Contents available at ScienceDirect

Diabetes Research and Clinical Practice

journal homepage: www.elsevier.com/locate/diabres

Predicting different factors that affect hospital utilization and outcomes Among diabetic patients admitted with hypoglycemia using structural equation modeling

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A R T I C L E I N F O

Article history:
Received 16 April 2019
Received in revised form
8 May 2019
Accepted 23 May 2019
Available online 29 May 2019

Keywords:
Hypoglycemia
Diabetes
Utilization
Hospital length of stay
Costs of care
And structural equation modeling

A B S T R A C T

Background: Hypoglycemia (HG) is a common complication among diabetic patients. Many diabetics who experience HG are admitted to hospitals and usually utilize more resources. While plenty of studies examined multiple HG risk factors, there is limited knowledge about the correlation between different risk factors of HG and their impact on utilization.

Objective: To identify key factors influencing utilization among diabetic HG patients and to examine the mechanisms and interactions between those factors.

Design: A quantitative, non-experimental, and retrospective design that is based on the selection of the study subjects from the Healthcare Cost and Utilization Project National database for the years of 2012–2014. We employed Andersen Behavioral Model of Health Services Use as the main framework for this study.

Results: Structural Equation Modeling was used as the main multivariate statistical method for the analysis. Total sample size was 4822 patients. We found that diabetes complications, renal disease, hypertension, and high Charlson comorbidity index score had the strongest impact on length of stay (LoS) as well as total charge. Geographical location of patients strongly influenced total charge. Age had an indirect impact on LoS and total charge.

Limitations: The use of secondary data seems to be the primary limitation for this study as some relevant risk factors for hypoglycemia were not available in the database.

Conclusions: This study examined the multilevel character of different factors leading to high utilization of healthcare services among HG patients admitted to hospitals. Findings of this study help clinicians and policy makers to formulate policies and protocols that aid in providing efficient care to HG patients with less utilization of resources.

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https://doi.org/10.1016/j.diabres.2019.05.031

1. Introduction

Diabetes is a national health problem in the U.S. that affects about one in every ten Americans, which is about 30 million people [1]. That number is expanding as there are about 1.7 million new cases of diabetes diagnosed annually [2]. From an economic perspective, diabetes imposes a substantial burden on society. In 2017, the estimated total economic cost of diabetes care in the U.S. was $327 billion [3]. Medical expenditures incurred by diabetic patients are estimated to be $13,700 per year, which is approximately 2.3 times higher than non-diabetic patients [4], with an average patient's out-of-pocket expenditure of $1373 per year [5]. Hospital inpatient care for diabetic patients is considered to be the largest component of their medical expenditures, which is about 43% of the total medical costs related to diabetes [4]. According to the American Association of Clinical Endocrinologists (AACE) and American Diabetes Association (ADA), more than 20% of all hospital inpatient days were related to the care of diabetic patients [6].

Hypoglycemia (HG) "a condition characterized by abnormally low BGL, usually less than 70 mg/dl" is a common complication among diabetic patients [7]. The incidence of HG episodes is estimated to be 20 times per year, according to a 2015 systematic review and meta-analysis [8]. Although many of these attacks are self-managed, sometimes patients experience severe symptoms that require hospital admissions. In 2011, about 300,00 ED visits in the U.S was because of HG among diabetic patients [2]. About one-third (29.3%, CI, 21.8–36.8%) of these cases need to be admitted to hospitals for further management, according to a study published in the Journal of the American Medical Association (JAMA) [9]. In general, many studies found that diabetics with HG have a 3-times higher chances of being hospitalized [10–14]. Furthermore, utilization of healthcare resources among those admitted cases tend to be higher than others who do not have HG. Their LoS is usually 3 days more than others [15–18]. Also, the cost of treatment of those cases is significantly higher [15,19,20].

The literature is loaded with multiple risk factors that contribute to the development of HG events that require hospitalization. These studies also show that different factors play different roles in the severity of the attack as well as the prognosis and outcomes [21]. However, there is very limited knowledge about the correlation between different risk factors of HG and their impact on utilization of healthcare services. Therefore, the primary goal of the study is to identify different factors influencing utilization among those patients and to examine the mechanisms and interactions between those factors. Furthermore, the study seeks to explore the magnitudes of the main effects of each of the predictor variables and their interaction effects on health services use.

2. Theoretical framework

Ronald M. Andersen developed a Behavioral Model of Health Services Use (BM) in the 1960s that is a highly respected model to be used as a framework to identify predictors of health care utilization [22–27]. Since the BM was introduced, it has frequently been used in different studies that examined the level of health care utilizations [28]. These studies investigated a broad spectrum of diseases such as diabetes, hypertension, depression, heart diseases, cancer, and many others, with the level of patients' utilizations of healthcare services. While the BM has been used to examine wide varieties of illnesses including diabetes, it was not applied to examining factors influencing HG care utilization.

The BM is a robust framework that categorizes different individual determinants of health services utilization into three components: Predisposing (P), enabling (E), and need-for-care (N).

Predisposing component (P): Ps are "individual characteristics which exist prior to the onset of specific episodes of illness" [22]. These characteristics are primarily social and demographic factors, which perhaps differ from one person to another and hence impact the level of utilization of medical services [27]. This study included age, gender, and ethnicity under (P) because they have been considered in many studies that examined risk factors of HG [29]. The study also included other factors such as dementia, depression, tobacco use, alcohol use, and drug abuse as they are usually considered in different studies that employed the BM [28].

Enabling component (E): Es are factors that enhance or inhibit the use of healthcare services for people who already have the predisposing component [23,30]. Medical insurance type, socio-economic status, geographical location of the patient, and the geographical location of the hospital area all relevant factors considered in this study under E as they have repeatedly shown a strong influence on utilization for patients with HG [29].

Need-for-care component (N): is the level of illness perceived by the patient [26]. Regardless of the presence or absence of the previous two components, once N present, patients start to seek medical care and therefore it is considered the most important component that lead to healthcare services use [22,31]. This study included the following common factors that impact the level of utilization among HG patients: DM complications, type of DM, BMI underweight, hypertension, liver failure, kidney disease, uncontrolled DM, and the Charlson Comorbidity Index (CCI) (Table 1).

3. Methods

We used a quantitative, non-experimental, and retrospective design in this study that is based on the selection of the study subjects from the Healthcare Cost and Utilization Project (HCUP) National database for the years of 2012, 2013, and 2014. Using the International Classification of Diseases Ninth Revision (ICD-9) diagnostic codes, the study only included adults 18 older, who presented to ED with T1DM or T2DM, and have HG. Since gestational diabetes is beyond the scope of this study, pregnancy cases were excluded from this study. A detailed description of the sample and the variables used is described in details in a previous published article, which used Decision Tree Regression (DTREG) analysis [32].

Initially, we determined descriptive statistics of the data using the SPSS software and examined the presence of any missing results. Afterward, we conducted correlation analysis

Table 1 – List of study variables.

Predisposing	Enabling	Need-for-Care	Utilization	Outcome
1. Age 2. Sex 3. Ethnicity 4. Dementia 5. Depression 6. Tobacco use 7. Alcohol use 8. Drugs Abuse	1. Insurance status 2. Socioeconomic Status 3. Hospital Location 4. Patient Location	1. DM Complications 2. Type of DM 3. BMI underweight 4. Hypertension 5. Hyperlipidemia 6. Liver Failure 7. Renal Disease 8. Uncontrolled DM 9. Cancer 10. Charlson Comorbidity Index (CCI)	1. Hospital LoS 2. Cost	1. Severity of the adverse outcome

among all variables under different component. We excluded highly correlated variables (>0.9) to avoid multi-collinearity problem in the model. Then, Structural Equation Modeling (SEM) was used as the main multivariate statistical method for the analysis. This is because SEM is a very versatile method that allows for the examination of latent constructs with multiple indicators; accounts for measurement errors; and conducts Confirmatory Factor Analysis (CFA). Moreover, because this study employs the BM, multiple hypotheses needed to be examined, and SEM effectively served this purpose. Another advantage of SEM is that it can establish causal sequence and confirm the stability of the measurement model over time. For this study, the IBM® SPSS® Amos Graphics 22 software was used to construct the measurement models. Then, CFA was conducted to test the construct validity of the measurement models and make any modifications based on the results. Lastly, a structural equation model was performed, based on the BM, and then analyzed by the goodness of fit statistics of the model.

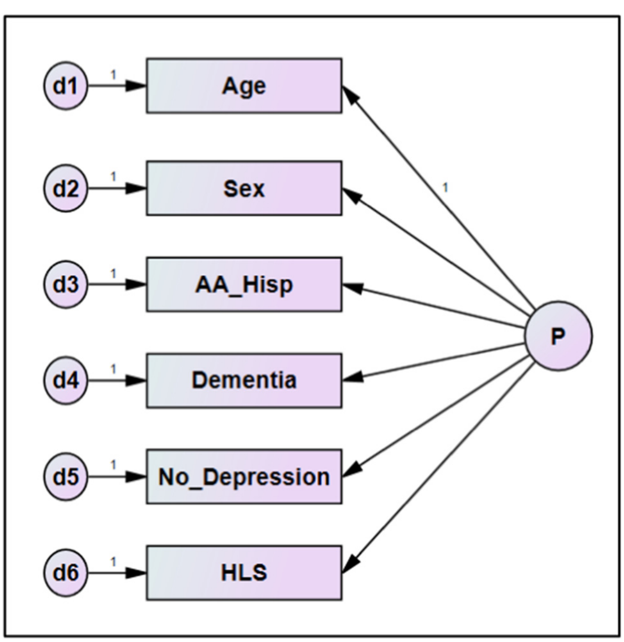

Fig. 1 – Measurement Model for the Predisposing Component (Risk Propensity as an Exogenous Latent Variable).

3.1. *Measurement models*

Measurement models illustrate the relationships between latent constructs and their indicators. The model validation process included validating each measurement model developed, followed by a causal model in the SEM to determine the integrity of the proposed causal model.

The first component is the predisposing component or risk propensity profile (a latent exogenous variable). As a latent construct, risk indicators including age, gender, ethnicity, depression, dementia, and healthy lifestyle (HLS) were coded consistently in the same direction. Factors with higher scores were considered to have an increased in the risk propensity (see Fig. 1).

Next is the enabling latent construct, which includes four indicators as shown in the following illustration (see Fig. 2):

N is assumed to be affected by P or E, and therefore, N was categorized as an endogenous variable. The following diagram shows the measurement model for N (see Fig. 3):

Based on the BM, a Structural Equation Model with the Measurement Models was proposed for LoS and another one for total charge. The models were formulated to examine the inter-relations between P and E on N as well as their impact on U, which are represented by LoS and total charge (see Figs. 4 and 5):

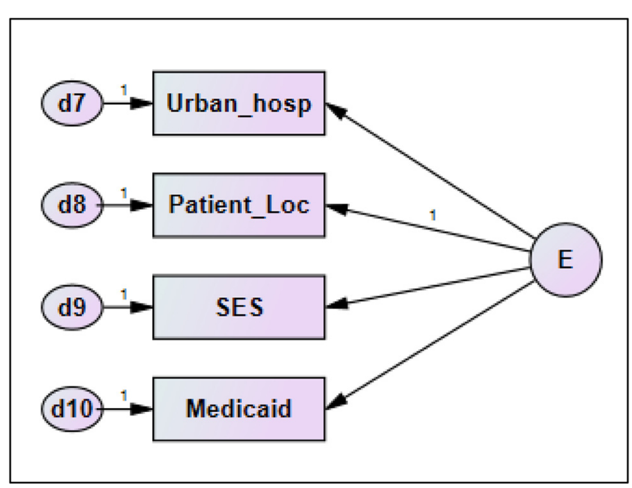

Fig. 2 – Measurement Model for the Enabling Component (Exogenous Latent Variable).

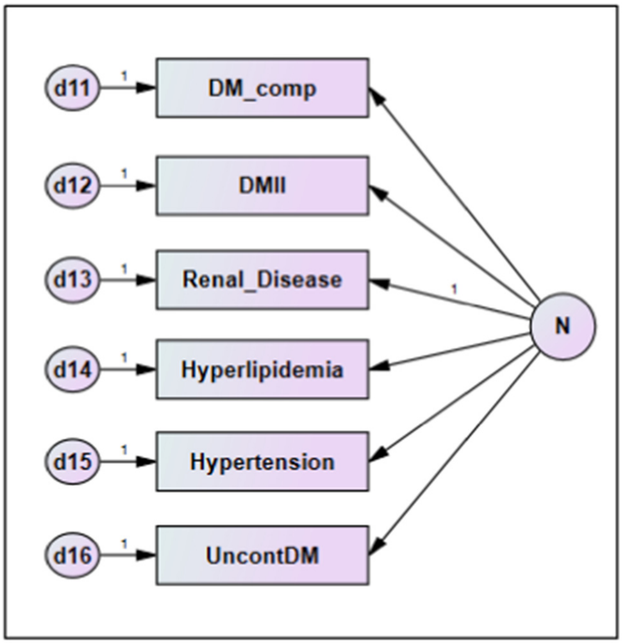

Fig. 3 – Measurement Model of the Need-for-Care Component (Need-for-care as an Exogenous Latent Variable).

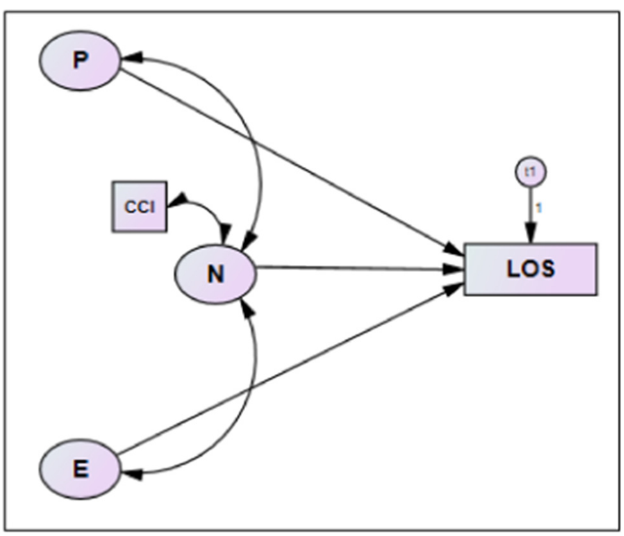

Fig. 4 – Andersen Behavior Model of Healthcare Utilization: Predictors of Hypoglycemia LoS - Simplified.

As is shown in the above figures, P and E are correlated with N. Also, all three components (P, E, and N) have a direct impact on LoS or total charge. CCI is a control variable that is correlated with N. This configuration was constructed based on the findings of previous studies of HG that show how different factors that were inter-related with each other impacted the level of utilization and outcome among HG patients.

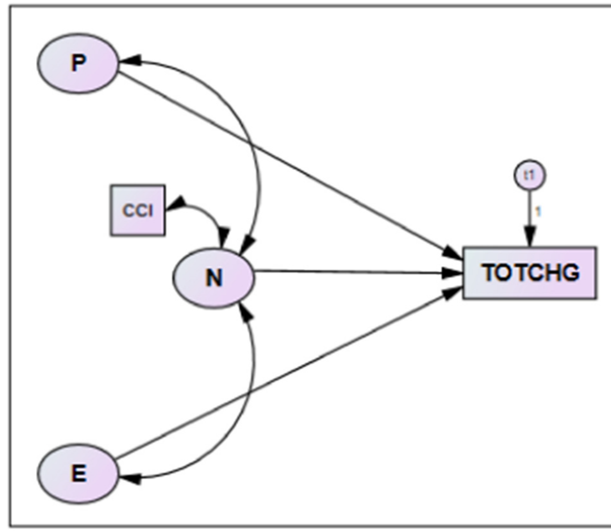

Fig. 5 – Andersen Behavior Model of Healthcare Utilization: Predictors of Hypoglycemia Total Charge - Simplified.

4. Results

Total sample size was 4822, which is sufficient for SEM. Descriptive statistics revealed some missing data in few variables (sex, AA_Hisp, patient_loc, Medicaid, and SES). However, the missing data for each of the variables was not more than 5% and we replaced them by the calculated mean. Then, we inspected the normality for each variable and all were normally distributed except for LoS and total charge. Outliers among those two variables were less than 0.3% of the data, and achieve normality, we excluded them. We also examined skewness and kurtosis indices for each variable. The SEM guidelines consider absolute values for skewness >3.0, and >10.0 for kurtosis extreme and not fit for the analysis [33,34]. Only three variables under_wt, liver_dis, and cancer showed extreme skewness or kurtosis and they were excluded. Last, correlational analysis revealed that no variable is highly correlated with the other.

4.1. *Confirmatory factor analysis (CFA)*

This study has three latent variables: P, E, and N and all are exogenous variables. A separate measurement model was developed for each of the latent variables and then independently validated by CFA.

4.2. *The predisposing component (P) or risk propensity*

As mentioned earlier, the P construct was composed of six indicators: age, sex, AA_Hisp, dementia, depression, and HLS. Using AMOS Graphics 23, a CFA model was formulated:

As depicted in Fig. 6, all indicators had a strong positive correlation with the latent variable P except for sex and AA_Hisp where the correlation was very weak. However, all indicators for the construct were statistically significant at <0.05 with critical values >1.96 except for sex, where P = 0.81

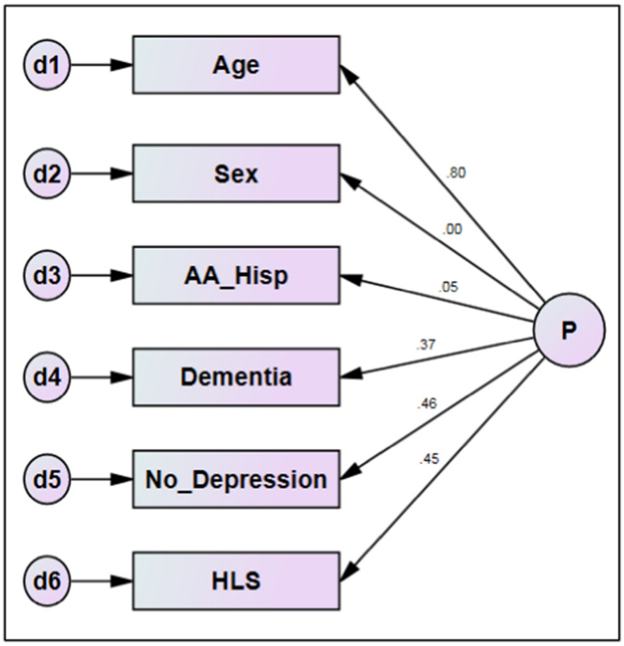

Fig. 6 – Measurement Model for the Predisposing Component (An Exogenous Latent Variable) - Generic.

and CR = 0.24. Therefore, those two variables were excluded from the original model in the modified/nested model (see Fig. 7):

As is shown in the above-modified model for P, all indicators had a strong positive correlation with the latent variable P. In addition, there was a correlation between HLS and no_depression, which indicated an indirect effect on the latent variable P. The modified model had all critical ratios >1.96 and they were statistically significant at $p \leq 0.05$.

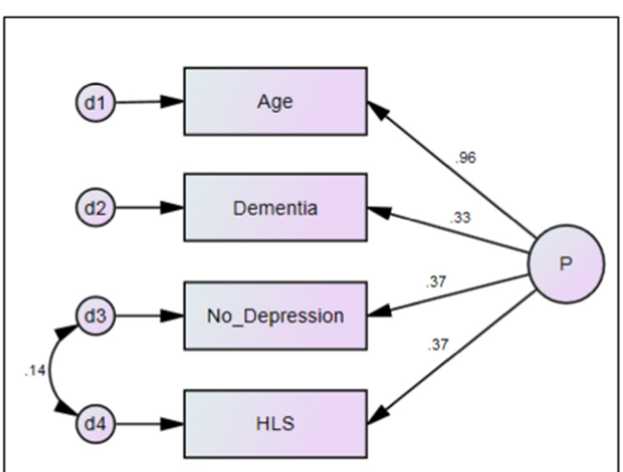

Fig. 7 – Measurement Model for the Predisposing Component (An Exogenous Latent Variable) - Modified.

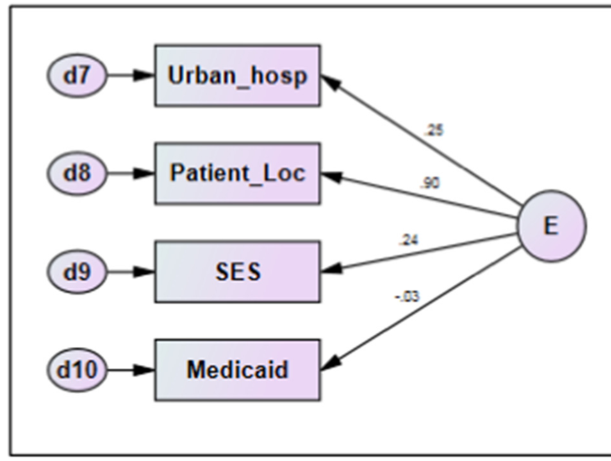

Fig. 8 – Measurement Model for the Enabling Component (An Exogenous Latent Variable) - Generic.

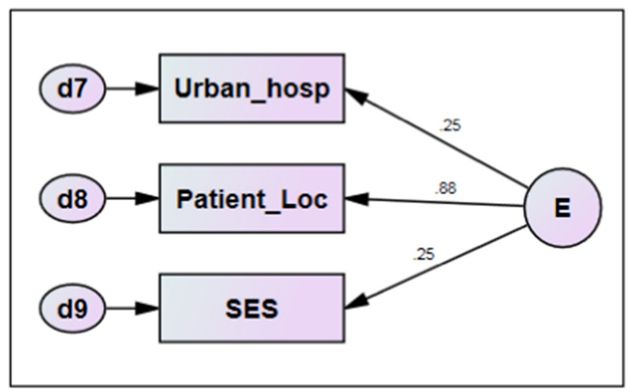

Fig. 9 – Measurement Model for the Enabling Component (An Exogenous Latent Variable) - Modified.

4.3. *The enabling component (E)*

The E construct was composed of 4 indicators: urban_hosp, patient_loc, SES, and Medicaid. Using AMOS Graphics 23, a CFA model was formulated (see Fig. 8):

As is shown, all indicators had a strong positive correlation with the latent variable E except for Medicaid, where the correlation was very weak and adverse. In addition, all indicators for the construct were statistically significant at <0.05 with critical values >1.96 except for Medicaid, where P = 0.171. Therefore, the variable "Medicaid" was excluded in the modified model (see Fig. 9):

The above modified model for E shows that all indicators had a strong positive correlation with the latent variable P. In addition, the modified model had all critical ratios >1.96 and they were statistically significant at $p \leq 0.05$.

4.4. *The need-for-care component (N)*

As mentioned earlier, the N construct was composed of six indicators: DM_comp, DMII, renal_disease, hyperlipidemia, hypertension, and uncontrolled_DM. using AMOS Graphics 23, a CFA model was formulated:

As shown in Fig. 10, all indicators had a strong positive correlation with the latent variable N except for uncontrolled_DM, where the correlation was negative. In addition, all indicators for the construct were statistically significant at <0.05 with critical values >1.96 except for uncontrolled_DM, where P = 0.09. Therefore, uncontrolled_DM was excluded in the modified model (see Fig. 11):

As is shown, the above-modified model for N shows that all indicators had a strong positive correlation with the latent variable (N). In addition, some correlations between the indicators had been established to improve the model fit. The modified model had all critical ratios >1.96 or <−1.96 and they were statistically significant at $p \leq 0.05$.

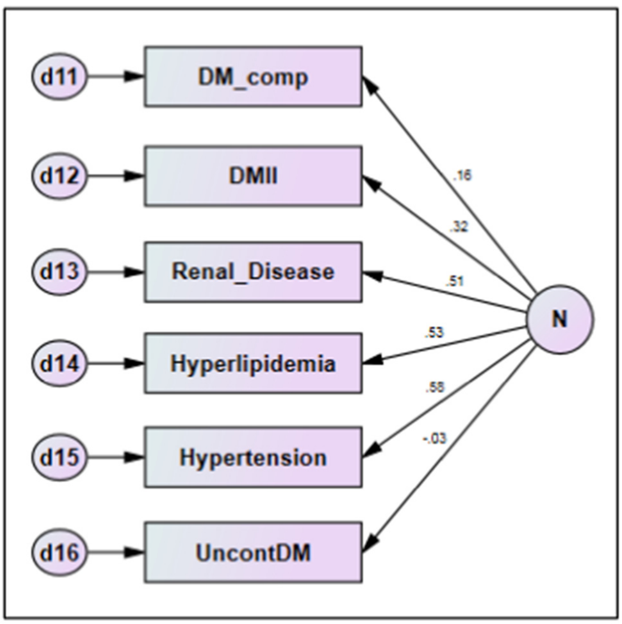

Fig. 10 – Measurement Model for the Need-for-Care Component (An Exogenous Latent Variable) - Generic.

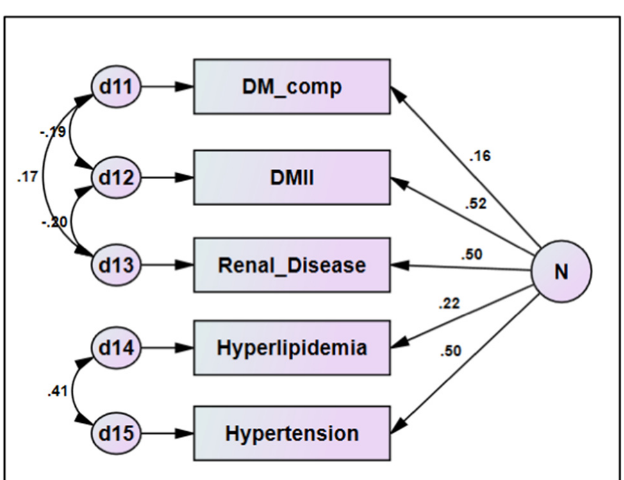

Fig. 11 – Measurement Model for the Need-for-Care Component (An Exogenous Latent Variable) – Modified.

4.5. *Structural equation modeling with the measurement models*

After revising the models for P, E, and N, two separate models were developed and examined, one using LoS and another one for total charge. The first model for LoS was constructed based on the BM (see Fig. 12):

As is shown, N had the strongest impact on LoS, P had a very weak one, while E had an insignificant relationship with LoS. Diabetes complications, renal disease, hypertension, and CCI seems to have the strongest impact on LoS. There was also an inter-relation between P and N, which indicated an indirect effect of age on LoS.

Regarding the model's goodness-of-fit, it seems that the model was not optimally fit because the likelihood ratio was 39.6. However, some indicators such as RMSEA and GFI showed that the model was reasonably fit. In addition, additional modifications can be made in the model that might improve its fit to the data.

A second model was constructed for total charge (see Fig. 13):

Similar to the LoS model, N in this model had the strongest impact on total charge. Also, Diabetes, renal disease, hypertension and CCI appear to be the strongest factors that influence total charge. However, unlike LoS, E appeared to have a moderate impact on total charge, while P was the weakest. The geographical location of patients showed a strong impact on total charge. The inter-relation between P and N was also present as well as the correlation between CCI and N. The model was also reasonably fit, as some of the indices were at the target level while others were not.

5. Discussion

The SEM analysis clearly revealed that all the three factors: P, E, and N had different impacts on LoS. N was found to have the strongest impact on LoS, while P and E had a very weak direct impact on LoS. N had the strongest impact on total charge, followed by E. On the other hand, P seemed to have a very week direct impact on total charge. When considering LoS, N showed the strongest significant direct effect on LoS, while P had a very weak but significant effect on LoS, and E had a non-significant effect. Regarding total charge, all factors showed a statistically significant impact. However, N still had the strongest effect. When examining the models, we noted that there were no inter-relations between E and N. However, there was a strong inter-relation between P and N in the LoS model as well as the total charge model (SRW = 0.25 for both models). These findings indicated indirect effects on LoS.

The results indicated that different elements in the behavior model vary in terms of their impact on the level of utilization and outcome among HG patients. It also showed that the most important predictor for length of stay and total charge was the need-for-care component. Moreover, important inter-relations were found between some components such as the predisposing and need-for-care components, which

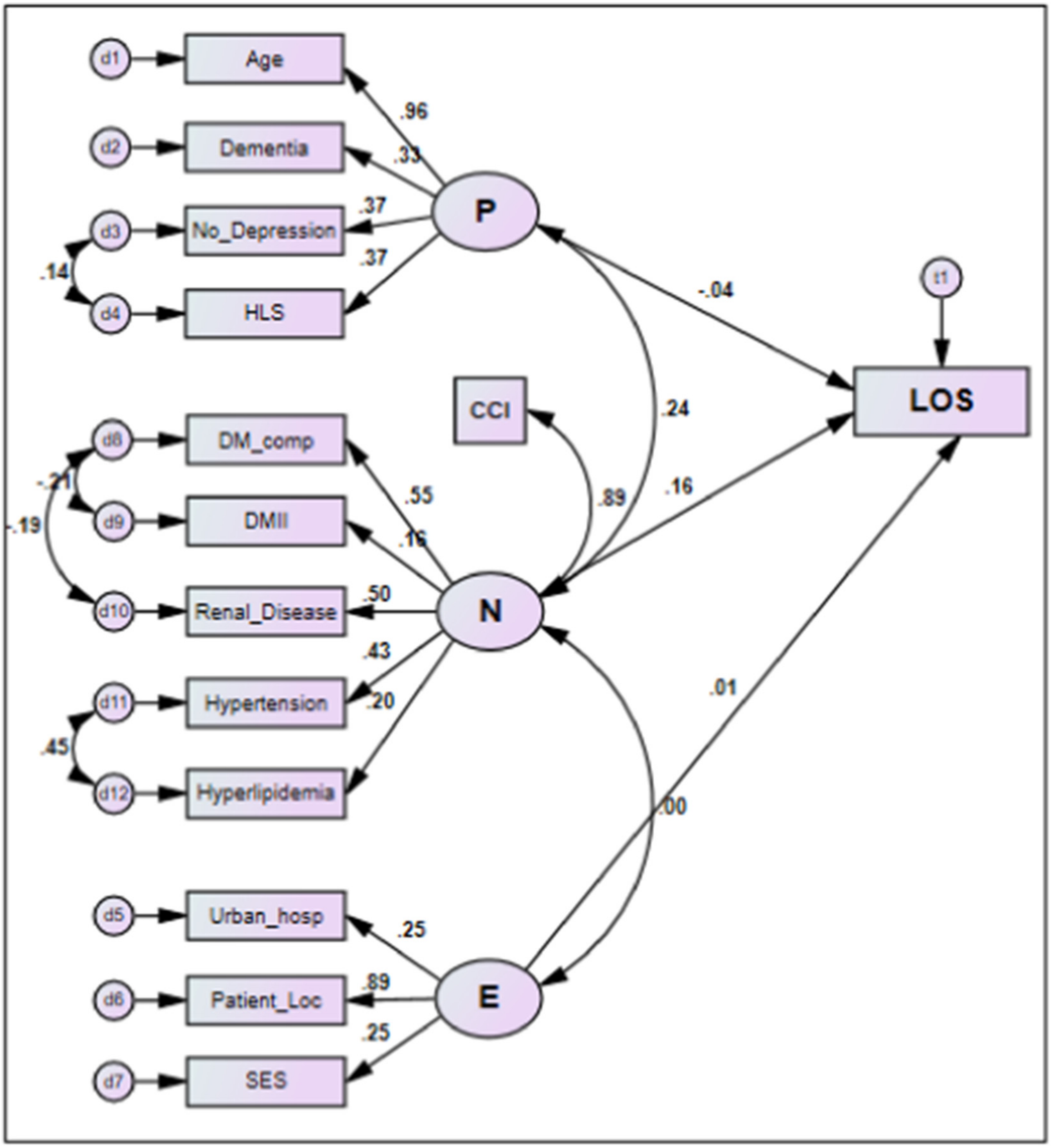

Fig. 12 – Structural Equation Model with the Measurement Models for LoS and Outcome.

indicated that these components had indirect impacts on utilization along with their direct ones.

5.1. *Impact of different components on length of stay*

Results of the SEM for length of stay did go along with the theoretical background for this study; the results showed that the three different components (predisposing, enabling, and need-for-care) had different impacts on utilization. Moreover, the results indicated that the need-for-care had the strongest effect on the duration of stay with a weight of 0.16. This mimics the classical findings of the original developer of the BM, Ronald Andersen [22,23]. The predisposing component had a smaller effect, but statistically significant impact on patients' length of stay. This means that patients with some risk factors under the predisposing component or the enabling component will likely be expected to stay longer in the hospital. For example, older patients with diabetes complications who are located in larger metropolitan areas are expected to spend more time in the hospital. Last, the enabling component shows no effect on the duration of stay among diabetic patients with hypoglycemia. This means that the socioeconomic status and geographical location do not play a significant role in determining the duration of stay in hospitals among those patients. Thus, when trying to tackle the issue of length of stay among HG patients, this study suggests a focus on issues related to factors under the predisposing and need-for-care components rather than the enabling one.

However, this study showed that the main influence on patients' length of stay is when there are factors related to illness, which was clearly demonstrated by the inter-relation between the predisposing component and need-for-care. In turn, this finding goes along with the BM, where the predisposing component had a weak direct impact on utilization but a stronger indirect impact through need-for-care. Thus, patients who have some factors under the predisposing com-

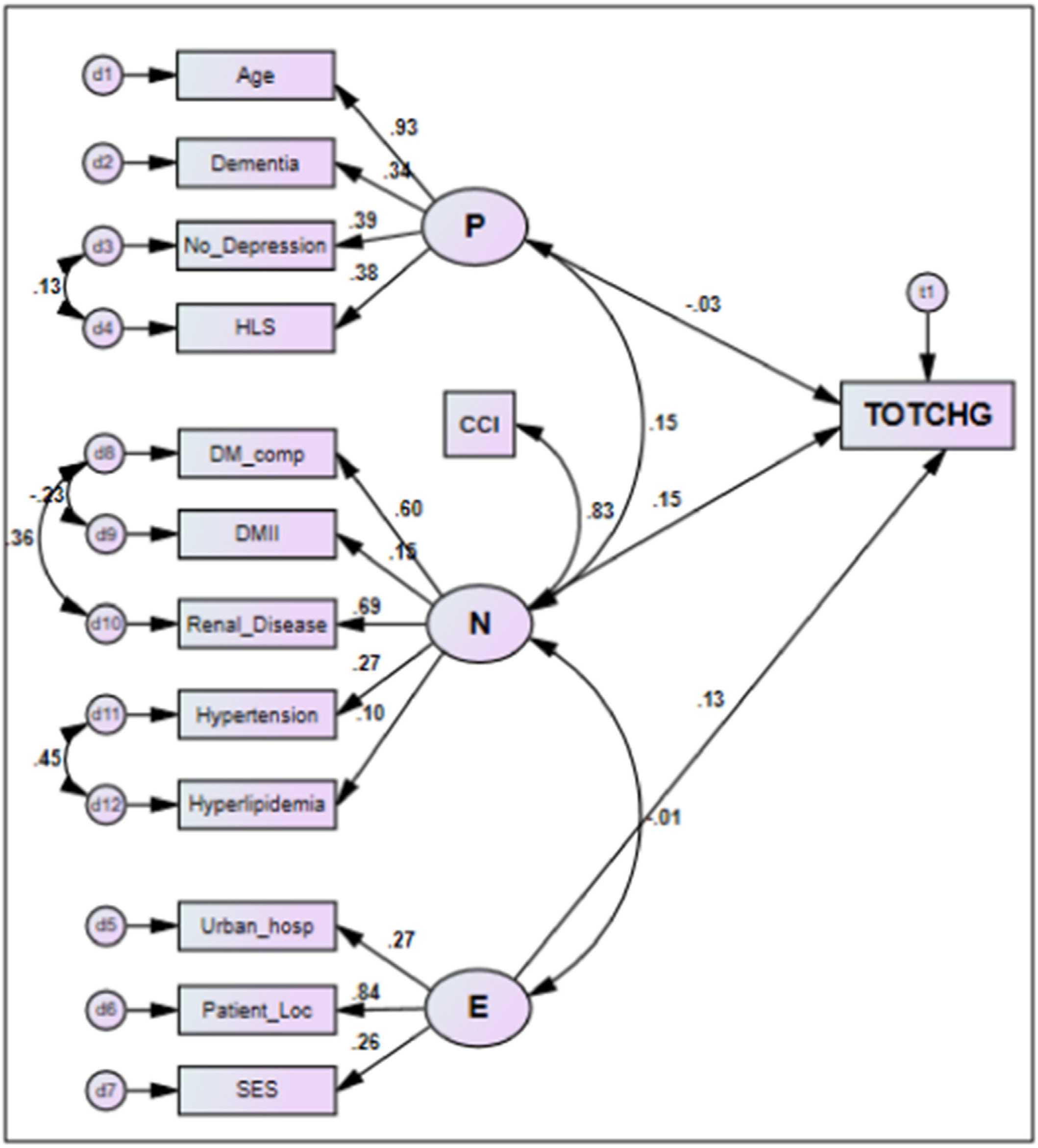

Fig. 13 – Structural Equation Model with the Measurement Models for Total Charge and Outcome.

ponent do not necessarily have longer stays in hospital unless they have other factors under the need for care component. This means that patients who have renal disease and diabetes complications are more likely to stay longer in hospitals if they are older and have dementia. In contrast, older patients with dementia are not likely to stay longer in hospitals if they do not show any diabetes complication, renal diseases, or other factors under the need-for-care component.

These findings also support the findings from other studies in which certain factors such as dementia, tobacco use, alcohol use, or drug use played an important role in patients' behavior, including adherence to medication, regular follow-ups for screening and prevention, and self-care measures [35,36]. Consequently, those patients demonstrated more comorbidities and illnesses, which lead to longer stays in the hospital.

Another finding is related to comorbidities, demonstrated as the control variable CCI. Since these comorbidities have a great impact on utilization and outcome, the CCI variable was applied as a controlled variable in an attempt to hold it constant during the statistical analysis in order to test the relative relationship among the main component in the model. The strong correlation between comorbidities and the need-for-care component shown in the results was expected because of the great number of previous studies that reported the impact of different comorbidities on the severity of illness among HG patients. This relationship provides great knowledge to healthcare providers when considering the issue of length of stay among HG patients. This is because comorbidities seem to have a major impact on the severity of illness as well as the health consequences among HG patients. Therefore, investing more effort and time in treating those comorbidities might help to reduce the severity of HG episodes as well as the duration of stay in hospitals.

5.2. *Impact of different components on total charge*

When exploring the results of the SEM for the second element of utilization, total charge, this study found once more that the three different components had different impacts on utilization, with the need-for-care being the strongest with a S.R. W of 0.17. Thus, patients who have some factors under the need-for-care component are more likely to incur higher charges, regardless the presence or absence of any other factors under the predisposing or enabling component. However, the results also show inter-relations between the predisposing and the need-for-care components. This means that some factors such as patients' age and dementia can have an impact on the total charge if there are other factors under the need-for-care component such as renal disease and hypertension present in the patient. Likewise, the DTREG results showed that the presence of renal disease and DM complication, as factors under the need-for-care component, were the key factors in defining the total charges associated with the admission. Yet, higher chargers were found to be among older patients, a factor under the predisposing component, who have renal diseases and DM complications.

Regarding comorbidities, the findings in the total charge model are similar to those in the length of stay model. The results show a great relation between comorbidities and the need-for-care component. This means that patients with a higher comorbidity index are more likely to incur higher charges for their admission. Thus, when considering reducing the charges among HG patients, it is important to invest more time and effort in treating other comorbidities associated with those patients.

5.3. *Implications*

One important finding in this study is that level of utilization is correlated with the geographical location of diabetic patients with HG. Therefore, this study suggests that more effort is needed toward residents in rural areas such as evaluating the availability of healthcare resources as well as the access to diabetes care. Another major finding of this study is the great impact of age on utilization and outcome among diabetic patients with HG. Thus, this study indicates a recommendation for decision makers to employ the Knowledge, Attitude, Preventive Practice, and Outcomes (KAP-O) framework to improve their health literacy, enhance their adherence to medications, and be more encouraged to perform regular prevention and screening visits [37–39].

The BM offers a framework for examining the impact of different risk factors for HG utilization and outcome. Employing SEM to analyze the magnitude of effects of different factors provided a conceptual understanding of the relationship between all the components of the BM. Moreover, the BM emphasizes the direct and indirect impact of different components on utilization and outcome. Thus, the use of advanced statistical methodologies such as SEM was crucial to examining these relationships and showing the difference between the direct and indirect impacts of each component on utilization and outcome. In addition, each of the components was conceptualized and examined separately as a latent construct. This provided in-depth knowledge regarding each of the different risk factors under each component and the presence of any inter-relations among them.

5.4. *Limitations*

While this study employed a powerful statistical approach and provided affluent results about the interrelationship among different HG risk factors and how they influence utilization, the use of secodary data seems to be a major limitaion. Ufortunately, some relevant risk factors such as the duration of DM [40,41], patient's educational level, medications used especially the type of glucose-lowering medications [42–46] and antibiotics [47,48], previous history of HG, and transfer to ICU [49,50] were not included in the database. In addition, patients with multiple admissions because of HG couldn't be traced in the database. Also, patients who developed HG after admissions were not identified because of the nature of the data.

5.5. *Recommendations for future research*

The use of SEM revealed the inter-relationship among different risk factors and how they can impact the level of utilization directly and indirectly. However, some key variables were not examined in this study because they were not available in the database. Therefore, we suggest that future studies be designed in a prospective format, add those key variables, and analyze results with SEM to explore the direct and indirect impact of all different factors of utilization among hospitalized HG patients. Also, since this study was conducted in the U.S., we recommend similar studies to be conducted in other countries to examine similarities and differences in risk factors among other nations. Last, the application of SEM on the BM in this study revealed interesting results. Thus, we recommend that future studies apply similar approach on other common diseases such as hypertension and cancer.

5.6. *Conclusions*

This study examined the multilevel character of different factors leading to high utilization of healthcare services among HG patients admitted to hospitals. The study found that high CCI, DM complications, renal disease, and hypertension are the primary factors that leads to longer stays in hospitals and higher charges among those patients. Age has an indirect impact on LoS and total charge. Geographical location of patients has some impact on total charges and a very minimal impact on LoS. With the increasing number of older people with higher rates of diabetes, these findings help clinicians and policy makers to formulate policies and protocols that aid in providing efficient care to HG patients with less utilization of resources.

Acknowledgments

W.K. wrote the manuscript and researched data. A.A. reviewed/edited the manuscript.

Affiliations

The authors thank Dr. Thomas Wan, University of Central Florida, for his valuable comments on initial draft of this manuscript.

Declaration of Competing Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article. This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.diabres.2019.05.031.

REFERENCES

[1] Diabetes.org. Statistics About Diabetes. Availabe online: http://www.diabetes.org/diabetes-basics/statistics/?referrer=https://www.google.com/ [accessed on 2/1/2016].

[2] CDC. National diabetes statistics report: estimates of diabetes and its burden in the United States. Availabe online: http://www.cdc.gov/diabetes/data/statistics/2014statisticsreport.html [accessed on 3/9/2016].

[3] ADA. The cost of diabetes. Availabe online: http://www.diabetes.org/advocacy/news-events/cost-of-diabetes.html [accessed on 8/may/2019].

[4] ADA. Economic costs of diabetes in the U.S. in 2012. Diabetes Care J 2013;36:1033–46. https://doi.org/10.2337/dc12-2625.

[5] Cunningham P, Carrier E. Trends in the financial burden of medical care for nonelderly adults with diabetes, 2001 to 2009. Am J Managed Care 2014;20:135–42.

[6] Moghissi ES, Korytkowski MT, DiNardo M, Einhorn D, Hellman R, Hirsch IB, et al. American association of clinical endocrinologists and american diabetes association consensus statement on inpatient glycemic control. Diabetes Care J 2009;32:1119–31. https://doi.org/10.2337/dc09-9029.

[7] ADA. Hypoglycemia (Low Blood Glucose). Availabe online: http://www.diabetes.org/living-with-diabetes/treatment-and-care/blood-glucose-control/hypoglycemia-low-blood.html (accessed on 5/20/2016).

[8] Edridge CL, Dunkley AJ, Bodicoat DH, Rose TC, Gray LJ, Davies MJ, et al. Prevalence and incidence of hypoglycaemia in 532,542 people with type 2 diabetes on oral therapies and insulin: a systematic review and meta-analysis of population based studies. PLoS One 2015;10:e0126427. https://doi.org/10.1371/journal.pone.0126427.

[9] Geller AI, Shehab N, Lovegrove MC, Kegler SR, Weidenbach KN, Ryan GJ, et al. National estimates of insulin-related hypoglycemia and errors leading to emergency department visits and hospitalizations. JAMA Int Med 2014;174:678–86. https://doi.org/10.1001/jamainternmed.2014.136.

[10] Ginde AA, Espinola JA, Camargo Jr CA. Trends and disparities in U.S. emergency department visits for hypoglycemia, 1993–2005. Diabetes Care J 2008;31:511–3. https://doi.org/10.2337/dc07-1790.

[11] Jakubczyk M, Rdzanek E. Economic resources consumption structure in severe hypoglycemia episodes: a systematic review and meta-analysis 813–822 810p. Expert Rev Pharmacoeconomics Outcomes Res 2015;15. https://doi.org/10.1586/14737167.2015.1076338.

[12] Hsu P-F, Sung S-H, Cheng H-M, Yeh J-S, Liu W-L, Chan W-L, et al. Association of clinical symptomatic hypoglycemia with cardiovascular events and total mortality in type 2 diabetes: a nationwide population-based study 894–900 897p. Diabetes Care J 2013;36. https://doi.org/10.2337/dc12-0916.

[13] Davis TM, Brown SG, Jacobs IG, Bulsara M, Bruce DG, Davis WA. Determinants of severe hypoglycemia complicating type 2 diabetes: the Fremantle diabetes study. J Clinical Endocrinol Metabol 2010;95:2240–7. https://doi.org/10.1210/jc.2009-2828.

[14] Majumdar SR, Hemmelgarn BR, Lin M, McBrien K, Manns BJ, Tonelli M. Hypoglycemia associated with hospitalization and adverse events in older people: population-based cohort study. Diabetes Care J 2013;36:3585–90. https://doi.org/10.2337/dc13-0523.

[15] Curkendall SM, Natoli JL, Alexander CM, Nathanson BH, Haidar T, Dubois RW. Economic and clinical impact of inpatient diabetic hypoglycemia. Endocrine Practice 2009;15:302–12. https://doi.org/10.4158/EP08343.OR.

[16] Gómez R, Guijarro R, Zapatero A, Barba R, Guijarro A, Tinahones F, et al. The frequency and impact of hypoglycemia among hospitalized patients with diabetes: a population-based study. J Diabetes Complicat 2015;29:1050–5. https://doi.org/10.1016/j.jdiacomp.2015.07.018.

[17] Signorovitch JE, Macaulay D, Diener M, Yan Y, Wu EQ, Gruenberger JB, et al. Hypoglycaemia and accident risk in people with type 2 diabetes mellitus treated with non-insulin antidiabetes drugs. DiabetesObes Metab 2013;15:335–41. https://doi.org/10.1111/dom.12031.

[18] Turchin A, Matheny ME, Shubina M, Scanlon JV, Greenwood B, Pendergrass ML. Hypoglycemia and clinical outcomes in patients with diabetes hospitalized in the general ward 1153–1157 1155p. Diabetes Care J 2009;32. https://doi.org/10.2337/dc08-2127.

[19] Zhang Y, Wieffer H, Modha R, Balar B, Pollack M, Krishnarajah G. The burden of hypoglycemia in type 2 diabetes: a systematic review of patient and economic perspectives. J Clinical Outcomes Manage 2010;17. 547–557 511p.

[20] Quilliam BJ, Simeone JC, Ozbay AB, Kogut SJ. The incidence and costs of hypoglycemia in type 2 diabetes. Am J Managed Care 2011;17:673–80.

[21] Berkowitz SA, Aragon K, Hines J, Seligman H, Lee S, Sarkar U. Do clinical standards for diabetes care address excess risk for hypoglycemia in vulnerable patients? A systematic review. Health Serv Res 2013;48:1299–310. https://doi.org/10.1111/1475-6773.12048.

[22] Andersen R, Newman JF. Societal and individual determinants of medical care utilization in the United States. Milbank Mem Fund Quart Health Soc 1973;51:95–124.

[23] Aday LA, Andersen R. A framework for the study of access to medical care. Health Serv Res J 1974;9:208–20.

[24] Andersen R, Aday LA. Access to medical care in the U.S.: realized and potential. Med Care J 1978;16:533–46.

[25] Andersen R. Revisiting the behavioral model and access to medical care: does it matter? J Health Soc Behav 1995;36:1–10.

[26] Chern JY, Wan TT, Begun JW. A structural equation modeling approach to examining the predictive power of determinants of individuals' health expenditures. J Med Syst 2002;26:323–36.

[27] Wan T, Soifer S. Determinants of physician utilization: a causal analysis. J Health Soc Behav 1974;15:100–8.
[28] Babitsch B, Gohl D, von Lengerke T. Re-revisiting Andersen's Behavioral Model of Health Services Use: a systematic review of studies from 1998–2011. Psychosocial Med J 2012;9(Doc11). https://doi.org/10.3205/psm000089.
[29] Bloomfield HE, Greer N, Newman D, MacDonald R, Carlyle M, Fitzgerald P, Rutks I, Wilt TJ. Predictors and Consequences of Severe Hypoglycemia in Adults with Diabetes – A Systematic Review of the Evidence. Department of Veterans Affairs: Evidence-based Synthesis Program; 2012.
[30] Wan T, Yates A. Prediction of dental services utilization: a multivariate approach. Inquiry: J Med Care Org Provision Financ 1974;12:143–56.
[31] Wan T, Soifer S. A multivariate analysis of the determinants of physician utilization. Socio-Econ Plan Sci 1975;9:229–37. https://doi.org/10.1016/0038-0121(75)90007-5.
[32] Kattan W, Wan TTH. Factors Influencing Variations in Hospitalization for Diabetes with Hypoglycemia. J Clin Med 2018;7. https://doi.org/10.3390/jcm7100367.
[33] Weston R, Gore PA. A brief guide to structural equation modeling. Couns Psychol 2006;34:719–51. https://doi.org/10.1177/0011000006286345.
[34] Kline RB. Principles and practice of structural equation modeling. Guilford Press; 2005.
[35] Patel I, Erickson SR, Caldwell CH, Woolford SJ, Bagozzi RP, Chang J, et al. Predictors of medication adherence and persistence in Medicaid enrollees with developmental disabilities and type 2 diabetes. Res Soc Admin Pharm J 2015. https://doi.org/10.1016/j.sapharm.2015.09.008, doi:10.1016/j.sapharm.2015.09.008.
[36] Yamashita T, Kart C, Noe D. Predictors of adherence with self-care guidelines among persons with type 2 diabetes: results from a logistic regression tree analysis. J Behav Med 2012;35:603–15. https://doi.org/10.1007/s10865-011-9392-y.
[37] Marathe KR, Wan TTH, Marathe S. A systematic review on the kap-o framework for diabetes education and research. Med Res Arch 2016:4.
[38] Wan T. A transdisciplinary approach to health policy research and evaluation. Int J Publ Policy 2014;10:161–77. https://doi.org/10.1504/IJPP.2014.063094.
[39] Wan TTH, Terry A, McKee B, Kattan W. KMAP-O framework for care management research of patients with type 2 diabetes. World J Diabetes 2017;8:165–71. https://doi.org/10.4239/wjd.v8.i4.165.
[40] Karges B, Rosenbauer J, Holterhus PM, Beyer P, Seithe H, Vogel C, et al. Hospital admission for diabetic ketoacidosis or severe hypoglycemia in 31,330 young patients with type 1 diabetes. Eur J Endocrinol 2015;173:341–50. https://doi.org/10.1530/EJE-15-0129.
[41] Amiel SA, Dixon T, Mann R, Jameson K. Hypoglycaemia in Type 2 diabetes. Diabetic Med J 2008;25:245–54. https://doi.org/10.1111/j.1464-5491.2007.02341.x.
[42] Thompson AE. Hypoglycemia 1284-1284. Jama 2015;313. https://doi.org/10.1001/jama.2015.0876.
[43] Monami M, Dicembrini I, Kundisova L, Zannoni S, Nreu B, Mannucci E. A meta-analysis of the hypoglycemic risk in randomized controlled trials with sulphonylureas in patients with type 2 diabetes (Provisional abstract). In: Monami M, Dicembrini I, Kundisova L, Zannoni S, Nreu B, Mannucci E, editos. BMC endocrine disorders: BMC endocrine disorders; 2014.
[44] Chan SP, Colagiuri S. Systematic review and meta-analysis of the efficacy and hypoglycemic safety of gliclazide versus other insulinotropic agents. Diabetes Res Clin Pract 2015;110(1):75–81.
[45] Heller SR, Frier BM, Herslov ML, Gundgaard J, Gough SC. Severe hypoglycaemia in adults with insulin-treated diabetes: impact on healthcare resources. Diabet Med 2015.
[46] Handelsman Y, Bode BW, Endahl LA, Mersebach H, King AB. Patients achieving good glycemic control (Hba1c <7%) experience a lower rate of hypoglycemia with insulin degludec than with insulin glargine: a meta- analysis of phse 3a trials. Endocrine Practice 2015.
[47] Dzygalo K, Kowalska A, Szypowska A. The beneficial effect of insulin degludec on nocturnal hypoglycaemia and insulin dose in type 1 diabetic patients: a systematic review and meta-analysis of randomised trials. Acta diabetologica 2015.
[48] Kendall C, Wooltorton E. People with diabetes should avoid antibiotic gatifloxacin. CMAJ Can Med Assoc J 2006;174:1089–90. https://doi.org/10.1503/cmaj.060356.
[49] Hermanides J, Vriesendorp TM, Dotsch R, Rosendaal FR, Zandstra DF, Hoekstra JBL, et al. Hypoglycemia is associated with intensive care unit mortality. Crit Care Med 2010.
[50] Gangji AS, Gerstein HC, Goldsmith CH, Clase CM. A systematic review and meta-analysis of hypoglycemia and cardiovascular events: a comparison of glyburide with other secretagogues and with insulin. Diabetes Care J 2007.