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The Cumulative Complexity Model and Repeat Falls

A Quality Improvement Project

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ABSTRACT

Purpose of Project: The purpose of this article is to demonstrate the effectiveness of the Cumulative Complexity Model as a framework to build an Excel tool and a Pareto tool that will enable inpatient case managers to predict the increased risk for and prevent repeat falls. The Excel tool is based on work explained in a previous article by C. Stevenson and K. Payne (2017) and uses a macro to analyze the factors causing the repeat falls and then calculate the probability of it happening again. This enables the case manager to identify trends in how the patient is transitioning toward goals of care and identify problems before they become barriers to the smooth transition to other levels of care. Thus, the case manager will save the facility money by avoiding unneeded days of care and avoiding the costs that result from rendering medical care for the patient who has fallen.

Primary Practice Settings: In July 2015, a group of nurses at a small Veterans Health Administration Hospital in the Northwest collaborated to find ways to reverse a trend of increasing falls and repeat falls.

Methodology and Sample: A retrospective chart review of all falls and repeat falls ($N = 73$) that happened between January 2013 and July 2015 was used to generate a list of top 11 contributing variables that enabled evaluation of the data. A bundle of 3 interventions was instituted in October 2015: (1) development of a dedicated charge nurse/resource nurse, (2) use of a standardized method of rounding, and (3) use of a noncontact patient monitoring system ("virtual nurses"). Falls pre- and postimplementation ($N = 109$) were analyzed using linear and logistic regression analyses. Data were entered into an Excel sheet and analyzed to identify the major contributing factors to falls and repeat falls and to identify trends. These data were also evaluated to find out whether length of stay and nurse workload contributed to falls.

Results: Fifteen months after implementation of the aforementioned interventions, falls on the unit went down from 30 aggregate falls in 2015 to 17 aggregate falls in 2016. Repeat falls in 2015 went from 9 repeat falls after admission to the unit down to 2 repeat falls in 2016. Each additional extrinsic variable that was present added an additional 1.43 to the odds ratio (OR) for a fall. Similarly, each additional intrinsic variable present added 2.08 to the OR for a fall. The linear regression of length of stay and falls demonstrated that 17.5% of falls correlated with length of stay, $F(1,36) = 7.63$, $p = .009$, $R^2 = .175$, adjusted $R^2 = .152$. Workload correlated with work 17% of the time, as measured by using ward days of care, $F(1,100) = 20.84$, $p = .00001$, $R^2 = .17$, adjusted $R^2 = .16$.

Implications for Case Managers: Two examples of the how to use these tools are located in the "Discussion" section of the article:

1. The use of our Excel approach suggested that macro will allow the case manager to predict the probability of future falls and demonstrate patients' response to interventions.
2. The Pareto tool will help prevent future falls by assisting in the identification of the major contributing variables so that they can be addressed before they turn into obstacles to progression of care.
3. The identification of these data trends and major contributing factors will empower the inpatient case manager to influence the improvement in delivery of care and build effective and efficient individualized plans of care based on the specific risk factors involved.

Key words: *Cumulative Complexity Model, fall prevention, repeat falls*

The purpose of this article is to demonstrate the effectiveness of the Cumulative Complexity Model (CuCoM) as a framework to build an Excel tool and a Pareto tool that will enable inpatient case managers to predict the increased risk for, and prevent, repeat falls. This process was based on the work explained in a previous article by Stevenson and Payne (2017, pp. 23–24). This process makes use of a macro (see Table 1 and Figure 1) to analyze the contributing factors related to repeat falls and then calculates their probabilities.

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TABLE 1
Definitions/Explanations of Terms

We used a continuous bedside monitoring system that uses a sensor placed under the mattress of the bed that continuously monitors heart rate, respiratory rate, patient motion, and bed exit. This system provides an "electronic virtual nurse" that continuously monitors patient cardiorespiratory status and alerts the nursing staff of potential issues before they turn into serious conditions, such as patient exiting the bed, and this, in turn, is sent to a text pager carried by the nurse. These text pages give the nurse the ability to prioritize how to deliver care when confronted by multiple tasks that are vying for his or her attention at the same time! The monitoring system continuously monitors pulse and respiratory rates so that the nurse or nurse aide knows in advance if there are any changes in the patient condition that might warrant further assessment before getting a patient out of bed. The system was installed on all 27 beds on the unit in October 2015.
Extrinsic variables: Socioeconomic and environmental risk factors; many of which are potentially modifiable, for example, housing quality, building design, floor surface, and room lighting (Lopez-Soto et al, 2016, p. 436). Some examples of this would be medications/side effects, home hazards, footwear.
Intrinsic variables: Biological and behavioral risk factors, such as age, chronic medical conditions, adverse medication effects, and poor lifestyle habits, sleep disorder, and cognitive impairment (Lopez-Soto et al., 2016, pp. 436, 443). Some examples of this would be psychological diseases, incontinence, history of falls, gait and mobility impairment, visual and sensory deficits.
Linear regression: "The idea is to find the line that best fits the data with the least amount of vertical distance between the fitted line and the actual data among the many lines that could be fitted to the data." "The better the fit of the line through the data and the smaller the sum of residuals, the better predictive value of the model." "The better the line fits, the more accurately it tells about how much variance the independent variable explains or predicts on the independent variable" (Kim & Mallory, 2014, pp. 196–197).
Macro: "A sequence of instructions that automates some aspect of Excel so that you can work more efficiently with fewer errors (Walkenbach, 2010, p. 795).
Multivariate logistic regression: "Provides the relationships of several independent variables to a response variable" (Daniel & Cross, 2013, p. 576). "Repeat falls" was selected as the response variable to compare with the other dependent variables. The closer to one the value gets, the higher the probability the event will occur.
Odds ratio: "The odds ratio is a measure of the how much greater (or less) the odds are for subjects possessing the risk factor to experience a particular outcome" (Daniel & Cross, 2013, p. 572).
Pareto analysis: "Pareto analysis could be characterized as an analytical technique in decision making that is used for the selection of a limited number of tasks that produce significant overall effect. The Pareto principle, also known as the 80/20 rule, encompasses the notion that by doing 20% of the work you can generate 80% of the benefit of doing the whole job. Likewise, in terms of quality improvement, a large portion of problems (80%) are produced by a few key causes (20%). At times these two groups are also referred to as the vital few and the trivial many" (Kros & Brown, 2013, p. 300).
Pareto diagram: "Greatly enhances communication of the information, most notably in convincing upper management of the source of a problem and gaining support for a proposed course of action" (DeFeo, 2016, p. 193).
Pareto principle: "States that in any population that contributes to a common effect, a relative few of the contributors—"the vital few"—account for the bulk of the effect" (DeFeo, 2016, p. 193).
Throughput: Refers to the patient's progression of care and the various touchpoints that impact efficiency. Throughput is a product of the services, treatments, interventions ordered for the patient, and the efficiency in which those services, treatment, and interventions are delivered (Tahan et al, 2016, p. 116).
Ward days of care: Ward days are calculated by dividing the number of hours a patient is in the hospital by 24, giving the number of patient days (i.e., the higher the ward days of care, the higher the nurse workload).

There is an example of how the case manager can use this information to see how the patient is transitioning toward his or her discharge goals and identify problems before they become barriers to the smooth transition to other levels of care. Thus, the case manager can save the facility money by avoiding unneeded days of stay in the hospital and avoid the cost that results from caring for the patient who has fallen. Falls and repeat falls are costly and can result in extended inpatient stays. The cost of falls varies due to severity ranging from $1,139 for falls without injury up to $30,931 for falls with serious injuries (Spetz, Brown, & Aydin, 2015, p. 53). Furthermore, patients who did not have an inpatient fall had shorter stays than those with inpatient falls (Dunn, Gaboury, & Ashe, 2014, p. 398). The course of this article is as follows: present the background and history of events leading up to the project, explain briefly the methodology of the project, provide a literature review with key definitions, show statistical output with discussion about the results, give examples of how to apply the Pareto tool in a case study, and, finally, go over three major implications for inpatient case managers.

Background

In calendar Year 2015, the nurses working on a 27-bed general medical–surgical unit formed a work group to investigate why the unit had experienced

Falls and repeat falls are costly and can result in extended inpatient stays. The cost of falls varies due to severity ranging from $1,139 for falls without injury up to $30,931 for falls with serious injuries.

```
raw data for falls paper.xlsx - Module1 (Code)
(General)                                   Probabilities_For_Falls

Sub Probabilities_For_Falls()
'
' Probabilities_For_Falls Macro
' Calculates the probabilities for the top 11 variables for falls.
'
' Keyboard Shortcut: Ctrl+f
'
    ActiveCell.FormulaR1C1 = "=SUM(RC[-11]:RC[-1])"
    Range("O8").Select
    Selection.AutoFill Destination:=Range("O8:O11"), Type:=xlFillDefault
    Range("O8:O11").Select
    Range("P8").Select
    ActiveCell.FormulaR1C1 = "=EXP(-RC[-1])"
    Range("P8").Select
    Selection.AutoFill Destination:=Range("P8:P11"), Type:=xlFillDefault
    Range("P8:P11").Select
    Range("Q8").Select
    ActiveCell.FormulaR1C1 = "=1+RC[-1]"
    Range("Q8").Select
    Selection.AutoFill Destination:=Range("Q8:Q11"), Type:=xlFillDefault
    Range("Q8:Q11").Select
    ActiveWindow.SmallScroll ToRight:=3
    Range("R8").Select
    ActiveCell.FormulaR1C1 = "=1/RC[-1]"
    Range("R8").Select
    Selection.AutoFill Destination:=Range("R8:R11"), Type:=xlFillDefault
    Range("R8:R11").Select
    ActiveSheet.Shapes.AddChart2(201, xlColumnClustered).Select
    ActiveChart.SetSourceData Source:=Range("Sheet3!$R$8:$R$11")
End Sub
```

FIGURE 1
Example macro for Excel file on calculating probabilities (logistic regression) for falls.

an increased number of falls and, more importantly, repeat falls from the previous year (see Figure 2). The following article presents the findings. It is a follow-up to the article by Stevenson and Payne (2017) that used the CuCoM to develop a tool that enabled case managers to recognize the major stressors from congestive heart failure (CHF) on their clients' lives that were contributing to hospital readmissions (pp. 23–26). Boehmer, Shippee, Boeebe, and Montori (2016) used the CuCom as a "conceptual model" applied to 137 patients undergoing dialysis at a medical center in Minnesota. They found that chronic medical conditions cause symptoms and functional limitations that "contribute to the burden of illness." They further stated that patients with "reduced physical, financial, and mental capacity reported higher disruption and represent a vulnerable group that may benefit from innovations in minimally disruptive medicine" (Boehmer et al., 2016, p. 227).

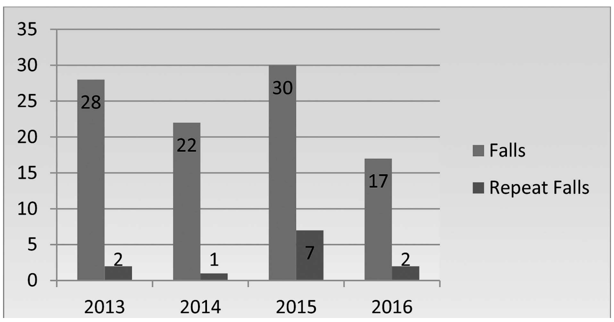

FIGURE 2
Falls and repeat falls.

The CuCom used in Boehmer et al.'s (2016) study was based on the work by Shippee, Shah, May, Mair, and Montori (2012). Stevenson and Payne (2017) used this model as a foundation to show how the different variables added to and potentiated each other's effect on the person, which caused the increased probability of hospital readmissions. Stone, Celi, and Csete (2015) explained further how these vulnerabilities develop: "As the system approaches its theoretical limits of performance, the actuators that maintain this performance saturate; that is, they have no further capacity to meet demands." The second point is that systems with low mean and high variability are healthy. Alternatively, systems with high mean and low variability indicate systems on the cusp of failing (p. 652.e4). An example of this would be when persons are engaged in strenuous physical activity, their average or mean blood pressure increases to help meet their bodies' need for more oxygen and nutrients. However, if after resting their average blood pressure does not go back to normal, but stays elevated, this shows a body system that is still under stress. As time goes on if this average blood pressure does not return to normal, the heart does not get the chance to rest and this can lead to heart problems or even stroke (Hornsten et al., 2016, p. 2063).

This article uses the CuCom, a later work by Boehmer et al. (2016) and Shippee et al. (2016), and the work by Stone et al. (2015), to show that repeat falls are a symptom of a "failing system" that enable inpatient case managers to avoid obstacles that could delay patient progress for discharge and potentially avoidable days of stay in the hospital (Tahan, Powell, Provine, Stanton, & Treiger, 2016, p. 117).

Methods

A retrospective chart review of the post-fall assessment and nursing notes for falls (N = 73) that occurred between January 2013 and July 2015 was completed to look for the presence of top 11 contributing variables. The contributing variables to be examined were broken down into two categories, intrinsic and extrinsic. The *extrinsic variables* were toileting, reaching for something, not using call bell, psychotropic and narcotic medications, and poor footwear (Abraham, 2016b, p. 124; Lopez-Soto et al., 2016, p. 436). The *intrinsic variables* included confusion, physical weakness, poor balance, and other conditions such as syncope or poor vision (Abraham, 2016b, p. 122; Lopez-Soto et al., 2016, pp. 436–443; see Figure 3).

The total of 109 falls was drawn from the following groups: the preimplementation data for 73 falls and repeat falls, seven falls and repeat falls that occurred from July 2017 to December 2017, plus 17 falls and repeat falls in calendar Year 2016, and 12 falls on other units that happened during the same hospital stays. The variables that were nonmodifiable such as age, gender, and race were left out of the analysis as the fall prevention interventions to be discussed target modifiable variables. It was decided to treat repeat falls as a response variable for the purposes of data analysis. Length of stay (LOS) and nurse workload were also included in the initial data analysis. The de-identified data were entered in the Excel sheet as follows: 0 = not present, and 1 = variable contributed to the fall and then analyzed using odds ratio (OR), multivariate logistic and linear regression analyses, and the use of Pareto charts. For an explanation of the method of multivariate logistic regression and the equation used, see Stevenson and Payne (2017). Both LOS and nurse workload were found to have minimal impact on the outcomes and so were left out of the final product.

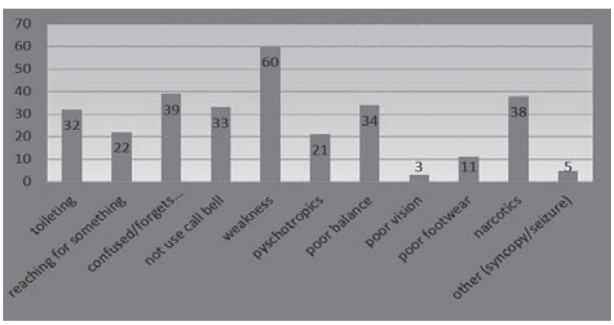

FIGURE 3
Contributing variables.

> *...repeat falls are a symptom of a "failing system" that enable inpatient case managers to avoid obstacles that could delay patient progress for discharge and potentially avoidable days of stay in the hospital.*

Literature Review

A literature review was performed in OVID and PubMed. The authors used only articles published after 2014 to verify the variables selected for the data analysis and the three interventions employed during the project.

Abraham (2016a) reported the results of a qualitative study conducted in the state of Michigan. They asked 160 managers working on inpatient psychiatric units what they felt was the role of intrinsic and extrinsic factors for falls. The analyses for the two questions indicated the participants believed that intrinsic factors were more strongly related to the likelihood of patient falls than were extrinsic factors (p. 25).

A second article by Abraham (2016b) reported that "the intrinsic factors integrated in this study included unsteady gait, history of falls, agitation, comorbidities, advanced age, multiple medications, cognitive impairment, and the ambulatory nature of psychiatric patients" (p. 122). The extrinsic factors used included "teamwork, physical therapy evaluation, supervision, toileting." The participants had a high level of agreement (mean of 4) regarding the need for adequate staffing levels on the psychiatric inpatient unit to reduce patient falls (p. 124).

Brosey and March (2015) supported the use of a proactive approach of systematic rounding to meet patient needs before these needs could lead to negative patient outcomes. This was especially helpful with those patients with altered mental status, those with physical weakness, those who might try reaching for items out of reach, and those who might stand up without assistance. A rate of 7.02 patient falls per 1,000 patient-days was noted in the prior year (November 2011 to February 2012) and a rate of 3.18 resulted following implementation (November 15, 2012, to February 14, 2013). This reflected a 57.7% reduction from the previous year during similar time periods (p. 156).

The groups concluded that an effective fall prevention program involves not only completing a fall risk assessment and marking high fall risk patients but also understanding what factors contribute to patients' fall risk. Furthermore, they concluded that depending on the fall risk factors, clinicians needed to modify the prevention interventions, thus indicating that preventing falls is not just about indicating fall risk patients but also about implementing appropriate patient-specific interventions to help decrease the risk.

In addressing the medical comorbid conditions that contributed to some of the falls, both Brown, Terrence, Vasquez, Bates, and Zimlichman (2014, p. 229) and Slight et al. (2014, pp. 1864–1865) speak compellingly to the positive effects of continuous patient vital sign monitoring on transfers to higher levels of care, LOS, and cost savings through preventing serious hospital-related events, such as codes and rapid response team alerts.

Dunn et al. (2014) conducted an observational study of 622 inpatients and found that the average LOS for inpatients with falls was longer than those who did not have a fall during their inpatient stay. Their results were as follows: The average LOS for those with in-hospital fall (IHF) cases was 37.2 days (median = 26.5 days, interquartile range [IQR] [14, 54]) and 25.7 days (median = 13 days, IQR [5, 33] for matched control patients. Survival analysis results indicated that patients who did not have an IHF were 2.4 times (95% CI [2.1, 2.7]; $p < .001$) more likely to be discharged earlier from acute care than patients who had an IHF (p. 398).

An article by Garcia, Dias, Azevedo da Silva, and Dias (2016) contained results of a longitudinal study of 116 elderly women and found that 64 (55.2%) of them had falls. The hamstring muscle strength was associated with falls (OR = 0.974) and with recurrent falls (OR = 0.966). The history of falls was associated with recurrent falls (OR = 1.336; pp. 136–137).

Lee, Warden, Szuck, and Lau (2016) conducted a study of 56 breast cancer survivors. For the study, a strengthening and balance program was created that was geared specifically to improve the muscle wasting and the nerve damage caused by the cancer treatment regimen. The study showed that their physical strengthening and balance improvement therapies decreased the risk for falls posttreatment ($p < .05$; pp. 564–565).

Lopez-Soto et al. (2016) looked at 763 falls from elderly hospitalized patients. It was found that falls typically took place in the patient's hospital room (72%) and bathroom (23%). Major causes were patient instability (32%) and accident (13%), and most occurred when not wearing footwear (45%) (pp. 438–439).

Stone et al. (2015, p. 652.e4) used the concept of "control" in the engineering sense to explain how "evolved controls maintain normal homeostasis" to explain that disease occurs when the control systems fail. They used the examples of "the role of control in physiology (heart rate variability, immunity), pathophysiology (sepsis), and therapeutic devices (artificial pancreas used in treating diabetes)" to provide "clinical insights" (p. 652.e4).

Van Kamp, Santos, Du, Olivier, and Hatfield (2014) conducted a qualitative study that looked at fall risks from the perspective of 124 older Australians living in Sydney. Input from the community residents on how they perceived the risk of falls in their community was collected using 47 focus discussions and 124 individual interviews. The authors looked at the following factors: vision, physical handicap, medications used for sleep or depression, use of alcohol, environmental hazards, gender, age, and history of falls. In total, 35.5% of the participants reported falls or near falls. About 30% of participants reported repeat falls, 41% reported poor vision, 80% reported the presence of physical handicaps, 23% reported using sleep medications, and 16% reported use of medications for depression (p. 5).

Wilson et al. (2016) conducted focus group discussions on 13 different medical–surgical units to look at the use of fall prevention interventions in three risk factor categories: mobility, elimination, and medications from nurses' perception. The groups concluded that an effective fall prevention program involves not only completing a fall risk assessment and marking high fall risk patients but also understanding what factors contribute to patients' fall risk. Furthermore, they concluded that depending on the fall risk factors, clinicians needed to modify the prevention interventions, thus indicating that preventing falls is not just about indicating fall risk patients but also about implementing appropriate patient-specific interventions to help decrease the risk (p. 1030).

Selection of Interventions

The team studied the preliminary data and accompanying evidence from the literature review and

TABLE 2
Odds Ratios for Variables Pre- and Postimplementation

Variable	Odds Ratio	Prob > χ^2	Lower 95%	Upper 95%	Logistic Regression
Toileting					
Pre	1.19	.79	0.33	4.35	0.77
Post	1.15	.78	0.40	3.37	0.76
Reaching for something					
Pre	3.01	.20	0.56	18.84	0.95
Post	2.03	.26	0.59	7.42	0.88
Not use call bell					
Pre	1.34	.68	0.31	5.56	0.79
Post	2.74	.09	0.86	9.11	0.94
Use of psychotropics					
Pre	5.41	.03	1.16	31.22	0.99
Post	4.96	.02	1.29	22.69	0.99
Presence of poor footwear					
Pre	2.88	.29	0.40	22.49	0.95
Post	None present	NA	NA	NA	NA
Use of narcotics					
Pre	0.17	.0043	0.04	0.59	0.54
Post	0.19	.0019	0.06	0.55	0.55
Comorbid conditions					
Pre	7.64	.07	0.87	92.90	0.99
Post	1.17	.87	0.19	7.62	0.76
Altered mental status					
Pre	4.80	.02	1.29	20.60	0.99
Post	2.02	.19	0.70	5.79	0.88
Presence of weakness					
Pre	3.11	.27	0.44	32.73	0.96
Post	1.49	.58	0.36	6.82	0.81
Presence of poor balance					
Pre	3.30	.07	0.90	12.88	0.96
Post	4.66	.003	1.69	13.69	0.99
Presence of poor vision					
Pre	0.79	.90	0.02	40.37	0.69
Post	1.84	.61	0.19	40.31	0.86

Note. NA = not available.

decided to use a three-pronged approach to come up with interventions to address the contributing factors. The *first intervention* was the establishment of a dedicated charge nurse for all shifts who was assigned a reduced patient load so that he or she could act as a resource nurse to help with workload issues and answering call bells. The *second intervention* involved implementing a systematic program for the performing and documenting of hourly rounding. The *third intervention* involved the purchase of a continuous, noncontact heart and respiratory inpatient safety monitoring system.

...the number of falls on the unit went down from 30 aggregate falls in 2015 to 17 aggregate falls in 2016.

Results

As shown in Figure 2, the number of falls on the unit went down from 30 aggregate falls in 2015 to 17 aggregate falls in 2016, and repeat falls in 2015 went down from 7 repeat falls to 2 repeat falls in

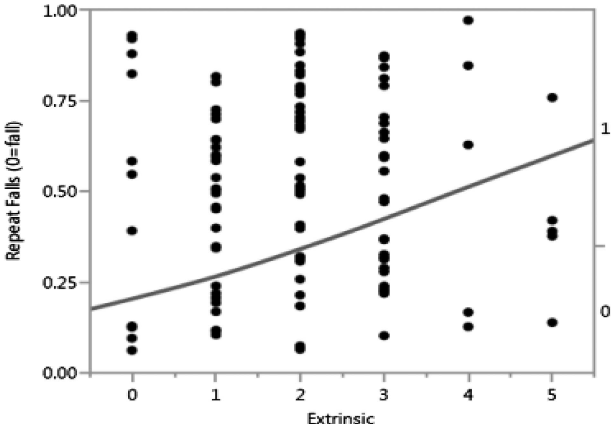

FIGURE 4
Cumulative effect for extrinsic variables.

2016. The average LOS went down from 9.23 days preimplementation to 6.45 days postimplementation.

Table 2 gives the ORs of the contributing variables to falls. Calculations for the OR were done before and then postimplementation for the three interventions. The OR dropped for the extrinsic variables: toileting, reaching for something, use of psychotropic medications, and presence of poor footwear. The same trend was observed for the intrinsic variables: comorbid conditions, altered mental status, and presence of weakness, except for two: not using call bells, which increased, and narcotic, whose probability increased minimally. The only ones that demonstrated statistical significance ($p < .05$) were those for the use of narcotics and use of psychotropic medications. Table 2 also showed that the ORs decreased postimplementation for intrinsic variables such as comorbid status, altered mental status, and presence of weakness. Two intrinsic variables, poor vision and poor balance, had an increased OR after implementation. Table 2 also demonstrates that only one (use of narcotics) of the six extrinsic variables had an OR that increased from 0.17 to 0.19.

Statistical analysis of the predictive variables revealed that each additional extrinsic variable added 1.43 to the OR for a fall (see Figure 4 and Table 3). Similarly, each additional intrinsic variable added 2.08 to the OR for a fall (see Figure 5 and Table 4), showing that the more fall risk variables a patient has, the higher the chance for falls.

Figure 6 is a Pareto chart that shows that preimplementation, the driving forces behind falls were as follows: (in the descending order) use of psychotropic medications, comorbid conditions, altered mental status, presence of weakness, presence of poor balance, reaching for things, and poor footwear. Figure 7 is a Pareto chart that shows that post implementation, the driving forces behind falls were as follows: (again in the descending order) use of psychotropic medications, presence of poor balance, not using call bell, reaching for items, altered mental status, poor vision, and presence of weakness.

A multivariate logistic regression analysis of 35 falls analyzed postimplementation showed that 29 of 35 or 83% of these repeat falls indicate that the cumulative effect of the variables increased the probability of a repeat fall. See Figure 8 for an example.

As mentioned earlier, LOS did decrease after falls postimplementation, but linear regression analysis showed that LOS correlated with falls in only 17.5% or 19 of the 109 falls. Similarly, nurse workload correlated with patient falls in only 17% or 18 of 109 falls (see Table 5). This contrasts with the findings of Nantsupawat, Nantsupawat, Kunaviktikul, Turale, and Poghosyan (2016, p. 87) and Abraham (2016b, p. 124).

Discussion

As previously stated, the purpose of this article is to demonstrate the effectiveness of the CuCoM as a framework to build an Excel tool and a Pareto tool that will enable inpatient case managers to predict the increased risk for and prevent repeat falls.

The benefits of being able to predict the increased probability of a fall is explained in the following example using an Excel file.

Case Study 1: Use of the Excel File

Imagine a busy Wednesday afternoon in a small Veterans Health Administration Medical Center somewhere in the Northwest. You have just been contacted by the medical providers that they want to discharge

TABLE 3
Cumulative Effect for Extrinsic Variables

Parameter Estimates						
Term	**Estimate**	***SE***	**χ^2**	**Prob> χ^2**	**Unit Odds Ratio**	**Odds Ratio**
Intercept	−L3682201	0.4148872	10.88	.0010*		
Extrinsic	0.35463234	0.1681649	4.45	.0350*	1.4256564	5.88944461

*For log odds of 0/1.

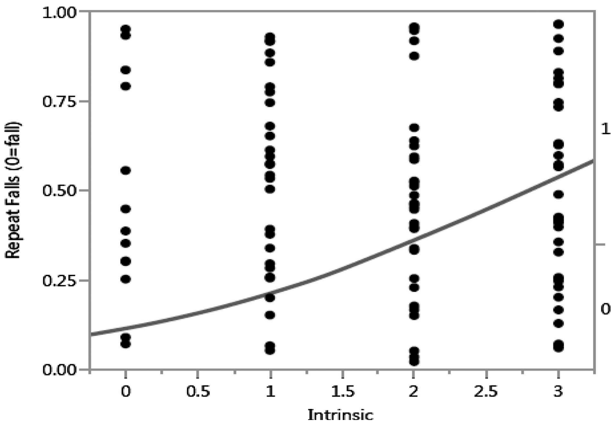

FIGURE 5
Cumulative effect for intrinsic variables.

Mr. Ivan Fallovich to a rehabilitation center prior to his being able to go home with his wife. You look through his chart and find the following information in the nursing and medical provider notes:

The veteran with altered mental status was admitted Monday morning related to a urinary tract infection:

a. Mr. Fallovich is experiencing altered mental status (oriented to person only), not remembering to use the call bell to ask for help to get up out of bed or the chair. Chair and bed alarms have been used but are not effective, as the veteran will not accept the use of a walker. Ivan has also been pulling his intravenous catheter out, making it difficult to receive his antibiotics for his infection. The medical providers have been prescribing oral quetiapine fumarate to help mitigate his behavior.
b. Mr. Fallovich is very deconditioned (i.e., weakness, problems with balance).
c. Mr. Fallovich has chronic back pain due to a crushing injury while in the Army in Vietnam. He has had numerous back surgical procedures and normally takes long-acting oral morphine.
d. The veteran has fallen four times since admission.

Armed with this information, you then organize what you have found. You have a list of top 11 contributing factors for falls along with how they affect the probability for falls (see Table 2). You enter the values from the Logistic Regression column found under the row for Post into an Excel file. See Table 6 for an example of the one we used. You then implement the macro found in Figure 1 and you get the results shown in Figure 8. The mathematics behind the equation used in the macro is explained in the article by Stevenson and Payne (2017, p. 25). For an explanation of how to generate a macro, see Walkenbach (2010, pp. 796, 802–806).

This graph reveals several trends that can assist you in predicting the probability of a future fall if the contributing variables were not to change. The first trend is that between the first and second falls, there was an increased probability for a fall. The initial pattern demonstrates how Mr. Fallovich's body (system) was evincing a system under duress. This demonstrates the trend explained by Stone et al. (2015) as what happens to a system when it approaches its "theoretical limits of performance." In other words, his body's weakness, poor balance, pain, and altered mental status were too much for Mr. Fallovich to compensate for and resulted in his experiencing repeat falls (Stone et al., 2015, p. 652.e4).

The second trend was that there was no change in the probability for falling between the second and third falls. The second pattern seen between the second and third falls is alarming because the average of the two did not change but stayed high. Stone et al. (2015) explained this as "the high mean/low variability pattern represents a system in the throes of failure" (p. 652.e4). In other words, Mr. Fallovich's system was being overwhelmed by the additional burdens placed on his body due to his altered mental status, weakness, etc., and the fall interventions were not working to reduce this additional workload. If this trend continues, it is not a question whether the patient will fall, but when he will fall.

The third trend was that the probability for a fall went down between the third and fourth falls.

This pattern is more reassuring, because the probability for a future fall is coming back down to a point even lower than the first fall. This also tells you that the interventions being used by the nursing and medical staff are working to relieve the stressors being placed on Mr. Fallovich. In fact, you verify

TABLE 4
Cumulative Effect for Intrinsic Variables

Parameter Estimates						
Term	**Estimate**	***SE***	**χ^2**	**Prob> χ^2**	**Unit Odds Ratio**	**Odds Ratio**
Intercept	−2.039117	0.5077879	16.13	<.0001*		
Intrinsic	0.73239716	0.225363	10.56	.0012*	2.08006087	8.99970206

*For log odds of 0/1.

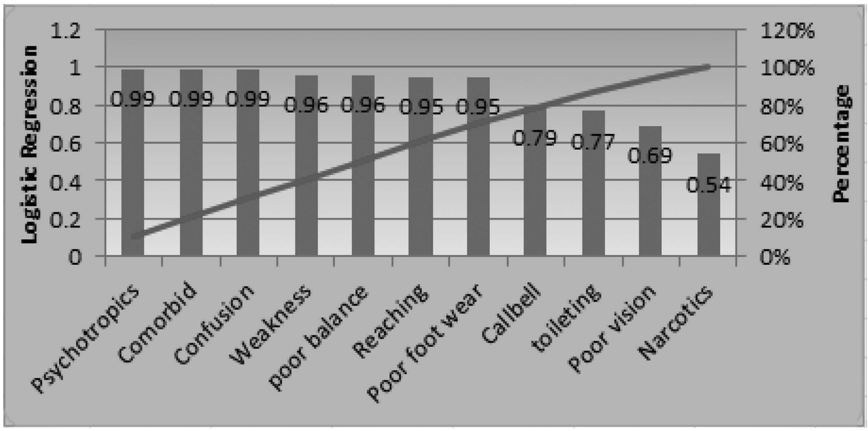

FIGURE 6
Pareto chart for preintervention variables.

from the physical therapy note that Mr. Fallovich is receiving physical therapy, which is helping improve his balance issues. The medical providers' notes show that they converted his antibiotics to oral dosing, which he is tolerating better, and took him off the psychotropic medications. The medical providers restarted his home regimen of pain medications.

A quick check of the OR for use of pain medications demonstrates that the use of narcotics is protective for falls (i.e., OR close to or <0.5). This was explained in a journal article by Helminen, Sinikallio, Valjakka, Vaisanen-Rouvali, and Arokoski (2016). They conducted a study of 111 individuals and found that fear of pain resulted in decreased functioning with knee osteoarthritis (p. 898). Similar results were reported by Oliashirazi, WilsonByrne, Shuler, and Parvizi (2017), who performed a pooled analysis of 1,882 postoperative patients from three random controlled trials and found that better postoperative pain control resulted in not only improved mobility but also fewer negative medical outcomes (p. 205).

These changes show how the CuCom explains the impact of "medical conditions that cause pain, fatigue, and other symptoms, as well as functional limitations, which contribute to the burden of illness." Mr. Fallovich is an example of a "vulnerable individual that may benefit from innovations in minimally disruptive medicine" (Boehmer et al., 2016, p. 227).

Armed with this information, you, the case manager, contact a local rehabilitation center closest to the veteran's home and fax copies of the patient's record to the facility for them to review. After a time, they call you and bring up a possible barrier to admission to their facility. They are worried about the multiple falls he had. You send them a copy of Figure 9 and tell them that the probability of a repeat fall is decreasing to levels below even the first fall, which shows he is responding well to the antibiotics and is doing better in getting around safely and this should not be a barrier for his transferring to their program. They agree and say they will send someone over to interview the patient tomorrow morning. The next day you report to their representative that there

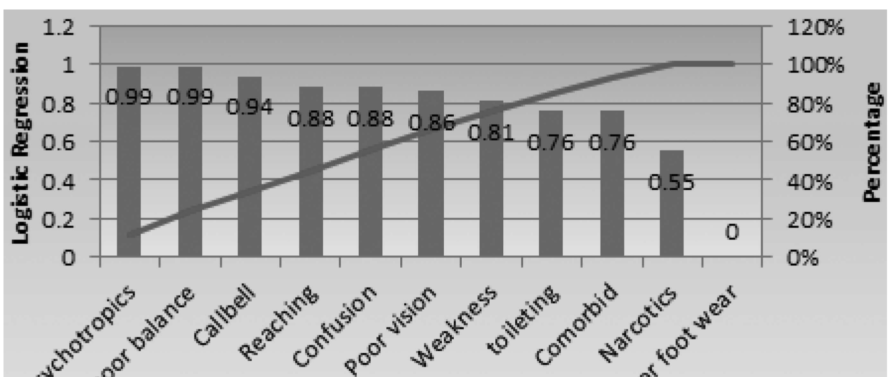

FIGURE 7
Pareto chart for postintervention variables.

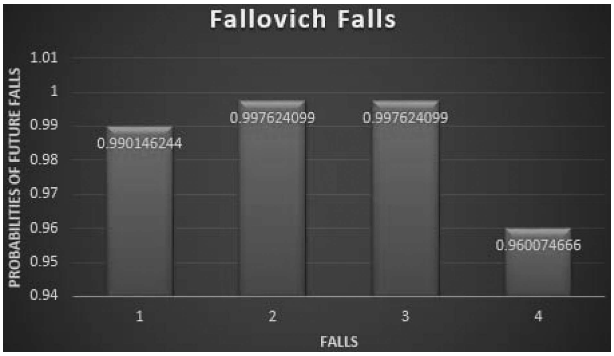

FIGURE 8
Graph showing the increased probability of a fall and the high mean and low variability pattern for Mr. Fallovich as explained by Stone et al. (2015).

has been no further falls in 24 hours and you go with them to introduce them to the veteran.

Case Study 2: Use of the Pareto Chart

The following example will show how use of the Pareto tool can help prevent falls.

You, as the case manager, are preparing for a team conference regarding the problems Mr. Toomany Falls is having reaching his goals of care. One of the major topics to be discussed is Mr. Falls frequent ground-level falls. You read the notes from nursing, medical providers, and physical therapy and identify the contributing variables for falls and, using Figure 1 as a reference, you then organize them into an Excel file (see Table 7).

You use this information to make a Pareto chart. YouTube has several examples on how to make a Pareto chart using an Excel sheet. The Pareto chart shows the following:

a. There is a combination of intrinsic (poor balance, confusion, and weakness) and extrinsic variables (psychotropic medications and reaching for items out of reach) involved in the falls.
b. There are three areas of the graph that reveal interesting trends:
    1. The first group—use of psychotropic medications and poor balance—each contributes 22% toward the burden his medical condition places on his body.
    2. The next group—confusion and having to reach for items out of reach—each contributes about 19% to the burden he is experiencing.
    3 These two groups are making up 82% of the load he is carrying.
    4. The other 18% of his burden stems from the physical weakness he is experiencing.

What the Evidence Shows

Each causative variable places an additional burden on a system already at risk (see Table 7).
Each additional extrinsic variable adds an extra 1.43 to the OR for a fall (see Table 3 and Figure 4).
Each additional intrinsic variable adds an extra 2.08 to the OR for a fall (see Table 4 and Figure 5).

You would get the best results in improving Mr. Falls progression toward discharge by prioritizing any medical, nursing, and physical therapy interventions that target the intrinsic variables (because they have a higher OR) such as poor balance and then address the extrinsic variables (which have an OR less than intrinsic variables) such as confusion etc. The elimination of these major contributing variables will prevent falls by decreasing the major stressors that are driving the repeat falls.

This knowledge will put the case manager in the strategical "high ground," which enables the case manager to assist the medical and nursing staff to apply the principles advocated in Wilson et al. (2016). First, understand the fall risk factors or "vulnerabilities" for each patient that are indicative of where they need the most immediate help. Second, the case manager can advocate for the patient by assisting the medical and nursing staff in "critical thinking when selecting and implementing fall prevention interventions to mitigate those risks" or "vulnerabilities" (Wilson et al., 2016, p. 1030).

Summary

Our purpose for this article was to demonstrate how the CuCoM could be used as a framework upon which to build a structured and efficient tool that could be used to predict the probability for and prevent falls. A retrospective chart review was done for veterans who fell during a 3-year period to identify top 11 contributing variables. These variables were validated by a literature review of recent research articles using some

TABLE 5
Linear Regression for Length of Stay and Nurse Workload Versus Patient Falls

Variable	*df*	Residual	*F*	*p*	R^2	Adjusted R^2
Length of stay	1	36	7.63	.009	.175	.152
Nurse workload	1	100	20.84	.000014	.17	.16

TABLE 6
Example Excel Sheet for Mr. Ivan Fallovich

Number	Date	Repeat Falls	Toileting	Reaching for Something	Confused/ Forgets/ Limitations	Not Use Call Bell	Weakness	Pyschotropics	Poor Balance	Poor Vision	Poor Footwear	Narcotics	Other Syncope Episodes, Seizure
15d	May 23, 2017	0	0	0	0.88	0.94	0.81	0.99	0.99	0	0	0	0
15a	May 23, 2017	1	0	0.88	0.88	0.94	0.81	0.99	0.99	0	0	0.55	0
15b	May 24, 2017	1	0	0.88	0.88	0.94	0.81	0.99	0.99	0	0	0.55	0
15c	May 24, 2017	1	0	0	0.88	0.94	0.81	0	0	0	0	0.55	0

commonly known search engines. The group then implemented evidence-driven interventions during a 15-month period and looked at the OR and logistic regression for the variables pre- and postimplementation. The results for the project were presented and organized into reference tables that were ready to be entered Excel files that could be used by the case manager to analyze the trends in the probabilities for future events and examine the ranking of contributing variables so that individualized plans of attack could be developed. Two examples were given that demonstrated how case managers could use the CuCom and our tools to accomplish some common occurring tasks they face on any given day. Also provided was a macro that would help the reader develop an Excel file that could be used to generate the data described.

These tools can be used to generate similar tools for the veteran with other medical conditions. An example of this was presented in a previous article by Stevenson and Payne (2017). They used these same tools and the CuCoM to develop a tool that enabled case managers to recognize the major stressors being placed on veterans with CHF that were contributing to hospital readmissions.

The CuCom is an ideal framework upon which to build these tools because it emphasizes the delivery of medical care geared toward reducing the burden the individual is experiencing due to his or her illness. This was shown in another article by Stevenson, Pori, Payne, Black, and Taylor (2015) that presented the concept that veterans think in terms of symptoms that increase the impact of CHF on their lives (p. 183).

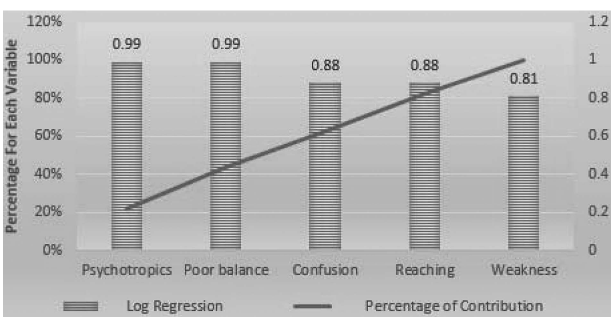

FIGURE 9
Pareto chart for Case Study 2.

Limitations

There are some limitations to this project. The sample was drawn from veterans living mostly in a rural setting. More research needs to be done to see how the same variables would present themselves in nonveteran or urban settings. The statistical analysis as performed by the statistician eliminated any bleed over between variables on the finished data.

Implications for Case Managers

The 2016 Core Curriculum for Case Managers published by the Case Management Society of America (CMSA) is a great reference for individuals working in, or aspiring to entry into, the field of case management. The authors used the following statements from the aforementioned reference to anchor comments to their tool and explain their relevance to the inpatient case managers.

The CMSA stated in the Core Curriculum that "using the practical Pareto approach, the case manager can concentrate on those patients at most risk for progression of care obstacles that may delay transition and add readmission risk" (Tahan et al., 2016, p. 116).

The same reference states in the section on Crossing the Acute Care Continuum, "Case managers have no positional authority so they have to rely on other means to influence improvement in delivery of care." One of these means explained on the same page was the "capture and quantification of information on the touchpoint obstacles encountered that result in a delay of progression of care day, or a potentially avoidable day" (Tahan et al., 2016, p. 117).

In the section on Risk Factors for Falls in the Elderly, the CMSA Core Curriculum states, "Case managers should tailor the care interventions to the specific risk factors" (Tahan et al., 2016, p. 168).

TABLE 7
Fictitious Patient's Vulnerabilities (Variables) Involved With a Fall

Vulnerabilities	Log Regression Values	Driving Forces for Fall
Psychotropics	0.99	22%
Poor balance	0.99	44%
Confusion	0.88	63%
Reaching	0.88	82%
Weakness	0.81	100%
Total	4.55	

This article contributes to helping inpatient case managers who are trying to incorporate the aforementioned guidance into their practice in several ways.

1. The use of our Excel approach and suggested macro will allow the case manager to predict the probability of future falls. This approach not only works for falls but can also be used to predict similar results in other health situations. This is a valuable triage tool that will enable the case manager to prioritize cases, give guidance to doctors and nurses and, as demonstrated in our example earlier, and assist in identifying when a patient is responding to therapy and is ready for transition to other levels of care. It will also let the case manager know when the veteran is not responding to the medical plan and is not ready for transition to the subacute level after discharge.
2. The Pareto tool will help prevent future falls by assisting in the identification of the major contributing variables so that they can be addressed before they turn into obstacles to progression of care. The Pareto chart will show the major contributing factors in a ranked order so that the case manager can identify potential barriers quickly and efficiently before they can turn into barriers that interfere with throughput. Serial Pareto charts can also be used to show the progression of contributing factors through the continuum of care. Two examples of this are pre- and postintervention Pareto charts seen in Figures 6 and 7. Notice how the interventions shifted the major contributing variables as explained in the "Results" section. This also demonstrated the effect of the three interventions on the contributing variables.
3. The identification of these data trends and major contributing factors will empower the inpatient care manager to influence the improvement in delivery of care and build effective and efficient individualized plans of care based on the specific risk factors involved.

Both Tahan et al. (2016) and Wilson et al. (2016), in their aforementioned quotes, stressed the importance of targeting interventions to specific risk factors. The ability to do so with surgical precision based on evidence-based analysis tools will empower the inpatient case manager to be a catalyst for improving medical outcomes for our veterans.

Patients with repeat falls have a dynamic, ever-changing risk for future falls. The CuCoM provides a unique way of viewing this complex problem and serves to focus our attention on the interaction between patients and the increased load placed on them by the different aspects of their medical condition. It is these contact points that have the potential to become obstacles to how our veterans transition through the continuum of care. It is the case manager who, if armed with reliable analysis tools and information, can be strategically placed to perceive and help assist the veteran, and all patients, progress efficiently and effectively through the continuum of care.

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