CIN: Computers, Informatics, Nursing • Vol. 31, No. 6, 274–280 • Copyright © 2013 Wolters Kluwer Health | Lippincott Williams & Wilkins

FEATURE ARTICLE

Evaluation of Health Alerts From an Early Illness Warning System in Independent Living

MARILYN J. RANTZ, PhD, RN, FAAN
SUSAN D. SCOTT, MSN
STEVEN J. MILLER, MA
MARJORIE SKUBIC, PhD
LORRAINE PHILLIPS, PhD, RN
GREG ALEXANDER, PhD, RN, FAAN
RICHELLE J. KOOPMAN, MD, MS
KATY MUSTERMAN, RN, BSN, MBA
JESSICA BACK, LMSW

Passive sensor networks were deployed in independent living apartments to monitor older adults in their home environments to detect signs of impending illness and alert clinicians so they can intervene and prevent or delay significant changes in health or functional status. A retrospective qualitative deductive content analysis was undertaken to refine health alerts to improve clinical relevance to clinicians as they use alerts in their normal workflow of routine care delivery to older adults. Clinicians completed written free-text boxes to describe actions taken (or not) as a result of each alert; they also rated the clinical significance (relevance) of each health alert on a scale of 1 to 5. Two samples of the clinician's written responses to the health alerts were analyzed after alert algorithms had been adjusted based on results of a pilot study using health alerts to enhance clinical decision-making. In the first sample, a total of 663 comments were generated by seven clinicians in response to 385 unique alerts; there are more comments than alerts because more than one clinician rated the same alert. The second sample had a total of 142 comments produced by three clinicians in response to 88 distinct alerts. The overall clinical relevance of the alerts, as judged by the content of the qualitative comments by clinicians for each alert, improved from 33.3% of the alerts in the first sample classified as clinically relevant to 43.2% in the second. The goal is to produce clinically relevant alerts that clinicians find useful in daily practice. The evaluation methods used are described to assist others as they consider building and iteratively refining health alerts to enhance clinical decision making.

KEY WORDS

Aging in place • Independent living • Long-term care • Technology

Early detection of illness or exacerbation of chronic illness is critical to prevent significant decline in health or functional status of older adults and enables early interventions when treatment is most effective.[1,2] Sensor technology provides a cost-effective way to monitor older adults in their home environments, detect signs of impending illness, and alert clinicians so they can intervene and prevent or delay significant changes in health or functional status. The University of Missouri (MU) Center for Eldercare Rehabilitation Technology (CERT) (www.eldertech.missouri.edu) installed passive sensor networks in apartments of independent living residents at

Author Affiliations: Sinclair School of Nursing (Drs Rantz, Scott, Phillips, and Alexander and Mr Miller); Department of Electrical and Computer Engineering (Dr Skubic); Curtis W. and Ann H. Long Department of Family and Community Medicine (Drs Koopman and Rantz); TigerPlace, Sinclair School of Nursing (Mss Musterman and Back), University of Missouri, Columbia.

This article is based on the results of National Institute of Nursing Research (NINR)–funded research, 1R21NR011197-02 (Dr Rantz, principal investigator, 2009–2012; Technology to Automatically Detect Early Signs of Illness in Senior Housing). The results and conclusions are the responsibility of the researchers and are not the opinion of NINR. The authors gratefully acknowledge the residents and staff of TigerPlace who graciously participated in their technology development research and the students and faculty of the Center for Eldercare Rehabilitation Technology Research Team at the University of Missouri.

The authors have disclosed that they have no significant relationship with, or financial interest in, any commercial companies pertaining to this article.

Corresponding author: Marilyn J. Rantz, PhD, RN, FAAN, S 406 Sinclair School of Nursing, University of Missouri, Columbia, MO 65211 (rantzm@missouri.edu).

DOI: 10.1097/NXN.0b013e318296298f

TigerPlace and developed alerts based on the sensor data that notified clinicians of changes in activity patterns. Early recognition of an increase or decrease in the quantity and/or frequency of activity is important because a change in usual activity for a person may signal a change in health status that warrants prompt assessment.[3] The purpose of this article was to report the analysis of iterative refinement of health alerts to improve clinical relevance to clinicians as they use alerts in their normal workflow of routine care delivery to older adults living in elder housing. The evaluation methods used are described to assist others as they consider building and iteratively refining health alerts to enhance clinical decision making.

BACKGROUND

TigerPlace is a retirement community helping older adults age in place. The goal of aging in place is to allow older adults to remain at home through the end of life by providing supportive services when needed.[4] TigerPlace was established in 2004 by Americare Systems, Inc, in partnership with the MU Sinclair School of Nursing for evaluation of the aging in place model.[5]

To facilitate aging in place, Sinclair Home Care Aging in Place provides registered nurse (RN) care coordination and home care services to residents of TigerPlace. Care coordination revolves around a wellness center where residents may have their vital signs assessed, discuss potential health issues with a nurse, receive assistance with medications, and have minor problems addressed. The wellness center is open 5 days per week. The RN coordinates all residents' healthcare with physicians, physical therapists, other healthcare providers, and family members. The residents receive semiannual comprehensive health assessments to monitor health status and facilitate care coordination. An RN is on call 24 hours per day, 7 days per week to triage emergency situations and answer questions. Home health aides are on-site 24 hours a day to assist residents with scheduled care and urgent care concerns. Residents have access to four prepaid, nurse, or licensed social worker private visits in their apartments per year to assess and assist with occasional health or psychosocial problems. Sinclair Home Care Aging in Place provides exercise classes 5 days per week and a variety of social activities.[6] Residents may pay additional fees for care packages at different levels including services such as medication management, bathing, and dressing.

The MU CERT Research Team is developing an integrated in-home sensor network to support care coordination and facilitate aging in place at TigerPlace. The CERT Research Team is an interdisciplinary team of nurses, social workers, physicians, health informatics experts, and electrical and computer engineers. Inexpensive passive infrared motion sensors are placed in each room of the resident's apartment to monitor activity and presence in their natural environment. A bed sensor, located under the bed linens or placed in a chair in which the resident sleeps, monitors restlessness, pulse, and respiration.[7] People do not need to wear any devices or do anything special as everything is embedded in the environment. The team designed the system in this way because compliance with using traditional telemonitoring equipment (like blood pressure, weight, or devices that require a person actively "do something" routinely) decreases over time.[8] To address this compliance issue, the team uses sensors in the environment instead of a wearable device that may be considered invasive to the residents. A secure Web-based interface was developed and refined to display sensor data for clinicians and researchers[7] in a format that healthcare providers find easy to use and interpret and that is readily available and clinically relevant.

Initial Alert Development

Retrospective analysis of the sensor data before and after health events (emergency department visits, hospitalizations, and falls) revealed patterns that could be used to alert healthcare providers to possible changes in health status.[9] Based on these preliminary analyses, alerts were developed from the sensor data to notify clinicians and researchers of potential changes in the health status of TigerPlace residents. The initial alerts were based on the normal distribution of the sensor data from the previous 14 days. If the total of number of sensor hits for the current day was significantly outside the mean for the previous 14 days, an alert was generated.[10] In original algorithms, an alert was generated if any of the current day's sensor parameters was four standard deviations outside the mean. Algorithms were iteratively refined based on clinician input. Revised algorithms use different standard deviations based on the type of sensor and whether the total numbers of sensor hits is increasing or decreasing to adjust for clinical relevance.

Pilot Study to Evaluate the Clinical Impact of Alerts on Health Outcomes

The MU Institutional Review Board (IRB) approved a 1-year pilot study that was conducted from June 2010 to June 2011 to evaluate the effects of using health alerts in everyday clinical care on the health and functional outcomes of participants. A convenience sample of 42 people was recruited: 20 people with sensor networks (intervention) and 22 without the sensors (control). All participants signed an informed consent. The average age of the participants was 84.6 years (range, 64–96 years).

One control participant was Asian; the remaining participants were white. There were 27 women and 14 men in the study, including four married couples. Complete study description and results are reported elsewhere.[3]

The research team of several clinicians received the alerts. The team consisted of three PhD-prepared nurses, including an advanced practice RN who was a gerontology expert, a family medicine physician, the TigerPlace care coordinator, and staff nurse. A social worker, who joined the team in June 2011, began receiving the alerts as the pilot study ended.

During the pilot study, when the clinicians received an e-mail alert, they would visit the secure Web site that displayed the sensor data to determine if clinical intervention was warranted. If the alert was clinically relevant, the TigerPlace nurse care coordinator, staff nurse, or social worker would assess the intervention group participant, intervene as necessary, involve other healthcare providers as appropriate, and document the actions taken within the resident's electronic health record (EHR). Based on the sensor data analysis, the clinical researchers who received alerts would analyze the sensor data and recommend an intervention, such as "needs to be assessed by the care coordinator for potential health problem," by notifying the care coordinator and documenting the need for intervention in a log maintained for the research.

Control participants received standard care from Sinclair Home Care. As potential problems were identified through routine assessment or self-report, the nurse took appropriate nursing actions, assessed the resident, involved other healthcare providers as necessary, documented interventions within the EHR, and followed up with family members.

Alerts were sent via secure e-mail to the clinicians and researchers (Figure 1). To protect the research subjects' identities, only the participant number was included in the e-mail. No medical information is stored in the sensor database and the researchers did not have access to medical information. Only TigerPlace clinical staff had access to the resident's EHR. In the alert e-mail, there is a link to a feedback webpage that enabled clinicians to rate the "significance" of the alert on a 5-point Likert scale, with 5 indicating that the alert was very significant and 1 indicating that the alert was insignificant (Figure 2). "Significance" for this scale was defined as "clinically significant," not significant in the context of testing statistical significance. In addition, the clinician provided comments regarding each alert in a text box.

Because participants in the pilot study showed statistically significant improvements in function as compared with the control group in the Short Physical Performance Battery gait speed score at quarter 3 ($P = .03$), left hand grip at quarter 2 ($P = .02$), and right hand grip at quarter 4 ($P = .05$) and the functional ambulation profile of the GAITRite analysis mat at quarter 2 ($P = .05$),[3] the sensor system alerts continue as part of standard care at TigerPlace. The nurse care coordinator, social worker, and a doctorally prepared nurse who was a coinvestigator of the pilot study continue to receive, review, rate significance, and provide feedback on each alert. Based on the alerts, the nurse care coordinator and social worker are evaluating residents, intervening when necessary, and documenting specific interventions.

To provide additional insights and to further refine alert algorithms, two qualitative deductive content analyses[11] were approved by the University IRB and were completed using clinician and researcher written comments as they evaluated each health alert. Content was analyzed for 5 months at the end and immediately following the pilot study (after adjustments were made to

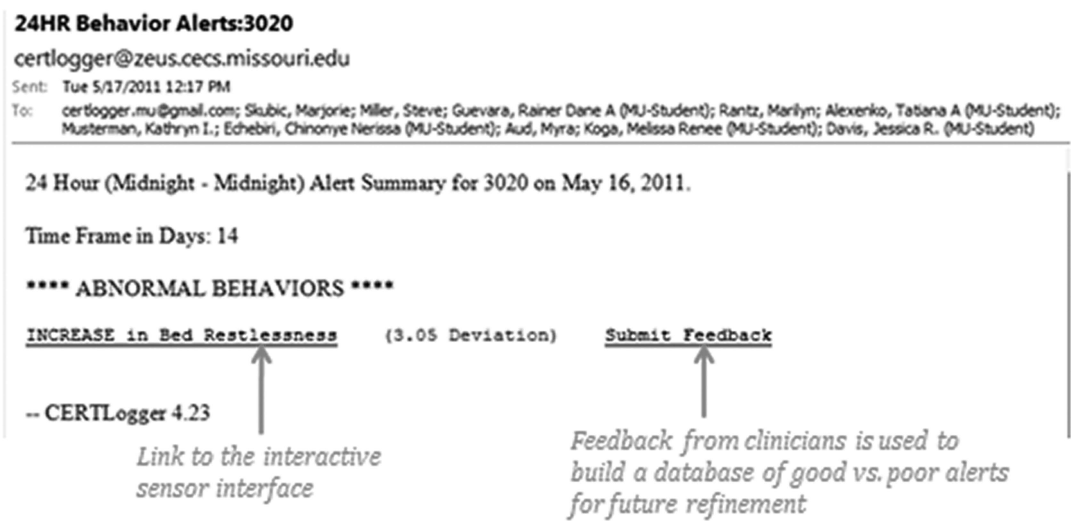

FIGURE 1. Early illness alerts from e-mail.

FIGURE 2. Alert feedback from clinicians.

the health alert algorithms based on pilot study results and clinician advice) and then for 3 months after additional adjustments were made. This provided two post–pilot study samples for analysis after iterative adjustments were made to the algorithms. The goal is to produce clinically relevant alerts that clinicians find useful in daily practice.

METHODS

Two deductive content analyses were completed to categorize the clinicians' comments in response to data-driven alert generated from environmentally placed sensors. Content analysis is a research method for formulating replicable and valid inferences from data in their context.[11] In deductive content analysis, a categorization matrix is developed and the data are coded according to this matrix. The deductive method is used to compare categories at different time periods.[12] A deductive analysis was used to evaluate the changes in clinical relevance of the alerts over time as determined by categorization of clinicians' written responses to the alerts.

Two master's-prepared research staff (S.D.S., S.J.M.) independently reviewed and qualitatively coded the clinical relevance of each of the comments written by seven clinicians in response to the 385 alerts between the time period of April 12, 2011, and October 3, 2011. A preliminary matrix of coding categories was created based on the common themes[11] identified within the notes; these included "clinically relevant" comments about interventions, potential interventions, or recommended interventions and "not clinically relevant" comments about alerts such as being out of the apartment, visitors in the apartment, questioning sensors or the alert. The coders were encouraged to add codes if the content did not fit into one of the preliminary categories. During this review process, the coders were blinded to the clinician reviewer's alert significance ratings (see Figure 2, which displays 1–5 ratings, with 5 indicating very significant). After independent review, the coders met and reviewed the comments that they coded differently and reached consensus. The results of the initial analysis were summarized to guide additional analytic steps.

More than one clinician may have received and rated alerts from a particular resident. Therefore, an alert may have generated more than one comment. The goal of the content analysis was to determine which alerts were clinically relevant, so they could be used to refine the alert algorithms; as a result, an additional step was necessary to clarify each alert's clinical relevance and eventual categorical placement. If an alert's comments (submitted by one or more clinicians) were placed in two different categories, the coders met, reviewed the comments, and decided in which clinical relevance/no relevance category to place the alert. This step resulted in each alert being placed in only one category. The coders were *not* blind to any of the information during the final categorization of the alert so that they could use alert significance rating information to inform the final clinical relevance categorical placement decision.

Using the same process, a second content analysis was conducted on comments of more recent alerts. From December 2011 to February 2012, 88 alerts were generated from an algorithm to which additional adjustments had been made to improve clinical relevance; these alerts were received by three of the original seven clinicians. The results of both content analyses were compared to measure the progress of improving clinical relevance of the health alerts.

RESULTS

Two samples of clinician written responses to data-driven alerts were analyzed and are displayed in Table 1. First, Table 1 displays the results of the initial content analysis from April 12, 2011, to October 3, 2011. A total of 663 comments were generated by seven clinicians in response to 385 unique alerts; there are more comments than alerts because several clinicians may have rated the same alert. Second, Table 1 contains results from December 4, 2011, to February 27, 2012. A total of 142 comments were produced by three clinicians (TigerPlace nurse care coordinator, social worker, and a PhD prepared nurse) in response to 88 distinct alerts.

There were two overall categories: clinically relevant and not clinically relevant. The clinically relevant group included intervention coding categories (when a clinician actually interacted, assessed, or intervened with the resident), potential (when the clinician saw something in the sensor data that could potentially indicate early signs of illness or exacerbation of chronic illness), and recommended intervention (when a research clinician who is not routinely at TigerPlace recommended that the care coordinator at TigerPlace assess the resident and appropriately intervene). The *not* clinically relevant category included when the clinicians indicated that the alert was not clinically relevant, such as when the resident seemed to be out of the apartment, when the resident may have had visitors in the apartment such as family or housekeeping staff, when the clinicians had questions about the alerts or sensors, or when the clinicians were trying to determine meaning by combining and coordinating the data from various sensors but did not reach a clinical conclusion.

As expected, the average alert significance ratings by the clinicians using the alerts were higher for the clinically relevant categories than the not clinically relevant ones (recall 1–5 rating, with 5 indicating very significant). The average rating by clinicians for all of the clinically relevant categories (intervention, potential, or recommended intervention) ranged from 3.9 to 3.5 in sample 1 (Table 1). It improved in the second sample (4.1 to 3.4). The not clinically relevant group (not clinically relevant, out of apartment, visitors in apartment, coordination, alert questions, and sensor questions) ranked lower in both samples, with the average rating ranging from 3.0 to 2.4 in

Table 1

Content Analysis of Clinicians' Responses to all Health Alerts

	Number of Responses in Category		Average Alert "Significance" Rating[a]	
Alert Category	**Sample 1**	**Sample 2**	**Sample 1**	**Sample 2**
Clinically relevant				
Intervention	18	13	3.9	4.1
Potential	68	11	3.6	3.4
Recommended intervention	42	14	3.5	3.4
Subtotal	128 (33.3%)	38 (43.2%)		
Not clinically relevant				
Not clinically relevant	147	23	2.5	2.2
Out of apartment	23	9	2.4	2.9
Visitors in apartment	57	17	2.5	1.6
Alert question	4	1	2.8	1.0
Sensor question	15	0	3.0	
Coordination, combining sensors together	11	0	2.8	
Subtotal	257 (66.8%)	50 (56.8%)		
Total	385	88		

Sample 1: April 12, 2011, to October 3, 2011. Sample 2: December 4, 2011, to February 27, 2012.
[a]Five-point Likert scale, with 5 indicating that the alert was very significant and 1 indicating that the alert was insignificant. Significance for this scale was defined as clinically significant, not significant in the context of testing statistical significance.

the first sample and even lower (2.9 to 1.0) in the subsequent sample. The intervention category had an average clinical significance rating of 3.9 in the first sample and increased to 4.1 in the second sample; the not clinically relevant category declined from 2.5 in the first sample to 2.2 in the second. These changes are all moving in the direction indicating that the iterative algorithm adjustments recommended by clinicians are improving clinical relevance.

The overall clinical relevance of the alerts, as judged by the content of the qualitative comments by clinicians for each alert, improved from the first to the second analysis. In the initial content analysis, 33.3% of the alerts were classified as clinically relevant. In the second sample, 43.2% of the alerts were classified as clinically relevant, a marked increase.

DISCUSSION

Based on the content of the written comments and the numerical ratings of alerts by clinicians using them, results demonstrate that clinical relevance of the health alerts is improving. Overall clinical relevance, measured by the percentage of alerts classified into one of the clinically relevant categories that involved an intervention (directly, potential, or recommended), improved markedly from 33.3% to 43.2%. Moreover, the average alert significance rating of the clinically relevant intervention category improved (3.9 to 4.1), while the not clinically relevant category declined from 2.5 to 2.2. Based on results of the qualitative comment categorization and quantitative alert significance, the iterative adjustments the computer engineering experts are making to improve performance of the algorithms for early illness detection are also improving the clinical relevance of the health alerts.

In related research, Skubic and colleagues[13] used computer computational methods and alert significance ratings (four or five that are most significant) from the clinicians for a sample of the sensor data and alerts that the data generated for several months during the early illness pilot study.[3] Results revealed that the simple one-dimensional algorithms achieved less than 40% accuracy for alerts. The results of this qualitative analysis of actual clinician comments and ratings of alerts from samples after the pilot study confirm that the algorithms are performing similarly in clinical relevance; they improved from 33% to 43% with iterative adjustments. In the computer computational study,[13] the researchers applied multidimensional classifiers to the data, and the algorithms improved to 85%. In the future, as clinical use and evaluation of the health alerts progress, the team will consider adding multidimensional methods into the health alert algorithms. It is likely that the accuracy of the alerts can be improved and it is likely that clinicians will find them even more clinically relevant.

Following completion of the pilot study,[3] the TigerPlace RN care coordinator and social worker have integrated the health alert system as part of standard care provided by Sinclair Home Care Aging in Place for all residents with sensor networks. The differences in discipline and approach between nursing and social work add to the ability to assess alerts from perspectives of both physical and mental health. These clinical experts consider the alerts from the sensor network to be a valuable tool and use them as part of their workflow and routine care delivery. Changes in health conditions are detected and treated early with the advance alerts from the sensor network.[14]

While improvements have been made within the alert algorithms, additional work is still required to further refine the algorithms. It must be noted that only 43.2% of the alerts in the second sample were categorized as clinically relevant, which resulted in actual interventions, potential or recommended, by the clinician working with the older adults. For the system to be widely adopted and routinely used by clinicians, we anticipate that a higher rate is required. Additional use of the system, more data collection, data analysis, and algorithm refinements are needed.

Because the pilot study produced some statistically significant results in four clinical outcome measures,[3] a larger randomized intervention study is proposed to further test the effect of the alerts on clinical outcomes. Based on results of the content analyses presented in this article, additional refinement can be made to improve clinical relevance. With larger samples and ongoing use of the system, the refinement process can be accomplished more quickly. We will continue to use evaluation methods such as those described in this article to iteratively refine and improve the health alerts of our system to enhance clinical decision making.

The ultimate goal is to generate customizable alerts based on the clinicians' feedback. Since each person is unique, a "one size fits all" model is not likely to work. Currently, the algorithm is modeled for each person, based on change detection from one day compared with prior days. We anticipate tailoring algorithms to each individual based on clinician feedback, making them even more clinically relevant. We anticipated moving from the one-dimensional algorithms to multidimensional ones to improve accuracy as well.

With additional refinement and testing, the team envisions that an integrated in-home sensor network system could be installed in other elder housing, long-term care settings, and eventually, private homes. Health alerts to clinicians regarding early signs of illness and exacerbation of chronic disease enables earlier intervention, often when interventions are most effective, less costly, and with less loss of functional decline. It is our vision that with early illness detection, we can help older adults to age in place as well as improve their function, health outcomes, and quality of life. Improving the clinical relevance of health alerts is key to seeing our vision become reality.

REFERENCES

1. Ridley S. The recognition and early management of critical illness. *Ann R Coll Surg Engl*. 2005;87(5):315–322.
2. Boockvar KS, Lachs MS. Predictive value of nonspecific symptoms of acute illness in nursing home residents. *J Am Geriatr Soc*. 2003; 51(8):1111–1115.
3. Rantz MJ, Skubic M, Koopman RJ, et al. Automated technology to speed recognition of signs of illness in older adults. *J Gerontol Nurs*. 2012;38(4):18–23.
4. Marek K, Rantz MJ. Aging in place: a new model for long term care. *Nurs Adm Q*. 2000;24(3):1–11.
5. Rantz MJ, Marek KD, Aud MA, Johnson RA, Otto D, Porter R. TigerPlace: a new future for older adults. *J Nurs Care Qual*. 2005; 20(1):1–4.
6. Rantz MJ, Phillips L, Aud M, et al. Evaluation of aging in place model with home care services and registered nurse care coordination in senior housing. *Nursing Outlook*. 2011;59(1):37–46.
7. Skubic M, Alexander G, Popescu M, Rantz M, Keller J. A smart home application to eldercare: current status and lessons learned. *Technol Health Care*. 2009;17(3):183–201.
8. Daly JM, Jogerst G, Park J-Y, Kang Y-D, Bae T. A nursing home telehealth system: keeping residents connected. *J Gerontol Nurs*. 2005;31(8):46–51.
9. Rantz MJ, Skubic M, Alexander G, et al. Improving nurse care coordination with technology. *Comput Inform Nurs*. 2010;28(6):325–332.
10. Alexander GL, Rantz M, Skubic M, et al. Evolution of an early illness warning system to monitor frail elders in independent living. *J Healthc Eng*. 2011;2(2):259–286.
11. Krippendorff K. *Content Analysis: An Introduction to Its Methodology.* Beverly Hills, CA: Sage Publications; 1980.
12. Elo S, Kyngas H. The qualitative content analysis process. *J Adv Nurs*. 2007;62(1):107–115.
13. Skubic M, Guevara RD, Rantz M. Testing classifiers for embedded health assessment. Proceedings, International Conference on Smart Homes and Health Telematics; June 12–15, 2012; Artimino, Italy. pp 198–205.
14. Rantz MJ, Skubic M, Koopman R, Phillips L, Alexander GL, Miller SJ. Using sensor networks to detect urinary tract infections in older adults. Proceedings of the 13th IEEE International Conference on e-Health Networking, Application, & Services; June 13–15, 2011; Columbia, MO. pp 142–149.