience. In 2021, Emory University's HR department unveiled ALEX®, an online benefits counselor that is trained to help employees find a personalized and lowest-cost plan based on their needs. Other organizations around the nation also have been incorporating ALEX to aid their employees with the selection of benefits; however, some organizations—such as the Washington State Health Care Authority—have already terminated offering ALEX, citing a lack of use and employees using different resources to inform their health insurance plan choices. This paper examines whether ALEX has had an impact on consumers' health insurance experiences and health insurance and health care related costs for Emory University and Emory Healthcare employees. After analysis, it was revealed that ALEX has a minimal impact on change in product, Emory medical coverage tier, and health care costs with the implementation of ALEX. However, there is the most variation of change in changes in product, meaning that ALEX is likely to induce change in healthcare product more than tier and costs.

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1. Introduction

Large insurance companies and employers have recently started transforming towards a more consumer-centric mindset, a mission that other industries have already adopted. With big tech on the rise and powerhouse companies like Amazon and Google dipping their toes in healthcare, health organizations have begun to incorporate different strategies to improve the consumer experience. Health insurance is a complex field, and more so choosing the right health plan is commonly a difficult and confusing feat. In a survey of insured U.S. adults, only 14% were able to answer 4 multiple-choice questions regarding the definition of simple cost-sharing features: deductible, co-pay, co-insurance, and out-of-pocket maximum (Bhargava & Loewenstein, 2015). This complexity stems from a variety of areas, one of which being the wide variety of health insurance parameters including deductibles, co- payments, co-insurance, and out-of-pocket costs and limits. To make an informed decision, a health plan enrollee must evaluate the trade-offs and values of the various cost-sharing features and premiums, while also navigating which services and providers are covered by their respective insurance (Zheng & Caban-Martinez, 2021).

One initiative to combat this complexity is ALEX®—an online benefits software that uses behavioral science, financial statuses, and other technologies that aim to help employees choose the most cost-effective health plan. Developed by a software company called JellyVision, the virtual benefits counselor uses an interactive and engaging foundation to provide employees with personalized decisions on their insurance choices. In addition to Emory, the University of California System, Harvard University, DC Government system, among hundreds of others have already incorporated ALEX (The Jellyvision Lab, 2024). However, in some other organizations, ALEX has not delivered the benefits that it was expected to do. For example, the University of Wisconsin-Madison has exhibited significant underperformance with ALEX, largely due to a lack of use of the tool by employees (La Follette School of Public Affairs, 2019). Similarly, school employees in Washington sought different sources of health information than ALEX, leading to a diminished value of ALEX when compared to its pilot year (Pray, 2019). Therefore, this paper aims to evaluate the effect of ALEX on Emory University and Emory Healthcare employees' health plan election and healthcare-related costs as well as provide more insight regarding the effect of digital transformation on health insurance at Emory University.

1.1. Emory's Health Insurance Landscape

Emory employees receive a wide range of benefits from basic life insurance, retirement plan contributions, tuition reimbursements, and most importantly for this study, employees can opt in for medical, dental, vision, and supplemental life insurance. To be eligible for these benefits, individuals must be full-time or part-time employees working 20 hours or more per week. An employee's dependents are eligible for medical, dental, vision and life insurance coverage too; these include the employee's legal spouse and legal child(ren) up to age 26 or if they are disabled and unmarried (with additional conditions). Emory offers three medical plans: Aetna Health Savings Account (HSA) plan, Aetna Point of Service (POS) Plan, and Kaiser Permanente Plan. First, the Aetna HSA plan allows the employee authority over how their health care dollars are spent as it comes with a tax-advantaged health savings account (HSA), which the employee can use to decide how their health care dollars are spent. Aetna HSA has a higher deductible and out-of-pocket maximums than the other plans, however, the employee contribution amounts are lower. Perhaps the most traditional medical plan is the Aetna POS (Point of Service) plan, which uses copays and coinsurance for health care costs. Co-pays are fixed amounts that the enrollee pays whenever they require a medical service, while co-insurance is the proportion of expenses that the enrollee pay. The deductible and out-of-pocket maximum are lower than Aetna's HSA plan, but the employee contribution amounts are higher. The last option is Kaiser Permanente's Plan, which provides care under all 600+ Kaiser Permanente-specific providers in which the enrollee is only responsible for co-pays and no deductibles (Services, 2024).

Picking the right health insurance plan is a complex task, especially when you consider other factors such as your dependents, past medical history, and general health preferences. To help facilitate the process, Emory began employing the ALEX® in 2021**,** to help employees find the lowest-cost medical plan options and provide personalized and confidential recommendations (Long, 2020). Additionally, ALEX acts as an education tool too as it explains common health insurance terminology such as deductibles and coinsurance making the whole health plan election less intimidating for users.

1.2. Background of ALEX®

ALEX was created by JellyVision in 2009 as they branched out into the benefits space. Before that, Jellyvision specialized – a longstanding software company specializing in video game development since its founding in 1989. *Who wants to be a Millionaire,* and most notably *Jackbox Games.* It wasn't until 2009, that JellyVision branched out and moved into the benefits space and created ALEX® which is now being used by over 1,500 customers. JellyVision's vision for ALEX® was to be able to "integrate the lighthearted environment of gaming into an interactive benefits counselor to make it easier and more enjoyable to learn, shop, and enroll in benefits plans" (Labs, 2024)

1.3. ALEX in other Environments

Health insurance enrollment has a longstanding history of being a difficult decision for individuals, with low health literacy and overall lack of knowledge causing barriers in the process. To add on, the decision on which health plan to enroll in is fueled by many factors, including premium costs, health status, past medical history, and more. To help aid the decision-making process, informed decisions can have a big impact, especially with new digital resources changing the way health insurance information is consumed. With the rise of new digital tools, a group of researchers at the University of Florida recently evaluated which tools have a significant influence on health insurance decision-making from the following sources: benefits representatives' meetings, printed materials from providers, friends and family, websites, and virtual benefits counselors (VBCs). A virtual benefits counselor is an AI tool that mimics one-on-one conversations with benefits counselors and provides personalized support in the decision process—the VBC being evaluated here is ALEX. In one instance, studies concluded that more individuals searched the web for medical information rather than talking to medical professionals, and that federal websites were considered the most trustworthy outlets of health information (Dutta-Bergman, 2003; Hesse et al., 2005). These results are consistent in Colón-Morales et al.'s study, where ALEX ranked second to official University of Florida and State of Florida health information sources in terms of the number of participants that use each respective resource (Colón-Morales et al., 2021).

1.4. Other Health Insurance Decision Making Tools on the Market

The *Show Me My Health Plan* (SMHP) tool is another digital tool developed in Missouri that combines a cost-estimator, plan feature preference assessment, and recommendations in simplified software to improve self-efficacy and confidence in the health insurance decision-making process (Politi, 2016). Politi et. Al builds on previous literature with results from new digital tools such as SMHP and VBCs to evaluate the sources of information used to support individuals' health insurance decisions and the factors that led them to the sources they used.

Through a web-based survey denoted as the "Health Insurance Information Sources Survey" (HIISS), respondents answered 27 questions regarding their demographics and employment status, sources of health insurance information used, health insurance literacy, and technology acceptance and experience with virtual chatbots. The paper found interesting trends in the usefulness of virtual agents and sources of information. With the usefulness of virtual agents, 34.9% of 126 respondents had tried virtual agents with an average reported usefulness of 4.72 on a 1 (not useful at all) to 10 (extremely useful) scale. In addition, 51.6% of respondents have used virtual agents' multiple times, and of those respondents, there was a slightly improved usefulness score of 6.51. When asked to rank their selected sources of information in order of importance, state and employer websites were ranked first by 49.2% of respondents, while ALEX (VBC) was ranked first by 21.4% (Colón-Morales, 2021). Overall, the researchers concluded that ALEX was used as a supplementary resource as it had more second-place votes than first-place votes, and even in a higher educated population, most individuals deferred to websites and federal websites when making health insurance-related decisions.

Another study evaluated the acceptability, feasibility, and implementation of an online health insurance navigation tool called the Health Insurance Navigation Tool (HINT). HINT's methodology centered around tools that explored trade-offs between cost-sharing features and premium costs for consumers to calculate their healthcare expense estimate. The authors argued that there was a widespread gap in health insurance literacy, which could lead to the avoidance of preventive and non-preventive medical procedures and services (Zheng & Caban-Martinez, 2021). While these authors also referenced the internet, mail, and television as the most frequently used tools for health insurance decisions, this research built on the previous literature and declared that consumers had low trust in those sources (Furtado et al., 2016). The HINT algorithm is a digital tool geared to improve this process, where through a questionnaire aimed to elicit health insurance consumer information. After completing of the questionnaire, HINT would generate a report that would compare the consumer's information across a Health Maintenance Organization (HMO), Preferred Provider Organization (PPO), Exclusive Provider Organization (EPO), and Point of Service (POS). After the study concluded, 83.9% of study participants found the HINT tool to be concise lengthwise, with 89.3% and 85.7% participants finding it to be easy to read and overall helpful respectively. The survey showed that HINT had raving reviews with consumers denoting it as "very effective" and a "great tool", and 98.2% of respondents reporting that they would suggest it to a friend if they were in a similar situation (Zheng & Caban-Martinez, 2021). Overall, the majority of the 57 respondents reported having no difficulty in using the digital tool, and the implementation of HINT was easily and successfully implemented by the respondents. While ALEX was used as a secondary resource to official websites and healthcare guides at the University of Florida, HINT had a positive impact; with the research supporting the fact that this novel instrument is to be implemented in health insurance decisions.

In a more specific case, cancer patients and survivors often suffer from a lack of inadequate insurance coverage and other difficulties when leveraging insurance to pay for healthcare expenses. From confusing plan details, lack of decision support, and other barriers to healthcare coverage, uninsured and underinsured cancer patients and survivors are susceptible to receiving less care and experiencing more harm. To support this problem, the Improving Cancer Patients' Insurance Choices (I Can PIC*)* health insurance decision tool was created to support cancer patients and supporters. Similar to ALEX, the I Can PIC tool streamlines health information more comprehensively with plain language and visuals, tailors the information to the specific consumer, and provides cost estimates, among other features. Tailored towards reducing financial toxicity and helping consumers manage their healthcare costs, the following measures were investigated in I Can PIC tool's consumers: health insurance knowledge, decision self-efficacy, health insurance literacy, financial toxicity, and delay or avoidance of care (Politi et al., 2020). Politi et al's results revealed that the I Can PIC group had significantly higher health insurance knowledge and confidence and those who did not use the I Can PIC tool were more inclined to keep their current insurance plan and be resistant to change. However, there was no explanation if the unchanged study participants did not see a need to change based on their benefits or did not understand the complexity of health insurance. In addition, the study participants were evaluated after a 3–6-month period, and health insurance knowledge between the groups was investigated. As hypothesized in the study, those who used the I Can PIC tool had significantly higher health insurance knowledge and lower financial toxicity than the control group. To add on, the group who used I Can PIC were less likely (if any) to delay or even avoid their care – when taking both non-cancer and cancer-specific care into account. While the results suggest that I Can PIC is a possible resource to improve health insurance plan decisions and improve health insurance knowledge, the study noted that there were limited health insurance options available and there was little room to switch plans regardless of any interventions like I Can PIC. On the other hand, the study denoted that the I Can PIC tool could have been used in a supplementary format that was the catalyst for consumers to enact and feel validated to make health insurance plan changes (Politi et al., 2020). Like the background of this study, Emory only provides three plans to its employees, meaning that Emory faces a similar problem to this study where there are limited health insurance options. This may push the effectiveness of ALEX to seem less than it is since consumers only have a slim number of choices with little room to change plans. However, the success of I Can PIC tool set a positive foundation for ALEX's effectiveness and possible consumer benefits post-implementation.

1.5. Acceptance of Technology in Healthcare

A big factor in these new tools is with regards to the acceptance of technology in the healthcare sector, as in most cases, healthcare professionals are persuaded by the benefits of technology, while patients and consumers place a higher weight on ease of use. As the effectiveness of technology in healthcare is influenced by personal norms, beliefs, and overall consumer reluctance, there are other factors to take into consideration when enhancing healthcare technology such as medical information and diagnosis databases. One limitation is the lack of oversight on these technology innovations, which allows developers to spread misinformation, give biased results, or deceive consumers with unfavorable decisions. Unlike the drug development process, the healthcare technology space does not have a legal control system like the FDA (Food and Drug Administration), which can help mitigate corruption and risks (Gücin & Berk, 2015). While that study does not take a specific look into a specific innovation in the healthcare payer world, it provides an overview of the dangers of digital transformation in healthcare.

In the digital age, there has been a significant increase in online health information accessible to consumers. However, recent studies have been conducted to explore the lack of credibility and quality of the efficacy of online health information leading to discussions regarding whether consumers can trust online health information. Some of the factors that go into a consumer's trust in online health information including but are not limited to interactions between the source, channel, and consumer characteristics, easiness of reading, source prestige, and design (Wathen & Burkell, 2002). With these factors as a framework, another study evaluated a variety of correlates of consumer trust in online health information with consumer characteristics of personal capital, social capital, experience and attitude of offline health information, and different information features (Ye, 2020). Previous research has offered differing conclusions regarding personal capital and trust. Some studies say that more educated individuals and those who self-rate their health higher are associated with more trust in others, mass media, the healthcare system, and drug information (Alesina & La Ferrara, 2002). On the other hand, some research has shown that there is high trust in healthcare providers among lower-income individuals, and another one concluded that income, education, or health were not predictive of trust in health information (Benkert et al., 2008). In Ye's study, participants were prompted to indicate their level of schooling, annual income, and overall health status to view the relationship between individuals who are more "well-off" and trust. With personal capital as a focal point of Ye's research, they found that education, income, and subjective health status are not associated with trust in online health information.

The next area of focus in Ye's study was regarding social capital and trust which relates to building virtual relationships and social networking sites usage' impact on trust. Ye found that relationships that were made virtually were not as strong or sustainable and that overall visiting social networking websites isn't significantly related to trust in online health information. As ALEX is a virtual tool, it could be perceived that most individuals would not trust it as much as the bonds they make with the virtual benefits counselor are not sustainable. Ye also found a positive correlation between trust in health information from government agencies and revealed generational differences in trust. For individuals 65 years or older, their trust in online health information is more influenced by personal beliefs and attitudes while for those 55 or older, computer use and attitudes towards health influenced their decision. On the other hand, for those in the 35-49 and 18 to 34 age ranges, federal source usage was absent, and more likely to search for this information online. The information here will be important when evaluating generational gaps in using ALEX, and how different age ranges use online tools given their trust. Lastly, Ye also evaluated information features and trust in online health information that were correlated with higher trust in health information. Two features stood out in the study: easiness to locate and understandability of health information which seemed to be critical to trust in online health information providers. ALEX prides itself on ease of use and understandable explanations, which per Ye's investigation would mean that ALEX should have a high level of trust in consumers (Ye, 2010). As my study is looking specifically at Emory University employees, a good proportion of whom are highly educated and in good health, this removes some of the concerns regarding my project's limitations with a single-institution study.

Creating a more patient-centered experience is a common motive within digital transformation in healthcare; whether that's during medical care itself or other healthcare related initiatives. As stated earlier, the health industry and technology are headed in a direction that focuses primarily on patients and incorporates enhanced experiences of personalization, comfort, and speed of healthcare services. Because healthcare has the lowest level of digital innovation when compared to other industries like retail, finance, media, etc., systemic changes are needed in this space (Gopal et al., 2019). ALEX was created on a similar concept, where there was a lack of guidance in a field that was full of complexity, confusion, and frustration in their consumers.

One way to improve healthcare personalization is by leveraging information technology to improve communication, patient needs, and varying service procedures. One study investigated the impact of transforming healthcare to be accessible anytime and everywhere through eHealth (healthcare services provided electronically via the Internet) services that allow for timely care, support, and medical record management. Although this improves the consumer experience, it also supports healthcare systems to distribute services more efficiently and equally. However, in that study's context, eHealth corresponds to electronic health records, computer–aided diagnosis, and other examples of digital medical technology—not necessarily the virtual benefits counselors studied in my project. Nonetheless, eHealth has been evident to improve patients' health and physicians' performance and proved to be an important factor of technology acceptance in healthcare (Stoumpos et al., 2023). Another area of digital transformation Stoumpos investigated was telemedicine, which relates to both clinical and non-clinical healthcare services, education, research, and management asynchronously. Telemedicine is a benefit for remote areas especially as it offers added health access opportunities, and the World Health Organization stated that telemedicine was a vital investment towards improving diagnoses, clinical management, and healthcare (World Health Organization, 1998). Perhaps the most important effect researched for that project was with regards to the educational impact of eHealth, where Stoumpos' and his team concluded that with increasing digital transformation, consumers would have to understand how to conjoin both online health information and human interaction as well, connoting to the mentality that online health information would be used in a supplementary sense. These results relate to previous studies that concluded that digital tools were being used as more of a supplementary source to federal and government sources (Colón-Morales, 2021). In ALEX's case, future studies could evaluate whether it is used as a primary or supplementary source of online health information for Emory employees. Overall, while there were many articles and case studies evaluated during this study (287 studies evaluated), there is no conclusive answer on whether digital transformation is a clear benefit in healthcare, making projects that study the obstacles and effects of digital tools more important as we continue through this digital age. While this article does not investigate a specific digital tool, it goes through the different characteristics and attitudes that are impacted by online healthcare, as well as the possible implications of digital transformation in the future (Stoumpos et al., 2023). It is evident that the development of ALEX comes at a time when digital tools are omnipresent, and per these studies predictions, has the potential to push people to become more accepting of digital tools in healthcare.

1.6. Past Study Limitations

Previous literature offers a multitude of research on different types of digital health insurance aids on the market. However, the studies that have evaluated ALEX have only focused on the engagement and usage statistics of it. Our study will take it a step further and look specifically at if ALEX is having a tangible impact on health plan election and healthcare costs, rather than just investigating the usage at Emory University. Past studies also mainly examined the trust and acceptability of health insurance tools in the digital world, rather than seeing the impact that these tools had in the payer landscape.

2. Methods

2.1. Participants

The deidentified data used for this research study were provided by the Emory Department of Work Life and Benefits. The data contains information on health insurance plan enrollment for subscribers over the years 2020, 2021, and 2022 and include demographic information such as age, company affiliation (Emory University versus Emory Healthcare), medical coverage tier, and details on medical and pharmacy expenses. The data include around 43,064 subscribers across three years, who have been enrolled in an Emory health plan for at least one enrollment period in any observed year. Since this is a pre/post analysis with deidentified data that has already been collected and extracted, this study was exempt from oversight by the Emory University Institutional Review Board (IRB).

2.2. Data Manipulation

The analysis included only individuals who subscribed to Emory's health plans for all three years (2020, 2021, and 2023). Additionally, if at any point within those three years, there was missing information on Product or Emory Medical Coverage Tier, that subscriber was excluded from analysis as well. After the removal of these subscribers, there were 24,631 subscribers left in the dataset who were enrolled in a health plan for all three years and had values for all necessary variables. Because the Emory Work Life and Benefits department has a 36-month data library, data for only August-December were available for the year 2020. To ensure that cost outcomes (total cost, total out of pocket cost, pharmacy cost, pharmacy out of pocket cost, medical cost, and medical out of pocket cost) are measured over comparable time periods, I used the following equation to extrapolate the observed 5-month period of 2020 data to a full calendar year:

$$2020\ Estimated\ Total\ Cost = \left(\frac{2020\ Total\ Cost}{5}\right) * 12$$

This equation calculates the per month estimated cost for each subscriber and multiplies by 12, to get an estimated annual cost value. Although this approach is not optimal, the full data of 2020 would not have been helpful, as the COVID-19 pandemic induced different extremes in healthcare spending due to lock-down measures.

2.3. Measures of Analysis

The key outcomes were ALEX Indicator, Change in Product, and Change in Emory Medical Coverage Tier which were all binary. The ALEX Indicator value was "1" when ALEX was available for subscribers and a "0" for when ALEX was not present. To clarify, enrollees made their health plan elections a year in advance, so they were making choices for 2021 in 2020, and 2022 in 2021. This means that there were only two open enrollment periods in my dataset – 2021 and 2022. Change in Product and Change in Emory Medical Coverage Tier were similar in nature in which there was a "1" if there was a change between the Product and Emory Medical Coverage Tier values from 2020 to 2021 and 2021 to 2022. If there was no change, the Change in Product and Change in Emory Medical Coverage Tier values would denote a "0".

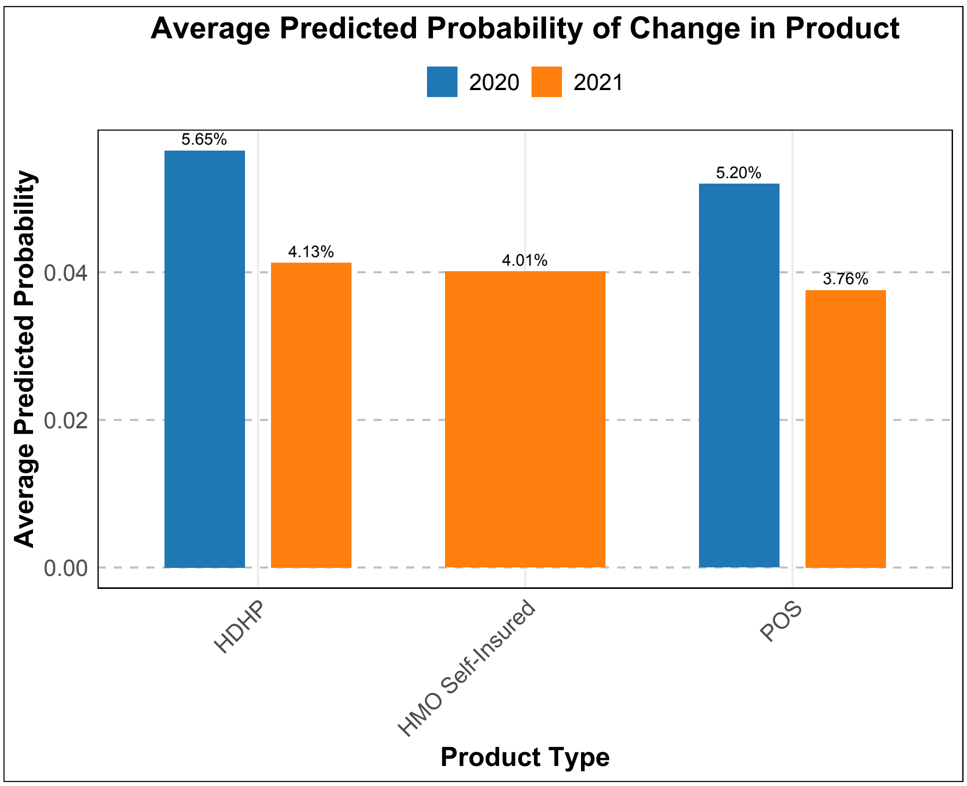
2.4. Statistical Analysis

I fitted logistic regressions to evaluate ALEX's association on product change and tier change. A generalized linear regression was used for healthcare spending data across total, pharmacy, and medical costs. For all analyses, the standard errors were clustered at the subscriber level to adjust for correlated errors across observations. Within each logistic regression, an odds ratio was estimated to measure the association between the exposure of ALEX and the outcomes stated above. Given that healthcare financial data are usually skewed to the right with some extremely high costs, to find ALEX's impact on costs and out-of-pocket costs, I used a generalized linear regression with the log link and gamma distributions functions. The results were analyzed assumption of a level of statistical significance of 5%. This study was conducted in RStudio Versions 2022.02 and in accordance with ethical guidelines for research involving human participants. Data were de-identified to ensure privacy and confidentiality, and only aggregated results are reported to prevent the identification of individual subscribers.

3. Results

3.1. Change in Product Type

Emory employees were offered a choice of three health plan options: High Deductible Health Plan (HDHP), Point of Service (POS), and Health Maintenance Organization (HMO). To evaluate change in product type, a logistic regression was run with change in product in the subsequent year as the outcome and an indicator of whether ALEX was available to assist with health plan choice as the key predictor, while controlling for demographics.

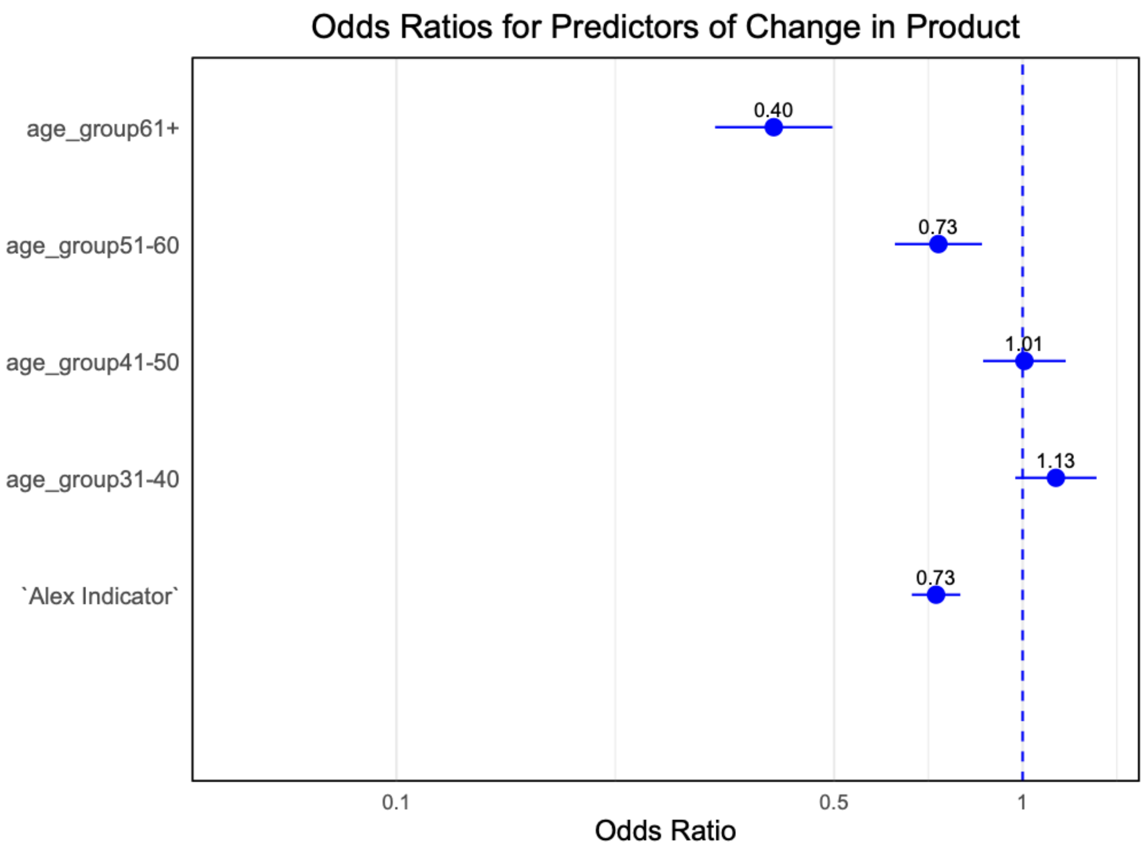


In the graph above, the average predicted probability of change is plotted on the y-axis, product type is on the x-axis, and the colors denote the year that is being evaluated (dark blue: 2020 and orange: 2021). There was a slight decrease across all health plans after the implementation of ALEX, as ALEX was introduced in 2021. For HDHP plans, the average predicted probability decreases by 1.52% - from 5.65% to 4.13%. For POS, there was a similar decrease of 1.44%, from 5.20% to 3.76%. While there was no pre-post analysis for HMO Self-

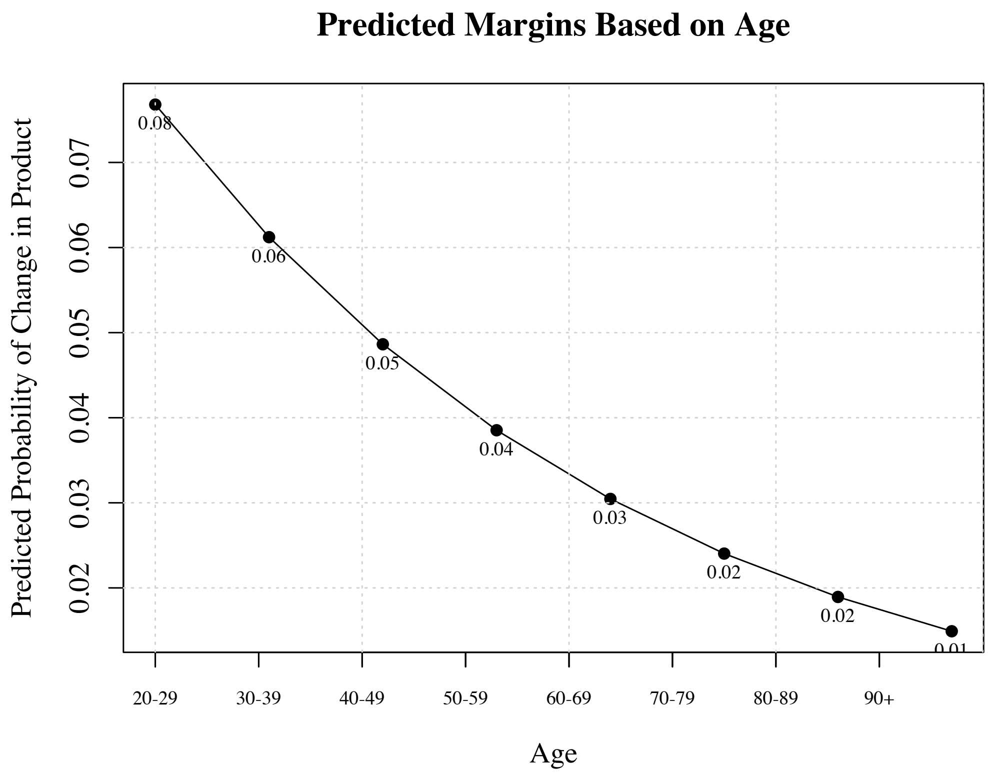
Insured plans, the average predicted probability of change in product is consistent with the other two plans. A logistic regression was also run to further test ALEX's impact on change in product across age groups:

```
(Intercept) `Alex Indicator`   age_group31-40   age_group41-50   age_group51-60     age_group61+
 0.06296394       0.72738187       1.13021317       1.00659167       0.73372478       0.40046569
```

With the availability of ALEX, the odds of change in product type decreased by around 27.7% on a 95% confidence interval.



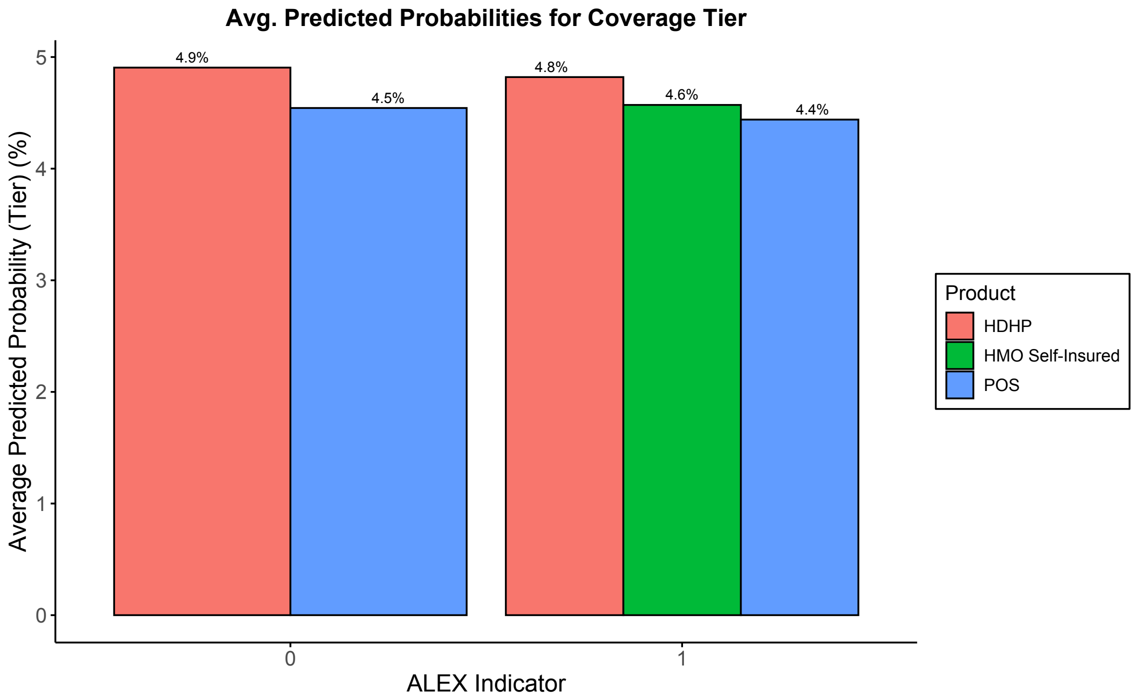
For the age groups, the reference level is the 26-30 age group, so when evaluating the remaining age groups. For the age group 31-40, there is around 13% higher odds of change in product when compared to the 26-30 age group. The odds of change in product decrease as age groups get older, with the 51-60 age group sitting at a 26.6% decrease when compared to the reference group.



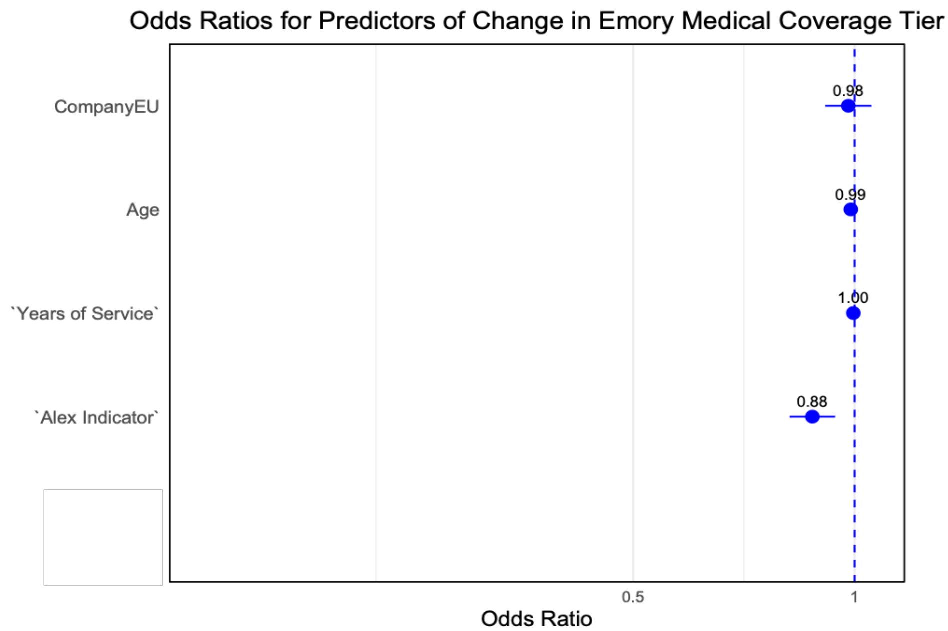
As an additional visualization, the predicted probability of change in product is mapped against the different age groups. There is a monotonic decrease in predicted probability as the age groups become larger, starting from ~8% in the 20-29, all the way down to ~1%-~2% in the older age groups of 80-90+.

3.2. Change in Emory Medical Coverage Tier

There are nine coverage tiers at Emory: Employee + Spouse, Employee Only, Employee + Family, Employee + Child(ren), Eligible Employee/Dependent over 65 years, Eligible Employee/Dependent over/under 65 years, Eligible Employee under 65 years, Eligible Employee/Family over/under 65 years, and Single over 65 years. A similar analysis for predicted change in product was done for predicted change in Emory medical coverage tier.

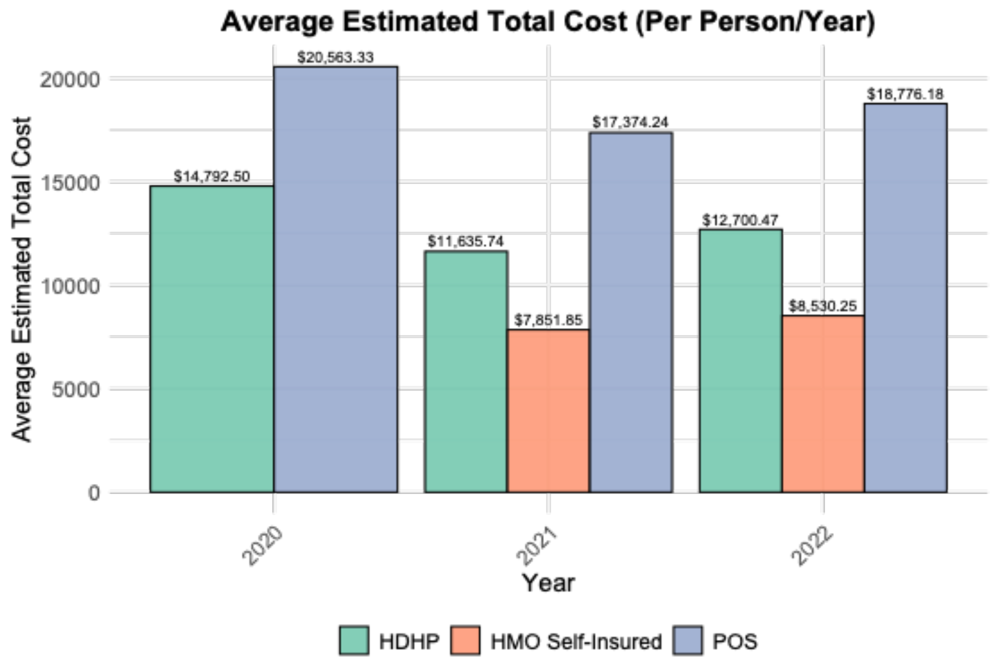


We found similar predicted probabilities of coverage to the predicted probabilities of product, with the average predicted probabilities for tiers ever so slightly decreasing for all products. For HDHP plans, the predicted probabilities dropped from 4.9% to 4.8% while for POS decreased from 4.5% to 4.4%. For HMO Self-Insured, the predicted probability was at 4.6%, which is consistent with the predicted probabilities for the other products. The odds ratio logistic regression of change in Emory Medical Coverage Tier are displayed below. The ALEX Indicator estimates 0.88, meaning that there are 12% lower odds of change with Emory Medical Coverage Tier. The odds ratios for the control variables, Company, Age, and Years of Service, are also displayed with the odds ratios for those variables at 2% 1%, and 0% respectively. The observed changes are predominantly driven by external shifts in family structure rather than choice. Having said that, we anticipate no, or reduced effects associated with ALEX. However, there is potential for ALEX to assist existing families (with given structures) to realize the benefits of splitting or combing health plans.

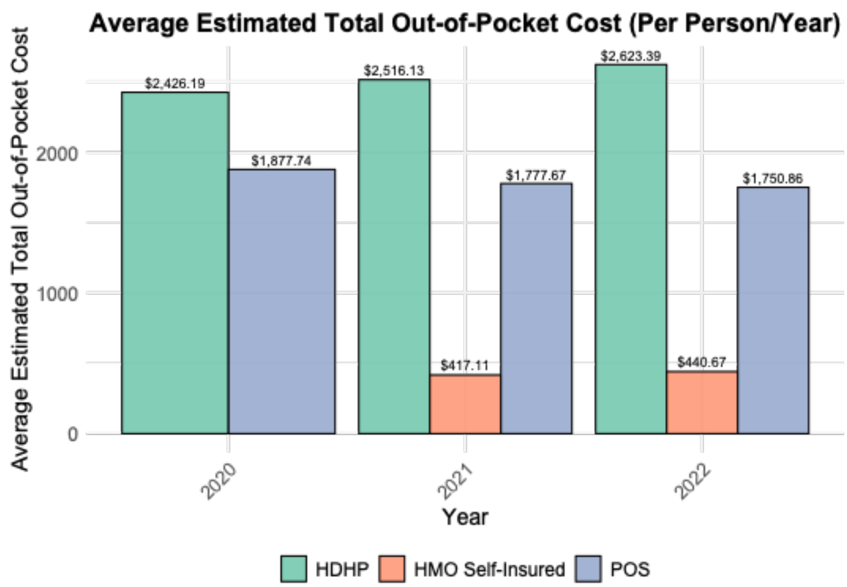


3.3. Cost Analysis for Total Costs and Total Out-of-Pocket Costs

In the analysis, total paid, total out of pocket costs, medical paid, medical out of pocket costs, pharmacy paid, and pharmacy out of pocket costs. When evaluating total paid and total out of pocket costs, ALEX had a minimal effect on both total cost and total out of pocket.

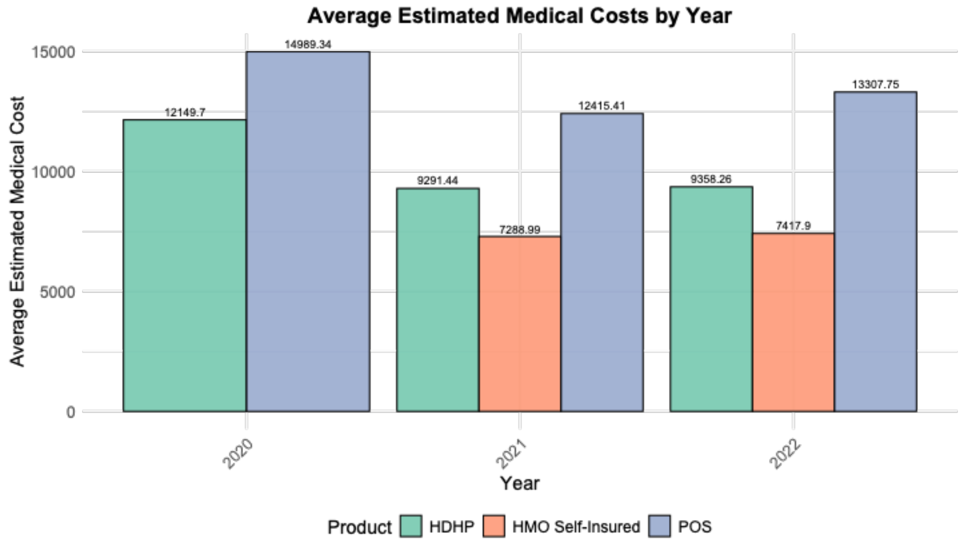


For total cost across 2020, 2021, and 2022, there is minimal change across all three years for all health plans. For HDHP, the average estimated total cost starts at $14,792.50 in 2020, before going down to $11,634.74 in 2021 and $12,700.47 in 2022. For POS, we can see a similar trend with 2020 sitting at $20,563.33, $17,473.24 in 2021, and finally $18.776.16 in 2022. For HMO plan, the cost increased slightly from 2021 ($7,851.85) to 2022 ($8,530.25).

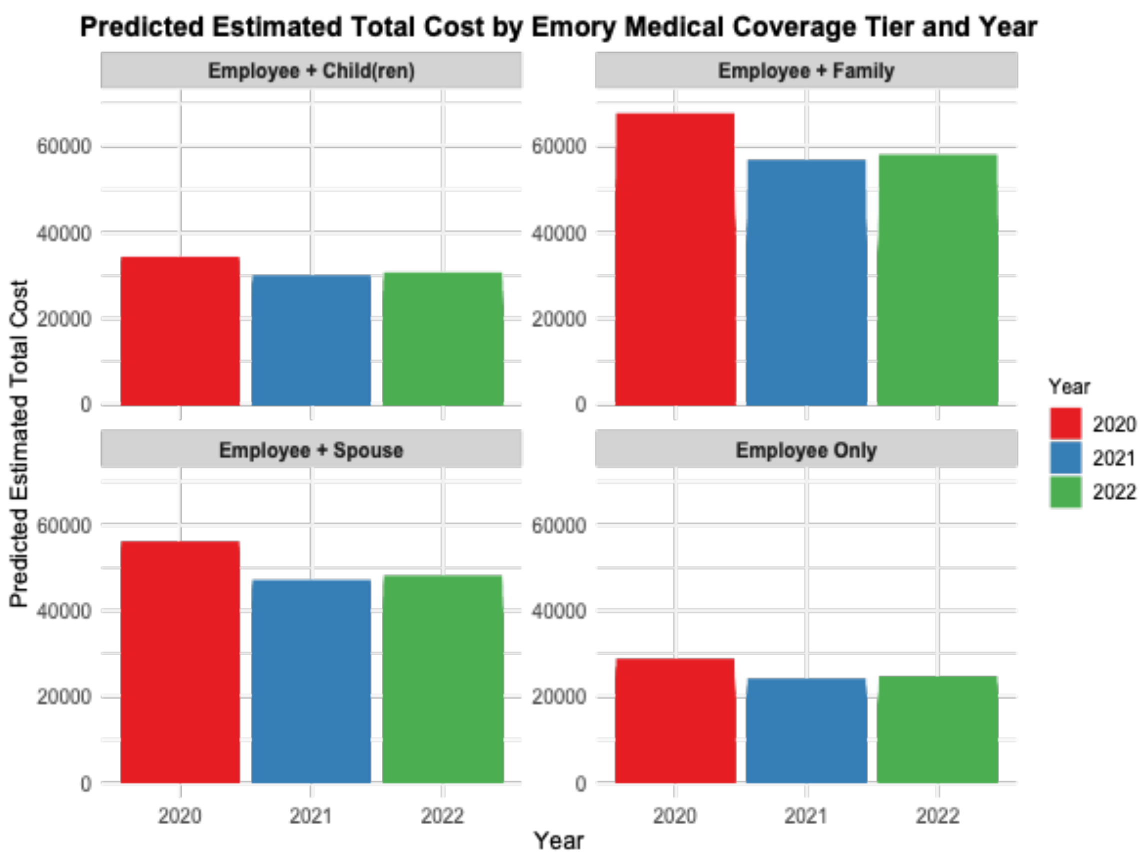


Looking at the estimated total out-of-pocket costs, there is also a very minimal change in costs with ALEX. For HDHP, there is a slight increase through the three years, with 2020 at $2,426.19, 2021 at $2,518.13, and $2,623.39. For POS, there is a slight decrease through three years, starting at $1,877.74 in 2020, $1,777.67 in 2021, and $1,750.86 in 2022. HMO plans' average total out of pocket costs increased from $417.11 in 2021 to $440.57 in 2022. When looking specifically at medical costs and medical out-of-pocket costs, there is also not a significant magnitude of change.

3.4. Cost Analysis for Medical Costs and Medical Out-of-Pocket Costs



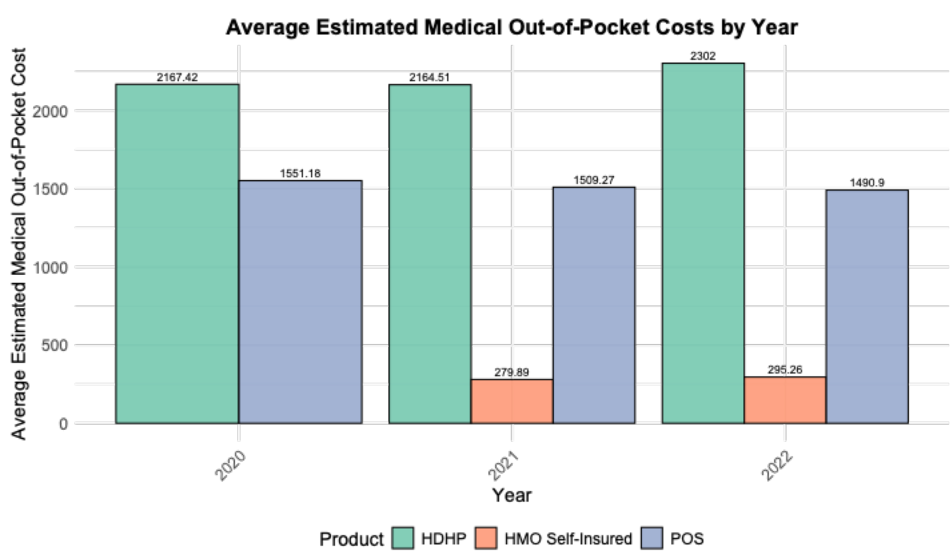
For HDHP plans, the average estimated medical costs by year was at $12,149 in 2020, $9,291 in 2021, and $9,358 in 2022. For POS, the 2020 average estimated medical costs was at $14,989, $12,415 in 2021, and finally $13,307 in 2022. HMO plans were stagnant across the 2021 and 2022, only changing from $7,290 in 2021 to $7418 in 2022. Like estimated total costs, the estimated medical costs decreased slightly from 2020 to 2021 and then increased again in 2022.



In the graph above, we breakdown the estimated total costs down to policyholder level due to the differing average estimated total cost across different policies. Employee-only plans will have a lower estimated total cost than Employee + Spouse plans since it only accounts for one person while Employee + Spouse has two people under the plan. Therefore, the Employee + Family plan has the highest spending since the plan takes into consideration the policyholder and all parties under their family plan. Across all four coverage tiers, it is evident that there is a slight increase in predicted estimated total cost from 2021 to 2022. 2020 costs are higher than 2021 and 2022, but that is likely due to the estimation that had to be calculated for costs that year. The minimal impact that ALEX has on predicted estimated total cost is expected and can be attributed to how ALEX was created to help individuals choose the right health plan rather than to reduce costs.

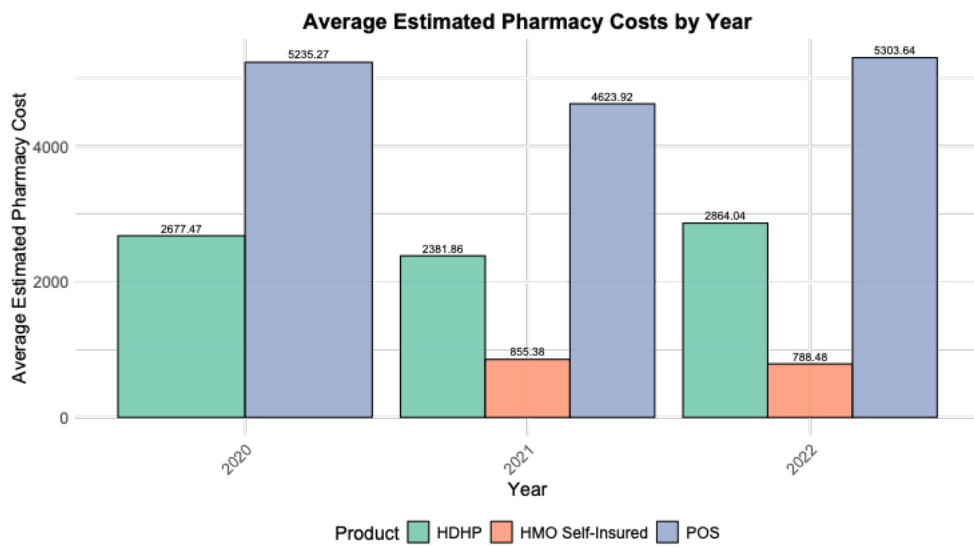
```
glm(formula = `Estimated Total Cost` ~ `Emory Medical Coverage Tier` +
    `Alex Indicator` + Emory_Alex_Interact, family = Gamma(link = "log"),
    data = filtered_combined_years)

Coefficients: (4 not defined because of singularities)
                                              Estimate Std. Error t value Pr(>|t|)
(Intercept)                                    9.82733    0.05773 170.240  < 2e-16 ***
`Emory Medical Coverage Tier`Employee + Family  0.46431    0.05391   8.613  < 2e-16 ***
`Emory Medical Coverage Tier`Employee + Spouse  0.44598    0.06414   6.953 3.62e-12 ***
`Emory Medical Coverage Tier`Employee Only     -0.35290    0.04635  -7.614 2.71e-14 ***
`Alex Indicator`                               -0.18996    0.06990  -2.718  0.00658 **
Emory_Alex_InteractEmployee + Family.0          0.05097    0.09499   0.537  0.59154
Emory_Alex_InteractEmployee + Spouse.0         -0.05789    0.11320  -0.511  0.60904
Emory_Alex_InteractEmployee Only.0             -0.05281    0.08149  -0.648  0.51696
```

An interaction effect was created to better understand the relationship between Estimated Total Cost and Emory Medical Coverage Tier. The Emory_Alex_Interact interaction calculated the product of Alex Interaction and Emory Medical Coverage Tier in a numeric form. These estimates show the differential effect of ALEX on cost for the employee with the implementation of ALEX. For the Emory Employee Alex Interaction and Family variable, the differential effect is around -0.14 since it considers the estimate for Alex Indicator (-0.19) and the Estimate for the Emory Employee Alex Interaction and Family variable (0.05) as well.

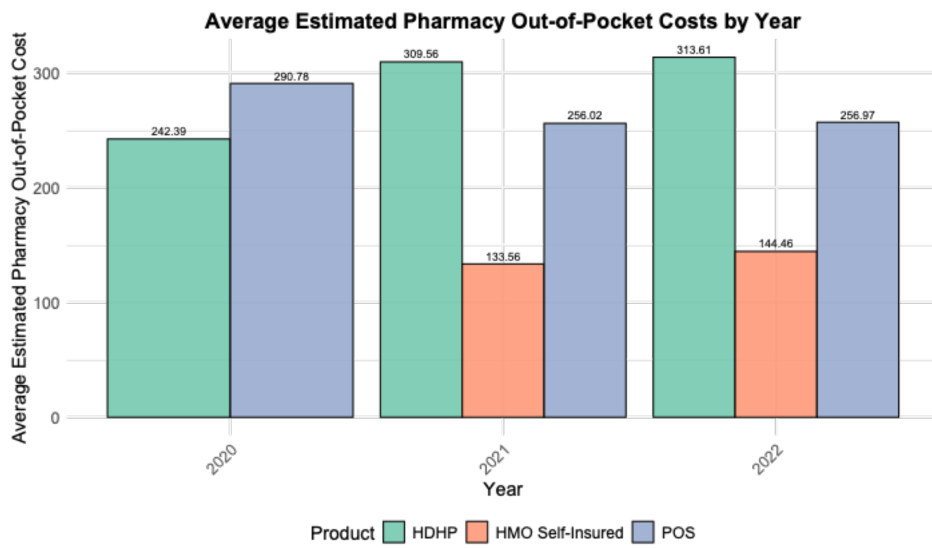


The average estimated Medical Out-of-Pocket costs follow a consistent trend with the other cost analysis, except for the average estimated medical out-of-pocket costs for the POS plan staying more constant through the three years ($1,551 in 2020, $1,509 in 2021, and $1,490 in 2022).

3.5. Cost Analysis for Pharmacy Costs and Pharmacy Out-of-Pocket Costs



If we continue to drill down the total costs, we also can investigate the average estimated pharmacy costs per year. When evaluating this cluster graph, there is minimal change in the average estimated pharmacy costs through all three years across all plans. For HDHP plans, there is only a range of $482.18, $679.72 for POS plans, and HMO decreased by $66.90 from 2021 to 2022.



For estimated pharmacy out-of-pocket costs, there is a bit more variation in the HDHP plans, the costs increased from $242.39 in 2020, to $309.56 in 2021, and $313.61 in 2022 – a ~29.38% increase in cost. For POS plans, there the estimated pharmacy out of pocket costs decreased from $290.78 in 2020, to 256.02 in 2021, and $256.97 in 2022, resulting in a ~11.6% decrease. The HMO plan had a small increase in costs from $133.56 to $144.46.

4. Discussion

The objective of this study was to evaluate the association of the availability of ALEX and health plan choices of Emory employees, specifically examining if ALEX invoked health plan or coverage tier change and reduced costs for Emory health plan subscribers. Although no study has previously studied health plan choice and cost changes, I hypothesized that ALEX would have a small but meaningful impact on health plan product and tier choice. I also hypothesized that ALEX would help subscribers choose the right health plan, and thereby reduce their medical and pharmacy costs as well. Because ALEX was implemented in 2021, this pre/post analysis compared outcomes in 2020 and 2021.

For change in product, ALEX had a minimal impact on the predicted probability of change in product across all plans. For HDHP plans, the predicted probability dropped from 5.65% in 2020 to 4.13% in 2021, and a similar decrease for POS with 5.2% in 2020 and 3.76% in POS; meaning that subscribers were less likely to change their product after the implementation to ALEX. This slight change was expected, as ALEX was designed to help enrollees pick the best health plan, although we see a small percentage of change due to the novelty of ALEX.

By taking a more granular scope with the ALEX and age interaction, the different age groups can be evaluated by using the 0-30 age group as a reference. The odds ratio shows that with the availability of ALEX, the odds change in product decrease by approximately 27.7%. The 31-40 age group had 13% higher odds of change in product as compared to the 0-31 group, the highest percentage out of all age groups. The 41-50 age group has a minimal higher odd of change in product at ~0.65%, while the 51-60 group and 61+ age group have lower odd of change in product at ~26.62% and ~60% respectively. When breaking down change in product into its age groups, the younger age groups 31-50) were at a higher likelihood of change when compared to the reference group, while the older ages (51-61+) were less likely to change products. This could be due to more knowledge in the health insurance terminology, more experience with their health plan, or the fact that families are less likely to change in terms of individuals in one's family, leading to less health plan changes. With the odds change in product for ALEX indicator at -27.74%, that with ALEX there is a decrease likelihood of change. It is possible that with ALEX, enrollees can realize the best plan possible, while those without ALEX are unsure change plans to give other plans a try. As expected, there is also a small percentage of change for Emory Medical Coverage Tier, with the average predicted probabilities with ALEX implemented decreasing by just ~0.1% for both HDHP and POS plans. For HDHP plans, the average predicted probabilities of change in tier decreases from just 4.9% in 2020 to 4.8%, while POS plans decrease from 4.5% to 4.4%. The odds ratio change for tier tells a similar story as for every one unit increase in ALEX indicator, the odds change in tier decreases by approximately 12.38%. When looking at the other controls, there is insignificant odds change ratio on tier, with Company, Age, and Years of Service resulting at 2% 1%, and 0% respectively. With these results, it seems like if ALEX was affecting health plan election, it has a larger effect on health product type rather than health plan election, as there is more variation in change in product than tier. The minimal changes are likely due to external factors, such as change in family structure, that would have a more dominant impact on coverage tier change than the implementation of ALEX.

The results of cost analyses for total and out-of-pocket costs displayed a small change in average estimated cost per person per year across all plans. For estimated average total costs, HDHP plans went down by $3,157.76 from 2020 to 2021 ($14,792.50 to $11,634.74. For POS, the average estimated cost per person was reduced by $3090.09, a similar amount to HDHP, from $20,563.33 in 2020 to $17,473.24 in 2021, and then $18.776.16 in 2022. On the other hand, for the HMO plan, the cost increased slightly from 2021 ($7,851.85) to 2022 ($8,530.25). The percentage change of estimated average total costs pre and post implementation of ALEX was a 21.3% decrease for HDHP and a ~15.1% decrease for POS from 2020 to 2021. However, the more important variable here is the estimated out-of-pocket cost, or how much the subscriber is paying with their own dime. For HDHP plans, the average estimated out-of-pocket costs slightly increased from $2,426.19 in 2020, $2,518.13 in 2021, and $2,623.39 in 2022. For POS, there is a slight decrease through three years, starting at $1,877.74 in 2020, $1,777.67 in 2021, and

$1,750.86 in 2022. HMO plans average total out of pocket costs increased from $417.11 in 2021 to $440.57 in 2022. In a pre/post evaluation of out-of-pocket costs, HDHP plans average out-of-pocket costs increased by ~3.78%, and for POS plans, it decreased by ~5.33%. These results show that the implementation of ALEX did not have a significant impact on reducing out-of-pocket costs for Emory subscribers.

4.1. Limitations

There are some limitations to this study to consider. First, we were not able to observe the subscribers who used ALEX versus the ones who did not. The only data received was from JellyVision directly, that showed overall engagement across time, meaning the Emory subscribers did use ALEX, but we are unable to pinpoint which subscribers exactly utilized the tool. Therefore, this study was only able to take a general estimate of change based off the year ALEX was implemented, 2021, incorporating an intention to treat analysis. Additionally, as previous research indicates, ALEX is not the only health information resource out there. Official websites, government resources, friends and families are all different sources that could enact different types of changes in health plan election for Emory employees. As mentioned previously, it was not possible to track which individuals used ALEX, so it is a possibility that any changes we see in the results could have been caused by other factors outside of ALEX. Another factor that could have played into health plan chances is general health insurance literacy. Although previous studies have mentioned that Americans in generally have low health insurance literacy, we were not able to measure Emory subscriber’s health insurance literacy either (Bhargava & Loewenstein, 2015). Whether the population of Emory has higher or lower health insurance literacy could have played a role in the subscribers changing health plans based off their own knowledge, but that was not measured in this study either. 2020 was also a limitation to this study, as the Emory Work Life and Benefits Department only had a lookback period of 36 months, the data collected (specifically for costs) was only from August 2020 to December 2020. The COVID-19 pandemic could have also played a role into how health care costs played out but given that we only had 4 months of data from 2020, there is no way of knowing how 2020 could have played a role in health care costs for Emory. Lastly, at the time ALEX was introduced in 2021, the new Kaiser Permanente health plan (HMO Self-Insured in our analysis) was also up for selection for subscribers. Some of the changes seen pre/post ALEX implementation could also be induced by the availability of a new health plan.

4.2. Future Research

The present study was just a single-institution study of with limited generalizability. Thus, to improve the generalizability of findings, it would be necessary to expand this analysis across multiple institutions of different demographics and sizes. Additionally, as my study was a observational study, future research could incorporate a randomized control trial to randomize people who used ALEX versus those who did not. A more consistent measure of whether ALEX was used by subscribers is needed to have a more accurate estimation of the magnitude of impact ALEX has on health plan election and costs. As ALEX continues to be a tool for Emory employees, it would be helpful to see the long-term impact with more data across multiple years to determine whether ALEX is a worthwhile investment for Emory. With more data, we would have a better understanding of how ALEX affects health plan choices and costs as more enrollees will likely be more familiar with the usage of ALEX. Since ALEX was just introduced in 2021, there could be a lack of usage or knowledge of ALEX for Emory employees, and more time with the tool at Emory would further investigate ALEX's impact on health plan changes and costs.

5. Conclusions

This study explored the impact of ALEX on health plan election and tier changes, as well as whether it reduced healthcare costs for Emory employees. We hypothesized that ALEX would have a small but significant impact on Emory employee's health plan changes, and with that have a decrease in out-of-pocket costs as well. For health plan changes, we saw a minuscule decrease in predicted probability of product change after the implementation of ALEX. Even then, the average Emory subscriber had low predicted probabilities of change in product at around ~4%; meaning that with or without ALEX Emory employees were unlikely to change their health plan product from year to year. However, it was exhibited that that when breaking down the predicted probabilities of change in product; the older the age groups, the less likely individuals were to change their health plan when compared to younger age groups. Emory health plan coverage tier changes were even less affected by ALEX, with both the odds ratio regression and cluster analysis showing a less than 2% change before and after the implementation of ALEX. ALEX also had a minimal impact on the healthcare costs for Emory employees since through our regression we found that there was not statistically significant effect on the ALEX interaction on estimated total costs.

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