Dr. Dismuke: Well, I’m very, very pleased today on behalf of HERC to introduce our speaker, Dr. Bruce Kinosian. Dr. Bruce Kinosian is a geriatrician and health services researcher at the Corporal Michael J. Crescenz VA MC in Philadelphia. And he is also Associate Professor of Medicine at the University of Pennsylvania. And finally, he is Associate Director of GEC-DAC, or the Geriatrics and Extended Care Data Analysis Center.

So, I will be hosting the questions at the end of Dr. Kinosian’s presentation and I’m very pleased to turn it over to Dr. Kinosian.

Dr. Kinosian: Thank you for joining us today. The High Needs High Risk 2 model was developed by a team at GEC-DAC led by Susan Schmidt with Orna Intrator, Karen Phipps, and myself, working on the model.

The High Need High Risk 2, or Version 2, predicts long-term institutionalization but also, identifies high-cost hospital use and death. For finding now pretty consistently over the last decade less than 30% of veterans that enter nursing homes for long-term residence receive help to remain in the community prior to nursing home placement.

Only 1% of veterans reside in long-term institutions, however, which makes identifying veterans before they go into a long-term institution akin to finding a needle in a haystack.

High Need High Risk Version 2 uses VA and Medicare diagnoses, demographics, healthcare use, and risk measures for frailty and medical complexity to identify the 1% who will be entering a nursing home long term.

The model identifies 4% of VA users that account for nearly 40% of the new long-term institutionalization each year; 19% of new spending in the year; 22% deaths. For every eight veterans identified at high risk for long-term institutionalization, in the next two to three years; three will die and one will enter a nursing home long term.

The motivation to develop HNHR2 was the RECAP Project, which Geriatrics and Extended Care is implementing now in three areas in Florida, in North Carolina, and in Ohio. That’s the Redefining Elder Care in America. The motivation for RECAP was that while 90% of Americans prefer to stay in their homes as they age instead of nursing homes, that to honor those preferences would require providing services that would prevent the necessary nursing home care.

Part of the financial motivation for avoiding unnecessary nursing home care is that over the next twenty years, the number of VA enrollees over the age of 85 is expected to increase by 70%, or nearly half a million. And the expected number of community nursing home beds paid by VA is expected to nearly double to grow by about 8,000 beds. In 2019 pre-COVID, the Community Nursing Home Program was paying for about 9,600 beds long term.

The role of HNHR2 is to identify veterans who aren’t clinically picked up who wouldn’t need services in order to avoid or delay their entry into a nursing home. Currently, about 40% of high-risk veterans are clinically identified and they receive non-institutional care supports. And HNHR2 is designed to identify the other 60% that will allow them to be screened for functional deficits and other needs that if they were alleviated, it might help delay their entry into a nursing home.

It’s become apparent in the last decade or so that home and community services don’t really prevent nursing home placement, that they delay nursing home placements. This is probably most clearly shown in a very carefully controlled study of PACE participants in Massachusetts with matched frail individuals also entering the long-term services and support system between 2007 and 2013.

As you can see from entry, the PACE participants have a delay in their entry into the nursing home of about 20 months compared to new entrants into the long-term services and support system, or their substantial early use of nursing home care. The effect of this 20-month delay over the study period was about 6,000 nursing home months between the two cohorts, and that amounts to a 28% reduction in nursing facility residency; about a 38% reduction in nursing facility residency per patient; and the reduction in nursing home months amount to 9% of the State’s LTSS spending to the PACE program.

The VA has a number of current risk tools as the CAN score that predicts hospitalization and death; Nosos predicts total VA costs; the JEN Frailty Index predicts both concurrent ADL dependencies, as well as one-year, long-term care needs.

Choose Home, the predecessor model to HNHR2, predicted two-year, long-term institutionalization or death. And then, in HNHR2, predicts two-year long-term institutionalization.

All of these measures run together and so the scores tend to be somewhat correlated.

Separately, there are population classifications that can also identify high risk. While all of these scores give you an interval scale in precise probability of an event, the population classification methods just create a bucket of elevated-risk individuals without an actual ordering of those individuals.

In GEC, we’ve used the Independence and all the qualifying criteria, which is a hospitalization, post-acute care in the prior 12 months; two or more ADL deficits; and two or more chronic conditions. And that seems to identify the group with the high level of ADL deficits, costs, hospital use, acute care, and long-term institutionalization.

High Need High Risk is a proxy of the independence and qualifying criteria that was developed only with VA data without the Medicare data to identify the fairly substantial post-acute care if it’s used outside of the system.

The issue of the current tools is that the positive predictive value or the chance of someone that is identified with those tools will actually experience LTI is somewhat low. This is because the LTI - long-term institutionalization - prevalence happens to be low.

One way to deal with this is to raise the threshold at which you identify an individual as being at high risk. However, the high positive predictive value by identifying a very small number of very high-risk people doesn’t really equal high impact, which has been a challenge with using some of the prior tools to target resources.

Another issue with the current - with some of the current - tools is that they’re estimated on poll populations. And in that sense, they can under-predict events in higher-risk sub populations. This shows a comparison for fiscal year 2016 in death and hospitalizations for all VA users, as well as just the independents and unqualified subset.

And as you can see for all VA users, CAN is right on the mark. The observed hospitalizations are exactly what one would expect. Deaths are about 30% higher than what one would expect from the actual CAN probabilities but fairly good perspective. Whereas for the independents and unqualified groups, this is a high-risk subset. Hospitalizations are off by 50% and deaths are under-predicted by almost 130%.

So, to develop High Needs High Risk 2 and try to obviate some of the problems of under-predicting for high-risk populations, we started with the target population of using fiscal year ’17 veteran users with one or more face-to-face VA diagnoses, an age range that encompassed all the possible veteran users that they had positive VA costs, and were alive at the end of the index year; that is, entering the period over which they could be experiencing LTI.

We excluded those who were in paid VA nursing home care for more than 90 days. Those that were identified by the Residential History File in being in a long-term institution at some point during the index year. And we excluded individuals that were currently enrolled in hospice, as well.

The outcome was two-year long-term institutionalization as defined by the Residential History File, which incorporates Medicare claims and MDS data, as well as VA data, to identify individuals who’ve had more than 90 days in an institution, their definition for long-term institutionalization.

For that cohort in fiscal year ’17, there were 62,000 episodes of long-term institutionalization; 371,000 deaths; and a little over 300,000 deaths for individuals who did not experience a long-term institutionalization prior to death. And the total veterans after all these exclusions was about 5.5 million, or about 1,000,000 less than the actual VA users for the year.

Our approach to high-risk LTI identification was to start from the large population and identify independents around qualify and high need high risk veterans. There’s some substantial overlap of the two but that amounted to about 450,000 veterans, or about 8.3% of the source population at elevated risk. Everybody else was considered to be at lower risk.

We then separately estimated the HNHR2 model on these two segments - elevated risk and low risk - and then, picked thresholds for those separate segments that would produce a number needed to screen of eight or a death in LTI positive predictive value of 0.5. Those were the efficiency criteria we used. And with those criteria and the separately estimated models, we could use a threshold of 6% for LTI risk in the elevated-risk group and a 7% threshold in the lower-risk group, and that identifies the group at high risk that is to be targeted in the RECAP pilot.

The way that we got there, we started with the Choose Home model, which had a target of positive predictive value of 0.5 for LTI or death. Estimated arms are fiscal year ’17 index populations that positive predictive value identified 66,000 individuals. It identified 3,900 episodes of long-term institutionalization where the VA paid for it so, it was available in VA data. That’s only 6% of the total LTI but it did meet the positive predictive value criteria with a number needed to screen about double or the goal.

Adding in Medicare data to define the outcome of long-term institutionalization and using a threshold of 7% risk or LTI identified a little under 120,000 individuals, a substantial increase in the amount of LTI identified. The sensitivity was about 23% with the target positive predictive value and number needed to screen.

The two-part model stratification with elevated risk and low risk separately when using the same threshold increases the number identified further to the 157,000, picks up an additional 4,000 LTI, and raises sensitivity to 0.3 with relatively little change in the efficiency criteria.

We then added additional covariates and expanded the diagnostic code and then, added the JEN Frailty Index, as well, with some modest improvement in sensitivity.

We then added Medicare data for the medical comorbidities with a one-year lookback and used the JEN Frailty Index coded with both Medicare and VA diagnoses. That increased the population, further increased sensitivity another 2%, and again, was able to maintain the same number needed to screen.

Top rate in real time, we had to incorporate data lags for the Medicare data. So, we accommodated that by extended the lookback period for IH qualification and for scoring the JEN Frailty Index to two years, and that was accommodating a six-month data lag. Using the same thresholds, that increased the sensitivity a little bit; again, maintaining roughly the same efficiency criteria.

We added VAMC fixed effects with very little change in sensitivity. However, because we were operating below the efficiency threshold, we actually lowered the threshold for the elevated-risk group and that gave us another 3% bump in sensitivity.

So, the final performance of the model is about 37% sensitivity with a positive predictive value of about 0.46 and a number needed to screen of eight.

Having the split segments with the adjusted thresholds accounts for about 25% of the sensitivity for the same number needed to screen in the positive predictive value.

We were told by care managers that when they got the names of high-risk individuals that they thought they would use the CAN score to rank them in terms of their actual risk. Looking at actual CAN event probabilities so, this is hospitalization or death, for either the low-risk population or the elevated-risk population. So, these are same model predictive risks but low-risk model or elevated-risk model.

The CAN medians, which are the color transition, as well as the 75th and 25th centiles, have substantial overlap across the whole range of LTI probabilities. The CAN score median is rising from about a score of 80 to a score of about 85 so, those are probabilities of about 0.2. And they’re rising from about a score of 90 to a score of about 95 or probabilities of about 38% in here. But again, substantial overlap across the actual CAN probabilities.

We looked to see whether we could use the CAN probabilities, as well as coding for missing CAN - missing a CAN score - and improve the ability to identify long-term institutionalization and the short answer is one can’t use the thresholds that identify about the same number of individuals with this CAN LTI model as High Needs High Risk. There are some small groups of individuals that are jointly identified by both models and they have an LTI risk of about 12%. There’s a much larger group of individuals that are missed by that CAN LTI model; again, with roughly similar LTI risk. There’s a small group of individuals with about a 3% risk that the CAN LTI model picks up that’s not identified by High Needs High Risk 2.

And then, there’s a relatively large share of individuals that are excluded by both versions of predicting LTI risk that amount to about 60% of LTI but the actual risk in the population is relatively low; about 0.7%.

This is intended to illustrate the potential value of having a split or stratified population for estimating these logistic models. When estimated in a single population, the predicted probabilities of LTI are both relatively low and large numbers of individuals are identified.

The high sensitivity is about 26% and that’s identifying about 370,000 individuals to screen. For a similar number of individuals identified using the split populations, the sensitivity’s improved substantially, about 32%, at something akin to where the HNHR2 operates that only 17% of the long-term institutionalizations are actually identified about 10,000. But the positive predictive value and the number needed to screen are modestly better.

The next two slides show the actual model. The one observation I’ll make is that in the elevated-risk group of individuals, a number of diagnoses, as well as other variables, are not statistically significant but all are significant in the lower-risk population. And the other observation is that most conditions are in the 0.1 to 0.3 range; a few are more noticeable. That’s roughly the same order of magnitude as having a missing CAN score.

The effect of variables in the elevated-risk group are generally less than those in the lower-risk group, although that’s probably driven by the difference in intercept of the two models.

HNHR2 is calibrated on the low - elevated- and low-risk populations. The discrimination is better in the lower-risk population. The statistic is 0.89 versus about 0.77 for the elevated-risk group. Sensitivity’s better in the elevated-risk population. Sensitivity’s about 0.59 for elevated-risk compared to about 0.27 for the lower-risk at a 6% threshold.

Low risk - the odds ratios for the lower-risk variables are substantially greater for some than they are in the elevated-risk group. Most of that’s driven by the intercept; however, for some of these, such as dementia, multiple sclerosis, and Parkinson’s, the outsized share of the low risk is even in excess of what you’d expect from the - comparing the intercepts.

Interestingly, both prior LTI and prior use of SNF are significant factors in predicting future use. However, the impact of SNF is relatively similar in both the lower-risk and the elevated-risk group.

The next two slides show the prevalence of conditions to give a sense of the people that populate these two strata. The elevated-risk group is what one would typically think of as higher-risk veterans; 30% with cancer, 40% with congestive heart failure, 53% with diabetes, 17% with dementia, 22% with substance abuse disorder.

Average costs in the elevated group are about $40,000 while there are about $8,000 in the lower-risk group. The one-year CAN, again, probability is about 0.3 or a score of around 90 in the elevated-risk group. It’s a probability of 0.8 or a score of about 55 in the lower-risk group.

Interestingly, in the elevated-risk group, 52% have an acute hospital stay since having an acute hospital stay is the entry criteria to get into the elevated-risk group. The reason for this is the artifact of having the two-year lookback period so that individuals who had their hospitalization occur in the second year of the lookback period are included in the elevated-risk group that don’t have a hospitalization in the 12 months preceding the scoring date.

We did a cross - bifold cross-validation for 2017 and got roughly similar performance characteristics for both thresholds of 7 and 7, as well as 6 and 7.

We also did multitemporal performance consistency. We calibrated the model on years 13 to 15 and then, ran it for years 16 to 18 and again, for 14 to 16 and then, ran it for an index year of 17 through 19 and got similar performance characteristics. So, pretty much over the decade, the model is transportable.

When we moved from the model to production, the biggest issues were data lags. The current data lags for VA data are pretty short. Death at a facility has a little lag. DSS and fee have lags of a few weeks or a month. Medicare data, diagnostic data, has a lag of about six months. The Residential History File, in particular, the minimum data set to identify LTI, should have a lag of three months. However, for the last year, it’s been more around nine months.

We hope to shorten the data lags; however, to accommodate the data lags, because they impacted estimating SNF use, LTI use, and the two flags that were used for the elevated-risk group, we needed to do an adjustment. And the adjustment, as noted before, was to extend the lookback period to identify the independents and unqualified. We went back two years prior to the scoring date. We kept one year for the JEN Frailty Index because that’s how the index was developed but we used the maximum score, which effectively met that if your maximum score was the first day of the 12-month lookback period, you were actually going back 24 months, or two years.

We had a 12-month buffer around prior LTI and that was because of some difficulties in being able to determine whether individuals who were moving between hospital and nursing home were ever really in the community. And that was really due to the data lag issue because all of the recent status was really determined by the Medicare data.

Comparing the production model to the research model - so, the research model doesn’t have data lags. Production model incorporated the data lags. For the elevated-risk group, about a third of the variables were outside of the confidence intervals for the research model.

And interestingly, the signs of obesity and the CAN probability of one-year events flipped and the direction of the change was to increase the CAN - odds ratio for the CAN probability.

We think the reason for the flip in the sign and for the reason that the odds were actually suggesting protection from LTI is that death and LTI are competing risks. And in the elevated-risk group, the CAN model was identifying individuals that are at a higher degree of death. And that when we increased it to two years, that lowered the risk of this group and we were able to actually see the increased risk for this population.

In the lower-risk model, the CAN year one probability is still significant but the actual direction, again, consistent with lowering the overall risk, was to drop the odds a bit.

We looked at how HNHR does across facilities. Most facilities, we achieved the target efficiency. There are about 30 facilities where the number needed to screen is greater than nine. For most of those in the nine to ten range, one can adjust the thresholds and keep the number needed to screen around eight.

For some of the other facilities, the issues have to do more with structural measures of their local LTSS environment, the availability of nursing homes or the availability of home and community services. And there’s not an apparent easy threshold adjustment to bring efficiency down to a level of eight.

The percents of high risk at VA facilities increased when we ran the production model on 2020 data. Some of this is, again, adjustable by changing thresholds and some of it is actually probably structural. But the number of facilities that have 6% or more in the high-risk categories, about 22.

This [interruption]…

Dr. Dismuke: Sorry, Bruce, is this a good time to - yeah, to ask a clarifying question?

Dr. Kinosian: Yup.

Dr. Dismuke: So, actually, it’s a question with three questions imbedded so, I’ll read it to you one at a time.

Can you provide a bit more detail about how you’ve defined elevated risk versus lower risk?

Dr. Kinosian: Well, so, elevated risk was you were either independents or unqualified so, that’s hospitalization in the prior 12 months, post-acute care in the prior 12 months, two ADL dependencies, or a JEN Frailty Index Score of 6 or more. And then, two chronic conditions.

Or you met the HNHR criteria, which was a proxy we created using only VA data for independents and unqualifying criteria.

So, that’s the limited way we use high risk here. But that pretty simple set of criteria actually identifies 6% of veterans that account for a quarter of all the hospitalizations, about 50% of the LTI, a quarter of the deaths. So, it’s a pretty concentrated risk group. And then, everyone else, we moved into the low-risk category.

The other questions about C-statistics; so, we think that - well, C-statistic may not be the best way to measure discrimination here because LTI is a relatively rare event. But we think the lower-risk group, the C-statistic is higher simply because the predictors for risk are more identifiable. Whereas in the elevated-risk group, there’s a lot less characterized measures that are probably going along in that group.

So, while we can say this group is at higher risk, the model’s not really as clearly identifying who’s going into LTI and who’s not. Whereas in the lower-risk population, the model’s doing a little bit better job. Okay?

Dr. Dismuke: Thank you.

Dr. Kinosian: Alright. And the observation that with millions of veterans, statistical testing adds relatively little is also correct.

Alright. So, this shows the flow of the populations, the high-risk group. This is for fiscal year ’17, the high-risk group for nursing home placement’s about 3.3% of the population. About 41% of that group were non-institutional care users; 24% got personal care services. It had 33% die over the next two years; about 12% had an LTI event; about 46% had LTI or death; and the costs were roughly $42,000 a year. In fiscal year ’18, they accounted for about $8 billion of spending.

And then, individuals who had risk thresholds that were between 2% and 6%, or 2% and 7%, depending on their segment source, were considered to be moderate-risk; again, for this group, about an 18% risk of death over the subsequent two years.

Those risk strata were placed in a population pyramid that’s used to identify cost so, costs descend as you go down the pyramid. Non-institutional care use; so, non-institutional care use rises as you go up the pyramid so, 40% of non-institutional care is deployed for this high-risk group and about 2% for the low-risk group. And then, a set of population interventions that are targeted at individuals at high risk or those who are moderate risk.

Relatively few interventions, other than preventive care’s part in this pyramid structure, is targeted for those at low risk. The problem is that about a quarter - while 42% of LTI does come from a high-risk group, about a quarter of LTI comes from this lower-risk group.

For new LTI in 2019, 65% of individuals did receive some kind of non-institutional care service prior to their entering a nursing home, which is an improvement over prior years. But only 22% of those individuals actually got personal care services.

So, one question is whether resources really should be deployed upward and taken away from this group or whether these individuals are being clinically targeted.

Certainly, the actual targeting of personal care services in the current system is for the high-risk group. Nearly half of all personal care services are used by high-risk veterans.

It’s also apparent that since only 20% of high-risk veterans actually get personal care services, and that’s half of the total, that there’s not enough personal care services in other tiers to actually develop - devote resources to the rest of those who aren’t getting them.

More important is that receipt of personal care services or non-institutional care is itself a marker for long-term institutionalization. So, this shows the low-risk segment, the elevated-risk segment. Blue are the observed LTI risks. So, in the low-risk segment, the LTI risks are really pretty low. The predicted LTI risks are also pretty low and pretty close to the observed risks. And since the buckets here are huge, that also doesn’t mean a lot.

The non-institutional individuals who have - or at low risk and do not receive non-institutional care have risks that are roughly equivalent to what has been predicted by the model for those who have received non-institutional care where the LTI risks are actually substantial in this last bucket, which is probably predicted probabilities in the range of 4% to 5%. Have an actual LTI risk of about 10%, or about nearly double, and certainly well within the range of individuals who are being targeted in the elevated-risk segment.

And we’ll talk about this if we have time. But one of the issues with whether to include non-institutional care is one of the risk factors in the model. We opted not to because the model was really screening in the absence of non-institutional care. But there’s a clear signal from non-institutional care views and LTI risk.

Over time, individuals who rise up the pyramid cost more; those who stay the same can get costly. The interesting thing here is that VA has about 15% of its long-term institutional group leave and wind up in lower tiers in the subsequent year. And this is about triple the usual community reversion rate of people who actually trip the long-term institutionalization \_\_\_\_\_ [00:40:51].

And this set of flows just shows that while there’s more total flow up into higher-risk tiers; for example, for moderate and low risk compared to the E-flux from high-risk mortality is really making up the difference and that over time, these populations have tended to be relatively stable.

The model works as an identifier for hospitalization. It’s not just long-term institutionalization.

Here’s a high-risk model with the thresholds of 6 and 7, it identified scores for the end of fiscal year ’17. It identified 80,000 hospitalizations in fiscal year ’18. And that’s about 11.3% of all the hospitalizations with a positive predictive value of 0.44. The independents or unqualifying criteria is about a quarter of hospitalizations, positive predictive value of about 0.41. And then, as you can see, within that elevated risk tier, as you go up the probability score, you get higher levels of sensitivity within that group; lower sensitivity across the whole group because you’ve excluded all the hospitalizations in the low risk.

The relevant issue, I think, is that these kinds of positive predictive values of about 0.41 and 0.44 is roughly the same level as a CAN score of about 0.41 - or a CAN score of 97.

We’ve used HNHR2 as a risk stratifier outside of Independents at Home qualifying criteria. So, independents at home qualifying criteria were developed for the Independents at Home demonstration, which is a test the VA use; HBPC model in the Medicare population. That demo showed that HBPC is cost-effective for that very high-risk group.

The question became; can you identify groups that are not Independents at Home qualified for whom HBPC may also be cost-efficient? And we found that for non-independents that are unqualified veterans, those who were at high risk - so, high risk but not IHQ - regardless of whether they’re key priority group for catastrophically disabled or not catastrophically disabled, HBPC can still be cost savings either in terms of VA total costs or direct costs. This graph shows the direct costs and it’s about a 30% savings for the catastrophically disabled high-risk group and about a 50% savings for the high-risk not catastrophically disabled group.

Whereas for the moderate-risk groups in HBPC, the cost of the interdisciplinary team’s a little bit greater than what a matched comparison group would cost.

So, future issues and things that we need to deal with. We miss 60% of new LTI and need some ways to identify those individuals, as well. There are some areas that - in the system that have a far poorer performance than the system as a whole and some adjustments beyond thresholds will probably be required for those sites. None of those sites are involved in the RECAP pilots that are being currently run.

The model misses things that we know affect long-term institutionalization, probably the main drivers; actual function, family support, social determinants of health.

Don’t incorporate episodic clinical assessments; that is, one can see by looking at those who receive non-institutional care, there is a very strong signal in the receipt of these services in terms of LTI risk.

One of the issues with process measures such as MDS or OASIS is clinical assessments to get measures of function. Have to do both with timing relative to the actual scoring time, as well as their episodic and then, somewhat selective nature. The logistic model does poorly with that kind of missing data. There are complicated ways in which one can incorporate that into logistic models.

And then, it’s not clear what future nursing home behavior is going to look like. Certainly, 2020 had a substantial shift in preferences in behavior with regards to nursing home use and whether post-vaccine it is going to revert to the behavior when these models were developed isn’t clear or if fear of a new pandemic is going to lead to greater desire for less congregate long-term living.

So, our next steps that we’re planning are to figure out how to incorporate MDS, OASIS, the clinical measures, some health factors, as well as the Area Deprivation Index, into the model. We’ve done some exploring of machine learning models. XGBoost was what we tested, as well as some latent class models and then, adding non-institutional care as a clinical assessment proxy.

So, I think the takeaways would be that HNHR2 is a useful risk stratification tool for LTI, hospitalization, death, and cost; that the multi-part estimation of a risk model can improve model performance; and that the current CMS-VHA arrangements allow for incorporating Medicare data into operational analytic tools, although you have to pay attention to data lags when doing that.

So, questions or comments?

Dr. Dismuke: Thank you so much, Bruce. So, we have a question that came in, I think, in the chat box that Maria passed on. And they state that they believe that these P values may be moot here because you pretty much have the entire population, the data. What other inference can be made to any larger population?

And then, second, they say, “Within as large as millions, most statistical tests will show significance for pretty small differences or effects anyway.” So, I don’t know how you want to respond to that.

Dr. Kinosian: Well, I think the millions is, in some ways, more an issue on the calibration for the low risk because the buckets are so large. The actual numbers that we’re looking at for these events are pretty small. We’re looking to identify - to sort out far more limited groups, to identify those that’ll be winding up going into long-term institutionalization.

Dr. Dismuke: Thank you, Bruce. Well, I’m waiting to see if more questions come in. But I actually have a question for you while we’re waiting for other questions. How did you choose the comorbidities? And did you see that Medicare data added many more comorbidities that were not already taken into account in the VA data?

Dr. Kinosian: Okay. So, the answer to the second is; in terms of identifying comorbidities in individuals, the Medicare data adds substantially to the number of comorbidities a given individual would have. Earlier times, when we’ve looked at this - so, this is like the mid-2010s - about two-thirds of the diagnoses would come from the Medicare side, about a third from the VA side.

In scoring models such as the JEN Frailty Index that are diagnosis-based, adding the Medicare data raises the thresholds that one needs to get similar risks in a population by about one point, which is about a 20% bump.

So, it has a substantial effect. There’s a lot of diagnostic data that comes in on the Medicare side.

How we chose the comorbidities in the model, we used the ones that were in the original Choose Home model, and that was developed by a variable deletion when the Providence COIN developed them. And then, we added the [interruption]…

Dr. Dismuke: And when was that model [overtalking] developed? Sorry.

Dr. Kinosian: Choose Home?

Dr. Dismuke: Yeah.

Dr. Kinosian: Yeah, the Providence COIN developed Choose Home for the Choose Home demonstration, which was done in 2018 and ’19. So, that was the predecessor to the RECAP project.

Dr. Dismuke: And I have another question for you, also. I saw that you had a model that included head injury, and I actually do research in the area of traumatic brain injury. And I know that in that case, you can have very young veterans who are in rehabilitation and long-term care facilities who - and I wonder if you’re seeing patterns that are different between, for example, younger veterans who may have had major injuries coming from the Department of Defense versus your older veterans with all their aging comorbidities.

Dr. Kinosian: Well, I mean, their clinical courses are certainly different. I think if you noticed back, the actual - where did we go? Head injuries actually weren’t significant for the elevated-risk group and that would sort of make sense because those young individuals wouldn’t necessarily have all the comorbidities that would get them into the IHQ group. However, it was significant for the lower-risk group.

When the original Choose Home model was estimated, if I recall, head injury wasn’t significant but it was felt it needed to be put in to make sure that those individuals - you know, younger individuals who need long-term institutionalization would be included. And I think it wasn’t significant, overall, mostly driven by risk from this elevated group. Then, when you separate it out, you can see that for the lower-risk group without a whole lot of more traditional medical comorbidities, that it is significant, for example.

Dr. Dismuke: Thank you. Yeah, I just picked up on looking through that head injury because of my own work there. Very, very fascinating.

I have another question. Great presentation, thank you. Can you talk a bit about how information from HNHR2 makes its way to clinicians when they make decisions about referring patients to home- and community-based services?

Dr. Kinosian: Well, right now, it doesn’t. The idea to use HNHR2 is as the back end to a high-risk registry that care managers at the RECAP sites will see. So, they’ll have the actual probabilities for - LTI probabilities that they can use for rank order individuals that they need to screen for home community services.

So, the current idea is not to put this in the Primary Care \_\_\_\_\_ [00:55:07] Act and so, this’ll be like another score along with the CAN score. It’s sort of more of a back-end way to identify people than the names going on a registry for care managers.

And then, separately on the research side, if one wants to get this - we need to work out a way in which this can become - make available to other research groups. And we have ways and get back to take some of our research products and make that available to the larger community.

And then, have we looked at regional variations? Yes, that was - where are we? Here. So, this is the distribution of how the model performs at different VAMCs. And in some, it’s the number needed to screen is between 10 and 11 and some, it’s greater than 11. And in some VAs, the high-risk share isn’t 3%; it’s actually 5% or 6%.

We’ve also aggregated these up to VISNs when you aggregate a bunch of medical centers and the differences narrow, although there are some VISNs that have a higher share of high risk than others. Alright?

Dr. Dismuke: And I see maybe a collaborator of yours is saying that the HNHR2 are available to sharing from Getback at Getback@VA.gov at the - and are currently available at the FYI level for all veterans who used VHA.

Dr. Kinosian: Right.

Dr. Dismuke: And that’s coming from Orna?

Dr. Kinosian: From Dr. Intrator, yup.

Dr. Dismuke: Intrator, yes. Wonderful. Well, we’re two minutes to the top of the hour so, I don’t see any other questions right now but people can - is there a contact information for you, specifically, that you would like to give?

Dr. Kinosian: Well, BruceKinosian@VA.gov. You know, it’s in the global. Or send questions to Getback, too.

Dr. Dismuke: Okay. And would you like to have any wrap-up? Final words before Maria takes over?

Dr. Kinosian: No, I think the takeaways were pretty clear. But the nice thing about this is with the work that we’ve been able to do with CMS and leadership at DACO, the long lags in Medicare data have really been shortened. And so, now, all that data can be incorporated into real operational tools. I think that’s the main point of this; that prior, the lags were too great to make it practical but now it can be. And we hope to make the lag shorter.

Maria: Well, I want to thank you, Dr. Kinosian, for preparing and presenting today. And thank you, Dr. Dismuke, for moderating the questions. And thank you, everyone, for joining us for today’s HSR&D cyberseminar.