



# A Longitudinal Analysis of Total Pain Scores for a Panel of Patients Treated by Pain Clinics

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## Abstract

**Background:** There is a critical necessity to identify psychometric properties of the total pain score as a measurement of pain management effectiveness in the clinic.

**Purpose:** In this article, we perform the analysis of the global pain scores from a panel of patients treated by 10 pain management physicians in a single group practice.

**Basic Procedures:** The pain measurement consists of 4 pain subscales, namely physical pain, emotions, clinical outcome, and activities. A panel of 130 patients with 4 pain measurements is available to perform longitudinal analysis of the total pain scores. The analysis includes the following: (1) confirmatory factor analysis of the global pain scores with 4 related dimensions, (2) the stability of the pain scores between 2 clinical visits, (3) the change trajectories of pain scores in 4 waves of the pain measurement, and (4) the detection of physician variability in patients' treatment outcomes measured by the reduction of total pain scores.

**Main Findings:** The global pain scores were relatively stable between time 1 and time 2 clinical visits. The analysis indicated that there was a decrease in pain with longitudinal advancement in treatment. It also indicated that there was no significant change in this improvement with respect to difference in physicians involved in providing treatment.

**Principal Conclusion:** While the results indicated a decrease in pain with an alleviation in treatment provided to the patient, the article delineates a well-thought scientific approach to the targeted problem.

## Keywords

validity and reliability in pain measurement, global pain score, and longitudinal analysis

## Introduction

Effective pain management requires the development and implementation of reliable, valid, and applicable instruments of pain measurement. The Global Pain Scale (GPS) is a comprehensive assessment of pain and pain-related emotions, clinic outcomes, and daily activities.<sup>1</sup> Pain management physicians frequently use it as a valuable tool for evaluation and treatment planning of interventional pain management and care for patients. This brief screening tool enables clinicians to make bedside assessment of baseline functioning and perform a repeated outcome measurement to assess change over time in both acute and chronic pain states of patients.

As a multidimensional scale, GPS represents several specific clinical and functional indicators and reflects self-reported patient outcomes associated with pain care.<sup>2,3</sup> The measurement includes the effect of pain on the patient's quality of sleep, comfort, medication consumption, mood,

independence, energy, work interference, perceived control over pain, health-care utilization, and satisfaction with health care received. More specifically, the GPS assesses the patient's perception on how the pain affects their ability to complete the activities of daily living functions such as shopping, chores, exercise, bathing, dressing, social activities, mobility, stamina, driving, and sexual activity.

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There are 4 subscales to measure a patient's pain, feelings, clinical outcomes, and activities. For the "pain" subscale, patient may indicate the degree of pain felt currently along with their best, worst, and average pain during the last week, as well as whether they have felt less pain in the last week. All other items required patients to agree or disagree with the given statements along an 11-point (0 through 10) Likert-type scale, anchored strongly disagree to strongly agree. The 11-point scale provides a midpoint and is familiar to people who are often asked to make a judgment from 0 to 10. The "feelings" subscale asks patients how they felt in the past week for the following emotions: depressed, anxious, afraid, hopeless, exhausted, and terrified. The "clinical outcomes" subscale asks about thoughts and behaviors related to their treatment outcomes and included items such as "During the past week I took fewer medications" and "During the past week I had more energy." The "activities" subscale asked about patients' ability to perform daily activities such as doing chores in the home and walking up or down stairs.

Global Pain Scale addresses the ceiling, floor, and average pain over the past week, as well as current pain state. In assessing the psychological impact of pain on the patient, the GPS screens of depression, anxiety, fear, hopelessness, and energy level. Although GPS was designed to capture multidimensional aspects of pain, it also can provide a single summary score that could be used to track changes as the result of a clinical intervention. The total score considers weighing the 4 subscales equally and provides a single number between 0 and 100 to describe overall pain and its effects. In practice, this could allow clinicians to see the effects of an intervention or a procedure in reducing pain, increasing mobility, or reducing the need for medication.

## Purpose

Research on the construct validity of GPS subscales and measurement is limited.<sup>2</sup> The validity of this important measurement instrument has yet to be demonstrated empirically. The purpose of this investigation is to examine the data collection protocols of pain measurement and evaluate the usability of clinical data from a pain management practice of 10 physicians for assessing pain management outcomes. Furthermore, psychometric properties of GPS and its subscales have yet to be examined in a longitudinal study. Ultimately, research findings may solidify the measurement validity and reliability of GPS and then guide the development of a predictive model of pain effects.

Four research questions pertaining to psychometric properties of GPS and its subscales are as follows:

1. What are the associations between GPS and its subscales?
2. Is GPS measurement relatively stable over time?
3. Can the patterns and change trajectories of GPS be detected in a longitudinal study?
4. Can the variability in the reduction of pain measured by GPS be explained by physicians?

## Basic Procedures

We used a GPS data set of a panel of 130 patients with 4 waves of data gathered by a pain management practice in 5 clinical sites located in a metropolitan area. The data set contains the assessment records of 1945 observations or visits with limited information on patient characteristics provided. The treatment plan for each visit was not documented in the data set shared with the investigator. The only variable listed in the data file was "number of medications prescribed" for each visit. The average age of patients treated by the clinics was 59.3, with a standard deviation of 14.84.

Initially, the data were sanitized and formed a panel group of 130 patients who have completed data on 4 waves of GPS measures and other clinical information. The analytical procedures are as follows:

1. Decompose the pain scale into 4 domains of a latent variable (pain); analyze the intercorrelations among subscales of physical pain, emotions, clinical outcome, and activities; and confirm the construct validity of GPS with 4 related subscales or domains.
2. Form multiwaves of a panel for 130 patients by combining 2 data sets on pain measurements provided by the clinic and then filtered all the account number and service date in 2016 to get a panel data set with 2 times, 3 times, and 4 times of service or treatment at the clinic. This allow us to compare if treatment time has any statistically significant effect on the total pain score (TS) through  $t$  tests. Outliers were eliminated from this data set.
3. Examine the stability or test-retest reliability of measurement for 4 domains of pain, using the subscales gathered in time 1 and time 2 visits of the panel group.
4. Conduct a latent growth curve modeling of the 2 growth trends (the initial growth pattern as shown in the intercept and the change trajectory in the slope) and detect the pain reduction effect over time.
5. Develop a regression model for a pain-relieving intervention including patient's age, provider (physician), and treatment time as explanatory factors.

## Main Findings

### *Correlations of 4 Domains of Pain Subscales: Physical Pain, Emotions, Clinical Outcome, and Activities*

Global Pain Scale is assumed to be a multidimensional scale with 4 related domains or subscales. Table 1 presents the intercorrelations among 4 pain domains. The clinical aspects of pain were moderately correlated with emotional (0.632) and activity (0.690) domains of the pain scale. Physical pain was also moderately associated with clinical aspects of pain (0.589). Further analysis by using total score (TS) was done to compare the correlations for 4 waves of pain measure (Table 2). Only moderately positive associations, ranging from 0.496 to 0.621, were found among them.

**Table 1.** Correlation Coefficients Among 4 Pain Domains or Subscales at Time 1.<sup>a</sup>

Subscale Score	Physical Pain I	Emotion I	Clinical I	Activity I
Physical Pain I	1			
Emotion I	.321 <sup>a</sup>	1		
Clinical I	.589 <sup>a</sup>	.632 <sup>a</sup>	1	
Activity I	.486 <sup>a</sup>	.477 <sup>a</sup>	.690 <sup>a</sup>	1

<sup>a</sup>Statistically significant at .01 or lower level.

**Table 2.** Correlation Coefficients Among 4 Waves of Total Pain Score.<sup>a</sup>

Global Pain Scale	Total Score 1	Total Score 2	Total Score 3	Total Score 4
Total score 1	1			
Total score 2	.621 <sup>a</sup>	1		
Total score 3	.620 <sup>a</sup>	.503 <sup>a</sup>	1	
Total score 4	.555 <sup>a</sup>	.496 <sup>a</sup>	.583 <sup>a</sup>	1

<sup>a</sup>Statistically significant at .01 or lower level.

### The Effects of Service Time

Because very few patients were recipients of more than 4 times of clinical services in 2016 from the clinics, the longitudinal analysis is limited to a panel group of 130 patients who have had 4 times of pain management service, using *t* tests (Table 3).

Table 3 shows that the mean pain score (TS) decreases as the service time increases from 54.7, 50.0, 47.2, to 47 for service time 1 to 4, respectively. From the sample *t* test, we can also find that the mean total pain score from service time 1 to service time 4 has significantly decreased or improved.

### The Stability or Test–Retest Reliability of the Pain Subscales or Domains

The construct validity of GPS, as a multidimensional scale, was evaluated by confirmatory factor analysis, assuming “pain” as a common factor shared by 4 related subscales of the GPS. The clinical subscale of the GPS has a much stronger correlation with GPS. Four subscales or domain are moderately strongly associated with the latent construct. We examine the stability of pain score domains, using subscales measured at time 1 (first visit) and time 2 (second visit) of the panel group. This enables us to perform a test–retest reliability analysis of 2 waves of the pain measurement as a latent construct or variable with 4 related domains of the pain scores. Figure 1 shows that the latent variable of pain with 4 related domains is relatively stable between 2 times of clinical visits, with a statistically significant reliability coefficient (0.56) for the latent construct measured between time 1 and time 2. The goodness-of-fit statistics ( $\chi^2$  value of 38.45 with 16 degrees of freedom; (RMSEA) of 0.07) also demonstrate that the measurement model of GPS has demonstrated with both construct validity and test–retest reliability for a panel of 130 patients.

### Autoregressive Model of Total Pain Scores (Time 1 Through Time 4)

The influence of prior pain scores on latter scores is demonstrated by an autoregressive model of total pain scores when moderately strong intercorrelations among 4 waves of pain scores are shown. The best fit model is presented in Figure 2 with 2 correlated residuals. The goodness-of-fit statistics reveals  $\chi^2$  value of 0.54 with 1 degree of freedom and *P* value of .46, RMSEA of 0.00, GFI of 1.00, and AGFI of 0.98. The  $\beta$  effects of prior scores on latter scores are 0.62 at TS2, 0.99 at TS3, and 0.92 at TS4. The findings suggest that prior pain scores are excellent predictors of latter pain scores in this study.

### Latent Growth Curve Model of Total Pain Scores (Time 1 Through Time 4)

We used linear growth curve modeling of 4 waves of pain measure to demonstrate the relationship of treatment time with chronic pain. The panel data (4 waves of the measurement and subsequent outcomes) allow us to hypothesize that the service time may affect the mean pain scores. It is also expected that the treatment benefit is positively associated with treatment time; the total pain score starts at a higher level and then decreases over time (Figure 3).

The results of the growth curve model of pain in Figure 3 are summarized as follows:

- A negative correlation (−0.037) exists between the 2 growth latent variables (intercept and slope). It suggests that patients with higher pain scores initially would experience a slower decline in latter periods (times).
- The growth pattern (intercept) shows statistically significant difference from time 1 to time 4, ranging from 0.88 at time 1 to 0.82. The change trajectories of pain scores are also statistically significant, ranging from 0.00 at time 2 to 0.51 at time 4.
- A nonlinear model of pain scores was also explored and tested. We assume that the 4 pain scores of the panel were not linearly distributed over time. A quadratic slope factor was introduced. Similar results on estimates of intercepts and slopes were found in the quadratic growth model. The detailed model can be obtained from authors at request.
- An estimation equation with 4 total pain scores can be formulated with the factor score weights in Table 4.

For a given performance or outcome variable ( $Y_{it}$ ), an equation can be written as follows:

$$Y_{it} = \eta_{0i} + \eta_{1i}X_t + \epsilon_{it},$$

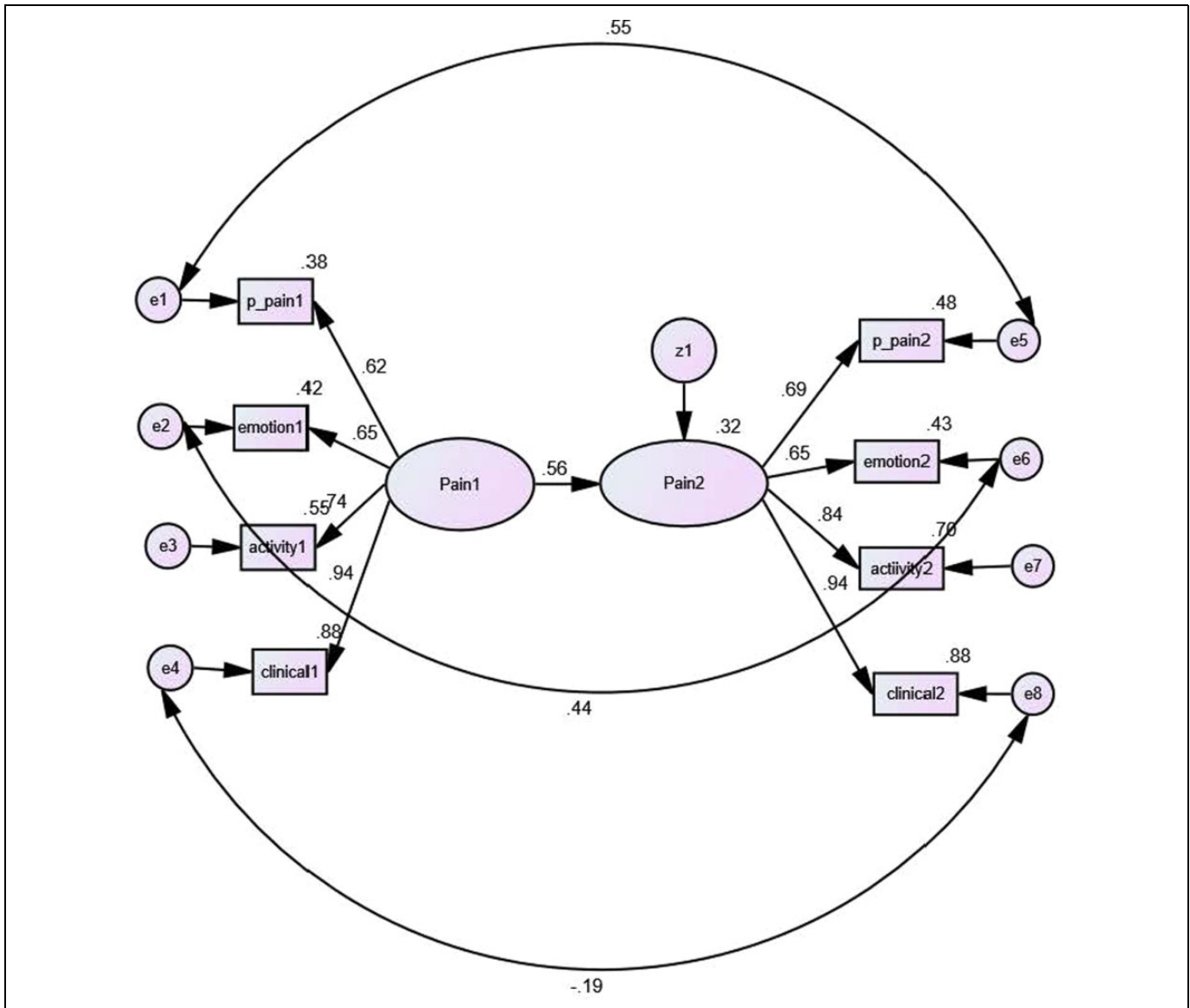
where  $X_t$  refers to predictor variables and  $\epsilon_{it}$  refers to a residual term.  $\eta_{0i}$  is a linear combination of 3 elements:  $\alpha_0 + \gamma_0 W_i + \zeta_{0i}$ , where  $\alpha_0$  is the mean,  $\gamma_0$  is the effect of an exogenous variable ( $W_i$ ) on  $\eta_{0i}$  at the initial level,  $\zeta_{0i}$  is a residual term. The slope  $\eta_{1i}$  also has 3 elements:  $\alpha_1 + \gamma_1 W_i + \zeta_{1i}$ , where  $\alpha_1$

**Table 3.** Four Times of Pain Management Services by Total Score (TS) for Pain Measures.

One-Sample Statistics				
	N	Mean	Standard Deviation	Standard Error of the Mean
TS 1	130	54.715	19.1662	1.6810
TS 2	130	50.023	20.0112	1.7551
TS 3	130	47.177	21.6564	1.8994
TS 4	130	46.988	20.3640	1.7860

One-Sample Test						
Test Value = 0						
	t	df	Significance (2-Tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
TS 1	32.549	129	.000	54.7154	51.390	58.041
TS 2	28.502	129	.000	50.0231	46.551	53.496
TS 3	24.838	129	.000	47.1769	43.419	50.935
TS 4	26.309	129	.000	46.9885	43.455	50.522



**Figure 1.** Stability of pain measurement: time 1 and time 2.

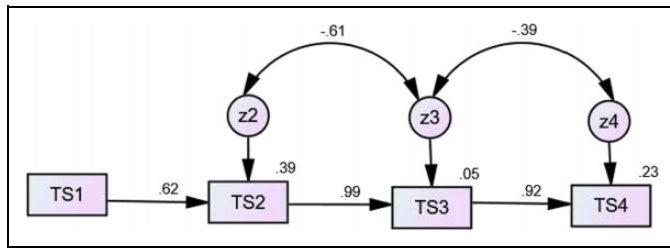


Figure 2. An autoregressive model of total pain scores in 4 waves.

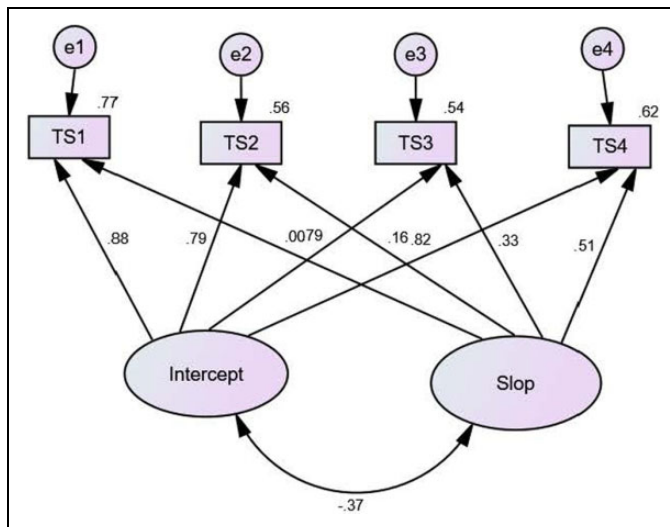


Figure 3. Growth curve model for total scores (TS) in 4 waves of pain management treatment.

Table 4. Factor Score Weights.

	TS3	TS2	TS1	TS4
Slope	-0.01	-0.01	-0.02	-0.01
Intercept	0.15	0.23	0.38	0.12

is the mean,  $\gamma_1$  is the effect of an exogenous variable ( $W_i$ ) on  $\eta_{1i}$  at the initial level,  $\zeta_{1i}$  is a residual term for this equation.

From Figure 3, we observe that chronic pain reduces as the treatment time increases. We can then hypothesize: when the treatment time increases, the dosage of medication-taking requirement decreases. This relationship is further examined in the following section.

### A Regression Model for a Pain-Relieving Intervention

Four waves of treatment were analyzed to detect if the number of pain treatment increased, the medication requirement would decrease. A panel of 122 patients with the complete pain medication history is included in the analysis by  $t$  tests for medication taken against 4 treatment times. The mean medication measure started at 5.418, declined slightly to 4.467 at time 2,

and then steadily increased to 4.500 at time 3 and 4.861 at time 4 (Table 5).

The mean dosage of pain medications taken was not decreasing in a linear fashion over time, although the second through fourth time of medications had a lower dosage as compared to the first treatment visit. Further analysis of age, provider (attending physician), and treatment time as predictors was conducted.

One-way analysis of variance (ANOVA) in total pain scores of a panel by patient age was performed. There was no age effect on mean scores. Similarly, mean pain scores by attending physician was also analyzed. No statistically significant differences in mean scores by physician were found. Detailed ANOVA tables of these results can be obtained from authors upon request.

Regression analysis of mean pain scores by treatment time and physician variables was performed. Table 6 shows TS1, TS2, TS3, and attending physicians as predictors of the total pain score at time 4. No physician differences in mean pain scores of patients were statistically significant when 3 waves of pain score were included as predictors for TS4 in the regression.

## Discussion

Four major findings in regard to our research questions are summarized and discussed. First, GPS and its subscales are moderately and positively related. The clinical subscale is the strongest domain of GPS. Confirmatory factor analysis of pain as a latent variable reveals that GPS of 130 patients has demonstrated its construct validity. Thus, the summation of subscales as an aggregate or total score does reflect important pain domains.

Second, GPS measured between the first and second visits of patients during 2016 is relatively stable. The test-retest reliability of GPS construct and its subscales is 0.56 as demonstrated in the 2-wave measurement model of pain.

Third, both autoregressive model and growth curve model of GPS in the longitudinal analysis show that pain measurement is time dependent as GPS changes over time during the pain treatment period. In analyzing GPS data of a panel of 130 patients treated by 10 physicians in their pain clinics, we found that a decreasing trend in pain scores was associated with an increasing number of treatment from time 1 to time 4 period. Patient's age and attending physician were not key explanatory variables for the variability in treatment outcome measured by the total pain score.

Fourth, the variability in GPS of 130 patients is explained by physician and number of medications prescribed. Because a limited number of personal attributes and treatment data were available from the group practice, it makes impossible to control any confounder variables statistically when the patient variability in pain is being investigated. Several limitations of this study are worthy of discussion. The limited patient data in pain management is a serious problem since it prevents us from performing more thorough analysis of the data. Because the

**Table 5.** *t* Tests of Medication (Med) Taken for 4 Treatment Times.

One-Sample Statistics				
	N	Mean	Standard Deviation	Standard Error of the Mean
Med 1	122	5.418	3.3816	.3602
Med 2	122	4.467	3.3431	.3027
Med 3	122	4.500	3.3532	.3036
Med 4	122	4.861	3.5867	.3247

One-Sample Test						
Test Value = 0						
	<i>t</i>	<i>df</i>	Significance (2-Tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Med 1	17.697	121	.000	5.4180	4.812	6.024
Med 2	14.759	121	.000	4.4672	3.868	5.066
Med 3	14.823	121	.000	4.5000	3.899	5.101
Med 4	14.968	121	.000	4.8607	4.218	5.504

**Table 6.** Total Pain Score at Time 4 (Dependent Variable) Regressed on TS1, TS2, TS3, and Attending Physicians (Physician 1 as a Reference).<sup>a</sup>

	Estimate	Standard Error	<i>t</i> Value	Pr (>  <i>t</i>  )
Intercept	8.90562	6.21947	1.432	0.154840
TS 1	0.23803	0.10918	2.180	0.031239
TS 2	0.22129	0.09363	2.363	0.019758
TS 3	0.30957	0.08715	3.552	0.000552
Physician 2	-6.09773	7.01306	-0.869	0.386364
Physician 3	-4.43056	5.84432	-0.758	0.449917
Physician 4	-1.68972	4.84867	-0.348	0.728097
Physician 5	7.04891	7.80787	0.903	0.368489
Physician 6	7.04662	5.89627	1.195	0.234466
Physician 7	-1.39200	10.01857	-0.139	0.889735
Physician 8	-0.98743	6.47929	-0.152	0.879135
Physician 9	-2.07685	6.08280	-0.341	0.733392
Physician 10	-2.96446	9.11039	-0.325	0.745464

<sup>a</sup>Multiple  $R^2$ : 0.4536; Adjusted  $R^2$ : 0.3975; *F*-statistic: 8.093 on 12 and 117 *df*.

analysis of pain data is based on a single pain management group practice, the results may not be generalizable to other pain management practices.

In recognizing the conceptual and methodological limitations of these pain data, the investigators identified following variables for future research: (1) medical history on pain, (2) timing of pain assessment and analysis, (3) predictive analytics, and (4) delineation between psychological determinants and somatization factors.

### Medical History on Pain

Because pain is a very subjective matter, details on the psychological and mental health profile should be gathered. For instance, information on prior use of pain medications (amount, frequency, and type) or other substances should be

documented. More specifically, it is imperative to document the history of substance abuse during the pain treatment period so that pain management protocols could be properly amended.

### Pain Assessment and Analysis

Although the Global Pain Scale is useful to serve as a summary of pain experienced by a patient, additional pain measures such as cognitive, affective, behavioral, and physiological indicators should be added.<sup>4,5</sup> Further psychometric analysis of pain measures should be carefully performed with a longitudinal data set generated from multiple practices on pain management, using a confirmatory factor analysis.

### Theoretical Specified Predictive Analytics

The validity of predictive models is based on the rigor of analytical approaches and theoretical frameworks used by researchers and practitioners. The predictive models should include time-dependent and time-varying predictors in the analysis. Thus, a better specified model with relevant predictor variables should be included in the future research. Pain management research requires further collaboration among scientists from multiple disciplines. It is highly recommended that a transdisciplinary approach to pain management be employed by integrating macro- or ecological correlates of pain experienced with micro- or personal factors as predictors of pain.<sup>6</sup> Thus, a decision support system based on a sound predictive model of pain measures for enhancing pain management of patients could be formulated in the future.

### Delineation Between Psychological Determinants and Somatization Factors

The complexity of etiologies of pain requires to conduct prospective studies on pain management.<sup>7</sup> The commonly used

research design such as retrospective studies could not generate specific causal models to guide pain research. Furthermore, factors such as socioeconomic status,<sup>8</sup> gender,<sup>9-11</sup> and coping mechanisms,<sup>12</sup> moderating or mediating the relationship between interventions and treatment outcomes of pain, should be considered in investigations.

## Principal Conclusions

In this study, the investigators have presented a detailed approach to improve a pain management process. It is important to note that this study involves the use of longitudinal data to conclude a necessary observation on reduction of pain while undergoing treatment. While this conclusion is somewhat anticipated, the investigators have provided a method to the readers for conducting an effective analysis of pain management measurement. The investigators have also provided necessary parameters that could have perhaps enhanced the study and made it more effective. Overall, the investigators believe that the described study advances the science of data science analytics with respect to pain management and the process is repeatable for a general pain management clinic. Furthermore, future research on pain measurements should identify behavioral cues to trigger pain responses associated with the ailments.<sup>13</sup>

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## Declaration of Conflicting Interests

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