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Understanding Patients' Preferences for Referrals to Specialists for an Asymptomatic Condition

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Abstract

BACKGROUND—A specialty referral is a common but complex decision that often requires a primary care provider to balance his or her own interests with those of the patient.

OBJECTIVE—To examine the factors that influence a patient's choice of a specialist for consultation for an asymptomatic condition and better understand the trade-offs that patients are and are not willing to make in this decision.

DESIGN—Stratified cross sectional convenience sample of subjects selected to parallel US population demographics.

PARTICIPANTS—Members of an Internet survey panel who reported seeing a physician in the past year whose responses met objective quality metrics for attention.

MAIN MEASURES—Respondents completed an adaptive conjoint analysis survey comparing specialists over eight attributes. The reliability of assessments and the predictive validity of models were measured using hold out samples. The relative importance (RI) of different attributes was computed using paired t tests. The implications of utility values were studied using market simulation methods.

KEY RESULTS—530 subjects completed the survey and had responses that met quality criteria. The reliability of responses was high (86% agreement) and models were predictive of patients' preferences (82.6% agreement with holdout choices.) The most important attribute for patients was out-of-pocket cost (RI of 19.5%, $p < 0.0001$ vs. other factors). Among the non-financial factors "collaboration and communication" with the primary care provider was the most important attribute (RI of 13.1% $P < 0.001$). Third in importance was whether the specialist practiced shared decision-making (RI of 12.2% $P < 0.001$ vs. other factors except *delay in consultation*). Cost did not dominate decision-making. In market simulations patients frequently preferred more expensive providers. For example, most patients (76.3%) were willing to pay more (\$80) to see a specialist who both collaborated well with their primary care provider and practiced shared decision-

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making. Most patients prefer to wait for a doctor that practices shared decision making: only a third (32.3%) of patients were preferred a paternalistic doctor that was available in 2 weeks over a doctor that practiced decision making, but that was available in 4 weeks.

CONCLUSIONS—*In the setting of a referral asymptomatic but serious condition*, out of pocket costs are important to patients; however, they also value specialists who collaborate and communicate well with their primary care providers and who practice shared decision-making. Patients have wide variability in preferences for specialists and referral decisions should be individualized.

Keywords

Patient Referral; Patient Preferences; Conjoint Analysis; Health Services Research

Introduction

Referrals from a primary care physician to a specialist for further care are common in the United States. Forrest et al. examined data from a total of 384,000 patients, culled from five health maintenance organizations, with primary care physicians in a “gatekeeper” role. In this setting, about 1 in 3 patients had a referral for specialty care, depending on the occurrence of co-morbid illnesses within a year (1). In an urban setting among Medicare patients, 63% of 6785 patients seen had received at least one referral per year (2). Overall, the probability of one ambulatory care visit generating a referral to a different physician is about 9.3% and the rate of referrals has doubled over the past decade (3).

A referral might be described as a complex but routine decision made in clinical care. Choice of specialist by physicians is based upon perceptions of medical skill, by past experiences with the provider, and by economics (i.e., will the specialist return the patient to the primary care physician?) (3,4). Patient oriented factors appear to play a less important role in the choice of a specialist. Kinchen et al. (4) found that only about half of primary care physicians (PCPs) rated “insurance coverage” for the specialist as a factor of “major importance” in choice and only about 25% of providers rated patient convenience as a factor of major importance. Barnett, et. al. also found “patient access” as the least important factor among PCPs and specialists when selecting a consulting physician (3). Both studies found that the most important factors to the surveyed physicians selecting a specialist is some measure of the specialist’s aptitude (“medical skill”) (4) or some proxy that allows the referring physician to get a sense of specialists’ ability to perform a consultation such as “patient experiences with specialist” or “previous experience with this specialist” (3).

Much that has been written about how to improve the referral process are clinician focused interventions. Interventions examined in a Cochrane review include improving the appropriateness of referrals via clinician education, standardizing referral communication and improving the referral rates through means such as financial incentives (5). Little work on has focused on how patients may be enlisted to help improve referral appropriateness and referral completion rates.

This paper examines how we might improve the process of referrals by identifying the most important attributes to patients when selecting a specialist for referral and in turn make the referral process more patient centric. In real life medical decisions often require both clinicians and patients to trade-off among many overall desirable attributes (6). Our approach utilizes conjoint analysis to mimic these trade-offs inherent in medical decisions. Conjoint analysis is a theoretically grounded approach that can be used to examine the importances patients place on treatment attributes, and more importantly the trade-offs they would be willing to make across them (7). Our goal is to better understand the trade-offs that patients are and are not willing to make in the selection of a specialist for consultation, allowing providers to better tailor referral choices to patients and to maximize the chances of patients completing a prescribed referral.

Methods

Adaptive Conjoint Analysis

We created an adaptive conjoint analysis (ACA) survey that examined patient preferences for the attributes considered in the selection of specialists. Conjoint analysis approaches have been applied to identify treatment preferences (8,9), trade-offs patients make in treatment decisions (10), and preferences for health services (11). The experimental design followed established good research practices for conjoint analysis applications in health care (12). ACA is a hybrid approach that creates an initial estimate of a preference model using importance ratings and then refines this model with pairwise comparisons between varying combination of attributes. As the survey progresses it identifies attributes with greater importance for a participant. The ACA software creates pairwise comparisons that force participants to trade off among the attributes, progressively identifying attributes with greater importance for participants, thereby better reflecting real life choices (13). The “adaptiveness” of the survey allows for a larger set of attributes to be evaluated without overburdening the participant while producing estimates of individual preference models comparable to traditional conjoint analysis approaches (14,15).

Attribute and level selection

Attributes for the study were initially selected from a literature review and refined through a pilot study. Attribute constructs were first derived from published qualitative research on the referral process (16–18), a published study examining referral completion by primary care patients (19), and two other published studies on the importance of factors that physicians consider when selecting a specialist for consultation (3,4). The pilot study conducted in Utah consisted of cognitive task analysis interviews with 15 primary care physicians to identify case scenarios and attributes, and a survey of 25 patients to test and refine the attributes. The patient survey consisted of an ACA exercise conducted in person followed by a debriefing interview to help identify important attributes and troubleshoot level descriptions for the larger study (20). Eight attributes were used in the final survey (table 1). Level definitions were further refined according to good research practices (12). Specifically, each attribute was assigned 3 levels, levels were made specific and avoided open ended ranges, extreme values, and statements of absolutes to avoid a grounding effect.

Survey

Utilizing an Internet survey vendor (Answers and Insights), we recruited a sample of adults which roughly paralleled the US population and who had seen a health care provider within the last year. Participants provided demographic information including age, sex, education status, ethnicity, geographic location (zip code), insurance coverage, general health status, and co-morbidities. Quotas related to age, sex and ethnicity allowed oversampling of minorities to insure adequate representation and participants were compensated for survey completion based on the vendor's usual policies. Survey participants were provided descriptions of the attributes as well as a description of the circumstances for a hypothetical referral of an asymptomatic condition (a referral from their primary care doctor for difficult to control hypertension -see appendix).

To develop an individual level model of their preferences, participants followed the standard approach for estimating individual utility function using ACA. Participants first provided a rank ordering of the importance of each dimension of the model and then a rank ordering of the attributes within each dimension. Subsequently, subjects were presented a series of paired comparisons between two scenarios, one on the left side and one on the right (Figure 1). The scenarios were comprised of two or three attributes with differing levels for each attribute. Participants indicated the strength of their preference for a scenario on a nine-point scale by choosing the left scenario (1–4), right scenario (6–9), or indifference (5). The number of pairwise comparisons was 30 (21) (see appendix for determination); however, the total number of pairs of attributes evaluated by each subject was 34 with four additional choice questions added for validity and reliability analyses (see below). Choice questions had two attributes in the first fifteen comparisons and three attributes in the latter 15 comparisons.

Validity and reliability

Predictive validity and reliability were measured with 4 holdout pairwise comparisons. A 20-person sample was used to identify four pairs of choices where there was a high degree of heterogeneity of preferences in the population, two choices for validity measures and two for reliability measures. For predictive validity measurements, one two-attribute choice was placed at question 10 and one three-attribute choice was placed at question 25. After each individual's utility model was calculated (see below), we used this model to predict the holdout choices, giving an indication of the model's accuracy (22–24). Validity was assessed based on the rate of agreement between the observed and predicted choices. For reliability estimates, two three-attribute choices were placed at questions 18 and 33. Reliability questions poised identical choices except that the two scenarios were displayed on opposite sides of the screen and the order of the attributes describing the scenario was changed. Reliability was estimated based on the rate of agreement in the preferred choice across the two questions.

Analysis

Initial survey results were screened for data quality. Participants were excluded if they did not spend an adequate time completing the pairwise comparisons (median page view time < 5s) or if their pairwise comparison ratings showed little discrimination ($\geq 85\%$ identical

responses) (25). This information was obtained from the web server logs and the survey software.

We estimated individual utilities with hierarchical Bayesian (HB) analysis constrained by the level orders derived from the self-explicated data (26–28). There are many approaches of converting utilities from interval data for comparison of the importance of different factors in choice. To facilitate the interpretation of the results we calculated the relative importance or attribute weight of the attributes via the following:

$$RI_i = \frac{I_i}{\sum_{i=1}^m I_i} \text{ so that, } \sum_{i=1}^m RI_i = 1$$

where I is the largest utility difference for the levels of each attribute, i , and m is the total number of attributes in the survey (in this case $m=8$) (21).

To characterize the differences in importance across the population, we compared mean population importance weights and 95% confidence intervals. To understand how factors were related to each other, we computed the correlation between importance weights. We then examined associations between importance weights and demographic factors, adjusting for multiple comparisons using one-way analysis of variance methods.

To understand the importance of differences in utility among individuals, we conducted simulations based on utility models estimated for each participant and examined how participants would choose between specialist scenarios represented by various levels of the attributes (29). Using a randomized first choice model we calculated the percent of the sample population that would choose one scenario over another. The details of randomized first choice simulations have been previously outlined (30,31).

Survey data collection was completed via a web server running an instance of Sawtooth SSIWeb 8, utilities were estimated with Sawtooth's ACA/HB module (ver 3.2), and segmentation studies completed via Sawtooth's SMRT ver. 4.22 (32). Calculations of relative importance, graph generation, and statistical analysis (means, standard deviation, validity and reliability estimates) were performed using Stata version 12 (33). All analyses were performed at the individual level.

Results

The objective of the survey design was to recruit a convenience sample of persons who had seen a provider in the past year and whose demographics paralleled those of the United States. The Answers and Insights panel is not representative of the United States and does not require participants to respond to specific survey requests. As shown in a consort diagram (figure 2), 2496 participants responded to email advertisements for the survey and 706 participants completed the survey. The exact response rate of persons in the panel could not be calculated as multiple waves of email messages were used to recruit participants. As recruitment evolved, a substantial number (1480) of those who attempted the survey were

ineligible as a result of quotas for gender and ethnicity being filled at the time when they responded. Of the 706 participants completing the survey, 530 had adequate data quality as defined by time spent on a page for pair-wise question responses and variability in response items. On average, attentive participants completed the survey in 19 minutes.

After excluding inattentive participants, population demographics paralleled those of the US population as described by US census data (53.4% female, 30.8% minority, 9.4% aged 65 or older), but were better educated (82.1% with at least “some college” vs. 57.5% for general US population) (34). Participants came from 48 of 50 states. Insurance status was similar to the US population (31.3% Medicare/Medicaid, 16.3% uninsured) (35). Health status of the respondents was somewhat lower than that of the U.S. population but this probably reflects the requirement for participants to have seen a medical provider within the past year (17.6% reported “poor” or “fair” health) (36).

The input reliability assessments show an overall 85.4% agreement between the two holdout tasks that had the concepts reversed and reordered. Given this reliability, the maximum possible hit rate for predicting the validity holdouts is 92% (37). The validity holdout choices were predicted accurately 82.6% of the time. This is in line or exceeds the hit rates in other other ACA/HB studies with a similar number of attributes, levels, and pairwise questions, and far exceeds a correct choice by chance (50%). (38,39).

Figure 3 shows the relative importance of each of the attributes. The most important factor in patients’ choice was out-of-pocket cost (relative importance 19.5%, $p < 0.0001$ vs. other factors). However, among the non-financial factors, the “collaboration and communication” factor had the greatest weight-greater than shared decision making, delay in getting an appointment, other patients’ ratings, specialist’s experience level, travel time, and the cost-effectiveness of the specialist’s practice-style. ($P < 0.001$, Figure 3.) Third in importance was the decision making style of the provider ($P < 0.001$ vs other factors outside of wait time). The most preferred alternative was a shared decision making style, followed by patient led decision-making. The least preferred was provider led decision making.

Although the aggregate mean relative importance values show a distinct preference profile there is a significant minority of participants that vary greatly from the the mean. This variability is illustrated in box and whisker plot shown in figure 4.

The importance of attributes in the model was not associated with demographic factors. After adjustment for multiple comparisons using the Holms adjustment, there were no statistically significant associations.

Understanding the significance of utility values and relative importance weights derived from a conjoint analysis study can be difficult (21).

To better understand the implications of utility values and better reveal the contribution of individual preferences we studied how the utilities varied across choices with specific trade-offs We focused on comparisons on the relative value of the top four attributes to the participant group as a whole. Figure 5 shows three example trade-off simulations calculated via randomized first choice methodology: collaboration level vs. wait time for appointment;

shared decision making level vs. wait time for appointment; and collaboration+shared decision making vs. cost of the visit. As shown in the Figure, the majority (58.6%) of participants were willing to wait six additional weeks (eight weeks total) to get specialist who communicated at the highest level with their primary care physician. A little over two thirds (67.7%) of participants were willing to wait two weeks (4 weeks total) to be referred to a specialist who practiced shared decision-making. Most (76.3%) were willing to pay \$80 additional (\$100 total) out of pocket to get access to a specialist who had the highest level of communication with their primary care provider and practiced shared decision making.

Discussion

To our knowledge, this study is the first to look at patients' preferences for the choice of specialist in a referral context. Patients' preferences are important and should be considered within the referral process because some patients' non-adherence to a referral may be result of failure to consider patients' motivations, preferences, and needs (2). Non-adherence to referrals is common (up to 50% in one published study (2)) and failure to complete referrals is a common cause of diagnostic errors (40) and in some cases may have serious health consequences (41).

Failure to consider patients' preferences in referrals is a type of contextual error. Contextual errors are defined as "decision making errors that occur because of inattention to patient context" (42). Context, or contextual information refers to elements such as the patient's access to care, their attitude towards their illness, their preferences towards treatment options, and their financial situation (43). Studies on contextual information suggests that ignoring patient preferences in health care decisions may prevent the patient from receiving the most appropriate and individualized care (44).

Prior research suggests that primary care physicians have relatively strong preferences when choosing a specialist. In a qualitative study, the most important factor was choosing a person known to the primary care provider, someone they were confident they could work with (16). In survey-studies, physicians rate clinical skill or previous patient experience with a specialist as the most important factors in referrals (3,4); however, patients' appear to have different views.

Our results show that out of pocket costs were the single most important factor in patients' decisions, contrary to what providers consider the most important factors. The difference in utility between a provider who costs \$20 and \$500 for patients to see (the range of alternatives in our study, table 2) is large and can drive the choices of many patients. However, out of pocket cost is by no means the dominant factor. The majority of patients were willing to trade-off higher out of pocket costs to access specialists that demonstrated the other most valued traits—communication and close collaboration with the primary care provider and a willingness to practice shared decision making with the patient. When examining the utility of communication and collaboration between providers, we studied 3 levels of choice: close collaboration and almost instant communication, such as might be given by interoperable electronic health records systems; working at a distance with delays in communication, which aimed to reflect collaboration via fax or consultation letter; and

working at distance with hit or miss collaboration, which aimed to reflect a specialist or practice that might forget to send a consultation letter or change medications without letting the primary care provider know. Several studies show that direct communication between primary care physicians and specialists improves the referral completion rate and provide patient management outside of a referral appointment (45–47). Our results indicate that patients' appreciate the importance of good physician communication and interoperability. In our pilot study, patients often related the importance of data sharing as not only providing better coordination of care, but to reduce the burden of being one's own data repository. Recent efforts as part of Meaningful Use (MUse) to improve the efficiency of care through electronic transmission of consultation requests and relevant data should also make care more patient-centric, given patients' preferences (48,49). Transmission of case summaries with referral requests and medication resolution when changing contexts of care, as required by MUse should improve communications. However, current MUse regulations do not require specialists to respond with electronic communications. True collaboration may require two-way communications capabilities (or perhaps even a phone call.)

A heretofore-unappreciated factor in patients' preferences is the extent to which specialists practice shared decision-making. The difference in utility between a provider that encourages a shared decision versus a provider who makes decisions for the patient is large—greater than many other factors. National quality metrics currently do not rate providers on shared decision-making practice; yet, some satisfaction surveys explore patient involvement in decision making. For example, the Press Ganey (50) survey used at the University of Utah explores attributes of shared decision making as part of measurement of satisfaction. Publication of this data may be important to helping patients chose the right specialist.

There were a number of other factors in our model, including delay in getting an appointment and travel time for the visit. Patients did not rate the cost effectiveness of a provider's practice style as an important attribute in selecting a provider. This is probably because there are few incentives for patients under the current system to chose cost effective providers. Since out of pocket costs were an important factor economic incentives may be the best approach to nudge patients to more cost sensitive choices. Patients in this survey also did not place as high value on other patients' ratings of their experience with the provider or on the level of experience of the provider with their particular disorder as other attributes in our study. Further research may be needed to understand how to make descriptions of quality of a provider more salient in patients' decision-making. It is important to note that no single factor dominates in decision-making and providers should tailor decisions to the individual patients' preferences.

Limitations

The primary limitation of this study is the use of a convenience sample recruited through an Internet survey panel. While they all claimed to be patients the population of this panel may be different from patients as a whole. The higher educational level and income level may make it more feasible for this group of patients to trade off expense, travel time, and other factors to have providers that collaborate and practice shared decision making. However, there is no evidence that use of an Internet panel resulted in poor quality or unreliable

measurements. On the contrary, both the reliability of assessments and the predictive validity of the resulting utility model was high.

This study examined patients' preferences for referrals in the context of a referral for hypertension. There were no symptoms to be controlled or stated consequences of the delay. In many clinical settings, patient symptoms, perceived urgency, and the quest for relief of those symptoms may drive choice. However, there are many asymptomatic conditions in internal medicine that should generalize to the scenario described. Future work should examine how changes in the context reflect patients' preferences for referrals. Subsequent work should examine the impact of tailoring of the choice of specialist to patients' preferences on satisfaction with care and adherence to referrals.

Conclusions

Patients appear to prefer to be referred to specialists who communicate well with their primary care providers and who practice shared decision-making. They appear to be willing to wait to see such providers, travel, see providers who are less experienced in their disease, and a majority would even pay out of pocket to receive care from specialists who communicate well and share decisions. However, in any given situation, a sizable minority of patients may have different preferences and choice of specialist should be tailored to patients' preferences.

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Appendix

This appendix is to provide additional background on the survey approach.

Paired comparisons

The participants were presented a series of paired comparisons between two scenarios, one on the left side and one on the right (Figure 1). The scenarios were comprised of two or three attributes with differing levels of attributes for each attribute on each side of the comparison. Participants indicated the strength of their preference for a scenario on a nine point scale by choosing the left scenario (1–4), right scenario (6–9), or indifference (5). The number of pairwise comparisons presented was based on the recommendation that the number of observations exceeds three times the number of parameters available to minimize individual measurement error (1). The suggested number of pairs is

$$3(K - k - 1) - K$$

where K is the total number of levels across all attributes and k is the number of attributes. Our study called for at least $3(24 - 8 - 1) - 24 = 21$ pairs. We presented 30 pairs to build a preference model. Total number of pairs questions was 34 due to added holdout questions for validity and reliability (see below). Compared scenarios were comprised of two attributes

for the first fifteen comparisons and three attributes for the latter 15 comparisons. Previous simulations indicate little benefit in reducing measurement error by exceeding three attributes per comparison(2). Last, after completion of the survey, participants were able to review estimated importances for each attribute provided by an ordinary least squares calculation integrated into the survey.

Survey Introduction

When considering the questions and scenarios in the following survey imagine that you have had high blood pressure that has been adequately controlled for several years but now has been slowly getting worse over the last few months. Your primary care doctor is concerned that this may lead to serious health problems if not addressed.

Your primary care clinician would like you to see a specialist to explore other treatment options.

You will be asked about the following attributes associated with a specialist you might choose to see:

The survey will take you through three different sections:

1. Set the order of importance of descriptive values for some attributes.
2. Rate values of each attribute in importance.
3. Rate paired comparisons between scenarios made up of possible values of the attributes.

Appendix Table

Attribute	Description
Insurance	Your Insurance coverage for this specialist
Travel time	Your travel time to the specialist's office
Availability	The availability of the specialist for an appointment
Expertise	The specialist's expertise with treating your problem
Previous Experience	Other patient's experience consultation experience with the specialist as a star rating
Communication	How the specialist and PCP share health information
Decision Making	The specialist's approach to medical decision making
Cost effectiveness	The specialist's approach to utilizing health care resources

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Figure 1.
Example of a pairwise comparison with a 9 step rating scale for a scenarios composed of two attributes.

Figure 2.
Recruitment diagram for survey.

Figure 3.

Attribute relative importance for the aggregate. Error Bars indicate ± 1 SE. The out of pocket costs attribute has significantly greater importance weight than the non financial factors. Asterisks indicate attributes with significantly less importances weight than Interoperability and Communication. Daggers indicate attributes with significantly less importance weight than decision making style ($p < 0.001$).

Figure 4.

A Box and whisker plot of the attribute relative importance for the aggregate. White line indicates median relative importance, IQR is indicated by black box, and the whiskers indicate the minimum and maximum (1.5 times the IQR) relative importance values for an attribute excluding outside values.

Figure 5.

Three example trade-off simulations calculated via randomized first choice methodology: collaboration level vs. wait time for appointment; shared decision making level vs. wait time for appointment; and collaboration+shared decision making vs. cost of the visit.

Table 1

Attributes used in the ACA study. The level descriptions were used to construct the questions in the survey.

Attribute	Definition	Levels (constructs)
Out of Pocket Cost	Your out of pocket costs for seeing this specialist	The specialist is considered “in network” for your insurance (visit cost = \$20) The specialist is considered “second tier” for your insurance (visit cost = \$100) The specialist is considered “out-of network” for your insurance (visit cost = \$500)
Travel time to the specialist	Your travel time to the specialist’s office.	Your travel time to the specialist office is 10 minutes Your travel time to the specialist office is 30 minutes Your travel time to the specialist office is 90 minutes
Delay in getting an appointment	The availability of the specialist for an appointment.	An appointment with the specialist is available in two weeks An appointment with the specialist is available in four weeks An appointment with the specialist is available in eight weeks
Specialist expertise	The specialist’s expertise with treating your problem.	The majority the of cases the specialists sees are similar to yours Many of the cases the specialists sees are similar to yours Few of the cases the specialists sees are similar to yours
Patients’ rating of specialist	Other patient’s experience with this specialist	Other patients rate their experience with this specialist as 5 out of 5 stars Other patients rate their experience with this specialist as 4 out of 5 stars Other patients rate their experience with this specialist as 3 out of 5 stars
Interoperability and communication	How the specialist and referring physician share health information	The specialist and primary care clinician collaborate and share information automatically and instantly The specialist and primary care clinician work at a distance and share information with some delays The specialist and primary care clinician work independently and share information in a hit-or-miss fashion with delays
Decision Making Style	How the specialist includes the patient in decision making	The specialist usually makes health care decisions on your behalf You usually make health care decisions yourself You and the specialist usually make health care decisions together
Cost effectiveness of practice	The specialist’s approach to utilizing health care resources	The specialist conducts an exhaustive and comprehensive diagnostic workup (labs, x-rays, etc.) The specialist conducts a deliberate and focused diagnostic workup (labs, x-rays, etc.) The specialist conducts a minimal and essential diagnostic workup, relying on history and course of disease instead of additional tests

Table 2

Demographics and characteristics of the sample population. Census data reflects 2010 census statistics (34–36).

Characteristic	Subjects (n=530)		Census (%)
Sex–no. (%)			
Male	247	(46.6%)	49.2%
Female	283	(53.4%)	50.8%
Age – no. (%)			
18–30	78	(14.7%)	23.6%
31–49	186	(35.1%)	35.3%
50–64	216	(40.8%)	24.5%
65–80	45	(8.5%)	12.1%
81 +	5	(0.9%)	4.5%
Race – no. (%)			
Native American	20	(3.8)	1.6%
Asian	64	(12.1)	5.6%
African American	69	(13.0)	13.6%
Pacific Islander	10	(1.9)	0.4%
Caucasian	367	(69.2)	76.4%
Ethnicity–no. (%)			
Hispanic	49	(9.3)	16.4%
Highest Education Level – no. (%)			
Have not graduated high school	8	(1.5%)	14.1%
Graduated high school or obtained GED	87	(16.4%)	28.4%
Some college	200	(37.7%)	29.0%
4 year college degree	153	(28.9%)	17.9%
Advanced degree	82	(15.5%)	10.6%
Income – no. (%)			
Less than \$20K	95	(17.9)	
\$20–50 K	186	(35.1)	
\$51–100 K	173	(32.6)	
\$101–250 K	72	(13.6)	
\$250K or greater	4	(0.8)	
Insurance			
Medicare/Medicaid	166	(313)	30.4%
Private Insurance	278	(52.5)	63.9%
No insurance	86	(16.2)	16.3%
Reported Health – no (%)			
Excellent to Good	437	(82.4)	89.7%
Fair to Poor	93	(17.6)	10.3%
Number referrals in the last year – no. (%)			
None	305	(57.6)	

Characteristic	Subjects (n=530)		Census (%)
At least one	100	(18.9)	
Two or more	125	(23.5)	

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