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RESEARCH ARTICLE

Psychometric Properties of the Patient Activation Measure among Multimorbid Older Adults

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Objectives. The Patient Activation Measure (PAM) quantifies the extent to which people are informed about and involved in their health care. Objectives were to determine the psychometric properties of PAM among multimorbid older adults and evaluate a theoretical, four-stage model of patient activation.

Methods. A cross-sectional analysis was used to assess the psychometric properties of PAM. Internal consistency was assessed using Cronbach α. Construct validity was evaluated using general linear modeling to compute associations between PAM scores and health-related behaviors, functional status, and health care quality. Latent class analysis was used to evaluate the theoretical four-stage structure of patient activation.

Study Setting. Participants in a randomized trial of Guided Care ($N = 855$), a model of comprehensive health care for older adults with chronic conditions that put them at risk of using health services heavily during the coming year.

Principal Findings. Higher PAM activation scores and stage were positively associated with higher functional status, health care quality, and adherence to some health behaviors. Latent class analysis supported the multistage theory of patient activation.

Conclusions. The PAM is a reliable, valid, and potentially clinically useful measure of patient activation for multimorbid older adults.

Key Words. Patient activation, self-management, chronic conditions

The U.S. health care system is about to be confronted with a newer and larger generation of older patients than experienced previously (Committee on the Future Health Care Workforce of Older Americans 2008). These new patients will be more educated, have lower levels of poverty, more racial and ethnic diversity, and have fewer children. Over the past decade, little has been done to restructure the health care system to deal with this demographic challenge. For those older patients with chronic health conditions, the health care system can be a "nightmare to navigate" (Committee on Quality Health Care in

America 2001). As a result, it often fails patients with multiple chronic conditions and complex, ongoing care needs. With American society facing rapid growth in the number of older adults and an increase in chronic disease, there is an urgent need to reorient the way chronic health care is provided. A fundamental belief underlying efforts to reshape the system is that patients who are activated to participate in their own care are more likely to adopt healthy behaviors that lead to improved outcomes (van Korff et al. 1997; Bodenheimer et al. 2002a, b; Mosen et al. 2007). This is particularly important for chronic diseases, which require patients to play a major role in day-to-day management. Studies offer support for this notion, showing that collaborative care, in which patients are engaged participants, improves health-related behaviors and outcomes for patients with chronic conditions (Clark et al. 2000; Lorig et al. 2001; Chodosh et al. 2005). Patient activation is central to emerging models of chronic illness care (Boult et al. 2008), yet little is known about what it takes for patients—particularly multimorbid, older ones—to become informed, motivated, and involved in their health care. Accurate assessment of such patients' level of activation will be important in the development of methods for increasing activation.

Patient activation has been conceptualized as involving four sequential stages: (1) Patients believe they have important roles to play in managing their conditions. (2) They possess the knowledge needed to manage their health. (3) They take action, using their skills and behavioral repertoire to maintain their well-being. (4) Finally, they stay the course under stress. An individual's level of activation may provide a gauge of his or her propensity to engage in positive health behaviors that increase the likelihood of good outcomes. An instrument has been developed to measure patient activation: the Patient Activation Measure (PAM) (Hibbard et al. 2004). To date, however, the performance of the PAM has not been tested among at-risk, multimorbid older adults, who will soon make up a significant proportion of the U.S. population.

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Previous research has confirmed that the PAM is a valid tool that correlates with other theoretically related psychological measures and has high test–retest reliability. Its scores help to depict patients' positions along a multistage, hierarchical process of activation (Skolasky et al. 2009). A recent study of patients with a variety of chronic conditions showed that higher PAM scores were associated with better health behaviors such as adherence to medication. In addition, patients with higher PAM scores had higher satisfaction, quality of life, and physical and mental functioning (Mosen et al. 2006). Higher baseline PAM scores have been positively correlated with other health-related behaviors in the acute care setting, such as adherence to physical therapy after spine surgery (Skolasky et al. 2008). In addition, positive change in PAM scores has been related to positive change in several self-management behaviors (Hibbard et al. 2007). These findings suggest that the PAM may be a useful clinical tool to identify activated patients who are likely to benefit from interventions designed to improve their health-related knowledge, skills, motivation, and behaviors.

The objectives of our study were to determine the psychometric properties and construct validity of the PAM in an older, multimorbid population. We hypothesized that higher PAM scores are related to greater adherence to desirable health-related behaviors, higher functional status, and better health care quality. We also hypothesized that patients' level of activation is not correlated with their number of comorbid conditions. Finally, we hypothesized that groups of items in the PAM correlate with the Hibbard four stages of activation among older, multimorbid patients (Hibbard et al. 2004). We did not expect a correlation between the PAM and comorbid conditions because the PAM aims to assess psychological factors such as self-efficacy and personal competencies such as disease-specific knowledge, characteristics that should not be influenced by the number of a patient's comorbid illnesses.

METHODS

Setting

One model of chronic illness care that seeks to increase patient activation is "Guided Care": primary health care infused with the operative principles of several successful innovations, including case management, disease management, self-management, transitional care, and caregiver support (Boyd et al. 2007). It targets patients 65 years or older who are in the upper quartile of risk for using health services heavily during the coming year, based on diagnoses from health insurance claims submitted during the previous year.

We recruited multimorbid, community-dwelling older patients and administered a baseline in-person interview that included the PAM. The procedures have been described in detail elsewhere (Boult et al. 2008). In brief, patients at eight primary care practices in the Baltimore–Washington, DC, area were eligible for initial screening if they were age 65 years or older and covered by fee-for-service Medicare Parts A and B, Kaiser Permanente Medicare Advantage, or TriCare. Potential participants' insurance claims for health care during the previous 12 months were screened by their insurers using the Hierarchical Condition Category (HCC) model, which estimates patients' risks for using health services heavily during the coming year (Pope et al. 2004). Patients were eligible if their HCC risk ratios were in the highest quartile of the population of older patients covered by their primary health care insurer. Participants were ineligible if they did not have a telephone, did not speak English, were planning extended travel during the following two and a half years, or failed a brief cognitive screen and did not have a proxy. The study was approved by the Institutional Review Boards of Johns Hopkins Bloomberg School of Public Health, Kaiser Permanente of the Mid-Atlantic States, and MedStar Research Institute.

The insurance records of 13,534 older patients were screened, identifying 3,692 (27.3 percent) at high risk for using health care services heavily during the following year. Of these, 2,391 were eligible; 904 (37.8 percent) consented to participate. Our analyses included the 855 participants who completed the baseline interview themselves. We excluded 49 respondents whose proxies completed the interview for them.

Participants

Patient characteristics are described in Table 1. The average age of the cohort was 77.3 years. Forty-six percent of the participants were men. Twenty-six percent of the respondents had less than a high school education, while 43 percent had completed some college and 15.2 percent had more than a 4-year degree. Nearly half (47.8 percent) were married. The cohort was nearly evenly split between white and African American participants. Approximately half of the 696 participants who responded to the question about household income reported earning <U.S.$30,000 per year.

The patients included in our analyses had multimorbidity (an average of four conditions each) and functional disability: 29.9 percent reported difficulty

Table 1: Socio-Demographic Features of the Guided Care PAM Cohort, by PAM Stage and Overall

			PAM Stage				
	N	*PAM Score, Mean (SD)*	*I*	*II*	*III*	*IV*	*Overall*
Age, mean years (SD)	855		79.3 (6.8)	77.4 (6.4)	76.8 (6.1)	76.0 (6.0)	77.3 (6.4)
BMI, mean kg/m^2 (SD)	836		26.9 (6.5)	28.4 (6.0)	29.0 (6.7)	27.9 (6.1)	28.3 (6.4)
Underweight (<18.5)		52.7 (14.0)	7.8%	2.2%	2.9%	2.9%	3.6%
Normal weight (18.5–24.9)		56.3 (12.6)	34.4%	25.2%	29.6%	30.1%	29.3%
Preobese (25.0–29.9)		57.0 (13.8)	33.7%	38.5%	30.9%	40.2%	35.2%
Obese (≥ 30.0)		56.6 (12.1)	24.2%	34.1%	36.7%	26.8%	31.9%
Gender	855						
Male		56.8 (13.1)	47.9%	44.7%	43.1%	51.2%	45.7%
Female		56.1 (12.7)	52.1%	55.3%	56.9%	48.8%	54.3%
Education							
Some high school	852	55.2 (12.7)	28.2%	28.5%	26.8%	19.4%	26.3%
High school graduate/GED		54.2 (11.0)	31.4%	28.4%	30.8%	17.0%	28.0%
Some college/2-year degree		56.7 (12.1)	20.8%	23.0%	23.8%	23.3%	22.9%
4-year degree		61.0 (14.4)	5.5%	7.4%	6.2%	13.4%	7.6%
>4-year degree		60.2 (15.3)	14.1%	12.7%	12.4%	26.9%	15.2%
Marital status							
Married	854	57.2 (13.6)	46.6%	47.6%	44.7%	56.3%	47.8%
Divorced		56.5 (12.7)	11.2%	6.6%	11.6%	7.1%	9.4%
Separated		58.7 (11.7)	0.6%	2.5%	2.0%	2.8%	2.0%
Widowed		55.5 (12.0)	35.5%	39.2%	38.9%	28.8%	36.7%
Never married		54.4 (12.9)	6.1%	4.1%	2.9%	5.0%	4.2%
Could have used more support with activity							
A lot	851	57.6 (13.4)	65.6%	71.7%	74.6%	87.0%	74.1%
Some		53.7 (11.0)	25.7%	23.7%	21.6%	12.3%	21.4%
No, none		50.8 (10.0)	8.7%	4.6%	3.8%	0.7%	4.5%

continued

Table 1. *Continued*

	N	PAM Score, Mean (SD)	PAM Stage				Overall
			I	II	III	IV	
Ethnicity							
Hispanic	853	54.9 (10.1)	1.8%	1.2%	2.3%	1.4%	1.8%
Non-Hispanic		56.5 (13.0)	98.2%	98.8%	97.7%	98.6%	98.2%
Race							
American Indian/Alaska Native	696	57.7 (9.3)	0.6%	0%	1.0%	0%	0.5%
Asian		67.2 (21.9)	1.2%	0.8%	0.7%	3.5%	1.3%
Native Hawaiian/API		58.3 (12.5)	0.6%	0%	0.7%	0.7%	0.5%
Black/African American		56.3 (13.3)	45.6%	44.5%	48.8%	44.8%	46.3%
White		56.4 (12.2)	50.1%	53.9%	47.0%	49.5%	49.9%
Other/Multiracial		55.2 (12.3)	1.8%	0.8%	2.0%	1.4%	1.5%
Household income							
<U.S.$10,000	855	56.9 (12.9)	9.2%	13.1%	12.3%	9.6%	11.5%
U.S.$10,000–U.S.$19,999		57.0 (13.2)	17.3%	19.5%	21.6%	16.8%	19.4%
U.S.$20,000–U.S.$30,000		53.7 (9.1)	22.3%	21.0%	20.0%	8.0%	18.5%
>U.S.$30,000		58.4 (13.8)	51.2%	46.5%	46.1%	65.6%	50.6%
Activities of Daily Living (ADL), mean (SD)	855		1.04 (1.43)	0.61 (1.06)	0.44 (0.98)	0.26 (0.71)	0.57 (1.10)
Instrumental Activities of Daily Living (IADL), mean (SD)	855		1.68 (1.76)	1.08 (1.28)	0.84 (1.22)	0.51 (0.96)	1.01 (1.37)

API, Asian Pacific Islander; BMI, body mass index.

with activities of daily living and 51.9 percent reported difficulty with instrumental activities of daily living.

Stratifying the sample by PAM activation stage revealed that individuals in the higher activation stage were more likely to be younger, college-educated, endorse no need for additional support with activities, and endorse fewer limitations in activities of daily living or instrumental activities of daily living (Table 1).

Data Collection

Baseline interviews were conducted in the participants' homes by trained, closely supervised professional interviewers who used computer-assisted interviewing. After baseline "in-person" interviews were completed, a supervisor randomly selected 10 percent of the interviews and contacted the participants by telephone. The supervisor verified that the participant was interviewed at the time and date reported, that compensation was paid, that the interviewer was courteous and clearly explained the study purpose as described in the protocol, and that the respondent understood and was able to answer the interview questions. The supervisor also re-asked randomly selected questions to verify that the interviewer had recorded the participants' responses correctly. Supervisors also used reliability testing where 10 percent of interviews were randomly selected and the supervisor listened to the interview as they were being conducted, and visually reviewed for accuracy the data recorded by the interviewer.

Measurement

PAM. In developing the PAM, Hibbard and colleagues used expert consensus and patient focus groups to identify psychological factors and personal competencies needed to self-manage chronic health conditions. Patient activation was revealed to be a developmental, hierarchical construct, implying that patients with low scores lack the beliefs and knowledge necessary to manage their chronic conditions, as compared with patients at the higher end of the continuum (Hibbard et al. 2004).

We used the 13-item version of the PAM, a participant-completed questionnaire from which a continuous activation score can be computed, with possible scores ranging from 0 (no activation) to 100 (high activation). Based on an examination of the results from a telephone survey of 1,515 respondents, a research team identified 9 items that could be removed from the original 22-item scale without appreciably diminishing the reliability or construct validity of the PAM (Hibbard et al. 2005). To calculate a raw score, all of the responses (range = 1–4) to the 13 questions are added (respondents receive 1 point for "strongly disagree," 2 for "disagree," and so on). The raw score is then converted into an activation score using an empirically derived calibration table.

The previously reported stages of activation are as follows: (1) believing an active role is important (items 1–2); (2) having confidence and knowledge to take action (items 3–8); (3) taking action (items 9–11); and (4) continuing healthy behaviors under stress (items 12–13).

Functional Status. Functional status was assessed using the SF-36 (Brazier et al. 1992), which has proven reliability and validity in a number of chronic diseases and injuries (Riazi et al. 2003).

Quality of Health Care. Quality of health care was assessed using the 20-item Patient Assessment of Chronic Illness Care (PACIC) (Glasgow et al. 2005) and the Primary Care Assessment Survey (PCAS) (Safran et al. 1998) scales. The PACIC consists of five subscales representing care processes such as being asked about one's goals of care, being given a written treatment plan, and being referred to dietitians, health educators, or counselors. Respondents indicate how often, during the past 6 months, these processes occurred. The PCAS is a multi-item questionnaire that measures characteristics of primary care including quality of the doctor–patient relationship and organizational features of care. Subscales of the PCAS included in this study were physician–patient communication and integration of care. Previous research has shown the PACIC and PCAS to be valid and reliable measurement scales (Safran et al. 1998; Glasgow and Wagner 2005).

Missing Data and Imputation. As part of the larger evaluation of Guided Care, missing PAM activation scores, number of conditions, PCAS items, and PACIC items were imputed using chain equations (Royston 2005). Multiple imputation methods have been discussed widely in the statistical literature (Reiter and Raghunathan 2007) and have been used in epidemiology, health, medicine, and psychology research (Kenward and Carpenter 2007; Newgard and Haukoos 2007; Harel and Zhou 2008; Klebanoff and Cole 2008). The use of multiple imputation allows us to reflect the uncertainty due to nonresponse. The method that we have used involved (i) imputation, (ii) analysis, and (iii) combination. During the imputation, five imputed datasets were created. During the analysis, each dataset was analyzed independently. In the combination, standard formulas are used to combine the five estimates that are found in (ii). Estimates, variances, confidence intervals, and *p*-values were computed using the Rubin combining rules (Rubin 1987). The individual items that make up the PAM raw scores were not imputed. As a result, our internal consistency and latent class analyses that require data on the individual items are based on the 804 patients who have no item-level missing data.

Data Analysis

Internal Consistency. We estimated internal consistency of the PAM using scores from the baseline PAM. We then computed Cronbach α. An α measure of at least 0.80 is generally considered evidence of good internal consistency.

Construct Validity. We examined construct validity of the PAM as both a continuous measure and as a hierarchical multistage measure of patient activation. The PAM activation score (0–100 scale) served as a continuous independent variable, and the PAM stage (0–4) served as a factor variable in these models. Measures of adaptive health behaviors (e.g., exercise, adherence to a recommended diet, and medication adherence), functional status (SF-36), health care quality (PACIC and PCAS), and the number of comorbid conditions served as the dependent variables. With the exception of number of comorbidities, the dependent variables were coded so that higher levels represented preferable conditions. To account for any potential confounding influence that socio-economic status (SES) may have, we also included these measures as covariates in our statistical models. We included measures of SES because previous research has demonstrated that SES may have a direct impact on health behavior (Gazmararian, Ziemer, and Barnes 2009; Rask, O'Malley, and Druss 2009). Because SES is a broad concept that includes cultural, social, and economic dimensions, we choose to include two measures from the Guided Care baseline interview. These included highest level of education attained and social support. Highest level of education attained was coded as less than high school graduation, high school graduation or GED, some college, 4-year college degree, and postcollege education; less than high school graduation served as the reference category. Social support was assessed using response to the following statement: "Could have used more support with household activities or health care in the last six months?" In this context, activity referred to usual household or recreational activities, such as housecleaning or grocery shopping or participation in hobbies, and to health care activities, such as attending appointments or managing medications. Response choices were: "A lot", "Some", and "No, none"; "No, none" served as the reference category. For comparative purposes, we report both unadjusted and adjusted analyses. Continuous, binary, and ordered categorical dependent variables were modeled using linear, logistic, and proportional odds regression, respectively.

We hypothesized that PAM activation scores would be positively associated with greater adherence to desirable health behaviors, higher functional status, and more favorable perceptions of quality of care. It was hypothesized that number of comorbidities would not be associated with PAM score. To test for a positive association, we evaluated whether the coefficient associated with PAM activation score is positive. For the comorbidity endpoint, we tested whether the activation coefficient is zero. Estimates and standard errors for the activation coefficient are reported. With the exception of the comorbidity endpoint, one-sided p-values are reported; a two-sided p-value is reported for the comorbidity analysis.

We also hypothesized that PAM activation stage would exhibit similar relationships with health behaviors, functional status, perceptions of quality of care and comorbidities as posited for the PAM activation score. For this analysis, we included the four PAM activation stages into the regression models using three indicator variables representing stages II, III, and IV. We evaluated our hypotheses regarding positive association by computing an approximation to the joint posterior probability that the regression coefficient for stage II is >0, the coefficient for stage III is greater than the coefficient for stage II, and the coefficient for stage IV is greater than the coefficient for stage III. For the relationship between PAM stage and comorbidities, we report the posterior probability of a nonpositive or nonnegative association.

An approximation of the posterior probability, based on large-sample theory, was computed by simulating 50,000 draws from a multivariate normal distribution with mean equal to the estimated regression parameters and variance–covariance matrix equal to the estimated variance–covariance matrix. It is important to note that this posterior probability is not to be interpreted in the same way as a p-value. A p-value is the probability, under the assumption that the null hypothesis is actually true, of observing the value of our test statistic or a value that is more extreme. In contrast, the posterior probability is the probability that our hypothesis is true given the data and model. Since we are appealing to large sample results, the posterior will not depend on the prior provided that the prior distribution is reasonably diffuse over the support of the parameter space.

The Bayes factor is the ratio of the posterior odds to the prior odds of our hypothesis. Assuming that the prior odds is one (i.e., prior probability that the hypothesis is true is 0.5), the Bayes factor is equal to the posterior odds. According to Kass and Raftery (1995), Bayes factors between 3 and 20, 20 and 150, and >150 represent positive, strong, and very strong evidence in favor of our hypothesis.

Latent Class. Latent class analysis was used to evaluate whether the theoretical four-factor structure for patient activation proposed by Hibbard and colleagues provided a good fit to the observed data. Latent class analysis explores a series of variables to determine a small number of groups into which they can be classified. The fit to the data of the four-factor structure was compared with the fit of alternate models. Four models were considered as alternates: one-, two-, three-, and four-factor models. Goodness-of-fit was tested using the Bayesian Information Criterion (BIC). (Schwarz 1978) The BIC assesses whether the improved fit provided by an additional variable is justified by the added complexity of the model. With the best fitting model, we estimated the association between the Hibbard four stages of activation and the latent class categorization using Goodman–Kruskal γ statistic, where values close to one indicate strong positive association.

RESULTS

Distribution of PAM Scores

At baseline, the mean patient activation score was 56.6 (SD = 12.9; range 16.5, 100). Eighteen, 29.1, 35.7, and 17.2 percent of patients were classified in PAM stages I, II, III, and IV, respectively (Table 2).

Table 2: Distribution of Respondents Based on Theoretical Model of PAM Stages and Latent Class

	PAM Latent Class			
PAM Stage	*I*	*II*	*III*	*Total*
I	144 (99.3%)	1 (0.7%)	0 (0.0%)	145 (18.0%)
II	62 (26.5%)	164 (70.1%)	8 (3.4%)	234 (29.1%)
III	2 (0.7%)	268 (93.4%)	17 (0.6%)	287 (35.7%)
IV	1 (0.7%)	15 (10.9%)	122 (88.4%)	138 (17.2%)
Total	209 (26.0%)	448 (55.7%)	147 (18.3%)	804

Internal Consistency

The items on the PAM demonstrated high internal consistency (Cronbach $\alpha = 0.87$).

Construct Validity

As shown in Table 3, the PAM activation *score* was positively associated with certain adaptive health behaviors, namely physical activity, structured exercise, and medication adherence. Specifically, a 10-point change in PAM activation score yields a 21, 16, and 13 percent increase in the odds of having higher levels of physical activity, structured exercise, and medication adherence, respectively. With a posterior probability of 0.847, there is strong evidence that physical activity is positively associated with PAM activation *stage* (Bayes factor 5.54); the evidence that structured exercise is associated with activation *stage* is weak (Bayes factor 1.49). The evidence that PAM *score* or *stage* is positively associated with maintenance of other adaptive health behaviors, including smoking, drinking alcohol, and following recommended diets, is not compelling.

PAM activation *score* was also positively associated with the physical and mental health components of the SF-36, with a 10-point change in the PAM score yielding a 1.78 and 1.46 change in the mean health component, respectively. While there is positive evidence that the physical component of the SF-36 is associated with PAM activation *stage*, the evidence for an association with the mental health component was much weaker.

In terms of quality of health care, PAM activation *score* and *stage* were positively associated with all the subscales of the PACIC and PCAS.

Consistent with our hypothesis, there is no evidence to suggest that number of comorbidities is positively associated with PAM activation *score*. Furthermore, there is an 88.4 percent posterior probability (i.e., strong evidence) that number of comorbidities is not positively or negatively associated with PAM activation *stage*.

Confirmatory Latent Class Analysis

Applying the BIC criteria showed that the three-class model was best suited to explain the variability in the data.

The response profile for the three-class model revealed that 26.0 percent of the participants were in Class 1, 55.7 percent in Class 2, and 18.3 percent in Class 3 (Table 2). The estimated value of the Goodman–Kruskal γ statistic is 0.96, indicating a very high degree of concordance between the latent classes

Table 3: Relationship between PAM Scores and Stages and Health-Related Behavior, Comorbidity, Functional Status, and Health Care Quality

	I	*II*	*III*	*IV*	*Posterior Probability (Bayes Factor)*	*Unadjusted Coefficient (SE)**	*Adjusted Coefficient (SE)*,†*
Health-related behaviors‡							
Currently smoke cigarettes, no	91.43%	90.56%	91.20%	91.51%	0.043 (0.045)	0.002 (0.009); $p = .40$	0.002 (0.100); $p = .49$
Currently drink alcohol, no	71.20%	69.21%	67.41%	61.81%	0.027 (0.028)	– 0.007 (0.006); $p = .89$	0.003 (0.006); $p = .29$
Physical activity in past week							
Never	58.95%	48.56%	40.33%	31.40%	0.847 (5.54)	0.025 (0.004); $p < .0001$	0.021 (0.005); $p < .0001$
1–2 times	21.45%	29.15%	32.35%	33.80%			
3–4 times	12.80%	13.06%	16.99%	18.31%			
5 or more times	6.71%	8.98%	10.13%	16.20%			
Structured exercise in past week							
Never	55.88%	48.89%	44.59%	33.52%	0.598 (1.49)	0.023 (0.005); $p < .0001$	0.016 (0.005); $p = .007$
1–2 times	14.71%	16.90%	20.21%	15.49%			
3–4 times	15.24%	18.03%	16.95%	24.05%			
5 or more times	14.09%	15.98%	18.25%	26.76%			
Medication adherence, no. of missed doses							
7/7 days	0.61%	1.23%	0%	0%	0.059 (0.063)	0.013 (0.006); $p = .025$	0.013 (0.007); $p = .028$
6/7 days	0.61%	0%	0%	0.71%			
5/7 days	0%	0%	0%	0%			
4/7 days	1.84%	0.82%	0.65%	0%			
3/7 days	0.61%	1.64%	1.64%	0.71%			
2/7 days	4.90%	4.93%	5.56%	4.99%			
1/7 days	20.83%	12.73%	19.29%	12.82%			
0/7 days	70.55%	78.60%	72.79%	80.71%			
How often followed recommended diet in past week							
Never	5.88%	6.93%	9.35%	5.56%	0.214 (0.272)	0.010 (0.007); $p = .094$	0.005 (0.008); $p = .23$
Rarely	7.84%	5.94%	6.47%	4.17%			
Some meals	33.33%	28.71%	18.71%	19.44%			
Most meals	25.49%	38.61%	42.45%	43.06%			
All meals	27.45%	19.80%	23.02%	27.78%			

continued

Table 3. *Continued*

	I	*II*	*III*	*IV*	*Posterior Probability (Bayes Factor)*	*Unadjusted Coefficient (SE)**	*Adjusted Coefficient (SE)*,†*
Comorbidity and functional status							
Number of comorbid conditions	4.35	4.35	4.18	4.08	0.884	– 0.009	– 0.005
	(1.91)	(1.78)	(1.81)	(1.73)	(7.62)	(0.005); $p = .053$	(0.005); $p = .35$
SF-36							
Physical Health	35.21	37.83	39.36	44.03	0.756	0.215	0.178
	(10.40)	(9.80)	(10.35)	(9.72)	(3.10)	(0.027); $p < .0001$	(0.027); $p < .0001$
Mental Health	45.62	48.65	51.97	52.70	0.234	0.193	0.146
	(12.16)	(12.36)	(10.07)	(11.57)	(0.31)	(0.031); $p < .0001$	(0.030); $p < .0001$
Health care quality							
PCAS							
Communication	61.65	67.04	71.34	76.64	0.993	0.339	0.299
	(19.36)	(15.09)	(14.72)	(15.34)	(141.86)	(0.043); $p < .0001$	(0.043); $p < .0001$
Integration	62.71	65.54	71.18	74.54	0.911	0.304	0.285
	(17.49)	(15.42)	(15.30)	(15.92)	(10.24)	(0.042); $p < .0001$	(0.043); $p < .000$
PACIC							
Patient Activation	2.29	2.42	2.58	2.77	0.796	0.011	0.010
	(1.04)	(0.97)	(1.02)	(1.17)	(3.90)	(0.003); $p < .0001$	(0.003); $p = .0002$
Delivery System	2.97	3.16	3.30	3.42	0.845	0.010	0.010
	(0.91)	(0.81)	(0.85)	(0.90)	(5.45)	(0.002); $p < .0001$	(0.002); $p < .0001$
Goal Setting	2.24	2.31	2.46	2.67	0.766	0.009	0.009
	(0.75)	(0.85)	(0.97)	(1.06)	(3.27)	(0.002); $p = .0001$	(0.003); $p < .0001$
Problem Solving	2.41	2.65	2.90	3.00	0.874	0.014	0.015
	(0.93)	(0.85)	(1.04)	(1.16)	(6.94)	(0.003); $p < .0001$	(0.003); $p < .0001$
Coordination	2.20	2.29	2.47	2.63	0.818	0.011	0.012
	(0.79)	(0.80)	(0.90)	(0.93)	(4.49)	(0.002); $p < .0001$	(0.002); $p < .0001$

*Statistical association between patient activation score and health-related behavior.

†Statistical significance based on statistical model accounting for multiple imputations of missing data and adjusting for participant education and social support.

‡Categorical variables reported as proportion and continuous variables reported as mean (standard deviation).

PACIC, Patient Assessment of Chronic Illness Care; PCAS, Primary Care Assessment Survey; SF-36, Short Form-36.

and the PAM activation stages. This provides strong support for a multistage theory of patient activation.

Discussion

We investigated the psychometric properties of the PAM in a population of multimorbid older adults. The data generally supported the construct validity for the PAM in this population, as PAM score was significantly associated with some health-related behaviors, with functional status, and with health care quality. Further, as expected, patient activation was not related to the number of comorbid illnesses. The latent class analysis offered partial support for the multistage theory of patient activation proposed by Hibbard et al. (2004).

Our findings that PAM scores are associated with health-related behaviors and functional status are in accord with similar research on other populations. In developing the PAM, Hibbard and colleagues conducted a telephone survey of 1,515 people, 45 years and older using a national probability sample. Respondents with high PAM scores were significantly more likely to exercise regularly, follow a low-fat diet, eat more fruits and vegetables, and not smoke. They also reported significantly better self-perceived health-related functioning as measured by the SF-8, a shorter version of the SF-36 (Hibbard et al. 2004).

Similarly, in a survey of 4,108 Kaiser Permanente members (mean age = 61.9 years) in seven regions of the country, Mosen et al. (2007) found that participants with Stage IV PAM scores were nearly three times more likely to report high medication adherence than those with Stage I PAM scores, and five times more likely to report high quality of life. Finally, Skolasky and colleagues found that individuals in higher PAM classes were more likely to adhere to physical therapy recommendations after lumbar spine surgery. Those in lower PAM classes were more likely to report low self-efficacy for physical therapy, low hope, and external locus of control compared with those with high activation (Skolasky et al. 2008).

As in the population of older adults studied here, weak associations were observed between patient activation and the presence of comorbid disease (Skolasky et al. 2009). We expected this to be the case because the PAM aims to assess psychological factors such as self-efficacy and personal competencies such as disease-specific knowledge, characteristics that should not be influenced by the number of a patient's comorbid illnesses.

Unexpectedly, we did not find evidence of positive associations between PAM stages and other health-related behaviors. These findings may reflect both sample response characteristics and/or a lack of measurement fidelity, rather than a lack of relationship between patient activation and these types of behaviors. The lack of association may be due to the lack of variability in certain responses. For example, members of the study cohort had excellent medication adherence overall (74 percent of those in the lowest tertile of activation reported missing no medication doses in the past 7 days) and a small percentage in each group smoked. In addition, the lack of association between alcohol use and PAM stage may be due to measurement artifact. The question on alcohol use was dichotomous and thus does not differentiate appropriate from potentially harmful alcohol use.

Hibbard and colleagues proposed a multistage, developmental model of patient activation, in which individuals move from one stage to the next as they acquire specific beliefs and skills. Our latent class analysis provided partial evidence in support of this multistage model (Hibbard et al. 2004). For example, respondents in Class I were likely to agree with items 1–3, 5–8, 10 and 13. This response pattern suggests that they believe to some extent that it is important to take an active role in their own health, and they are starting to develop the confidence and knowledge to take action, but they are not as activated as respondents in Class II, who agreed with all items in the PAM, or respondents in Class III, who agreed strongly with multiple items. Respondents in Class I were also likely to disagree with items 9, 11, and 12, indicating that they may not be able to follow through with effective self-care behaviors over time, or when new problems arise.

By contrast, the response profile of the participants in Class III—agreeing strongly with multiple items—indicates a higher degree of confidence in their ability to take an active role in self-management of their chronic disease, follow through on medical recommendations, and maintain lifestyle changes over time. Compared with respondents in Class III, those in Class I are still more likely to believe in an external locus of health control—that is, "the doctor will 'fix' them" (Hibbard and Mahoney 2005).

None of the respondents agreed strongly with the items indicating the highest level of activation, items 12 and 13 ("I am confident I can figure out solutions when new situations or problems arise with my health condition," and "I am confident that I can maintain lifestyle changes like diet and exercise even during times of stress"). This finding is interesting in light of the fact that Mosen et al. (2007) observed the lowest PAM scores among older adults (results not published). It is unclear whether these findings together reflect a reduced confidence in the ability to maintain health behaviors due to some factor related to old age.

Our study is the first to explore the association between the PAM and two measures of health care quality, the PACIC and PCAS. Our finding that patients in higher PAM stages reported better quality of care may indicate that delivery system characteristics, including patient–doctor communication, play a role in activating patients. This observation is also particularly important because it suggests that activated patients may seek—and obtain—better care. They may engage their physicians, participate in the development of their treatment plans, and through such behaviors, help bring about higher-quality health care for themselves.

Our study is the first to investigate the psychometric properties of the PAM in a large sample of older adults with multiple chronic conditions. Our respondents were, on average, 15 years older than participants in previous studies of the PAM (Mosen et al. 2007; Skolasky et al. 2008). As the U.S. population ages, it will become increasingly important to use limited resources wisely to improve health care for this population.

Previous research has suggested that increased patient participation and engagement in health care leads to improved outcomes (Clark and Janz 2000; Lorig et al. 2001; Chodosh et al. 2005). Patients that receive health coaching tailored to their level of patient activation demonstrate improvements in efficiency of disease management programs and in health outcomes (Hibbard, Greene, and Tusler 2009). Therefore, it may be possible for health care providers to use the PAM to identify individual patients who lack the knowledge or self-efficacy to participate actively in the management of their health conditions. Interventions could then be directed at patients and families most at risk for poor participation. Further, it may be possible to tailor the type of intervention—education, action planning, and behavioral contracting—to specific stages of activation. Having a valid tool for measuring activation among older patients is an important step in this process.

Our study has several potential limitations. First, it is not possible to determine causality using a cross-sectional design, although there are other studies that speak to this issue. Skolasky et al. (2009) found that higher levels of activation at baseline were related to higher rates of subsequent participation in postoperative physical therapy. Hibbard et al. (2007) reported that positive change in patient activation was related to positive change in a number of health-related behaviors; however, the results did not show that the intervention used in the study, a chronic disease self-management class for patients with illnesses including diabetes, hypertension, arthritis, and chronic lung disease, was effective in increasing activation. Additional data are needed to establish a clear link between changes in a patient's levels of activation and subsequent engagement in health behaviors.

One potential limitation is that approximately 38 percent of eligible participants chose to participate in the current study, which may limit the potential generalizability of the findings. Similar difficulties in recruiting high-risk older adults have been noted in other studies. However, in a study of recruitment methods among community-dwelling older Medicare beneficiaries, Boult et al. (1998) demonstrated using recruitment methods similar to those used in the Guided Care project, that those who consented to participate were no different than those who did not consent to participate with respect to mean hospital admissions in the previous year, probability of repeated admission, and racial composition (Boult et al. 2008). The study did, however, find that participants were more likely to be male and to be younger.

A related potential participation bias is that older adults who were willing to participate in the Guided Care study may be more activated than those who refused to take part. For this reason, it is possible that our results are not generalizable to the general population of elderly people with multiple chronic health conditions. Finally, we relied on self-report of health behaviors such as exercise, dietary, and medication adherence. This may have made it less likely that we would detect a difference between respondents who were more activated and those who were less activated, especially if those with lower activation scores tended to overestimate the extent to which they engaged in recommended activities.

CONCLUSIONS

Based on these observations, the PAM is a reliable, valid, and potentially clinically useful measure of patient activation for older adults. There remain many important questions in this line of inquiry. Of particular interest is whether the effects of interventions that have been shown to change health behaviors are mediated by patient activation. In addition, can health care providers and systems use the PAM to identify individuals at risk for suboptimal health engagement and tailor effective interventions to meet their needs? Future studies should explore these questions and seek to determine which interventions would be most effective in increasing patient activation.

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Appendix SA1: Author Matrix.

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