Original Paper

Linking Long-Term Care Information Seekers with Providers Through Improved Internet Market Segmentation

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Keywords: Health care providers, Consumer health information, Decision-making, Health care marketing

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Abstract

Background: As the internet has become a primary communication means in the long-term care (LTC) and health care industry, better understanding of market segmentations among LTC consumers is an indispensable step to respond to the consumers' informational needs.

Objective: This study was designed to identify underlying market segments of the LTC consumers who seek information online.

Methods: Data of the U.S. adult internet users (n = 2,018) were derived from 2010 Pew Internet and America Life Project. Latent class analyses were employed to identify underlying market segments of LTC online information seekers.

Results: Online LTC information seekers were classified into two sub-groups – heavy and light online information seekers. One in four heavy online information seekers used the internet for the LTC information while only 2% of the light information seeker did. The heavy information seekers also used the internet to search for all other health information such as a specific disease, treatment and medical facilities significantly more than the light information seekers. The heavy online information seekers were more likely to be younger, female, highly educated, chronic disease patients, caregivers and frequent internet users in general than the light online information seekers.

Conclusion: In order to effectively communicate with their consumers, providers who target online LTC information seekers can more carefully align their informational offerings with the specific needs of each subsegment of LTC markets.

Keywords: Health care providers, Consumer health information, Decision-making, Health care marketing
Introduction

It is widely acknowledged that the internet has become a primary marketplace for virtually any industry. Potential consumers should be able to access to necessary information for their decision-making. Today, health and long-term care (LTC) providers as well as the federal government have heavily utilized the internet to provide much of the information. Accordingly, it is not surprising that consumers also rely on the internet to inform their buying decision. In response, providers now acquire an abundance of data available online to guide their marketing efforts.

Current research on online information and knowledge exchange in the LTC marketplace reveals the criticality of these processes. For example, there has been an impact of the U.S. Centers for Medicare and Medicaid Services (CMS) 5-star rating system on online information exchange. Introduced as Nursing Home Compare, a U.S. public reporting system in December of 2008, the findings from these report cards were available via the internet. These researchers utilized a before and after design to determine whether or not published data on nursing homes’ quality measures created a shift in demand or in quantity demanded across nursing homes, once consumers have more relevant information. Their study revealed that consumers of nursing home services decreased their purchase of institutional care from poorly rated facilities and increased the share of services bought from highly rated (i.e., 5-star) facilities. Accessing such nursing home quality data via the internet was the primary vehicle that altered this important retail market adjustment process.

However, additional research indicates that LTC providers also have an opportunity to promote their facilities by being responsive to consumers’ informational needs in areas that extend beyond the mainstream quality measures such as the CMS’s Nursing Home Compare. Based on the focus groups and key informant interviews with persons 65 and older, and/or family members of nursing home residents, a study found that there is a body of information that transcends Nursing Home Compare and provide crucial information to the residents and their family members. Moreover, the nature of consumer informational needs differs across various demographic segments of the American population. Similarly, another study, in an analysis of the information-seeking nursing home behavior on Yahoo! Answers, identified a wide range of consumer-based informational needs and a market-based discordance between needs of current or prospective consumers in the LTC market, and the information provided by the LTC providers. Indeed, this study suggested that nursing home sites, may also need to provide assurances of quality care to potential LTC consumers’ family members.

In order for nursing homes and/or other LTC organizations to effectively communicate their informational contents to the prospective consumers who seek information via the internet, more refined marketing segmentation is needed. Research must move beyond mere demographic and/or socioeconomic data so that the psychographic, sociographic, and/or clinical informational needs of various subsets of consumers can be addressed. In
this respect, an analytical approach that allows the identification of subgroup differences in the online informational needs of consumers is useful.7

The internet provides an opportunity for all marketplaces to function more optimally as a source of timely information. Yet, there is paucity of research that specifically examines how LTC information is accessed, and how the available online information is in alignment with the information sought. This article seeks to initiate the process of remediating this void by advocating the use of market segmentation to better facilitate the exchange of online information between LTC consumers and providers.

**Conceptual Framework**

Building upon the insights from previous research that focused on health and medical information-seeking behaviors,8-10 this study uses a large data set of American adults to segment internet users who seek LTC information online. Even more importantly, it profiles the associated informational needs of identified subgroups of internet-users. Specifically, this paper uses Latent Class Analysis (LCA) – a person-centered approach to accomplish this task. A content analysis of past studies reveals a sole reliance upon the adoption of variable-centered approaches such as linear regression and binary logistic regression to determine whether significant differences in information-seeking activities occurred. This is not to say that such approaches are methodologically flawed. Indeed, the opposite is true.

Variable-centered approaches are sound when examining relationships between variables and developing the initial segmentation basis for internet users. However, such methodologies also embody several limitations in circumstances when more detailed segmentation data are required. First, the estimation and interpretation of models with more than one outcome variable can be a challenging task. As such, variable-centered approaches are generally not suitable for the simultaneous examination of multiple internet users’ information seeking behaviors (e.g., the data we used for this study). Second, the extent to which such statistical models are capable of identifying the characteristics of target populations is also somewhat restricted. Specifically, the effect of one characteristic (e.g., gender or education) on the outcome variable can only be examined while all other characteristics are held constant. Third, the traditionally used variable-centered approach measures an average effect of a predictor variable upon the outcome variable by utilizing the premise that all individuals were sampled from the same population. Such an approach explicitly bypasses underlying sub-population differences. Finally, in conjunction with the first three limitations, variable-centered approaches do not clearly identify the consumer sub-populations to whom LTC providers must be responsive at a micro-level. Indeed, most studies on the information seeking of consumers fail to consider the need for providers to direct responsive “answers” to these information-seeking consumers so that overall health outcomes can improve.

This article used a data of the first ever available consumer survey that includes the questions of internet search for LTC. It was also designed to address the limitations of the currently dominant variable-centered approaches while building upon the findings from previous studies on online health/medical information-seeking. More specifically, this study broadens dialogue by employing LCA.11 LCA has been increasingly used in medical,
The primary strength of this approach is the identification of underlying sub-populations that share similar sets of behaviors while separately developing profiles of multiple sub-populations. Stated differently, LCA allows providers of LTC services to customize the information they disperse to the unique knowledge needs of each subgroup. LCA assumes that unobserved groups (a.k.a., latent classes) are present and that these groups have highly refined needs and behaviors. Rather than modeling associations between variables, LCA first detects, and then characterizes previously unobserved groups of persons (i.e., sub-populations) within the larger sample. The use of the person-centered approach supports the profiling of the internet users who seek LTC information while simultaneously taking other factors into account. These factors include: 1) a summary description of the multiple health information-seeking behaviors displayed; and 2) the construction of a sociodemographic profile of the Internet users by identified sub-groups. When LTC providers better understand the informational needs of each subgroup, they can better respond to these needs via their website and/or other marketing materials. The present study was designed to answer each question below:

1. Who are the subgroups or unique market segments who search the Internet for LTC information?
2. What health, medical, and/or other knowledge is sought by the Internet users who seek online LTC information?
3. What are the sociodemographic and other characteristics of the Internet users who search the Internet for LTC information?

Based upon the answers to the above questions, recommendations can be made to LTC information providers regarding the type of information they should disseminate via online resources.

**Methods**

**Data Sources**

Data from the 2010 Princeton Survey Research Associates International for the Pew Internet and American Life Project (Pew Internet) were used to answer the three described questions. Collected through telephone interviews to adults age 18 years and older in August and September of 2010, the samples for this study were drawn from a pool of 20,985 landline users and 12,699 cell phone holders by Survey Sampling International, LLC. The Pew Internet database explores the impact of the internet on children, families, communities, the work place, schools, health care and civic/political life. In 2010, the Pew Internet and American Life Project included the first time ever a question of LTC health information-seeking over the Internet.

A series of survey items were included to assess key sociodemographic characteristics, internet use behaviors, and the health-related information sought by seekers of LTC information. Although these samples were not entirely representative of American adults, the samples, collected through random digit dialing, covered a large population of phone users. Because this unique dataset collects online health and medical data, and LTC information-seeking behaviors, it provides a unique opportunity for researchers to conduct a market segmentation study based upon internet use for LTC information. After excluding
non-internet users (n = 976) and missing values for key online information-seeking
behaviors (n = 6), the final sample size was 2,018.

**Measures**

**Outcome variable**
The primary outcome of interest was two identified latent classes (which is labeled class 1
vs. class 2). These differential subgroups were based upon a set of 15 online health
information-seeking behaviors with dichotomous responses (Yes/No) (see Figure 2). The
responses included: 1) Persons looking for information for themselves; and 2) Those who
were seeking long-term information and/or other health-related looking information for
someone else.

**Predictor variables**
A variety of demographic, socioeconomic, health status and caregiving status information
was included for each model. Age was recorded in years. However, persons older than 97
years of age were top-coded at 97. The more traditional demographic and socioeconomic
segmentation variables were included as predictor variables. These included: 1) Gender
(women vs. men); 2) race/ethnicity (black vs. white; Hispanic vs. white; others vs. white);
3) marital status (married vs. not married); and 4) employment status (employed vs. not
employed; retired vs. not employed). These dichotomous measures were used for purposes
of cross-classification. The number of persons in each household was measured as the
absolute count of total household members. Educational attainment was assessed based
upon a 5-point Likert-scale (1-5: none – post-graduate degree; see Table 2 for the complete
list). Household income was recorded using a 9-point Likert-scale ranging from less than
$10,000 to $150,000 or more. Uneven rather than even increments were used. As a result,
the income classes could not be treated as a continuous variable (e.g., by $10,000, $25,000
and $50,000; see Table 2 for the complete list). Self-rated health was recorded based upon a
4-point Likert-scale (1-4: Poor – Excellent; see Table 2 for the complete list). However, a
range of clinical variables as well as other segmentation factors were included. The number
of self-reported chronic conditions were counted based upon six major diseases – diabetes
mellitus, hypertension, lung disease, cardiovascular disease, cancer, and/or other chronic
diseases. Disabilities were accessed using six disability indicators based upon difficulties
with hearing, vision, memory, walking, dressing, and running errands. Two dichotomous
measures of caregivers were used: 1) one or more parents vs. non-caregivers; 2) caregivers
for adults who were not parent(s); and 3) non-caregivers (reference group). Finally,
internet usage was recorded based upon 7-point Likert-scale (1-7: Never - Several times a
day) either at home or at work. Internet users who reported “Never” but still used email
were classified as internet users in this study. Accordingly, the study included the
potentiality for many sub-segments based upon various permutations and combinations
of the included categories.

**Analytic Strategies**
Two primary areas of inquiry guided this research. At the first level, this study sought to
identify unique underlying subgroups or market subsegments who utilized the internet in
order to address their needs relative to informational LTC. This research also sought to
identify the health/medical information-seeking activities of consumers across various
subgroups. Accordingly, the first part of the analysis focused upon the identification of the latent classes of users. Figure 1 presents a path diagram of the theoretical proposition that was applied for latent class analysis. The analysis was completed in two sequential steps using Mplus version 7.

First, an LCA was conducted using the 15-online health-related and medical information-seeking behaviors. LCA is a special type of structural equation model (SEM) with unobserved/latent variable(s).\textsuperscript{11} Latent variables are commonly modeled with continuous observed variables (e.g. measurement model).\textsuperscript{15} In other words, LCA is a SEM with categorical latent variable.\textsuperscript{16} The number of final groups was chosen based on the average posterior class membership probability, classification quality, and interpretability in view of possible implications of the findings for LTC providers relative to the type of information they should supply via online mechanisms.\textsuperscript{7} In the preliminary analysis, the number of groups \((k)\) was set between 2 and 6 in LCA and full information maximum likelihood estimation was applied. With each “applicant”, several variables were analyzed including: 1) the specific group membership probability (0.7 or higher) (Nagin, 2005)\textsuperscript{17}; 2) the percentage of persons in the smallest class; 3) the classification quality indicator \textsuperscript{11} (entropy > 0.8); 4) bootstrap likelihood ratio test \textsuperscript{18} (BLRT: \(k\) vs. \(k-1\) specification), and 5) Akaike information criteria (AIC). Bayesian information criteria (BIC) and interpretability \textsuperscript{19} were also evaluated (see Table 1).

As a result, the model with two latent classes was determined to be optimal (the posterior membership probabilities > 0.95; entropy = 0.84, BLRT \(p < 0.05\)). Although AIC and BIC were smaller as the number of classes increased, other criteria indicated (e.g., entropy) that the model with 2 or 3 classes was “finer”. However, the two-class specification was chosen in view of the interpretability.\textsuperscript{19} On a related note, the covariates were not included in the final LCA model due to unstable identification of the latent classes. However, given the high-quality classification\textsuperscript{20} (entropy greater than 0.8) and the purpose of this study (i.e., profiling) or segmentation, the effects of covariates on each class membership were examined in the second step of the analysis.
Table 1: Comparisons between the Latent Class Analyses with Different Number of Latent Classes

<table>
<thead>
<tr>
<th>Number of latent classes</th>
<th>k = 2</th>
<th>k = 3</th>
<th>k = 4</th>
<th>k = 5</th>
<th>k = 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>The minimum percentage of one class</td>
<td>44.50%</td>
<td>22.8%</td>
<td>15.46%</td>
<td>10.50%</td>
<td>7.17%</td>
</tr>
<tr>
<td>The mean posterior class membership probability †</td>
<td>&gt; 0.96</td>
<td>&gt; 0.91</td>
<td>&gt; 0.83</td>
<td>&gt; 0.78</td>
<td>&gt; 0.77</td>
</tr>
<tr>
<td>Entropy</td>
<td>0.84</td>
<td>0.82</td>
<td>0.78</td>
<td>0.77</td>
<td>0.79</td>
</tr>
<tr>
<td>Bootstrap likelihood ratio test (k vs. k – 1) -2 log likelihood (degrees of freedom)</td>
<td>5,057.04 (16) ***</td>
<td>1,010.30 (16) ***</td>
<td>274.03 (16) ***</td>
<td>182.95 (16) ***</td>
<td>141.77 (16) ***</td>
</tr>
<tr>
<td>Akaike Information Criteria (AIC)</td>
<td>27,465.22</td>
<td>26,486.93</td>
<td>26,244.90</td>
<td>26,093.95</td>
<td>25,984.18</td>
</tr>
<tr>
<td>Bayesian Information Criteria (BIC)</td>
<td>27,639.12</td>
<td>26,750.59</td>
<td>26,598.32</td>
<td>26,537.13</td>
<td>26,517.12</td>
</tr>
</tbody>
</table>

*** p< 0.001; k = number of latent classes
† The model with k = 2 was selected as the final model considering the highest posterior class membership probability, entropy, statistically significant difference from the model with k = 3, and interpretability (i.e., more distinctive internet use behaviors between classes).

Two Latent Subgroups

Each latent class corresponded with an underlying subgroup of Internet users who visit online in search of information about the LTC marketplace. Figure 2 describes the percentages of internet information-seeking behaviors by the two classes. As can be seen, the class 1 members are appreciably more likely to seek health, medical and LTC information than the class 2 members. Also, for each specific online information-seeking behavior, the pattern was consistent (i.e., the class 1 is higher than the class 2).

In terms of LTC online information-seeking, the difference between these two classes was evident. The first latent class is characterized by a high probability of internet use behavior. As a result, class 1 users were labeled as “Heavy online information-seekers.” In contrast, class 2 is characterized by a low probability of internet use behavior. Thus, this segment of LTC current or prospective consumers was labeled as “Light online information-seekers.”

Table 2 represents a descriptive summary of both classes of users. The proportional odds binary logistic regression was used to examine the effects of both sociodemographic and other market segmentation variables. Specifically, the impact of health status, caregiving status, and internet usage on each primary class’s membership (i.e., Heavy vs. Light online information-seekers) was evaluated. It is important to note that, SAS version 9.4 [Copyright
was used because Mplus version 7 does not return the c-statistic (Hosmer et al., 2013; Swets, 1988) that was used to assess model quality. This fact assumes importance given that SAS and Mplus, at the time of this study, do not use the identical estimation algorithms. Therefore, the computed c-statistic may require caution in its interpretation.

Table 2: Descriptive Summary of Internet Users by the Identified Latent Classes

<table>
<thead>
<tr>
<th>Variables</th>
<th>Latent class 1</th>
<th>Latent class 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Heavy online information-seekers</td>
<td>Light online information-seekers</td>
</tr>
<tr>
<td></td>
<td>(n = 1,120)</td>
<td>(n = 898)</td>
</tr>
<tr>
<td>Age (years)</td>
<td>44.30 (15.97)</td>
<td>45.03 (17.91)</td>
</tr>
<tr>
<td>Women ***</td>
<td>63.70%</td>
<td>53.30%</td>
</tr>
<tr>
<td>White **</td>
<td>67.31%</td>
<td>60.89%</td>
</tr>
<tr>
<td>Black *</td>
<td>15.43%</td>
<td>19.56%</td>
</tr>
<tr>
<td>Latino</td>
<td>11.77%</td>
<td>13.62%</td>
</tr>
<tr>
<td>Others</td>
<td>5.49%</td>
<td>5.93%</td>
</tr>
<tr>
<td>Married (vs. not married) ***</td>
<td>53.91%</td>
<td>46.44%</td>
</tr>
<tr>
<td>Number of household members</td>
<td>2.18 (0.92)</td>
<td>2.19 (0.98)</td>
</tr>
<tr>
<td>Educational attainment (1-5)***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High school or less</td>
<td>3.62%</td>
<td>9.31%</td>
</tr>
<tr>
<td>Vocational school</td>
<td>22.00%</td>
<td>35.26%</td>
</tr>
<tr>
<td>Some college or associated degree</td>
<td>2.17%</td>
<td>2.79%</td>
</tr>
<tr>
<td>Bachelor’s degree</td>
<td>36.18%</td>
<td>31.02%</td>
</tr>
<tr>
<td>Post-graduate degree</td>
<td>36.03%</td>
<td>21.61%</td>
</tr>
<tr>
<td>Employed **</td>
<td>67.19%</td>
<td>60.20%</td>
</tr>
<tr>
<td>Retired</td>
<td>15.23%</td>
<td></td>
</tr>
<tr>
<td>Annual household income (1-9)***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than $10,000</td>
<td>4.45%</td>
<td>10.34%</td>
</tr>
<tr>
<td>$10,000 to under $20,000</td>
<td>9.28%</td>
<td>10.02%</td>
</tr>
<tr>
<td>$20,000 to under $30,000</td>
<td>8.64%</td>
<td>11.96%</td>
</tr>
<tr>
<td>$30,000 to under $40,000</td>
<td>11.69%</td>
<td>13.36%</td>
</tr>
<tr>
<td>$40,000 to under $50,000</td>
<td>9.28%</td>
<td>12.28%</td>
</tr>
<tr>
<td>$50,000 to under $75,000</td>
<td>18.42%</td>
<td>16.92%</td>
</tr>
<tr>
<td>$75,000 to under $100,000</td>
<td>14.99%</td>
<td>11.85%</td>
</tr>
<tr>
<td>$100,000 to under $150,000</td>
<td>12.83%</td>
<td>7.65%</td>
</tr>
<tr>
<td>$150,000 or more</td>
<td>10.42%</td>
<td>5.60%</td>
</tr>
<tr>
<td>Insured ***</td>
<td>90.12%</td>
<td>84.61%</td>
</tr>
<tr>
<td>Self-rated health</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Excellent</td>
<td>32.55%</td>
<td>33.27%</td>
</tr>
<tr>
<td>Good</td>
<td>54.40%</td>
<td>52.95%</td>
</tr>
<tr>
<td>Only fair</td>
<td>11.265</td>
<td>11.72%</td>
</tr>
<tr>
<td>Poor</td>
<td>1.78%</td>
<td>2.06%</td>
</tr>
<tr>
<td>Number of chronic conditions (1-6) *</td>
<td>0.21 (0.50)</td>
<td>0.63 (0.93)</td>
</tr>
<tr>
<td>Number of disabilities (1-6) *</td>
<td>0.33 (0.75)</td>
<td>0.33 (0.75)</td>
</tr>
<tr>
<td>Caregivers for adults ***</td>
<td>15.91%</td>
<td>8.53%</td>
</tr>
<tr>
<td>Caregiving for adults***</td>
<td>22.31%</td>
<td>14.11%</td>
</tr>
<tr>
<td>Internet usage (1-7)***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Never *</td>
<td>2.00%</td>
<td>3.40%</td>
</tr>
</tbody>
</table>
Results

The findings from the analysis reveals a contrariety. While a priori reasoning would suggest that persons in need of LTC and/or individuals with a chronic disease would be more compelled to use the internet for information-seeking, this was not the case. As mentioned, two latent classes existed among the study participants: heavy online information-seekers (n=1,120), and light online information-seekers (n=898). The heavy online information-seekers were more likely to be women (independently of race/ethnicity). These women were most often married, highly educated, employed, economically upper class, insured, less chronically ill, and in general, more active internet users.

Unsurprisingly, the heavy online information-seekers were more likely to be caregivers than the light online information-seekers. In this study, about 25% of the heavy online information-seekers reportedly looked for LTC information online, while only about 2% of light online information-seekers did so (see Figure 2). Moreover, the individuals who sought LTC information online were also more likely to use the internet to look for other health and medical information. Specifically, the majority of the heavy online information-seekers looked for the health and medical information related to a specific disease, medical treatment, health care professionals, hospitals, insurance, food safety and other health issues.

The results of the binary logistic regression were predictive of the latent class membership. This analysis revealed eight statistically significant predictors (see Table 3). Interestingly, older adults were less likely to be the heavy online information-seekers, and therefore, less likely to seek online LTC information, compared to younger adults. The membership of heavy online information-seekers was predicted by female gender, higher education, higher household income, and a greater number of chronic conditions. As expected, caregivers to parents and caregivers to adults who were not their parents had 1.94 times and 1.82 times odds of being the heavy online information-seekers than non-caregivers to any adult. That is, caregivers were significantly more likely to look for the LTC information as well as other online information than non-caregivers.

Table 3: Estimated Odds Ratios from Proportional Odds Binary Logistic regression on the Heavy Online Information-Seekers (Class 1) vs. Light Online Information-Seekers (Class 2)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Odds ratio (Standard error)</th>
</tr>
</thead>
</table>

Less often | 1.00% | 3.94% |
Every few weeks | 1.34% | 4.38% |
1-2 days a week | 4.90% | 10.29% |
3-5 days a week | 9.80% | 13.95% |
About once a day | 13.14% | 19.68% |
Several times a day | 67.82% | 44.36% |

*p< 0.05; ** p < 0.01***p < 0.001 for the t-test or chi-square test

a. Internet usage = Never, these respondents still used email and therefore, classified as internet users
Finally, the adults who used the internet more often also tended to be in the heavy online health-related as well as LTC information-seekers. Overall, individuals who had health issues (either their own or someone else’s) and/or caregiving responsibilities and particular characteristics (e.g., gender, higher socioeconomic status) were significantly more active in terms of online health, medical and LTC information-seeking behaviors.

**Discussions**

This study analyzed a large dataset of the internet users and identified the primary segments of users as well as the subsets within each larger segment of the adults who looked online for LTC as well as other health and medical information. However, the implications of this study extend far beyond the defined areas of inquiry. While multiple sources of LTC information exist online, long-term providers as the “suppliers” in LTC markets, can use findings such as these to ensure that the online information which they provide is easily accessible by these various segments of users, and includes the types of information which these various segments seek. The following sections provide brief discussions on the selected areas for future research.

**Heavy vs. Light Online Information Seekers**

One important finding from this study is the unobserved latent class memberships among the heavy and light online information seekers. The latent class membership is informative of multiple individuals’ online LTC and other health and medical information seeking behaviors. That is, when individuals seek LTC information online, there is a significant greater chance that they also use the internet to look for other health and medical information. Two practical implications can be drawn from the finding.
First, the volume of research on online health and medical information is significantly greater than that of LTC information. Accordingly, as LTC providers deliver knowledge and information to current and/or prospective users, this online LTC information should be designed in alignment with the rich literature on online health and medical information. Thus, this study provides a foundation for improvements in the “fit” between online information seeking by LTC consumers, and the information made available by LTC providers.

Second, LTC providers, depending on the nature of their services, can literally target the specific subpopulations identified in this study. For example, if the goal is to provide online LTC information to older adults who may need LTC services at some point in the future, LTC providers can target light online information seekers who can be identified based on a set of characteristics including age, gender, educational attainment, household income level, number of chronic conditions, caregiving responsibilities and general internet use. Similarly, given the findings on the heavy online information seekers, LTC providers can align their messages with non-LTC health and medical information sources. This is a highly effective strategy for reaching their audiences given that online information seekers tend to simultaneously look for LTC and health and medical information. Last, more practical strategies can also be used to better coordinate LTC providers and consumers health and medical information as additional research of this type is completed.

**Older Adults is not the information seekers**

This study reconfirmed findings from other researchers which indicated that older adults, despite their status as the primary LTC consumer segment, are significantly less likely to seek LTC information online. Citing data from the Pew Internet Report, one article confirms that while internet use has been increasing among older adults, usage levels continue to remain below those of younger adults. However, also using data from the Pew Research Center, another article found that in 2013, 53% of adults age 65 and older use the internet. Yet, while 86% of this total communicated via e-mail, a mere 27% utilized the internet for improving their health literacy through health-related information-seeking. This data suggests that there is an urgent need for LTC providers to assume a role of leadership in directing internet-based social marketing towards seniors. Munshi, Florez, Huang et al. describe the robust need for diabetes care among many LTC consumers. As this study reveals, health area specific unique informational needs exist among LTC consumers with chronicities.

**Information Gaps Between LTC Consumers and Providers**

A greater informational exchange between this sub-segment of LTC consumers and providers can potentially improve outcomes via better informed decision-making in LTC pre-planning prior to the emergence of aging-related severe cognitive and/or physical disabilities that require LTC services. That is, a knowledge informational gap in the LTC marketplace that can only be addressed when LTC providers and consumers experience better coordination in the online demand for, and supply of LTC information. As is known, the LTC marketplace as currently structured is one which is built upon minimum levels of dialogue between consumers and/or their representatives, and LTC providers. This tendency is revealed as one reviews the U.S. Centers for Medicare & Medicaid Services
document, *Your Guide to Choosing a Nursing Home or Other Long-Term Care.* This document recommends the use of Eldercare Locator, Agency and Disability Resource Centers (ADRCs), Long-Term Care Ombudsman, and other services. However, it also reveals the need for more direct informational linkages between LTC consumers and LTC providers. Again, an awareness of the unique informational needs of LTC sub-segments can be used to improve this dialogue.

**Women vs. Men as Seekers of LTC Information Online**
One study using data from 7,609 Medicare beneficiaries in the 2011 National Health and Aging Trends Study, found that, in general, males are more likely to use the internet than females. However, the results from this study revealed that females, perhaps because of their over-representation among caregivers, were more likely than males to seek online information on LTC than were their husbands, brothers, sons, fathers and/or other male relatives and friends. This finding suggests that if the LTC industry wishes to direct internet messaging to these unique segments of information-seekers, separate messaging content and information dissemination strategies will be required. A similar importance of research-driven market segmentation can also be found in any industry.

**Increase Access of the Internet Among Persons with Lower SES**
This study, as has been true with other analyses, also discovered that persons with higher incomes and higher levels of education are more likely to access LTC information online. Yet, in some respects, lower income persons with disabilities that require LTC find themselves engaged in a more complex network of financial transactions as they engage in eligibility screening (e.g., Medicaid), benefits establishment and dual-eligibility. Because low-income persons, due to lack of exposure to technology or financial resources, they are disproportionately likely to rely on cellphones rather than personal computers. LTC providers may consider disseminating information to this group via smartphone applications and/or mobile-friendly websites.

**Target Persons with More Chronic Diseases**
This study also found that persons with chronic diseases are more likely to engage in LTC and health-related information-seeking on the internet (arguably out of necessity). This finding on chronic conditions and online information-seeking suggest that LTC providers can disseminate reliable information to prospective residents regarding their services for managing various chronicities. One study criticizes the internet as a source of health information based upon fragilities, complexity of the information and the observed frequency of inaccurate information. Accordingly, LTC providers will need to ensure that the targeted market sub-segments are delivered accurate information in a format compatible with their informational needs.

**Conclusions**
This study applied latent class analysis as a tool for the segmentation of LTC internet information seeking into relevant sub-segments. Such person-centered approach can potentially improve the operations of LTC marketplace. The analysis of a large data of American adults identified two underlying market segments - heavy and light online information seekers – according to their online LTC, health and medical information-seeking behaviors. The study also revealed that the segmentation basis for LTC consumers
include but extend beyond demographic and socioeconomic variables such as age, gender, educational attainment, and household income level. Rather, chronic conditions, caregiving status, and general internet usage are predictive of class membership. Thus, identifying the latent classes with more or less usage of the internet for LTC, health and medical information was merely a starting point. The next step involves using the findings from this study to enhance online communications between LTC providers, and current and prospective LTC consumers. In this respect, the current study provided a foundation to generate greater dialogue regarding how various sub-segments of LTC information-seekers via the internet can be better linked with LTC service providers – the group that is best positioned to deliver information essential for decision-making.
REFERENCES


28. Zickuhr K, Madden M. Older adults and Internet use: For the first time, half of adults ages 65 and older are online. Washington, DC: Pew Internet & American Life Project. 2012.