Digital Phenotyping in Patients with Spine Disease: A Novel Approach to Quantifying Mobility and Quality of Life

David J. Cote[1], Ian Barnett[2], Jukka-Pekka Onnela[2], Timothy R. Smith[1]

OBJECTIVE: **To identify trends in mobility and daily pain levels among a cohort of patients with clinically diagnosed spine disease.**

METHODS: **Participants with spine disease were enrolled from a general neurosurgical clinic and installed a smartphone application (Beiwe) designed for digital phenotyping to their personal smartphone. This application collected passive meta-data on a minute-to-minute basis, including global positioning system (GPS), WiFi, accelerometer, text and telephone logs, and screen on and off time. The application also administered daily visual analog scale pain surveys. A linear mixed model framework was used to test for associations between self-reported pain and mobility and sociability from the passively collected data.**

RESULTS: **A total of 105 patients were enrolled, with a median follow-up time of 94.5 days; 55 patients underwent a surgical intervention during the follow-up period. The weekly pain survey response rate was 73.2%. By the end of follow-up, the mean change in pain for all patients was −1.3 points (4.96 at the start of follow-up to 3.66 by the end of follow-up). Increased pain was significantly associated with reduced patient mobility as measured using 3 daily GPS summary statistics (i.e., average flight length, maximum diameter travelled, total distance travelled).**

CONCLUSIONS: **Patients with spine disease who reported greater pain had reduced mobility, as measured by the passively collected smartphone GPS data. Smartphone-based digital phenotyping appears to be a promising and scalable approach to assess mobility and quality of life of patients with spine disease.**

INTRODUCTION

Few effective methods currently exist for objectively evaluating patient recovery after spine surgery. Among the most widely used and clinically evaluated are a broad set of measures known as the patient reported outcome measures (PROMs), which often consist of validated questionnaires aimed at determining a patient's quality of life in response to surgical treatment.[1] These are paper-based or electronic surveys that require significant clinician and patient investment, necessitating multiple in-office follow-up appointments and regular patient contact. Typically, these will be administered preoperatively and at several points postoperatively, with the exact timing of administration varying from practice to practice.[1-3]

However, questionnaire-based instruments have their limitations, both practical and conceptual.[1,4] First, they rely on patient recall at a particular moment in time, making them subject to bias. Second, they often require patients to return to the clinic or participate in a telephone call or other interaction with a care provider. Third, they require the patient to make reporting assumptions regarding all events subsequent to their previous encounter. If patients are asked to report their pain, they must determine whether that means their average pain since their previous visit, the average pain of that day, or their pain at that moment. Finally, surveys can only provide a limited view of a patient's life, determined solely by their ability to complete those tasks assessed in a particular questionnaire.

Key words
- Digital phenotyping
- Outcomes
- Spine

Abbreviations and Acronyms
GPS: Global positioning system
PROM: Patient reported outcome measure

From the [1]Computational Neuroscience Outcomes Center, Brigham and Women's Hospital, Harvard Medical School, Boston; and [2]Department of Biostatistics, Harvard T. H. Chan School of Public Health, Boston, Massachusetts, USA

To whom correspondence should be addressed: David J. Cote, B.S.
[E-mail: david_cote@hms.harvard.edu]

David J. Cote and Ian Barnett contributed equally; Jukka-Pekka Onnela and Timothy R. Smith contributed equally.

Citation: World Neurosurg. (2019) 126:e241-e249.
https://doi.org/10.1016/j.wneu.2019.01.297

*Journal homepage: **www.journals.elsevier.com/world-neurosurgery***

*Available online: **www.sciencedirect.com***

Table 1. Participant Demographic Information and Digital Phenotyping Data ($n = 105$)

Variable	n (%) or Mean ± SD
Demographic data	
Male gender	48 (45.7)
Age	52.0 ± 14.0
Surgery	55 (52.4)
Site of disease	
Cervical	35 (33.3)
Thoracic	6 (5.7)
Lumbar	64 (60.1)
Passive data collection	
GPS days	82.5 ± 68.4
Active data collection	
Daily survey response rate	
Mean	43.4
25%–75% quantile	23.2–69.8
Weekly survey response rate	
Mean	73.2
25%–75% quantile	50.6–100.0
Change in pain score, all patients	
Mean	−1.3
Start to end score	From 4.96 to 3.66
Daily digital phenotypes*†	
Time spent at home (minutes)	927.1 (623.9–1242.8)
Distance travelled (meters)	51,989.1 (18,691.9–97,833.3)
Radius of gyration (meters)	32,18.8 (846.8–9881.9)
Maximum diameter (meters)	13,828.1 (4867.5–29,382)
Maximum distance from home (meters)	13,296.5 (46,12.7–29,285.7)
No. of significant locations visited	2 (1–3)
Average flight length (meters)	236.0 (160.1–334.9)
SD of flight length (meters)	296.4 (173.3–487.3)
Average flight duration (seconds)	42.7 (32.0–74.3)
SD of flight duration (seconds)	98.2 (56.9–257.1)
Fraction of the day not moving	0.88 (0.79–0.94)
Significant location entropy	0 (0–0.28)
Missing GPS data (minutes)	1349.7 (1323.7–1379.2)
Circadian routine (0, low; 1, high)	0.59 (0.42–0.71)
Weekend/day stratified circadian routine	0.61 (0.44–0.73)
No. of outgoing texts	4 (0–14)
Total outgoing text length (characters)	165 (0–756)
Texting out degree	1 (0–3)
Number of incoming texts	4 (0–13)
Total incoming text length (characters)	188 (0–689)
Texting in degree	2 (0–4)
Text reciprocity	4 (0–15)
Text responsiveness	0.04 (0–0.28)
No. of outgoing calls	1 (0–4)
Total outgoing call lengths (seconds)	72 (0–561)
Call out degree	1 (0–3)
No. of incoming calls	1 (0–3)
Total incoming call lengths (seconds)	75 (0–619)
Call in degree	1 (0–2)
Call reciprocity	0 (0–2)
Call responsiveness	0 (0–0.44)

GPS, global positioning system; SD, standard deviation.

*Detailed descriptions and definitions of the mobility and sociability digital phenotypes are provided in Barnett and Onnela (2018).[11]

†Data presented as median (25%–75% quantile).

A recent study by Falavigna et al.[2] highlighted some of these major limitations, demonstrating that among an international community of spine surgeons, 31.9% never used PROMs for either research or clinical purposes. The reasons for the restricted use included the limited time in the clinic for administration (57% of all respondents), difficulty with follow-up after discharge (36%), and the lack of staff to assist in data collection (55%). Because of these limitations, novel methods to monitor patient outcomes has been proposed, including digital phenotyping.

Digital phenotyping has recently been defined as the "moment-by-moment quantification of the individual-level human phenotype in situ using data from personal digital devices," such as smartphones.[5,6] In this approach, subjects download and launch a smartphone application that collects both active data (e.g., surveys) and passive data (e.g., global positioning system [GPS] data) from the participants. These data are then used to study variations in patient behavior, including mobility (using GPS data), sociability (using text message and telephone logs), and sleep (using screen activity logs), among a variety of other measures. These objective measurements can be correlated with the patient responses to telephone surveys or any other data that might be available, including clinical examination findings conducted at the clinic.

Because smartphones have become ubiquitous, with ownership exceeding 77% of adults in the United States,[7] digital phenotyping for the purpose of improving patient outcomes through voluntary monitoring has become feasible and economical on a large scale. Digital phenotypes have been successfully used to link patient mobility to mood and depressive symptoms in a variety of clinical contexts.[8-10] Although digital phenotyping has been used in the study and treatment of psychiatric disorders, to the best of our knowledge, its use to monitor and aid patients with debilitating physical conditions such as spine disease has not been attempted.

Table 2. Daily Smartphone Mobility and Sociability Features Collected by Digital Phenotyping

Data Summary/Feature	Collection Type	Unit
Pain	Active (survey)	0—10 (low to high)
Time spent at home	Passive	Minutes (log$_{10}$ scale)
Distance travelled	Passive	Meters (log$_{10}$ scale)
Radius of gyration	Passive	Meters (log$_{10}$ scale)
Maximum diameter	Passive	Meters (log$_{10}$ scale)
Maximum distance from home	Passive	Meters (log$_{10}$ scale)
No. of significant locations visited	Passive	None
Average flight length	Passive	Meters (log$_{10}$ scale)
Standard deviation of flight length	Passive	Meters (log$_{10}$ scale)
Average flight duration	Passive	Seconds (log$_{10}$ scale)
Standard deviation of flight duration	Passive	Seconds (log$_{10}$ scale)
Fraction of time not moving	Passive	None
Significant location entropy	Passive	None
Circadian routine	Passive	None
Circadian routine (weekend/day stratified)	Passive	None
No. of outgoing texts	Passive	None
Cumulative length of outgoing texts	Passive	Characters (log$_{10}$ scale)
No. of people texts were sent to	Passive	None
No. of incoming texts	Passive	None
Cumulative length of incoming texts	Passive	Characters (log$_{10}$ scale)
No. of people texts were received from	Passive	None
Text reciprocity	Passive	None
Text responsiveness	Passive	None
No. of outgoing telephone calls	Passive	None
Cumulative length of outgoing telephone calls	Passive	Seconds (log$_{10}$ scale)
No. of people telephone calls were made to	Passive	None
No. of incoming calls	Passive	None
Cumulative length of incoming telephone calls	Passive	Seconds (log$_{10}$ scale)
No. of people telephone calls were received from	Passive	None
Call reciprocity	Passive	None
Call responsiveness	Passive	None

In the present study, we report, the first use of digital phenotyping for patients with spine disease to identify associations between behavioral data, passively collected from the patients' smartphones, and patients' daily self-reported pain. We found strong associations between self-reported pain and multiple aspects of patient mobility, as measured by digital phenotyping.

METHODS

Patient Recruitment

All patients included in the present study were neurosurgical patients with clinically diagnosed spine disease seen at a general neurosurgical clinic. Enrollment began in June 2016 and continued through May 2017. During the study period, 52.4% of the patients had undergone neurosurgical intervention (Table 1). Only adults were included in the present study (age ≥18 years), and those patients who did not own a smartphone were excluded. The institutional review board of Brigham and Women's Hospital approved the present study, and all patients had provided written informed consent to participate in the study. On enrollment, the research assistant helped each patient download the application to their smartphone in the clinic and established each participant's user account. The patients were then given uniform instructions on how to operate the application, including keeping it running as a background application and responding to the daily and weekly questionnaires.

Data Collection

The patients enrolled in the present study installed the Beiwe application (Harvard T. H. Chan School of Public Health, Boston, Massachusetts, USA), which is part of the Beiwe research platform developed by a subset of the authors, onto their personal smartphone. The Android and iOS Beiwe applications collect both active and passive data from patients and are accessible only with a unique username and password known only to the user.

The data collected by the current version of the Beiwe application includes GPS data, accelerometer records, Bluetooth and Wi-Fi data, telephone and text message logs (Android only), and screen on and off time. These data streams can be collected by the application at different customizable rates. In the present study, we configured Beiwe to collect GPS data for 1 minute every 5 minutes and accelerometer data for 10 seconds every 10 seconds. It also collected anonymized telephone and text message logs, which included information about the timing of communication events, anonymized identifiers of communication partners, and message length for text messages. The application did not record any of the actual content of the telephone calls or text messages. For modeling purposes, the collected raw sensor and telephone usage data were represented in terms of daily summary statistics that captured salient features of each data stream (Table 2). For each subject, the summary statistics are represented as a matrix, with the rows corresponding to different statistics and the columns to different days. A visual representation of the data matrix for a single participant is shown in Figure 1.

In the present study, the patients were surveyed once daily at 5:00 PM Eastern standard time with the following prompt: "Please rate your pain over the last 24 hours on a scale from 0 to 10, where 0 is no pain at all and 10 is the worst pain imaginable," with a sliding scale answer that ranged from 0 to 10. The Beiwe application encrypted the data as the data were collected, stored it temporarily on the user's smartphone, and then periodically uploaded the data to a secure server via Wi-Fi.[12]

Statistical Analysis

The overall trends in pain during the follow-up period were evaluated as the difference between the first and last survey pain scores submitted during the course of follow-up. To measure mobility, the raw GPS data for each patient were converted into a sequence of flights (straight-line movement) and pauses,[13] missing portions of data were imputed, and a variety of daily mobility summaries were produced.[14] Daily measures of sociability were summarized from the telephone call and text message logs. These passively collected GPS mobility measures and telephone call and text log sociability measures are listed in Table 2. To identify how a patient's pain was related to mobility and sociability during the course of the same day and to avoid biased and inaccurate responses, we excluded late survey responses submitted after midnight (>7 hours after the prompt).

Given the longitudinal nature of the data, to test for associations between the daily self-report of pain and daily mobility and sociability, we used a linear mixed model[15] For the daily mobility metrics, we ignored days that either had no GPS data or had no response to the pain survey. Similar to the analysis by Wang et al.,[8] we fit the following model for each of the 30 mobility and sociability passive data summaries: $y_{ij} = \beta_0 + \beta_1 X_{ij} + b_{i0} + b_{i1} X_{ij} + \varepsilon_{ij}$, where the outcome y_{ij} is self-reported pain score on a 0—10 scale, X_{ij} is 1 of the 30 passive data summaries, and ε_{ij} is the normally distributed residual for the ith subject on their jth day of data collection. The fixed coefficients are the intercept (β_0) and slope (β_1), with random patient-specific coefficients (b_{i0}) and slopes (b_{i1}). This mixed-effects model allows for patient-specific relationships (intercept and slope) between the predictor and pain. Two-sided inference was performed on β_1 using a likelihood ratio test, and this modeling and testing procedure was repeated, with each of the 30 passive data summaries or features taking turns as the predictor X_{ij}. With the performance of 30 different and correlated tests, we used the generalized higher criticism to correct for multiple testing and to identify statistically significant associations between the passive data features and the self-report of pain.[16]

To measure the tendency of patients to stay home during prolonged periods of pain or discomfort, we estimated a daily probability of moving <1 km, a somewhat arbitrary threshold that was selected to capture days of little to no movement within a reasonable margin of error. A Gaussian kernel, centered on the day of interest, averaged the indicator variables of whether the patient had moved >1 km across all the days of the patient's follow-up period. Kernel averaging gives greater weight to days closer to the day of interest. This process was repeated to calculate the probability for each day in the follow-up period.

RESULTS

During the enrollment period, 216 patients were approached for enrollment. Of these, 90 (42%) were immediately excluded because they did not own a smartphone. Of the remaining 126 patients, 15 (12%) could not recall the necessary telephone passwords for enrollment, 4 (3%) did not have their smartphone

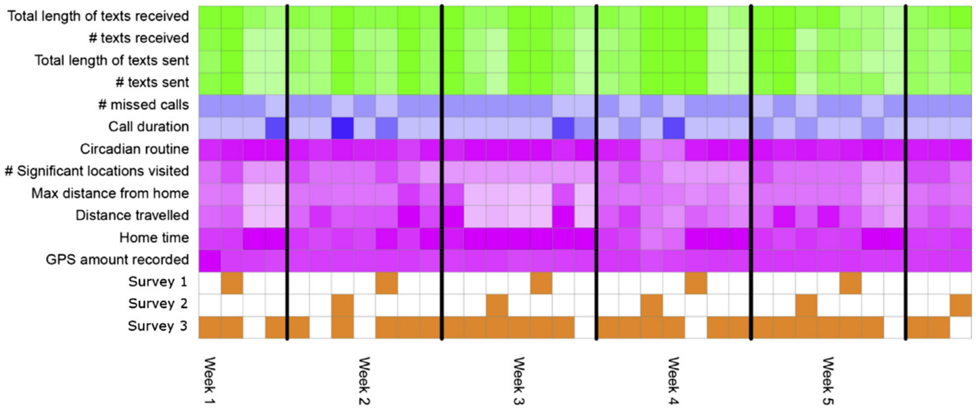

Figure 1. Visual display of daily summary statistics collected for a patient. Surveys are represented in *orange*. Measures of mobility obtained from smartphone global positioning system data (GPS) are shown in *purple*. Measures from telephone call logs are in *blue* and measures from text logs are in *green*. Measures were calculated from raw smartphone data on a daily basis. Only a smaller representative sample of the total set of measures both collected and calculated are displayed. A *darker color* represents a larger quantity or amount of the measure on a given day. Each *column* represents 1 day of data collection, with *vertical black lines* representing divisions between weeks.

accessible on the day of the visit, and 2 (1%) declined consent for data security concerns. The remaining 105 patients (83%) were enrolled.

The demographic data of the included patients and relevant data collection metrics are presented in Table 1. On average, the patients completed 43% of their daily surveys during the follow-up period; the weekly pain survey response rate was 73.2%. Of the surveys that were completed, 71% were completed on the day they were administered (Figure 2). The median follow-up time was 3.15 months from enrollment, and 52.4% of the patients had undergone a neurosurgical intervention during the study period. During the follow-up period, the mean change in pain for all patients was −1.3 (from an average of 4.96 at the start of follow-up to 3.66 by the end).

After correcting for multiple testing, the average flight length, maximum diameter travelled, and total distance travelled were each statistically significantly associated with the patient-reported level of pain. The mobility trace for each patient was broken into a sequence of flights (straight-line movement) and pauses (periods of stationarity). An average increase in self-reported pain by 0.1 was associated with 2.8-fold decrease in the average length of a patient's flights on the same day ($P = 0.002$),[17] a 5.1-fold decrease in a patient's maximum diameter, the largest distance between any 2 points the patient had traversed during that day ($P = 0.004$), and a 6.0-fold decrease in a patient's distance travelled during that day ($P = 0.004$). The associations between self-reported pain and various measures of mobility and sociability are presented in Table 3.

These cohort-level relationships between mobility and pain were averaged across all patients, and corresponded to β_1 from the model used.[13] The patient-specific relationships were captured by b_{i1} for the ith patient. Examples of patient-specific relationships between mobility and self-report of pain are shown in Figure 3. Representative results for 4 patients using kernel averaging are shown in Figure 4.

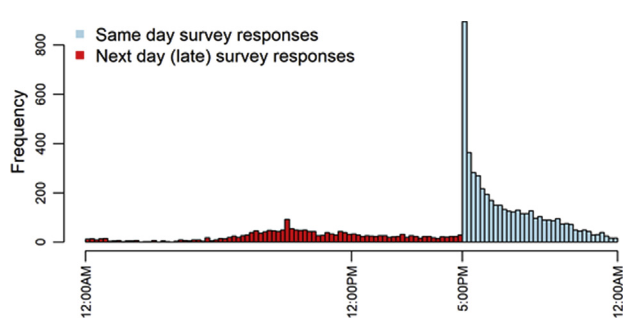

Figure 2. Response times to the daily smartphone pain score survey. The daily response times were combined across all patients in the cohort. The patients were prompted with a survey at 5:00 PM each day in which they were to report their pain during the course of that day. Late responses submitted by the patient on the next day were excluded from the analysis; 70.7% of all survey responses were submitted on the same day the patient had been prompted. Across all patients, 43% of these daily surveys were completed, late or on time. On average, the patients completed ≥1 survey each week 73.2% of the time.

Table 3. Associations Between Daily Passively Collected Variables and Self-Report of Pain Using Linear Mixed Modeling for Each Feature with a Random Slope and Intercept for Each Participant

Feature	Coefficient	Standard Error	*P* Value
Average flight length	−0.226	0.068	0.002
Maximum diameter	−0.142	0.047	0.004
Distance	−0.129	0.043	0.004
Radius of gyration	−0.134	0.051	0.011
Standard deviation of flight duration	−0.124	0.045	0.013
Standard deviation of flight length	−0.174	0.071	0.020
Maximum distance from home	−0.124	0.055	0.029
No. of significant locations visited	−0.740	0.408	0.077
Average flight duration	−0.108	0.062	0.089
Significant location entropy	−0.920	0.706	0.225
Text responsiveness	0.576	0.456	0.247
Text out degree	0.284	0.256	0.320
Physical circadian routine (weekend/day stratified)	−0.632	0.737	0.408
Call in degree	0.189	0.250	0.458
Text in degree	0.223	0.257	0.474
Outgoing texts	0.083	0.133	0.538
Call responsiveness	0.255	0.435	0.568
Time spent at home	0.023	0.045	0.651
Physical circadian routine	−0.341	0.800	0.676
No. of incoming calls	0.084	0.213	0.694
Call out degree	−0.074	0.195	0.705
Call reciprocity	−0.105	0.282	0.714
No. of outgoing calls	−0.044	0.195	0.820
Fraction of time stationary	−0.290	1.383	0.836
No. of incoming texts	0.030	0.142	0.837
Text reciprocity	0.018	0.132	0.892
Total incoming call lengths	0.006	0.045	0.892
Total outgoing text lengths	0.007	0.060	0.909
Total outgoing call lengths	−0.003	0.039	0.935

DISCUSSION

The limitations of clinical outcomes studies for patients with spine disease are well known and have been well described.[18] Comprehensive, quantitative evaluations of outcomes have been impeded by recall bias and poorly defined outcome measures. In clinical practice, patients with spine disease who are neurosurgical candidates are, at best, simply assessed with a validated PROMs instrument that can be used to track specific symptoms over time. In most cases, patients are asked about

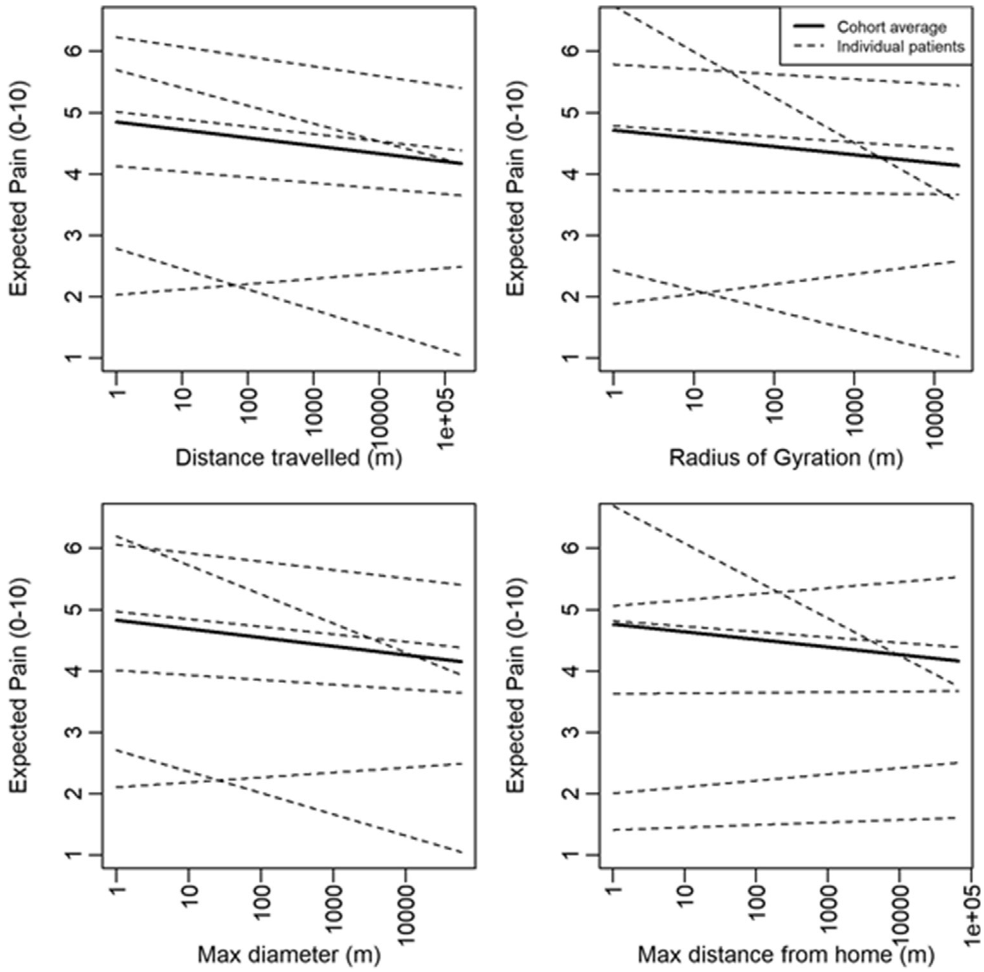

Figure 3. Patient-specific relationships between the self-report of pain and mobility on the same day. The data displayed from 6 patients were selected arbitrarily for demonstration purposes. The *dotted lines* represent the expected relationship between various mobility metrics and pain for individual patients, and the *solid line* is the average relationship across the cohort. These lines, representing the expected, or average, relationship between pain and mobility, resulted from fitting a linear mixed model with a random intercept and slope for each patient. A different model was fit for each mobility metric. The *x-axis* is on a logarithmic scale.

their symptoms, quality of life, and ability to complete their activities of daily living. Over time, changes in overall symptoms are tracked based solely on these patient reports and are not recorded in a systematic fashion.[1] In clinical research settings, PROMs surveys are administered at set intervals pre- and postoperatively, usually including a follow-up period for ≥1 year after surgery. In typical clinical practice, PROMs might not be used at all.[2] An international survey of spine surgeons by Falavigna et al.[2] demonstrated that almost one third of spine surgeons did not use PROMs at all for either research or clinical care.

Nevertheless, PROMs have frequently been used to assess the outcomes after spinal surgery since they began to emerge in the early 2000s.[1,2,19-23] The results of these studies have often demonstrated improvement in patient quality of life and symptoms postoperatively, although the limitations in follow-up and the quality of the survey instruments have limited the generalizability of these findings.[20,24]

In neurosurgical practice, the results of the limitations associated with PROMs and other classic survey instruments are serious. Often, neurosurgeons counsel patients on the benefits of surgical intervention based largely on subjective reports of pain and other symptoms, and imaging findings that might or might not correlate with the severity of disease presentation. Without high-quality data demonstrating reduced quality of life with spine disease in a particular patient or high-quality data demonstrating the effectiveness of a surgical intervention, decisions regarding the care of patients with spine disease are often made without strong evidence.[18,25,26]

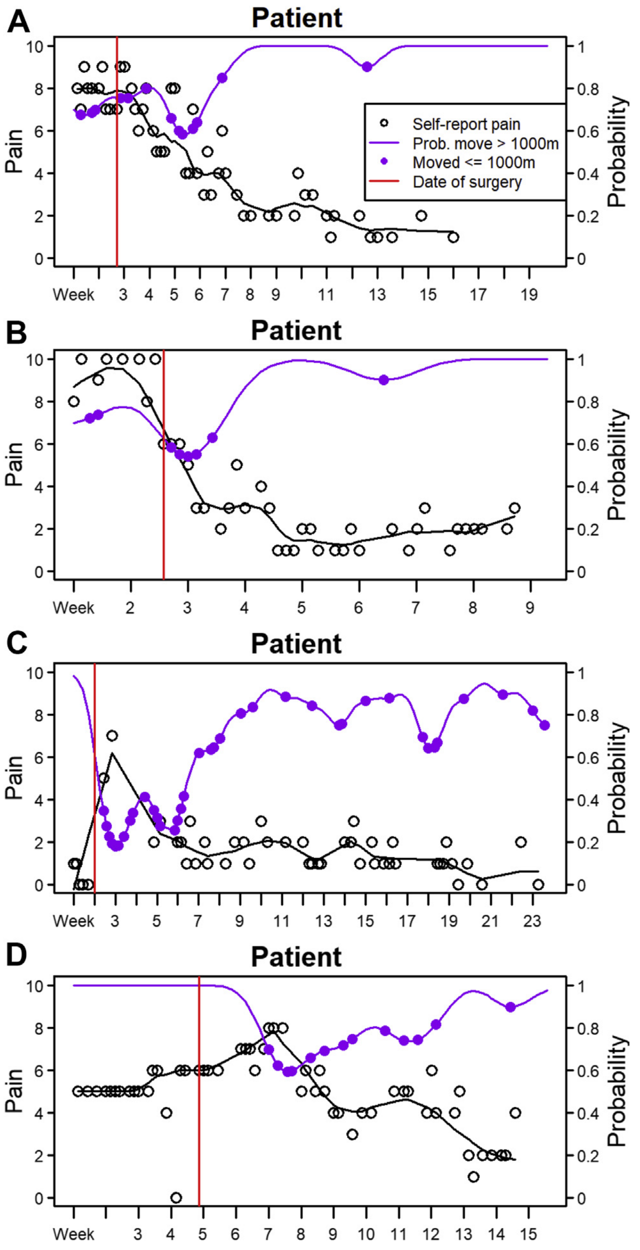

Figure 4. Patient pain and mobility trajectories over time. The trajectories of 4 patients are displayed during the course of their recovery after surgery. *X-axis tick marks* represent weeks, and each *point* represents a day. The *vertical red line* indicates the date of surgery. The *black line* is the smoothed pain trajectory over time. Days on which a patient traveled <1 km are highlighted with a *purple point*, with the patient traveling >1 km on all other days. Some patients stopped completing their smartphone surveys after recovery despite allowing the application to continue to collect smartphone GPS location and mobility data passively.

To the best of our knowledge, in the present study, we have reported the first-ever application of smartphone-based passive data collection for the objective measurement of patient mobility in a cohort of 105 patients with spine disease. During an average follow-up period of 94.5 days, we used the Beiwe smartphone application and research platform to collect both active and passive data from the included patients in an effort to identify trends in self-reported pain and objective measures of mobility and sociability. We have demonstrated statistically significant associations between patient self-reported pain and patient mobility but no associations between pain and sociability.

The relationship between pain and patient mobility has historically been difficult to study.[27-32] First, pain is an inherently subjective experience and is affected by a multitude of factors, including the patient's disease state, current pain medication regimen, daily activities, and mental health. It changes constantly, is impossible to measure objectively, and varies from patient to patient. Although it is reasonable to imagine that patients experiencing significant pain would have reduced mobility, it is just as possible that those patients who increase their mobility suddenly might provoke the development of significant pain. This multidirectional relationship has made identifying trends in patient quality of life using pain scales difficult. With the advent of wearable pedometers that track mobility, some research has recently been performed that uses these more objective patient measures to evaluate mobility.[33-35] In contrast to using smartphone-based software, these studies have typically required participants to wear an additional device, increasing the likelihood of patient noncompliance and subsequent missing data.

Similarly, the association between pain and other patient outcomes and sociability, social networks, or social support systems has also been difficult. Typically, studying these associations has involved in-depth interviews or PROM-like paper or electronic questionnaires completed by patients to identify their networks of social support.[36-38] Outcomes can be tracked as usual and compared statistically against objective measures of patient social networks. Most studies have demonstrated that patients with stronger social networks have reduced mortality and improved outcomes.[39]

The novel method of in situ human research used in the present study, known as digital phenotyping, has the potential to revolutionize the study of these types of quality of life measures. Digital phenotyping has previously been used to assess patient mobility with mood and depressive symptoms.[5,6,12] The introduction of smartphone data-driven approaches to patient outcomes in psychiatric research has provided an objective grounding for understanding of patient behavior. We believe that among patients with spine disease, digital phenotyping has the potential to revolutionize patient care, which has been increasingly driven by patient quality of life and personal outcome measures such as functional status and pain.

In the present study of patients with spine disease, we identified 3 statistically significant relationships between pain and mobility. Specifically, patients who reported increased pain showed reduced mobility in that they traveled shorter total distances across each day, traveled within a narrower diameter, and took shorter average trips. Although we did not identify associations between pain and patient sociability, future studies focusing on other illnesses, including brain tumors, will attempt to identify relationships between disease and objective sociability, as measured by telephone and text responsiveness.

Using noninvasive methods and data collected from a patient's own personal smartphone, digital phenotyping allows for the moment-by-moment analysis of the patient's behavior. Using historical trends, analysis of data obtained from the Beiwe application can allow for identification of deviations in expected trends, possibly even allowing for clinical intervention. In patients with spine disease, digital phenotyping allows clinicians to track symptoms, such as pain and mobility, objectively over time. This could play an important role in operative planning and in assessing patients' response to neurosurgical procedures. In the future, digital phenotyping could even be useful for identifying adverse events during the postoperative period, such as the development of a surgical site infection or changes in a patient's mental status.

The advantages of digital phenotyping are numerous and include the ubiquity of personal cell phones, the low cost of installing and using the application, the outstanding granularity of data collected, and the ability to assess patient's self-reported pain on a daily basis. Additionally, digital phenotyping is noninvasive and does not require patients to carry or use an additional device. Thus, digital phenotyping truly allows for an analysis of patient behavior and quality of life in situ. The electronic survey response is easy and quick for patients and has previously been shown to result in higher response rates than other modes, such as postal or telephone interviews.[40,41]

The limitations of the present study included the exclusion of patients without smartphones, which could have resulted in an underrepresentation of patients of lower socioeconomic status and the elderly, although recent data regarding cell-phone ownership have demonstrated increased smartphone ownership across the U.S. population.[7] Additionally, given that the collection of high-frequency sensor data causes some battery drainage, sensors will need to be sampled according to a sampling scheme that will unavoidably introduce some missing data by design. Some further missing data will occur because of human behavioral factors, such as individuals deactivating their smartphone GPS. The missing data must then be imputed or accounted for in the statistical calculations.

Despite these limitations, the present study nevertheless collected millions of data points for >100 patients with spine disease, providing the first objective measurement of pain and mobility in this patient population using in situ data rather than survey responses. The results of the present study have shown that patients with spine disease who report increased pain demonstrate reduced mobility, as measured by passively collected GPS data from personal smartphones and correlated with the daily self-report of pain. Digital phenotyping is a novel method to objectively assess the quality of life of patients with spine disease on a moment-to-moment basis. Digital phenotyping has the potential to revolutionize the surgical care of patients with spine disease by providing objective measures of patient symptoms and functional status, both before and after an intervention.

CONCLUSIONS

Patients with spine disease who report greater pain have reduced mobility as measured by passively collected smartphone GPS data. Smartphone-based digital phenotyping appears to be a promising and scalable approach to assess the mobility and quality of life in patients with spine disease.

REFERENCES

1. Faraj SSA, van Hooff ML, Holewijn RM, Polly DW Jr, Haanstra TM, de Kleuver M. Measuring outcomes in adult spinal deformity surgery: a systematic review to identify current strengths, weaknesses and gaps in patient-reported outcome measures. *Eur Spine J*. 2017;26:2084-2093.
2. Falavigna A, Dozza DC, Teles AR, et al. Current status of worldwide use of patient-reported outcome measures (PROMs) in spine care. *World Neurosurg*. 2017;108:328-335.
3. Nayak NR, Coats JM, Abdullah KG, Stein SC, Malhotra NR. Tracking patient-reported outcomes in spinal disorders. *Surg Neurol Int*. 2015;6(suppl 19):S490-S499.
4. Paulsen RT, Bouknaitir JB, Fruensgaard S, Carreon L, Andersen M. Prognostic factors for satisfaction after decompression surgery for lumbar spinal stenosis. *Neurosurgery*. 2018;82:645-651.
5. Torous J, Staples P, Shanahan M, et al. Utilizing a personal Smartphone custom App to assess the patient health questionnaire-9 (PHQ-9) depressive symptoms in patients with major depressive disorder. *JMIR Ment Health*. 2015;2:e8.
6. Torous J, Staples P, Onnela JP. Realizing the potential of mobile mental health: new methods for new data in psychiatry. *Curr Psychiatry Rep*. 2015;17:602.
7. Smith A. *US Smartphone Use in 2015*. Washington, DC: Pew Research Center; 2015.
8. Wang R, Aung MS, Abdullah S, et al. *CrossCheck: toward passive sensing and detection of mental health changes in people with schizophrenia. Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. New York, NY: Association for Computing Machinery; 2016:886-897.
9. Saeb S, Zhang M, Karr CJ, et al. Mobile phone sensor correlates of depressive symptom severity in daily-life behavior: an exploratory study. *J Med Internet Res*. 2015;17:e175.
10. Faherty LJ, Hantsoo L, Appleby D, et al. Movement patterns in women at risk for perinatal depression: use of a mood-monitoring mobile application in pregnancy. *J Am Med Inform Assoc*. 2017;24:746-753.
11. Barnett I, Onnela JP. Inferring mobility measures from GPS traces with missing data, [epub ahead of print]. *Biostatistics*. 2018. Accessed January 15, 2019.
12. Torous J, Kiang MV, Lorme J, Onnela J-P. New tools for new research in psychiatry: a scalable and customizable platform to empower data driven smartphone research. *JMIR Ment Health*. 2016;3:e16.
13. Rhee I, Shin M, Hong S, Lee K, Kim SJ, Chong S. On the levy-walk nature of human mobility. *IEEE/ACM Trans Netw (TON)*. 2011;19:630-643.
14. Khanolkar AR, Ljung R, Talback M, et al. Socioeconomic position and the risk of brain tumour: a Swedish national population-based cohort study. *J Epidemiol Community Health*. 2016;70.
15. Mclean RA, Sanders WL, Stroup WW. A unified approach to mixed linear models. *Am Stat*. 1991;61:54-64.
16. Deb S, Pendharkar AV, Schoen MK, Altekruse S, Ratliff J, Desai A. The effect of socioeconomic status on gross total resection, radiation therapy and overall survival in patients with gliomas. *J Neurooncol*. 2017;132:447-453.
17. Benjamini Y, Yekutieli D. The control of false discovery rate in multiple testing under dependency. *Ann Stat*. 2001;29:1165-1188.
18. Forsth P, Olafsson G, Carlsson T, et al. A randomized, controlled trial of fusion surgery for lumbar spinal stenosis. *N Engl J Med*. 2016;374:1413-1423.
19. Devlin NJ, Parkin D, Browne J. Patient-reported outcome measures in the NHS: new methods for analysing and reporting EQ-5D data. *Health Econ*. 2010;19:886-905.
20. Copay AG, Glassman SD, Subach BR, Berven S, Schuler TC, Carreon LY. Minimum clinically important difference in lumbar spine surgery

patients: a choice of methods using the Oswestry Disability Index, Medical Outcomes Study questionnaire Short Form 36, and pain scales. *Spine J.* 2008;8:968-974.

21. Brazier J, Jones N, Kind P. Testing the validity of the EuroQol and comparing it with the SF-36 health survey questionnaire. *Qual Life Res.* 1993;2:169-180.

22. BenDebba M, Heller J, Ducker TB, Eisinger JM. Cervical spine outcomes questionnaire: its development and psychometric properties. *Spine (Phila Pa 1976).* 2002;27:2116-2123 [discussion: 2124].

23. Auffinger BM, Lall RR, Dahdaleh NS, et al. Measuring surgical outcomes in cervical spondylotic myelopathy patients undergoing anterior cervical discectomy and fusion: assessment of minimum clinically important difference. *PLoS One.* 2013;8:e67408.

24. Baron R, Elashaal A, Germon T, Hobart J. Measuring outcomes in cervical spine surgery: think twice before using the SF-36. *Spine (Phila Pa 1976).* 2006;31:2575-2584.

25. Moojen WA, Van der Gaag NA. Minimally invasive surgery for lumbar spinal stenosis. *Eur J Orthop Surg Traumatol.* 2016;26:681-684.

26. Moojen WA, Arts MP, Jacobs WC, et al. Interspinous process device versus standard conventional surgical decompression for lumbar spinal stenosis: randomized controlled trial. *BMJ (Clin Res Ed).* 2013;347:f6415.

27. Kim CH, Chung CK, Choi Y, et al. The usefulness of a mobile device-based system for patient-reported outcomes in a spine outpatient clinic. *Spine J.* 2016;16:843-850.

28. Marcano Belisario JS, Jamsek J, Huckvale K, O'Donoghue J, Morrison CP, Car J. Comparison of self-administered survey questionnaire responses collected using mobile apps versus other methods. *Cochrane Database Syst Rev.* 2015: MR000042.

29. Zanoli G. Outcome assessment in lumbar spine surgery. *Acta Orthop Suppl.* 2005;76:5-47.

30. Bouras T, Zairi F, Loufardaki M, Triffaux M, Stranjalis G. Which functional outcome parameters correlate better with elderly patients' satisfaction after non-fusion lumbar spine surgery? [e-pub ahead of print]. J Neurosurg Sci https://doi.org/10.23736/s0390-5616.17.03977-7, accessed November 1, 2018.

31. Insel TR. Digital phenotyping: technology for a new science of behavior. *JAMA.* 2017;318:1215-1216.

32. Demir S, Dulgeroglu D, Cakci A. Effects of dynamic lumbar stabilization exercises following lumbar microdiscectomy on pain, mobility and return to work: randomized controlled trial. *Eur J Phys Rehabil Med.* 2014;50:627-640.

33. Elsworth C, Dawes H, Winward C, et al. Pedometer step counts in individuals with neurological conditions. *Clin Rehabil.* 2009;23:171-175.

34. Foley S, Quinn S, Jones G. Pedometer determined ambulatory activity and bone mass: a population-based longitudinal study in older adults. *Osteoporos Int.* 2010;21:1809-1816.

35. Ammendolia C, Cote P, Rampersaud YR, et al. The boot camp program for lumbar spinal stenosis: a protocol for a randomized controlled trial. *Chiropractic Man Ther.* 2016;24:25.

36. House JS, Landis KR, Umberson D. Social relationships and health. *Science.* 1988;241:540-545.

37. Dhand A, Luke DA, Lang CE, Lee JM. Social networks and neurological illness. *Nat Rev Neurol.* 2016;12:605-612.

38. Nagayoshi M, Everson-Rose SA, Iso H, Mosley TH Jr, Rose KM, Lutsey PL. Social network, social support, and risk of incident stroke: Atherosclerosis Risk in Communities study. *Stroke.* 2014;45:2868-2873.

39. Steptoe A, Shankar A, Demakakos P, Wardle J. Social isolation, loneliness, and all-cause mortality in older men and women. *Proc Natl Acad Sci U S A.* 2013;110:5797-5801.

40. Bowling A. Mode of questionnaire administration can have serious effects on data quality. *J Public Health (Oxf).* 2005;27:281-291.

41. Johnson AM, Copas AJ, Erens B, et al. Effect of computer-assisted self-interviews on reporting of sexual HIV risk behaviours in a general population sample: a methodological experiment. *AIDS.* 2001;15:111-115.

Conflict of interest statement: The present study was supported by a National Institutes of Health Training Grant (grant T32 CA009001 to D.J.C.).

Received 4 January 2019; accepted 31 January 2019

Citation: World Neurosurg. (2019) 126:e241-e249.
https://doi.org/10.1016/j.wneu.2019.01.297

Journal homepage: ***www.journals.elsevier.com/world-neurosurgery***

Available online: ***www.sciencedirect.com***