JAMDA 24 (2023) 1746–1754

JAMDA

journal homepage: www.jamda.com

Original Study

Data-Driven Analytics to Discover APRN's Impact on Nursing Home Hospitalization: Causal Discovery Analysis

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Keywords:
Nursing home
big data analysis
information technology
older adults
causal discovery analysis

A B S T R A C T

Objectives: Research shows advanced practice registered nurses (APRNs) embedded in nursing homes (NHs) reduce resident hospitalizations. However, the specific APRN activities that reduce hospitalizations have not been adequately investigated. This study aims to identify the causal links between APRN activities and NHs resident hospitalization. The study also examined relationships among other variables, including advanced directives, clinical diagnosis, and length of hospitalization.
Design: Secondary data analysis.
Setting and Participants: Residents of NHs participating in the Missouri Quality Initiative for Nursing Homes, 2016–2019.
Methods: We performed a secondary analysis of data from the Missouri Quality Initiative for Nursing Homes Intervention using causal discovery analysis, a machine learning, data-driven technique to determine causal relationships across data. The resident roster and INTERACT resident hospitalization datasets were combined to create the final dataset. Variables in the analysis model were divided into before and after hospitalization. Expert consensus was used to validate and interpret the outcomes.
Results: The research team analyzed 1161 hospitalization events and their associated NH activities. APRNs evaluated NH residents before a transfer, expedited follow-up nursing assessments, and authorized hospitalization when necessary. No significant causal relationships were found between APRN activities and the clinical diagnosis of a resident. The analysis also showed multifaceted relationships related to having advanced directives and duration of hospitalization.
Conclusions and Implications: This study demonstrated the importance of APRNs embedded in NHs to improve resident outcomes. APRNs in NHs can facilitate communication and collaboration among the nursing team, leading to early identification and treatment for resident status changes. APRNs can also initiate more timely transfers by reducing the need for physician authorization. These findings emphasize the crucial role of APRNs in NHs and suggest that budgeting for APRN services may be an effective strategy to reduce hospitalizations. Additional findings regarding advance directives are discussed.

In 2019, there were 54.1 million adults aged 65 and older in the United States, a 36% increase since 2009.[1] Moreover, adults aged 65 and older can expect to live almost another 20 years.[1] Although only a relatively small percentage of this population resided in nursing homes (NHs) in 2019, the number of older adults who may require residential long-term care is increasing. In 2022, more than 15,000 NHs in the United States provided care for nearly 1.3 million residents.[2] NHs are responsible for delivering clinical care to residents while making the environment as comfortable and home-like as possible. Interdisciplinary care teams, including nursing, social work,

This project is supported by grants 1E1CMS331080 and 1E1CMS331489 from the Centers for Medicare and Medicaid (CMS) Innovations Center and Medicare-Medicaid Coordination Office (http://innovation.cms.gov/initiatives/rahnfr/), which is focused on improving care and outcomes for Medicare-Medicaid enrollees residing in NHs. The content is solely the responsibility of the authors and does not necessarily represent the official views of CMS.

The authors declare no conflicts of interest.
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https://doi.org/10.1016/j.jamda.2023.05.003
1525-8610/

occupational therapy, physical therapy, and medicine, are primarily responsible for the care provided to older adults living in NHs. However, resident care has become increasingly complex due to shorter hospital stays and increased pressure to contain costs.[3] Consequently, quality indicators have been developed to measure and track the quality of care provided by NHs.[4]

One NH quality indicator is unplanned hospitalizations, many of which are potentially preventable. A hospitalization is potentially preventable if it results from an acute or worsening condition that might have been successfully treated with timely and appropriate outpatient management.[5] Examples include diabetes complications, hypertension, urinary tract infection (UTI), and bacterial pneumonia.[6] Hospital social workers play a crucial role in discharge, referrals, monitoring, and other essential aspects of patient self-management after discharge. In 2012, the Centers for Medicare and Medicaid Services (CMS) launched the Initiative to Reduce Avoidable Hospitalizations Among NH Residents.[7] As a participant in the project, the Missouri Quality Initiative for Nursing Homes (MOQI) was established to measure all hospitalizations and related Medicare expenditures for NH residents and determine which hospitalizations were potentially preventable.[7] MOQI also provided guidelines for interventions to reduce preventable hospitalizations, including staffing recommendations and guidelines for NH quality, known as the Interventions to Reduce Acute Care Transfers (INTERACT).[8] As part of the MOQI initiative, advanced practice registered nurses (APRNs), including both clinical nurse specialists and nurse practitioners, were embedded into participating NHs while working alongside existing care teams in these NH settings to obtain the necessary physician orders due to not having collaborative practice agreement with a physician.[9] The INTERACT tools allowed the APRNs to intervene early in a clinical event, thereby avoiding some potentially preventable hospitalizations and efficiently managing resident care and interfacility communication should a transfer be necessary. The MOQI initiative achieved a significant 7.9 percentage point reduction in all-cause hospitalizations and a significant 6.1 percentage point reduction in potentially preventable hospitalizations between 2014 and 2016.[10] These findings were echoed by a longitudinal analysis of outcomes from 2013 through 2019, which found that full-time APRNs in Missouri NHs were associated with reduced, potentially preventable hospital admissions.[9] Other studies also have demonstrated a positive association between care by nurse practitioners and reduced risk of preventable and all-cause hospitalizations in Medicare recipients.[11,12]

Despite the improvements in outcomes, some states are reluctant to employ full-time APRNs in NHs. This reluctance was reflected in the National Center for Health Worker Analysis conducted by the Health Resources and Services Administration.[13] The survey shows that in 2018, only 3% (n = 6430) of APRNs worked in long-term care NH settings nationwide. One reason is the complexity surrounding billing for Medicare patients by APRNs who are NH employees (eg, Medicare regulations, state regulatory restrictions, restrictions on visit billing, and a lack of authority to issue or alter orders), an issue that would require regulatory changes to address.[9,14,15] As per federal regulations requirements for long-term care facilities subsection 483.40, a qualified non-physician practitioner (such as a nurse practitioner or physician assistant) not employed by the NH may perform the initial visits, whereas those employed by the NHs may not. In addition, in a skilled nursing facility, the physician may not delegate the initial comprehensive visit mandated by the federal government, which shows such limitation bound by current regulations.[16] Another issue is a lack of clear understanding of what APRNs do that impacts health outcomes. APRNs assume various roles in NHs, including providing direct patient care, conducting patient oversight, educating staff, and tracking quality outcomes.[8] However, it is not clear what specific activities APRNs perform in NHs that affect unplanned hospitalization rates. Therefore, we aimed to conduct a data-driven study by applying causal discovery analysis to the MOQI dataset, produce a model of the causal relations among factors included in the MOQI datasets, and interpret this model to better understand how the presence of APRNs affects risk and protective factors in nursing facilities, including hospitalization.

Methods

Data Sources

During the MOQI, the project measured APRN-reported measures assessing the impact of APRNs impact on NHs during, before, and after resident hospitalization. We used 2 separate datasets for our analysis: (1) the resident roster, and (2) the INTERACT 4.0 survey. The resident roster is APRN-reported data regarding clinical events the residents experienced during their stay in NHs during Phase II of the MOQI (2016–2019). Specific clinical events monitored as part of the MOQI program included (1) acute or chronic condition changes, such as altered mental status or abnormal test results; (2) incidents or accidents with injury, such as falls, adverse drug events, or procedure complications; and (3) facility-acquired infections such as pneumonia, cellulitis, UTIs, and *Clostridium difficile* infection.[17] The data also covered the information outcomes of resident status after the hospitalization in the case when the transfer happened. A total of 103 resident-level variables (eg, name, date of birth, age, advance directives, change of condition and diagnosis during the stay, symptoms, date for hospitalization, and the outcome of hospital discharge) for 94,812 events were recorded by APRNs.

INTERACT 4.0 is an updated version of the hospitalization survey in NHs used in MOQI beginning in 2016. It shares a similarity with the resident roster (eg, APRN reported, NH resident personal information, hospitalization dates), but the INTERACT 4.0 survey focuses on clinical details and the involvement of APRNs in each hospitalization, which is different from the resident roster that includes data before, during, and after the hospitalization of residents. The INTERACT 4.0 survey asks what precipitated the transfer, who examined and consulted the resident, and what clinical testing or medical evaluation was done before the transfer. As data representing the involvement of APRNs were only available in INTERACT 4.0, we decided to use both datasets and proceed with the analysis to compare situations in which APRNs were involved. All responses for both datasets are de-identified.

Causal Discovery Analysis

To determine how factors in the study were related to each another, we used causal discovery analysis. The goal of causal discovery is to find the causal model that best fits the observed data. Eberhardt[18] defines causal models in the following way: For a given set of variables V {X1, . . . Xn}, a causal graph G = {V, E} represents the causal relations over the set of variables V, in the sense that for any directed edge e = Xi → Xj in E, Xi is a direct cause of Xj relative to variables in V. In order for causal discovery algorithms to be theoretically sound, certain assumptions must be made, the details of which differ greatly between different approaches.[18(p.82)] In the context of our study, the Causal Markov and Causal Faithfulness assumptions were both reasonable: (1) the only known phenomena that may violate Causal Markov occur in quantum physics and are unlikely to affect residents' behaviors; (2) a practical Causal Faithfulness violation becomes less likely as the sample size grows. The Causal Markov Assumption suggests that a variable X is conditionally independent of variables not causally downstream from it, provided X's immediate causes are statistically controlled. This assumption is similar to a dam in a river, where the water downstream is no longer influenced by the water upstream. Causal Faithfulness indicates that if Causal Markov does not suggest independence, then variables are

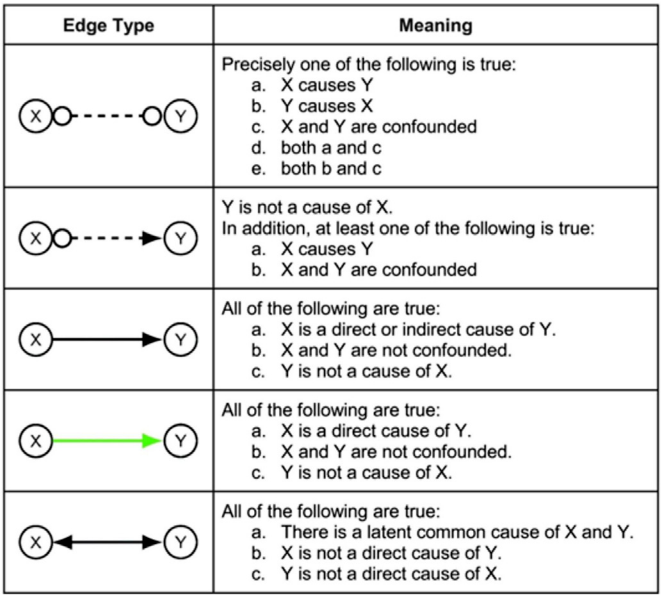

Fig. 1. Edge types in PAG.[20]

dependent. Together, they bridge the gap between testable statistics and causal structures. The Greedy Fast Causal Inference (GFCI) method was used for the analysis via the platform TETRAD 7.1.0 for causal discovery analysis.[19] GFCI uses a 2-step approach. First, it assumes no unmeasured confounders and applies a greedy yet accurate procedure, known as fast greedy equivalent search, to identify the optimal causal structure that maximizes log-likelihood while minimizing model complexity (measured by Bayesian information criterion score) to prevent overfitting. Second, it relaxes the assumption of no unmeasured confounding and applies conditional independence testing to identify parts of the graph that may be affected by unmeasured confounders, then makes appropriate adjustments. This results in an algorithm with good performance in small sample sizes that does not assume the absence of unmeasured confounding. The output of the GFCI analysis is a Partial Ancestral Graph (PAG). A PAG represents putative causal relationships with arrows, for example, an arrow pointing from node A to node B indicates that node A is a putative cause of node B. The type of vertex with arrowheads varies from directed, bi-directed, and undirected edges. Detailed definitions of edges are described in Figure 1.[20]

Sample

The resident roster and INTERACT 4.0 from the MOQI were merged and used for the analysis.

Data merge and preprocessing

The variables "nursing facility name," "date of transfer," and "date of birth" were used to merge the 2 datasets. The data integration resulted in 1579 hospitalization events. Of 1579 hospitalizations, 418 events were omitted because of missing data. As a result, a total of 1161 hospitalization events were included in the analysis. Data were then standardized (z-score).

Variables

Variables used for the analysis were organized based on whether they occurred before or after hospitalization. Specifically, we divided the variables into 4 time periods (before transfer–stage 1, before transfer–stage 2, after transfer–stage 1, after transfer–stage 2) and used this temporal contextual information in the analysis. Variable inclusion and exclusion were discussed with a domain expert (Marilyn Rantz). Variables with a frequency lower than 5% that showed no empirical evidence regarding NHs and APRNs were removed. For example, the variable "reason of hospital transfer—change in clinical status not otherwise specified" (n = 23; 1%) was removed from the analysis because of its vague definition and low frequency. See Table 1 for a detailed description of the variables.

Before transfer–stage 1 (BT1)

Before transfer–stage 1 referred to participants' inherent characteristics before admission to nursing facilities (ie, age; White versus others; dementia; other hospitalizations or emergency department visits in the past 12 months).

Before transfer–stage 2 (BT2)

Before transfer–stage 2 encompassed the variables that occurred during the participants' stay in the nursing facility before hospitalization (ie, symptoms during the stay including altered mental status, fall with/without injury, shortness of breath; advanced directives; involvement of APRNs and registered nurses (RNs) during the stay, transfer authorization). Any vague symptoms or those that did not align with the study's purpose were removed (eg, abnormal lab, abnormal vital signs, change in clinical status).

After transfer–stage 1 (AT1)

After transfer–stage 1 corresponded to the length of hospital stay during participants' hospitalization.

After transfer–stage 2 (AT2)

After transfer–stage 2 included discharge diagnosis during hospitalization (ie, fall with and without injury, pneumonia, sepsis, UTI). Diagnoses that accounted for more than 5% of all events (eg, 7.4% of events were diagnosed with pneumonia) were selected to avoid diluting the results from variables with minor incidents [eg, reason for transfer: abnormal lab was excluded due to having only 77 incidents (4.9%) of all 1161 events].

Causal Discovery Analysis

GFCI algorithm was used for the analysis. We provided time order information to the algorithm, including an assumption of no backward-in-time causation (eg, no variable measured in AT2 can cause a variable in BT2). The bootstrapping method (1000 repetitions) was used to test the model's stability (See Table 2). The only edges (ie, links) included in the final model were those present in at least 50% of the bootstrap models. By fitting a structural equation model using the lavaan package (lavaan 0.6-8 in R 3.5.8) based on the inferred causal relationships from GFCI, effect sizes were estimated.[21] Model fit was measured using comparative fit index (CFI) and root mean square error of approximation (RMSEA) (0.846, 0.068). The model demonstrated marginal fit regarding RMSEA (ie, between 0.08 and 0.1) and slightly below the threshold for good fit regarding CFI (ie, >0.9).[22] It is worth noting that the appropriate level of model fit in our case was more subjective than objective.[23] The figures only displayed edges with an absolute estimated effect size of at least 0.1 to make them more readable and focus on relationships with meaningful strength.

Results

Sample Characteristics

Data consisting of a total of 709 residents representing 1161 events of hospitalization were used for the analysis. The average age of the residents was 82.81 years (see Table 3 for sample characteristics).

Table 1
Measures of the Resident Roster and INTERACT 4.0 Used in the Analysis

Variable	Item(s)	Response Options
Age (BT1_Age)	Calculated from date of birth	
White versus Other (BT1_WvsO)	Race of the resident (White versus other)	1 – White, 0 – Other
Dementia Stage (BT1_Dementia)	Please select the stage of dementia that put the resident at risk for hospital admission or readmission	1 – Early, 2 – Middle, 3 – Late, 4 - Final
Cardiopulmonary resuscitation (CPR) Status (BT1_CPR)	What was CPR status of resident?	1 – Full Code, 0 – DNR
Hospitalization History (BT1_Hx)	Other hospitalizations or emergency department visits in the past 12 months?	1 – Yes, 0 – No
Reason for Transfer: Altered Mental Status (BT2_MS)	Nursing facility primary reason for transfer – Altered Mental Status	1 – Yes, 0 – No
Reason for Transfer: Fall with Injury (BT2_FwI)	Nursing facility primary reason for transfer – Fall with Injury	1 – Yes, 0 – No
Reason for Transfer: Fall without Injury (BT2_FwoI)	Nursing facility primary reason for transfer – Fall without Injury	1 – Yes, 0 – No
Reason for Transfer: Shortness of Breath (BT2_SOB)	Nursing facility primary reason for transfer – Shortness of Breath	1 – Yes, 0 – No
Advance Directives (BT2_AdvDirec)	Were advance care planning or advance directives considered in evaluating/managing the change?	1 – Yes, 0 – No
APRN Examination (BT2_APRNExam)	Did MU APRN examine resident?	1 – Yes, 0 – No
APRN Consultation prior to transfer (BT2_APRNConsult)	Was the MU APRN consulted prior to the transfer?	1 – Yes, 0 – No
RN Consult prior to transfer (BT2_RNConsult)	Was any RN consulted prior to transfer?	1 – Yes, 0 – No
APRN evaluation/communication prior to transfer (BT2_APRNEvalNComm)	What medical evaluations/communications were done prior to transfer: MU APRN visit	1 – Yes, 0 – No
APRN authorizing transfer (BT2_APRN_Auth)	Clinician authorizing transfer: MU APRN	1 – Yes, 0 – No
Primary Physician authorizing transfer (BT2_PP_Auth)	Clinician authorizing transfer: Primary Physician	1 – Yes, 0 – No
Specialist authorizing transfer (BT2_SP_Auth)	Clinician authorizing transfer: Specialist Physician	1 – Yes, 0 – No
Length of Stay (AT1_Diff)	How long have the resident stayed in the hospital during hospitalization?	1 – Less than a day, 2 – 1 to 3 days, 3 – More than 4 days
Hospital discharge diagnosis: Fall with Injury (AT2_FI)	Hospital Primary Discharge Diagnosis (ICD-9 Code) – Fall with Injury	1 – Yes, 0 – No
Hospital discharge diagnosis: Fall without Injury (AT2_FwI)	Hospital Primary Discharge Diagnosis (ICD-9 Code) – Fall without Injury	1 – Yes, 0 – No
Hospital discharge diagnosis: Pneumonia (AT2_Pne)	Hospital Primary Discharge Diagnosis (ICD-9 Code) – Pneumonia	1 – Yes, 0 – No
Hospital discharge diagnosis: Sepsis (AT2_Sep)	Hospital Primary Discharge Diagnosis (ICD-9 Code) – Sepsis	1 – Yes, 0 – No
Hospital discharge diagnosis: UTI (AT2_UTI)	Hospital Primary Discharge Diagnosis (ICD-9 Code) – UTI	1 – Yes, 0 – No

MU, University of Missouri.

Participants were primarily White (n = 589; 83%), followed by Black or African American (n = 106; 15%). The remaining races comprised less than 1% of the dataset (ie, Asian = 4, Multiracial = 4, Hispanic or Latino = 3, Native Hawaiian or Other Pacific Islander = 2, not applicable (race not reported) = 1). Regarding events during their NH stay, 447 were from residents with dementia (15% early, 47% middle, 36% late, and 2% final stage), and 56% of the events (n = 653) were from residents classified as "do not resuscitate" DNR. A total of 325 events had reasons for hospital transfers, including 37% altered mental status (n = 119); 31% fall with injury (n = 102), 6% fall without injury (n = 18), and 26% shortness of breath (n = 86). The mean length of hospital stay was 2.28 days, where 1, 2, and 3 represented values for the variable "duration of stay" (ie, 1: less than a day, 2" 1 to 3 days, 3: more than 4 days). A total of 330 events had discharge diagnoses, including 16% fall with injury (n = 54), 7% fall without injury (n = 23), 27% pneumonia (n = 90), 23% sepsis (n = 75), and 27% UTI (n = 88).

Causal Discovery Analysis

Figure 2 shows causal relationships between before and after hospitalization factors gathered for the MOQI project.

APRN involvement

Regarding APRN involvement in the causal discovery graph, findings show that a consultation with the APRN led to the APRN examination of the resident, followed by the APRN initiating medical evaluations and consults before transfer. Medical evaluations/communications done before the transfer by the APRN led the APRN to authorize the resident's hospitalization, which reduced duplicative activities surrounding authorization of hospitalization by primary physicians. In addition, a consultation with the APRN led to a consultation with the RN. However, there was no significant causal relationship between APRN activities and length of hospital stay or discharge diagnosis.

Advance directive

The causal discovery graph shows that advance directive considerations drove subsequent decisions and actions, including APRN and RN consultations. Also, providers considered advance directives when making transfer decisions about residents with mental status changes or shortness of breath. The graph also shows that younger resident age led to more advance directive considerations when determining hospital transfer.

Other causal findings

Falls with and without injuries led to shorter hospital stays (BT2_FwoI, BT2_FwI → AT1_Diff). Also, longer hospital stays were more likely to lead to a pneumonia or sepsis discharge diagnosis (AT1_Diff → AT2_Sep, AT2_Pne). A transfer for shortness of breath increased the chances of a discharge diagnosis of pneumonia. Also, findings showed a fall with injury and shortness of breath leading to decrease in altered mental status, which ultimately led to a hospital discharge diagnosis of UTI.

Discussion

The purpose of this study was to compare hospitalization-related factors reported by either nurses or APRNs to better understand the

Table 2
Causal Discovery Analysis Bootstrap Re-sampling Results

Interaction	Nodes		Proportion of 1000 Bootstrap Resamples						
	Node 1	Node 2	→	←	o→	←o	o—o	←→	None
o->	BT1_WvsO	BT2_AdvDirec	0	0	1	0	0	0	0
←	AT2_FI	BT2_FwI	0	1	0	0	0	0	0
o->	BT1_WvsO	BT2_APRNEvalNComm	0	0	0.974	0	0	0	0.026
←	AT2_FwI	BT2_FwI	0	0.956	0	0	0	0	0.044
←	AT2_Pne	BT2_SOB	0	0.995	0	0.004	0	0	0.001
o->	Age	BT2_AdvDirec	0	0	0.938	0	0	0	0.062
→	AT1_Diff	AT2_Sep	0.822	0	0.173	0	0	0.005	0
o->	BT1_Dementia	BT2_SOB	0.001	0	0.809	0	0	0	0.19
<-o	AT2_FwI	BT2_FwoI	0	0.29	0	0.709	0	0	0.001
o->	Age	BT2_APRNConsult	0	0	0.645	0	0	0	0.355
o->	BT1_Dementia	BT2_FwI	0	0	0.614	0	0	0.002	0.384
←	AT2_UTI	BT2_MS	0	0.612	0	0.285	0	0	0.103
o->	BT1_WvsO	BT2_RNConsult	0	0	0.551	0	0	0	0.449
←	AT1_Diff	BT2_FwI	0	0.471	0	0	0	0	0.529
o->	BT1_WvsO	BT2_MS	0	0	0.453	0	0	0	0.547
→	AT1_Diff	AT2_Pne	0.43	0	0.116	0	0	0	0.454
<-o	AT1_Diff	BT2_FwoI	0	0.169	0	0.37	0	0	0.461
o->	BT1_Dementia	BT2_RNConsult	0.001	0	0.369	0	0	0	0.63
→	AT1_Diff	AT2_FI	0.355	0	0.175	0	0	0	0.47
o->	Age	BT2_FwI	0	0	0.325	0	0	0	0.675
o->	Age	BT2_RNConsult	0	0	0.276	0	0	0	0.724
o->	BT1_Dementia	BT2_PP_Auth	0	0	0.261	0	0	0	0.739
o->	Age	BT2_APRN_Auth	0	0	0.238	0	0	0	0.762
<-o	AT2_Pne	BT1_CPR	0	0.001	0	0.202	0	0	0.797
o->	BT1_WvsO	BT2_FwI	0	0	0.198	0	0	0	0.802
o->	BT1_Hx	BT2_SP_Auth	0	0	0.184	0	0	0	0.816
o->	BT1_WvsO	BT2_SOB	0	0	0.176	0	0	0	0.824
o->	Age	BT2_MS	0	0	0.143	0	0	0	0.857
←	AT2_Sep	BT2_MS	0	0.14	0	0.071	0	0	0.789
<-o	AT2_Sep	Age	0	0	0	0.137	0	0	0.863
o->	BT1_CPR	BT2_FwoI	0	0	0.125	0	0	0	0.875
o->	BT1_Dementia	BT2_FwoI	0	0	0.111	0	0	0	0.889
o->	BT1_Hx	BT2_APRNExam	0	0	0.102	0	0	0	0.898
o->	Age	BT2_PP_Auth	0	0	0.096	0	0	0	0.904
o->	BT1_WvsO	BT2_PP_Auth	0	0	0.085	0	0	0	0.915
o->	BT1_CPR	BT2_APRN_Auth	0	0	0.084	0	0	0	0.916
←	AT1_Diff	BT2_SOB	0	0.083	0	0	0	0	0.917
o->	BT1_CPR	BT2_FwI	0	0	0.082	0	0	0	0.918
o->	BT1_Hx	BT2_MS	0	0	0.079	0	0	0	0.921
<-o	AT2_FI	BT2_APRN_Auth	0	0.037	0	0.074	0	0	0.889
<-o	AT2_UTI	BT2_FwoI	0	0.021	0	0.071	0	0	0.908
o->	BT1_CPR	BT2_PP_Auth	0	0	0.064	0	0	0	0.936
o->	BT1_Dementia	BT2_SP_Auth	0	0	0.058	0	0	0	0.942
o->	BT1_Hx	BT2_FwoI	0	0	0.05	0	0	0	0.95
←	AT2_Sep	BT2_AdvDirec	0	0.049	0	0	0	0	0.951
←	AT2_Pne	BT2_MS	0	0.036	0	0.007	0	0	0.957
o->	BT1_CPR	BT2_APRNConsult	0	0	0.029	0	0	0	0.971
←	AT2_UTI	BT2_AdvDirec	0	0.027	0	0	0	0	0.973
o->	BT1_Dementia	BT2_MS	0	0	0.027	0	0	0	0.973
o->	Age	BT2_APRNExam	0	0	0.025	0	0	0	0.975
←	AT2_UTI	BT2_APRN_Auth	0	0.021	0	0.016	0	0	0.963
←	AT2_Sep	BT2_APRNEvalNComm	0	0.02	0	0	0	0	0.98
o->	BT1_Dementia	BT2_APRN_Auth	0	0	0.02	0	0	0	0.98
<-o	AT1_Diff	BT2_APRNExam	0	0.007	0	0.019	0	0	0.974
o->	BT1_WvsO	BT2_APRNConsult	0	0	0.017	0	0	0	0.983
←	AT2_Sep	BT2_APRN_Auth	0	0.015	0	0.007	0	0	0.978
o->	BT1_Dementia	BT2_APRNExam	0	0	0.015	0	0	0	0.985
o->	BT1_Hx	BT2_APRN_Auth	0	0	0.014	0	0	0	0.986
o->	BT1_CPR	BT2_APRNExam	0	0	0.011	0	0	0	0.989
<-o	AT2_FI	BT2_FwoI	0	0.008	0	0.011	0	0	0.981
o->	BT1_WvsO	BT2_APRNExam	0	0	0.01	0	0	0	0.99
o->	Age	BT2_SOB	0	0	0.009	0	0	0	0.991
o->	BT1_CPR	BT2_AdvDirec	0	0	0.009	0	0	0	0.991
←	AT1_Diff	BT2_MS	0	0.008	0	0.002	0	0	0.99
<-o	AT2_UTI	Age	0	0	0	0.008	0	0	0.992
o->	BT1_WvsO	BT2_APRN_Auth	0	0	0.008	0	0	0	0.992
←	AT2_UTI	BT2_RNConsult	0	0.007	0	0	0	0	0.993
o->	BT1_Hx	BT2_PP_Auth	0	0	0.007	0	0	0	0.993
<-o	AT2_Sep	BT1_WvsO	0	0.001	0	0.007	0	0	0.992
o->	BT1_WvsO	BT2_FwoI	0	0	0.007	0	0	0	0.993
<-o	AT2_Pne	BT2_APRNExam	0	0.001	0	0.007	0	0	0.992
<-o	AT1_Diff	BT1_CPR	0	0	0	0.006	0	0	0.994

(*continued on next page*)

Table 2 (*continued*)

Interaction	Nodes		Proportion of 1000 Bootstrap Resamples						
	Node 1	Node 2	→	←	0→	←0	0—0	←→	None
o->	BT1_CPR	BT2_APRNEvalNComm	0	0	0.006	0	0	0	0.994
o->	BT1_CPR	BT2_SP_Auth	0	0	0.006	0	0	0	0.994
o->	BT1_WvsO	BT2_SP_Auth	0	0	0.006	0	0	0	0.994
←	AT2_Sep	BT2_PP_Auth	0	0.005	0	0.005	0	0	0.99
o->	BT1_CPR	BT2_SOB	0	0	0.005	0	0	0	0.995
<-o	AT2_UTI	BT2_SP_Auth	0	0.002	0	0.005	0	0	0.993
←	AT1_Diff	BT2_APRNEvalNComm	0	0.004	0	0	0	0	0.996
o->	BT1_Dementia	BT2_APRNConsult	0	0	0.004	0	0	0	0.996
o->	BT1_Hx	BT2_RNConsult	0	0	0.004	0	0	0	0.996
←	AT1_Diff	BT2_PP_Auth	0	0.003	0	0.003	0	0	0.994
o->	Age	BT2_FwoI	0	0	0.003	0	0	0	0.997
<-o	AT2_UTI	BT1_CPR	0	0	0	0.003	0	0	0.997
o->	BT1_CPR	BT2_MS	0	0	0.003	0	0	0	0.997
<-o	AT2_Pne	BT1_Hx	0	0	0	0.003	0	0	0.997
o->	BT1_Hx	BT2_APRNEvalNComm	0	0	0.003	0	0	0	0.997
<-o	AT2_Pne	BT2_APRN_Auth	0	0	0	0.003	0	0	0.997
→	AT1_Diff	AT2_UTI	0.002	0	0.001	0	0	0	0.997
←	AT1_Diff	BT2_APRNConsult	0	0.002	0	0	0	0	0.998
←	AT2_FI	BT2_APRNEvalNComm	0	0.002	0	0	0	0	0.998
←	AT2_UTI	BT2_FwI	0	0.002	0	0	0	0	0.998
←	AT2_UTI	BT2_PP_Auth	0	0.002	0	0.001	0	0	0.997
←	AT2_Sep	BT2_RNConsult	0	0.002	0	0	0	0	0.998
o->	Age	BT2_SP_Auth	0	0	0.002	0	0	0	0.998
<-o	AT1_Diff	BT1_Dementia	0	0	0	0.002	0	0.002	0.996
<-o	AT2_FI	BT1_Dementia	0	0	0	0.002	0	0	0.998
o->	BT1_Hx	BT2_APRNConsult	0	0	0.002	0	0	0	0.998
<-o	AT2_UTI	BT2_APRNExam	0	0	0	0.002	0	0	0.998
←	AT2_UTI	BT2_APRNConsult	0	0.001	0	0	0	0	0.999
←	AT2_Pne	BT2_APRNEvalNComm	0	0.001	0	0	0	0	0.999
←	AT2_Sep	BT2_SOB	0	0.001	0	0	0	0	0.999
←	AT2_UTI	BT2_SOB	0	0.001	0	0	0	0	0.999
←	AT2_Sep	BT1_CPR	0	0.001	0	0	0	0	0.999
o->	AT1_Diff	AT2_FwI	0	0	0.001	0	0	0	0.999
<-o	AT1_Diff	Age	0	0	0	0.001	0	0	0.999
o->	Age	BT2_APRNEvalNComm	0	0	0.001	0	0	0	0.999
<-o	AT2_FwI	BT1_Dementia	0	0	0	0.001	0	0	0.999
o->	BT1_Dementia	BT2_APRNEvalNComm	0	0	0.001	0	0	0	0.999
o->	BT1_Dementia	BT2_AdvDirec	0	0	0.001	0	0	0	0.999
o->	BT1_Hx	BT2_FwI	0	0	0.001	0	0	0	0.999
<-o	AT2_Sep	BT2_SP_Auth	0	0.001	0	0.001	0	0	0.998

impact of APRN presence in the nursing facility context. We used causal discovery analysis to conduct the data analysis and validate our findings. The results suggested no significant causal links between the presence of an APRN and implications regarding the specific clinical diagnosis of NH residents. Instead, the findings focused on the impact of advance directives as a crucial element that influenced both the APRN and RN involvement in the transfer and the symptoms of the clinical diagnosis/condition of the resident.

APRN Role

Describing how APRN activities influence outcomes is challenging because of an inability to define and measure such activities in ways amenable to quantitative analysis. APRNs have crucial roles in performing and directing resident care and providing early assessment and management of acute and deteriorating resident conditions. But APRNs also perform nondirect clinical activities, such as documentation, consultation, and medication reviews.[24,25] Attempts to define and document these APRN activities in a manner usable for statistical analysis would likely prove overly burdensome and impractical. Such an effort would also fail to capture the nonobservable elements of interpersonal interactions, professional judgment, and clinical decision-making, which are critical components of APRN work.

Nevertheless, causal discovery analysis of general categories of APRN activities surrounding resident transfers was an essential first step in understanding the APRN's role in preventing hospitalizations. For instance, our causal findings demonstrated that an APRN's clinical evaluations and interventions led to the APRN authorizing the resident transfer, thus reducing duplicative activities surrounding the need for the primary clinician to order hospital admission. This finding implies that APRNs have the potential to improve the management of residents' acute status changes by identifying and intervening earlier and by facilitating prompt acute care transfers when necessary. By doing so, APRNs in NHs could improve resident outcomes and increase the efficiency of the nursing staff and health care system. Furthermore, by supporting the delivery of resident care and treatment, APRNs can help communities that are experiencing a physician shortage.

APRN and advance directive

The results suggest that if NH staff considered an advanced directive in evaluating or managing a transfer, there was a greater likelihood that both the APRN and RN consultations occurred before the transfer. In addition, the findings show the APRN's consultation with the resident prompted the RN consultation. This causal relationship shows that APRNs play a key role in providing high-quality care by educating others and managing resources effectively. The study also supported the conclusion of another study that found APRNs improved patient outcomes by initiating advanced care planning discussions.[26]

In addition, it shows that both APRNs and RNs acknowledged the importance of advance directives as the crucial starting and decision-making space for residents, which influenced decisions made by APRNs and RNs. Furthermore, the finding suggested that staff members in the facility actively involved the APRN in the decision-making process when the resident had not signed an advance directive (for example, a resident who does not have a status of DNR), which highlighted the function of an APRN in the nursing facility system.

The positive causal effect from advance directives to both mental status changes and shortness of breath on the causal discovery graph may seem counterintuitive, as one would expect the opposite: either mental status changes or shortness of breath would prompt a review of a resident's advance directive. One theory is that an advance directive changes the decision-making process in response to the early, subtle deterioration in the resident's condition. Our study supports this theory, as we found no direct causal relationship between advance directives and falls. Falls are acute events usually discovered rapidly, whereas mental status deterioration or dyspnea may be subtle and unfold over hours or days.

The role of advance directives in the event of a resident's deterioration is not straightforward and can complicate the transfer decision. The NH staff needed to be familiar with the details of the advance directive and be prepared to implement the resident's stated wishes. However, an advance directive may not clearly apply to real-life situations, particularly with subtle, early-stage deterioration.[27] Advance care planning was not simply whether or not a resident has an advance directive but involved multiple assessments before deciding to transfer a resident. Some of these assessments included residents' current decision-making capacity and whether their current wishes were consistent with a documented advance directive. Also, NH staff needed to evaluate how the advance directive applied to the current clinical situation. This study's results on the role of advanced care planning in hospital transfers require further investigation.

Table 3
Sample Characteristics of Participants (n = 709) and Hospitalization Events (n = 1161)

Baseline Characteristics	n (M)	% (SD)
Age	(82.81)	(13.1)
Race		
White	589	83.1
Black or African American	106	15.0
Asian	4	0.6
Multiracial	4	0.6
Hispanic or Latino	3	0.4
Native Hawaiian or Other Pacific Islander	2	0.3
Not applicable (race not reported)	1	0.1
Dementia (n = 447)		
Early	67	15.0
Middle	211	47.2
Late	161	36.0
Final	8	1.8
DNR (n = 653)		
Yes	365	56.0
No	288	44.0
Reasons for hospital transfers (n = 325)		
Altered mental status	119	36.6
Fall with injury	102	31.4
Fall without injury	18	5.5
Shortness of breath	86	26.5
Length of hospital stay	(2.28)	(0.78)
Discharge diagnosis (n = 330)		
Fall with injury	54	16.4
Fall without injury	23	7.0
Pneumonia	90	27.3
Sepsis	75	22.7
UTI	88	26.7

Length of hospital stay where 1, 2, and 3 stands for values in the variable "duration of stay" (ie, 1: less than a day, 2: 1 to 3 days, 3: more than 4 days).

Duration of Hospitalization

Duration of hospitalization suggested (1) a fall, with or without injuries, resulted in a shorter duration of hospitalization, and (2) a longer duration of hospitalization led to a diagnosis of either sepsis or pneumonia. The finding that falls resulted in shorter hospitalization duration may be due to the presence of fractures requiring surgical repair and limited postoperative acute care. Falls are a major cause of disability and death in older people and are associated with multiple risk factors, including back pain, neurological and visual deterioration leading to cognitive impairment, sensory deficit, and clinical conditions such as Parkinson disease, chronic kidney disease, or glaucoma.[28-32] However, our findings (ie, falls causing a short duration of hospitalization) suggested the focus of the hospital admission related to the fall sequelae rather than its underlying causes. In addition, the longer duration of hospitalization leading to a diagnosis of sepsis or pneumonia corroborated what is known in the clinical setting: that hospital-acquired pneumonia or sepsis leads to longer inpatient stays. These findings helped confirm the validity of the data-driven causal discovery analysis.[33]

Limitations

This study had multiple strengths, including (1) it used a unique set of merged data that linked events of residents' hospitalization with factors that pertained to an APRN's involvement and clinical symptoms/diagnosis of residents before/after hospitalization; (2) it applied a causal discovery analysis that yielded data-driven results; and (3) it used expert consensus for the validity of the data interpretation.

However, the study had some limitations as well. First, after integrating the resident roster and INTERACT 4.0 datasets, we obtained crucial information on hospitalizations essential to achieving our study objectives. However, several factors had to be removed during the integration process, limiting our ability to distinguish between avoidable and unavoidable hospitalizations. Consequently, our study only focused on overall hospitalizations without the ability to identify preventable cases. Despite this limitation, our exploratory causal inference study on APRNs and general hospitalizations served its purpose. However, future research focusing on the impact of APRNs on avoidable or preventable hospitalizations could provide valuable insights for NH stakeholders and policymakers. Second, the lack of a variable describing the specific involvement of APRNs or not specifying an APRN's specific position (eg, clinical nurse specialist, nurse practitioner) might have masked the true impact of APRNs in NHs, which otherwise might have been identified through causal discovery analysis. The similarity among 3 APRN variables (APRN examination, APRN consultation before transfer, APRN evaluation/communication before transfer) did not help the interpretation of the APRN's involvement in NH hospitalization; however, the findings suggested consideration of a resident's advance directive status caused consultation conducted by the APRN. Third, the study did not assess or compare causal links of clinicians with those of APRNs, as we did not include clinician involvement factors in NHs other than ordering hospitalization. Although the study was designed to focus on causal links of APRNs, future studies will benefit from including the involvement of clinicians for comparison. Fourth, this study's methodology used GFCI, which primarily identified linear relationships; therefore, the study may not have detected nonlinear relationships accurately. Although GFCI can detect unmeasured common causes, its performance may not be as good as for direct relationships between measured variables, leading to potential undetected latent confounding. In addition, using GFCI in this study only detected independent effects and did not detect interactions, possibly reducing overall model performance and fit. Finally, although the model fit (RMSEA, CFI) in our study was marginal, it is noteworthy that our

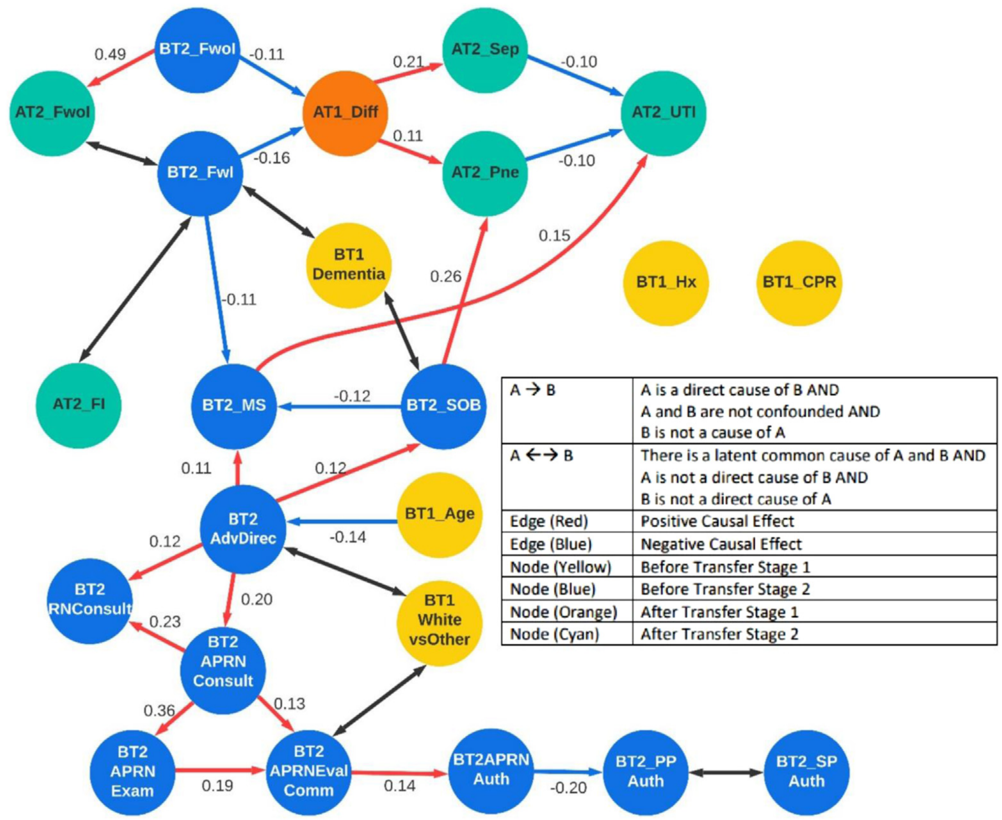

Fig. 2. The causal discovery graph using integrated data (resident roster and INTERACT 4.0). AdvDirec, advance directive planning; AT1, after transfer—stage 1; AT2, after transfer—stage 2; BT1, before transfer—stage 1; BT2, before transfer—stage 2; Diff, length of stay; EvalComm, evaluation/communication prior to transfer; FwI, falls with injury; FwoI, falls without injury; Hx, history; MS, altered mental status; Pne, Pneumonia; PP Auth, primary physician authorizing transfer; Sep, sepsis; SOB, shortness of breath; SP Auth, specialist authorizing transfer; UTI, urinary tract infection.

model was amenable because we used only the most stable edges, which resulted in a sparser model. It is possible to improve these values by including more edges.

Conclusions and Implications

This study addressed the role of the APRN in care delivery and its relation to RNs and other facility staff. Although this study found no causal links between the presence of APRNs and clinical diagnoses of NH residents requiring transfer, the findings emphasized the crucial role of APRNs in NHs. The data show hospital transfers for sepsis or pneumonia required long hospital stays. If APRNs detected subtle changes in resident status for these conditions, such hospital transfers might be avoided. APRNs embedded in NHs were associated with increased discussion and consultation among the APRNs and RNs when there were changes in a resident's status, reflecting better communication and collaboration among care providers. The data also showed onsite APRNs reduced the duplicative activities surrounding physician authorization for a hospital transfer, resulting in more timely assessment, transport, and treatment of residents undergoing critical status changes.

We presented how APRNs allocated nursing staff resources to maximize care delivery efficiency, and NH staff actively sought APRNs' involvement in their clinical decision-making regarding hospital transfers. In addition, we identified the use of advance directives as a preventive alert that helped nursing staff determine which clinical problems or cues to prioritize based on residents' advance directives. More research and follow-up analyses are needed to understand the impact of APRNs on NH residents' care, using datasets with factors that define the APRNs' activities and residents' clinical events before and after hospitalization. This information could assist stakeholders' efforts to improve care and services to residents by budgeting for and involving APRNs in care delivery.

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