The joint assessment of longitudinal multidimensional functionings in overweight and obese elderly with a time varying covariate

HYOKYOUNG GRACE HONG[*], SATRAJIT ROYCHOUDHURY[†], AND PULAK GHOSH[‡]

The occurrence of overweight and obese older adults in the US has increased substantially during the past decades. Toward the goal of overweight or obese elders' well-being, it is important to detect early functional decline. In contrast to the majority of the previous research, which considers a single dimension of the functioning of the elderly, we consider four-dimensional functionings for daily living- physical, sensory, emotional, and social functioning simultaneously. The challenge of our study is that functionings and some predictors are longitudinally measured and mixed types discrete form; physical functioning is measured by count variable exhibiting the excess zero. The other three functionings are on an ordinal scale. To deal with these complications, our technique utilizes a zero-inflated Poisson regression model to account for the excess zero in the physical functioning. The sensory, emotional, and social functionings are modeled via the ordinal model, and those four functionings are connected by correlated random effects and the model parameters are estimated using a Bayesian approach via Markov chain Monte Carlo algorithms. Analytical results based on the Second Longitudinal Study of Aging show that self-rated health commonly affects our interested dimension of the functionings, sensory functioning most obviously deteriorates with aging and emotional well-being remains relatively high in old age.

KEYWORDS AND PHRASES: Bayesian, Longitudinal data, Multivariate analysis, Ordinal response, Zero-inflated Poisson.

1. INTRODUCTION

More Americans are becoming overweight or obese: more than one-third of the US adults (35.7%) in 2009–2010 were obese (http://www.cdc.gov/obesity/data/adult.html), and this proportion is projected to grow further. While the prevalence of obesity is increasing in all age groups, the obesity has more deleterious effects on the elderly by exacerbating the age-related decline in physical functioning, leading to frailty (Villareal et al., 2005). In addition, the US is an aging society – the elderly, who are 60 years or older, accounts for 30% of the US population in 2012 and is expected to be 35% by 2030. Those facts imply that the number of the obese elderly will continue to increase, with a commensurate increase in public health issues.

Nation-wide efforts have been made to improve older adults' health and quality of life, which are important in both individual-level and public health policy makers' perspective. The comprehensive assessment of quality of life, used to measure and compare the effectiveness of different treatments and evaluate the impact of a treatment on how patients feel and function in their everyday lives, serves as a baseline to better understand immediate and long-term needs for the elderly and their families. The aforementioned may serve as a means to reduce the ever growing health care costs that plague our society. Among the many options to evaluate the quality of life of the elderly, functional status is commonly employed to demonstrate a person's ability to perform self-care, self-maintenance, and physical activities (Bierman, 2001; Hong and Zhou, 2013; Hong and He, 2010). However, health-related quality of life is a much broader concept and encompasses psychological (or emotional) and social (or environmental) domains as well as physical domains. While physical functioning is selected as the major component of quality-of-life assessment in literature, little reported research deals with multiple domains simultaneously. Associations among the multiple domains were simplified using the bi-directional relationship between two functionings or often neglected by lumping multiple functionings into a single measure. These approaches are not sufficient to fully reflect multi-dimensionality of quality of life and fail to capture the interactions among individual domains.

The combined effect of obesity and aging is likely to further impair the quality of life of elderly patients and increase their morbidity (Mokdad et al., 2000). Many researchers have focused on investigating the independent impact of social, economical, and clinical aspects on the obese elderly's quality of life. This lacks a systematic approach to observe

[*]Corresponding author.

the health status or quality of life in a more broad sense. Ropka (2002) also noted that multiple domains of the quality of life in the obese elderly need to be considered. Therefore, in this paper, we aim to evaluate the quality of life in the combined aspect of physical, psychological, and social domains for the overweight or obese elderly to provide a complete picture of one's quality of life. Particularly, we will choose four important functionings: physical, sensory, emotional, and social to measure physical, psychological, and social domains.

In a health survey data, assessment of functioning is commonly reported as discrete variables. In our data, the degree of disability for each functioning is measured in a discrete form; the sensory, emotional, and social functionings are measured by an ordinal variable, physical functioning is measured by count with excessive zeros. Not only the excessive zeros in the data violate the Poisson distribution assumption and tend to invalidate the data analysis, but also it is more meaningful to separate two distinct sources of zero counts for further empirical implications. For instance, when a person has a very good physical strength, disability may be nearly impossible, contributing to a zero physical disability measure. However, a subject whose health is marginal (i.e. a person who doesn't have very good physical strength nor very bad physical strength) also may report no physical disability. This excess zero problem in the physical functioning can be handled by modeling the zero-inflated Poisson (ZIP) model. Thus, we utilize this technique to consider the excess zero issues in the physical functioning.

In addition, in the longitudinal data the responses are recorded over time, at different time points, and these observations within each subject tend to be correlated. Therefore, the random effects for the subjects need to be considered in the model. Finally, the analysis of this mixed type discrete data would be more complicated in a longitudinal setting. As we understand, very limited statistical methodologies have been applied to deal with the multivariate discrete responses in the longitudinal framework.

Distinctively different from previous research, our data analysis deals with these complicated situations: multivariate mixed types of discrete responses with excess zeros in the longitudinal setting. By fully considering this, we believe that our analysis is more accurate and reveal the association between four important functionings of the obese elderly. Moreover, since the mixed type of discrete responses in clinical and economic data are not uncommon, the proposed method can be applied to other applications in similar settings.

In order to estimate the parameters in our model, we use MCMC algorithms for fitting Bayesian models. The details of the posterior and conditions will be explained in a later section. After introducing the motivating data set, selected study variables, and the definition of the four different functionings in Section 2, the proposed method used for the simultaneous estimation of four functionings is described in

Section 3. The proposed model is compared to the alternatives in Section 4. We apply our model to the LSOA II data set in Section 5, and conclude in Section 6.

2. SOURCE OF DATA AND STUDY VARIABLES

Data for the reference group came from a population based sample, the Second Longitudinal Study of Aging (LSOA II), which is available from http://www.cdc.gov/nchs/lsoa/lsoa2.htm. This survey was performed by National Health Statistics (NIHS) from 1994–2000 to provide a profile of scores describing a wide range of functioning for three different periods (Wave 1, Wave 2, and Wave 3). The LSOA II is a longitudinal study with a national representative sample consisting of 9,447 civilian, noninstitutionalized persons 70 years of age at the time of the LSOA II baseline interview. In order to classify the obese individuals in the LSOA II, we used standard cut points for overweight, i.e., body mass index (BMI; weight in kilograms divided by height in meters squared) ≥ 25. After deleting missing observations, 1,438 obese or overweight elderly are used for this study.

As predictor variables, standard demographic information (age and gender) and social variables (education, marital status), variables pertaining to self-rated health (SRH) are also extracted from the database. Particularly, SRH is measured at each time point.

The outcomes of interest for this study are four dimensions of the functioning, physical functioning: sensory functioning, social functioning, and emotional functioning. We briefly explain each functioning below.

Physical functioning (Y) Many measurement schemes have been proposed for physical functioning. In our analysis we follow McGwin et al. (2001) and utilize many physical indices available in the LSOA II data. More specifically, physical functioning is defined as a combined measure that is a sum of Activities of Daily Living (ADLs) limitations, Instrumental Activities of Daily Living (IADLs) limitations, and the Nagi items. The first set of measures focused on ADLs and queried subjects as to whether they had difficulties in bathing, dressing, eating, transferring, walking, going outside, or using the toilet. The second set of measures was based on IADLs. Subjects were asked whether they had difficulties in preparing meals, shopping for personal items, managing money, or using the telephone. Finally, functional limitations were assessed using items from the Nagi Disability Scale, including inability or difficulty in walking short distances, walking up 10 stairs, standing, sitting, stooping, reaching overhead, reaching out, using fingers, lifting light weights, and lifting heavy weights. The physical functioning was categorized into 0 to 22 according to a number of limitations that an elderly person found unable to perform from the Nagi, ADLs, and IADLs.

Sensory functioning (W_1) Sensory functioning is an important aspect of health, especially for the elderly. Declines in sensory functioning may be symptomatic of underlying disease and can affect personal safety (Anstey et al., 2005), quality of life, and perceived health (Østbye et al., 2006). In addition, a decline in sensory functioning may limit participation in intimate relationships and other types of social activities, which may in turn have additional negative consequences for health. An older person with vision problems may appear timid, hesitant, or confused, especially when confronted with a new situation. Similarly, older people with hearing loss may miss the nuances of conversation and appear confused, creating unjustified impatience on the part of those with whom they are speaking. These experiences may lead to isolation, disappointment, and frustration (Schumm et al., 2009).

In the LSOA II, respondents who reported having seeing or hearing disabilities were further categorized into three sensory classifications with an ordered code: "not disabled" (=1), "Seeing Disabled but Hearing Abled" or "Hearing Disabled but Seeing Abled" (=2), and both "Seeing and Hearing Disabled" (=3). Sensory problems are common experiences within our sample. In the LSOA II data, 18% reported blindness in one or both eyes or other troubles with seeing, 33.2% reported problems with hearing, and 8.6% reported problems with both hearing and seeing.

Social functioning (W_2) The ability of an individual to interact in a normal or usual way in society can be used as a measure of quality of life. The social functioning items cover general well being, role performance, family participation, and relations with friends. In the LSOA II, the social functioning items are measured by the desired levels of social activity; "Present social activities are too much, enough, or want more," where 1 = "too much"; 2 = "about enough"; 3 = "would like to do more". The question about the level of social activity may be a useful summary measure of social participation, and was used in other literature including Crews and Campbell (2004) to study the association between the social functioning and other functionings.

In our sample, about 0.02% of older people reported having too little social activity. By contrast, about 78% of older people reported "about enough" and 22% reported that they "would like to do more".

Emotional functioning (W_3) Emotional suffering may be among the most painful aspects of obesity, and it decreases a person's quality of life and can have an impact on his or her engagement in society and work. Research on all subjects, not just for the obese or over-weighted subjects, reported that 20% of community dwelling elders experienced symptoms of depression (Huisani et al., 2004). However, we found that about 40% of the subjects in our sample experienced depression all of the time.

Late-life depression can have serious repercussions, increasing mortality and disability, higher health care utilization, and longer hospital stays. The items on emotional functioning cover feelings of self-esteem, feelings toward personal

Table 1. Background of variables in LSOA II

Variable	Description
Physical functioning (Y)	a combined measure that is a sum of the Nagi items, ADL limitations, and IADL limitations (*count 0–22*)
Sensory functioning (W_1)	0 = no vision and hearing problems, 1 = vision or hearing problems, 2 = both vision and hearing problems
Social functioning (W_2)	desired level of social activity, 1 = too much, 2 = about enough, 3 = would like to do more
Emotional functioning (W_3)	How often felt sad/depressed in past 12 months, 1 = none of the time, 2 = a little of the time, 3 = some of the time, 4 = all of the time
sex	1 = male, 0 = female
SRH	Self-rated health, 1 = unhealthy(fair/poor) 0 = healthy (excellent/very good/good)
age	Age of the respondent (*conti. 70–99*)
edu	Completed years of education (*conti. 0–18*)
Mstatus	1 = married, 0 = not married (widowed, separated, never married)

relationships, and thoughts about the future, and life events. In the LSOA II, depression is an ordinal variable evaluated by the following question, "How often felt sad/depressed in past 12 months?" (1 = 'all of the time', 2 = 'some of the time', 3 = 'a little of the time', 4 = 'none of the time').

3. JOINT STATISTICAL MODEL

Since the physical functioning (Y) is a count variable, a possible approach to modeling a count data is to assume a Poisson distribution. However, we found that more than 30% of Y have zero counts, a common cause of over-dispersion. Thus, in order to account for the excess of zero counts, we employ a zero-inflated Poisson (ZIP) regression model. On the other hand, the sensory (W_1), emotional (W_2), and social functionings (W_3) are ordinal variables. We jointly model W_1, W_2, and W_3, where individual functioning is modeled as an ordinal regression, which assumes that underlying latent variables are continuous random variables and the ordinal level is decided by the cut-off. In this section, ZIP and ordinal regression are described in more detail, and how these models are connected is explained.

3.1 Zero-inflated Poisson model

Let Y_{ij} be the physical functioning status of the ith subject at the jth time points, $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$,

where m represents the number of subjects in the study, and n is the designed number of time units in the follow-up period. Following Lambert (1992), Hall (2000), Dagne (2004), and Ghosh et al. (2006), we further assume that for each observed event count, Y_{ij}, there is an unobserved random variable for the state of physical functioning, U_{ij}, where $P(U_{ij} = 0) = p_{ij}$ if Y_{ij} comes from the degenerate distribution, and $P(U_{ij} = 1) = 1 - p_{ij}$ if $Y_{ij} \sim$ Poisson λ_{ij}: the Poisson model as follows:

$$Y_{ij} = \begin{cases} 0 & \text{with probability } p_{ij} \\ \text{Poisson}(\lambda_{ij}), & \text{with probability } 1 - p_{ij}, \end{cases}$$

where Poisson(λ_{ij}) is defined by the density functioning $P(Y_{ij} = y_{ij}) = \exp(-\lambda_{ij})\lambda_{ij}^{y_{ij}}/y_{ij}!$. It should be noted that both the degenerate distribution and the Poisson process can produce zero observations. Such a formulation is often referred to as the zero-inflated Poisson (ZIP) distribution. It then follows that

$$P(Y_{ij} = 0) = p_{ij} + (1 - p_{ij})\exp(-\lambda_{ij}),$$
$$P(Y_{ij} = y_{ij}) = (1 - p_{ij})\frac{\exp(-\lambda_{ij})\lambda_{ij}^{y_{ij}}}{y_{ij}!}, \ y_{ij} = 1, 2, \ldots.$$

In our application, Y may be characterized by two latent groups: one comprised of subjects with a high propensity to be independent (no difficulty in accomplishing any physical functioning), and the other consisting of subjects with a substantial probability of having difficulties in carrying out at least one physical functioning. When a person has good physical strength, disability may be nearly impossible. But when a subject is not in good health, disability may occur according to a Poisson distribution.

We consider the simultaneous modeling of both λ_{ij} and p_{ij} by assuming the following logistic and log-linear regression models.

(1) $\quad \text{logit}(1 - p_{ij}) = \beta_1^p + \beta_2^p\text{sex}_i + \beta_3^p\text{Mstatus}_i$
$$+ \beta_4^p\text{edu}_i + \beta_5^p\text{SRH}_{ij} + \beta_6^p\text{age}_{ij} + b_{i1},$$

(2) $\quad \log(\lambda_{ij}) = \beta_1^\lambda + \beta_2^\lambda\text{sex}_i + \beta_3^\lambda\text{Mstatus}_i$
$$+ \beta_4^\lambda\text{edu}_i + \beta_5^\lambda\text{SRH}_{ij} + f^\lambda(\text{age}_{ij}) + b_{i2},$$

where b_{i1} and b_{i2} are the random effects, and SRH is a time-varying covariate. We also have "age" of the subject as a covariate. We assume that an age variable has a non-linear effect, so $f^\lambda(\text{age}_{ij})$ indicates the spline model for the age. The estimated coefficients in (1) and (2) have the straight forward implications. In Equation (1), the coefficients imply the odds ratio of being not independent. Equation (2) estimates the effects of each factor contributing to the log count of the number of physical disabilities.

3.2 Ordinal data modeling

Each sensory, social, and emotional functioning in the LSOA II are observed using the ordinal scale with three or four levels. However, since the process of disability is continuous, we assume that the underlying distribution is continuous and determined by its cut-off value. Further, we assume that these three functionings are not independently occurring, but rather related to one another. We model the muti-dimensional ordinal responses as follows. Let $\mathbf{W}_{ij} = (W_{ij1}, \ldots, W_{ijK})^T$ be a $K \times 1$ vector of ordered categorical scores for the ith subject in the K $(=1, 2, 3)$th response at the jth time point. Here the sensory, social, and emotional functionings are, respectively, W_{ij1}, W_{ij2} and W_{ij3}.

Then we define Z_{ijk}, which has the following link between W_{ijk} and Z_{ijk}.

$$W_{ijk} = l \text{ if } Z_{ijk} \in (\gamma_{k,l-1}, \gamma_{k,l}), \ \gamma_{k,0} < \gamma_{k,1}, \ldots < \gamma_{k,C_k},$$

where $\gamma_{k,0} = -\infty$ and $\gamma_{k,C_k} = +\infty$ and $\gamma_{k,1} = 0$ for ensuring identifiability.

Let $\mathbf{Z}_{ij} = (Z_{ij1}, \ldots, Z_{ijK})^T$ denote a $K \times 1$ vector of underlying continuous random variables distributed as $N_K(\mu_{ijk}, \Sigma_k = \sigma_k^2 I_k)$, where μ_{ijk} is the underlying mean functioning, and μ_{ijk}, $(k = 1, 2, 3)$ can be expressed as

$$\mu_{ijk} = \zeta_1^k + g^k(\text{age}_{ij}) + \zeta_2^k\text{sex}_i + \zeta_3^k\text{Mstatus}_i + \zeta_4^k\text{edu}_i + \zeta_5^k\text{SRH}_{ij} + V_{ik},$$

where ζ is the associated coefficients, $g^k(\text{age}_{ij})$ is the non-parametric spline functioning for age and V_{ik} is a random effect. We approximate the spline functioning $f(S_{ij})$ and $g(S_{ij})$ (suppressing the superscripts) by a piecewise polynomial of degree τ. Let the knots $\tilde{w} = (\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_m)$ are placed within the range of S_{ij}, such that $\min(S_{ij}) < \tilde{w}_1 < \tilde{w}_2 < \cdots < \tilde{w}_m < \max(S_{ij})$. Then $f(S_{ij})$ (similar for g) is approximated by

$$f(S_{ij}) \approx \nu_1 S_{ij} + \nu_2 S_{ij}^2 + \cdots + \nu_\tau S_{ij}^\tau + \sum_{c=1}^{C} u_c\gamma_c(S_{ij} - \tilde{w}_c)_+^\tau,$$

where $X_+ = x$ if $x > 0$, and 0 otherwise, $\nu = (\nu_1, \ldots, \nu_\tau)$, $\tilde{w}$ are the vectors for regression coefficients in the polynomial regression spline. Note that there is no intercept in the polynomial regression to avoid the identifiability. We assume $u_c \overset{iid}{\sim} N(0, \sigma_u^2); c = 1, \ldots, C$. In the above formulation one of the important issues is the choice of how many knot points and where to locate them. There is no clear rule on how many knot points to include or where to locate them in the spline functions. More knots are needed in regions where the function is changing rapidly (Ruppert, 2002). Sometimes subject knowledge may be relevant in placing knots where a change in the shape of the curve is expected. Using too few knots or poorly sited knots means that the approximation to

the curve will be degraded. By contrast, a spline using too many knots will be imprecise. We select the knots among the existing values, and they are equally spaced within the range $[\min(x), \max(x)]$. We choose about 10 knots and let γ_c choose the knots that the data choose. Thus, γ_c is like a variable selection parameter. The γ_c is the selector indices, that allow the spline coefficients to be included or excluded and that are defined for each knot. The γ_c are then drawn independently from a Bernoulli prior, viz., $\gamma_c \sim \text{Bernoulli}(0.5)$. By introducing this, we can select a subset of well supported knots from a larger space. For each knot point u_c the γ_c will weight the importance of a particular knot point.

Since Y is also related to $W_1, W_2,$ and W_3, ZIP and the ordinal modeling are connected by having correlated random effects, $\theta_i = (b_{i1}, b_{i2}, V_{i1}, V_{i2}, V_{i3})^T \sim N_5(\mathbf{0}, \Psi)$, where Ψ is the covariance matrix.

4. BAYESIAN INFERENCE

Under the joint model described above, the likelihood of the observed data for the ith subject, denoted by $\mathbf{U} = (\mathbf{Y_i}, \mathbf{W_{i1}}, \mathbf{W_{i2}}, \mathbf{W_{i3}})$, for $i = 1, \ldots, m$, based on the parameters set Ω and the random effects θ_i is proportional to

$$L_i(\Omega, \theta_i | \mathbf{U}) = \prod_{j=1}^{n} [(1 - p_{ij})]^{I_{[y_{ij}=0]}}$$
$$\times \left[\frac{p_{ij} \lambda_{ij} y_{ij} e^{-\lambda_{ij}}}{y_{ij}!(1 - e^{-\lambda_{ij}})} \right]^{1 - I_{[y_{ij}=0]}} \times \prod_{j=1}^{n} \prod_{k=1}^{3} P(W_{ijk} = l_k).$$

$$L_i(\Omega, \theta_{\mathbf{i}} | \mathbf{U}) = \prod_{j=1}^{n} [(1 - p_{ij})]^{I_{[y_{ij}=0]}}$$
$$\times \left[\frac{p_{ij} \lambda_{ij} y_{ij} e^{-\lambda_{ij}}}{y_{ij}!(1 - e^{-\lambda_{ij}})} \right]^{1 - I_{[y_{ij}=0]}}$$
$$\times \prod_{j=1}^{n} \prod_{k=1}^{3} \{\Phi(\gamma_{k,l} - \mu_{ijk}/\sigma_k) - \Phi(\gamma_{k,l-1} - \mu_{ijk})/\sigma_k\}.$$

Assuming independence between observations from different subjects, the resulting likelihood for all the observations from the m subjects is the product of these individual likelihood values. Then, marginalizing out all the random effects the likelihood of all the observed data is proportional to

$$L(\Omega | \text{data}) = \int_{\mathbb{R}} \int_{\mathbb{R}} \int_{\mathbb{R}} \int_{\mathbb{R}} \int_{\mathbb{R}} \prod_{i=1}^{m} L_i(\Omega, \theta_i | \mathbf{U})$$
$$\mathbf{m}(\mathbf{b}, \mathbf{V}) d\mathbf{b_1} d\mathbf{b_2} d\mathbf{V_1} d\mathbf{V_2} d\mathbf{V_3}.$$

To complete the Bayesian specification of the model, we assign priors to the unknown parameters in the above likelihood functioning. Thus, the set of parameters from the

model may be listed as:

$$\Omega = (\beta_1^p, \ldots, \beta_5^p, \beta_1^\lambda, \ldots, \beta_5^\lambda, \zeta_1^1, \ldots, \zeta_5^1, \zeta_1^2, \ldots, \zeta_5^2,$$
$$\zeta_1^3, \ldots, \zeta_5^3, \nu_1^p, \ldots \nu_\tau^p, \nu_1^\lambda, \ldots \nu_\tau^\lambda, \nu_1^1, \ldots \nu_\tau^1, \nu_1^2, \ldots \nu_\tau^2, \nu_1^3, \ldots \nu_3^\lambda,$$
$$\sigma_1^2, \ldots, \sigma_3^2, \Psi).$$

For each parameter in Ω we specify a prior: for each model specific regression coefficient (β's and ζ's) and each spline specific regression coefficient (ν's) we assume a normal density prior; for each variance parameter (σ^2) we assume an inverse-gamma (IG) prior and finally for the cross-part variance covariance matrix (Ψ) we assume an inverse Wishart prior. We choose these prior distributions as they are conditionally conjugate and this usually is the practice in the literature. We did check for prior sensitivity and found the results are not very sensitive to the choice of the prior distributions.

The posterior distributions are not analytically intractable. However, models described previously can be fit using Markov chain Monte Carlo (MCMC) methods such as the Gibbs sampler Gelfand et al. (1992). Since the full conditional distributions are not standard, a straightforward implementation of the Gibbs sampler using standard sampling techniques may not be possible. WinBUGS 1.4 is used to fit these models. Convergence of MCMC was monitored via the histories, auto-correlations, density plots, and Gelman-Rubin statistics (Brooks and Gelman, 1997) of each chain. Necessary simulations efficiently performed with the R2WinBUGS package in R. The samples from the posterior obtained from the MCMC will allow us to achieve summary measures of the parameter estimates and to obtain credible intervals (CIs) of the parameters of interest.

5. ANALYSIS

We investigated the health profile and functional performance of the overweight and obese elderly in our sample. Figure 1 shows that excess zero counts are observed in the physical disability; while the number of physical disability ranges from 0 to 22, about 41%, 36%, and 32% of the subjects have zero physical disability at Wave 1, Wave 2, and Wave 3, respectively.

Figure 2 presents the proportion of each category functioning. For sensory functioning, the majority of subjects in our sample do not have a disability in vision or hearing at the beginning of the survey; however, an increase in disability is observed for the subjects with either one or both of the vision and hearing impairments The change in pattern of social functioning is less obvious than the sensory functioning. Compared to Wave 1, more subjects feel that they want to do more social activity at Wave 3, indicating that their social activity is more restricted in the later life of the overweight or obese elderly. On the other hand, it is observed that the emotional functioning is more stable through all different time points. Note that the proportion
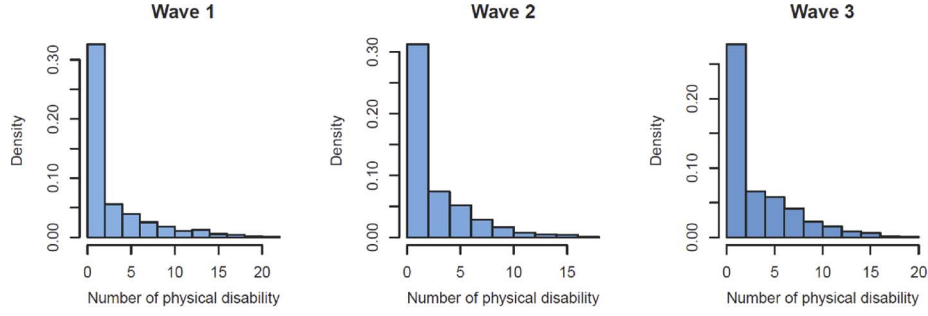
Figure 1. The number of physical disability at each time point.
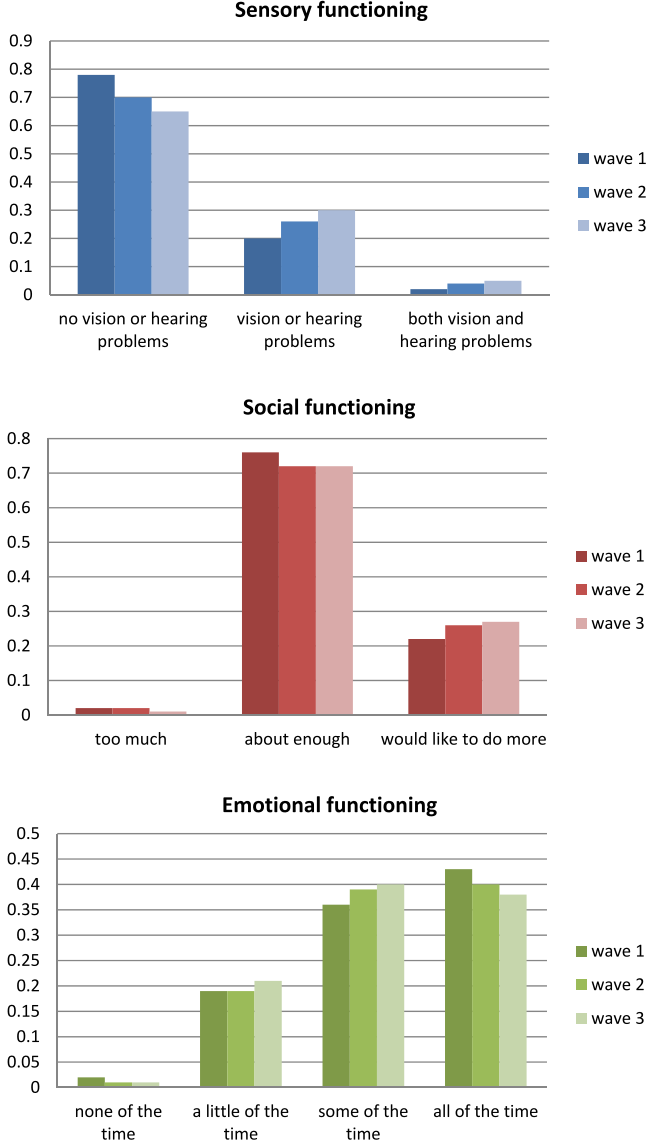

Figure 2. The change in sensory, social, and emotional functioning.

of the subjects who suffers from depression for all of the time tends to decrease as the subjects get older.

Before discussing our result we first compare our model with some other candidate models to test the quality of model fit that our model shows. To compare candidate models, we computed $P(Y_i|Y_{-i})$, which is the posterior predictive distribution of Y_i conditional on the observed data with a single data point deleted. This value is known as the conditional predictive ordinate (CPO) and has been widely used for model diagnostic and assessment Gelfand et al. (1992). For the ith subject the CPO statistics under model $M_l : 1 \leq l \leq L$ is defined as:

$$CPO_i = P(Y_i|Y_{-i}) = E_{\theta l}\left[P(Y_i|\underset{\sim}{\theta}l)|Y_{-i}\right],$$

where $-i$ denotes the exclusion of the data from subject i. The $\underset{\sim}{\theta}_l$ is the set of parameters of the M_l and $P(Y_i|\underset{\sim}{\theta}_l)$ is the sampling density of the model evaluated at the ith observation. The preceding expectation is taken with respect to the posterior distribution of the model parameter $\underset{\sim}{\theta}_l$ given the cross-validated data, Y_{-i}. For subject i the CPO_i can be obtained from the MCMC samples by computing the following weighted average:

$$\hat{CPO}_i = \left(\frac{1}{M}\sum_{m=1}^{M}\frac{1}{f(Y_i|\theta_l^{(m)})}\right)^{-1},$$

where M is the number of simulations, $\theta_l^{(m)}$ denotes the parameter samples at the mth iteration. A large CPO value indicates a better fit. A useful summary statistic of the CPO_i is the logarithm of the Psuedo-marginal Likelihood (LPML) defined as:

$$LPML = \sum_{i=1}^{n} log(\hat{CPO}_i).$$

Models with greater $LPML$ values represent a better fit. The LPML is well defined under the posterior predictive for density if it is computationally stable. We compared the following models using LPML:

Table 2. ZIP Model for Physical functioning (Y)

	Parameter	Mean	95% CI
Logit: $1-p$			
Intercept	β_1^p	3.18	[0.77, 5.45]
Sex	β_2^p	−0.73	[−1.88, 0.32]
Marital Status	β_3^p	0.96	[0.04, 2.07]
Education	β_4^p	0.15	[−0.01, 0.30]
Self-rated health	β_5^p	4.15	[2.58, 6.28]
age	β_6^p	0.36	[−0.96, 1.77]
Log: λ			
Intercept	β_1^λ	0.74	[−0.23, 1.96]
Sex	β_2^λ	−0.89	[−1.30, −0.48]
Marital Status	β_3^λ	0.43	[0.08, 0.80]
Education	β_4^λ	−0.06	[−0.12, −0.01]
Self-rated health	β_5^λ	0.23	[0.17, 0.30]

Figure 3. Age spline functionings for $\log(Y)$.

Model 1 Joint model used in the analysis and whose results we discuss below (proposed model).

Model 2 Model with correlated random effects but no age splines.

Model 3 Each part is modeled independently without Random Effects and spline.

The LPML values for models 1–3 are −4032.4, −5106.1 and −16891.34 respectively. The proposed model has the highest LPML values suggesting that it had the best fit among the candidate models. The large difference in the LPML values of our proposed model and other model indicated the presence of a nonlinear age effect and the need for correlated random effect in our analysis.

Table 2 shows the parameter estimations of the ZIP model for physical functioning (Y). The first part of the ZIP model estimates the propensity to be independent using the logit model. This may happen when a person has a good physical strength and disability may be nearly impossible. The second part of the ZIP model estimates the number of counts of disability based on the Poisson distribution with the log link.

It turns out that gender ($\beta_2^p = -0.73$ (-1.88, 0.32)), education level ($\beta_4^p = 0.15$ (-0.01, 0.30)), and age ($\beta_6^p = 0.36$ (-0.96, 1.77)) are not statistically significant. However, married ($\beta_3^p = 0.96$ (0.04, 2.07)) and poor self-rated health ($\beta_5^p = 4.15$ (2.58, 6.28)) are important factors to predict subjects' physical dependency. The result also shows that females suffer from the more physical disability ($\beta_2^\lambda = -0.89$ (-1.30, -0.48)). Meanwhile, unmarried ($\beta_3^\lambda = 0.43$ (0.08, 0.80)), higher education level ($\beta_4^\lambda = -0.06$ (-0.124, -0.01)), and good self-rated health ($\beta_5^\lambda = 0.23$ (0.17, 0.30)) reduce the number of disability levels.

Figure 3 indicates that more physical disability is related to aging. The oldest olds (age $\geq$ 85 years) had more difficulty than the older adults (70–74 years) in performing physical activities. This finding is also consistent with Kramarow et al. (1999).
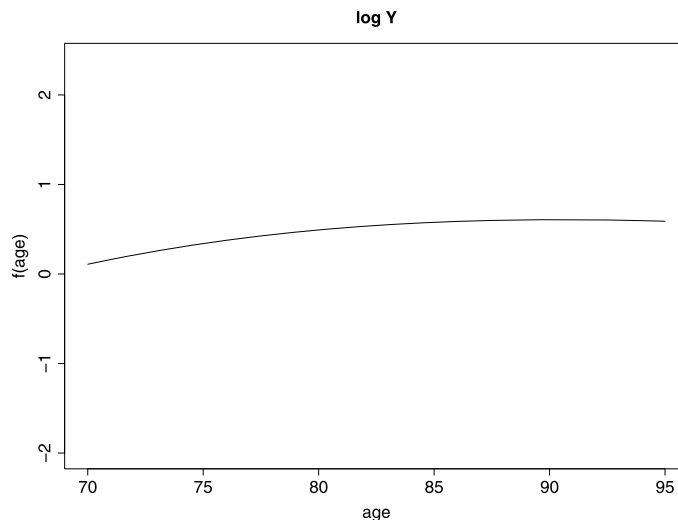
Table 3. Joint Ordinal Models of W_1, W_2, and W_3

	Parameter	Mean	95% CI
Sensory functioning: W_1			
Intercept	$\beta_1^{W_1}$	−0.76	[−3.50, 1.77]
Sex	$\beta_2^{W_1}$	0.39	[−0.06, 0.87]
Marital Status	$\beta_3^{W_1}$	0.23	[−0.19, 0.69]
Education	$\beta_4^{W_1}$	−0.01	[−0.07, 0.06]
Self-rated health	$\beta_5^{W_1}$	0.69	[0.39, 0.99]
Social functioning W_2			
Intercept	$\beta_1^{W_2}$	1.52	[−0.55, 4.82]
Sex	$\beta_2^{W_2}$	−0.59	[−1.12, −0.08]
Marital Status	$\beta_3^{W_2}$	0.06	[−0.40, 0.53]
Education	$\beta_4^{W_2}$	−0.05	[−0.12, 0.02]
Self-rated health	$\beta_5^{W_2}$	1.00	[0.68, 1.33]
Emotional functioning W_3			
Intercept	$\beta_1^{W_3}$	0.15	[−2.69, 3.29]
Sex	$\beta_2^{W_3}$	−1.25	[−1.68, −0.80]
Marital Status	$\beta_3^{W_3}$	−0.12	[−0.53, 0.29]
Education	$\beta_4^{W_3}$	−0.08	[−0.14, −0.02]
Self-rated health	$\beta_5^{W_3}$	0.81	[0.55, 1.07]

Table 3 shows the effect of each factor to the sensory functioning (W_1), social functioning (W_2), and emotional functioning (W_3). Although no gender effect is observed for sensory functioning ($\beta_2^{W_1} = 0.39$ (-0.06, 0.87)), male are more active in social functioning ($\beta_2^{W_2} = -0.59$ (-1.12, -0.08)) and report positive feelings more often than women ($\beta_2^{W_3} = -1.25$ (-1.68, -0.80)). For the elderly, compounded losses of spouse, siblings, and friends can cause tremendous changes and affect emotional well-being. Elderly women live longer and therefore suffer greater effects of loss and are more often widowed. This increased isolation in elderly women might be associated with depression. Marital status is not an important factor for three functionings ($\beta_3^{W_1} = 0.23$ (-0.19, 0.69)
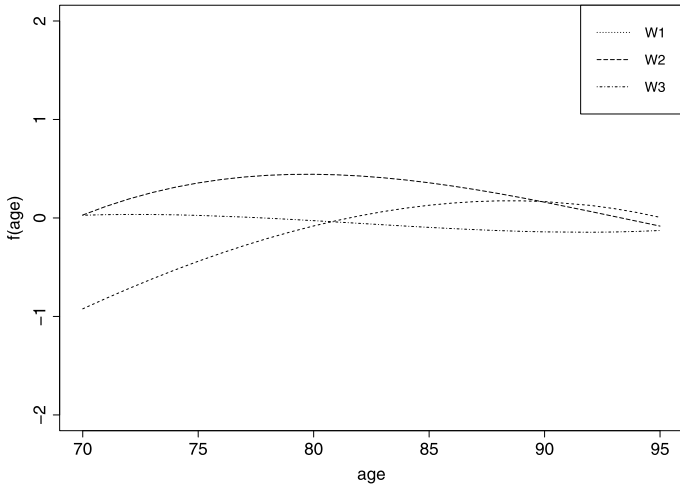
Figure 4. Age spline functionings for W_1–W_3.

and $\beta_3^{W_3} = -0.12$ $(-0.53, 0.29))$. Lower education level increases the depression $(\beta_4^{W_3} = -0.08$ $(-0.14, -0.02))$. Self-rated health affects all three functionings $(\beta_5^{W_1} = 0.69$ $(0.39, 0.99)$, $\beta_5^{W_2} = 1.00$ $(0.68, 1.33)$, and $\beta_5^{W_3} = 0.81$ $(0.55, 1.07))$; poor self-rated health decreases the sensory functioning, limits the social activity, and causes more depression.

Figure 4 shows that sensory functionings most obviously deteriorate with aging. A decline in sensory functioning in older adults is continuously growing until age 90, confirming the previous studies – between 9% and 22% of adults older than 70 years have some degree of dual sensory impairment and its prevalence increases with age (Campbell et al., 1999; Jee et al., 2005). Changes in the sensory functionings are undeniable: the eyes have lost their accommodation functioning at 60 and, due to yellowing of the eye-lens, discrimination of color differences in the blue part of the spectrum is no longer possible (Riemersma, 2000). A comparable picture can be sketched for the auditory functionings.

A desired level of social activity increased until 80 and declined after 80: decreases in social roles, deaths of friends and family members, and increased functional limitations that reduce social involvement (Carstensen et al., 1988).

The size of social networks of very old people (age 85–104 years) were nearly half of that of old people (age 70–84 years), primarily by reduction in 'not close' social relationships (Kim, 2007).

However, emotional functioning is stable for all ages. This result is in the same line with a growing body of research suggesting that the ability to regulate emotion remains stable and in some aspects may improve across the adult life span (Charles and Carstensen, 2007; Levenson et al., 1991; Tsai et al., 2000).

6. CONCLUSION

The growing obesity epidemic significantly affects the functioning of the geriatric population as excess body weight in the elderly is strongly correlated with chronic ill health, poor quality of life, functional decline, disability, and dependency (Elia, 2001). Successful aging is often defined as "the optimal state of overall functioning and well-being". Therefore, for the elderly, functioning is essential for the experience of successful aging.

Toward the goal of earlier detection of malfunctioning and improvement of obese elders' well-being, we proposed a method which models the four dimensions of the functionings simultaneously. More specifically, a zero-inflated Poisson (ZIP) regression model was used to account for the excess zero in the physical functioning. The sensory, emotional, and social functioning are modeled via the ordinal model, and those four functioning are connected by the correlated random effects.

Our proposed method enables us to detect multiple decrements in functioning or discriminate between different patterns of functional loss among the obese elderly. Some interesting findings from our data analysis are summarized: i) Self-rated health was commonly affecting our interested dimension of the functionings. It decreases the physical functioning and sensory functioning, limits the social activity, and causes more depression, confirming the previous study that the self-rated health is an important measurement for a quality of life of the elderly; ii) Sensory functioning most obviously deteriorates with aging; iii) Despite age-related losses, emotional well-being remains relatively high in old age; iv) There is a positive relationship between emotional well-being and social activity in later life of obese people. The elderly who are more social might be better protected against depression than unsocial people. Thus, not being completely sedentary would be helpful in reducing the amount of physical activity accomplished with difficulty.

Considering that obesity is difficult to reverse, an emphasis should be placed on lifelong prevention and treatment of disabled functioning of obese people. Even though the loss in the sensory functioning might be unavoidable, policies, programs, and practices can improve other functionings in the elderly such as physical functioning, emotional, and social functioning. For instance, community can help the overweight or obese elderly through health education programs to gain an understanding and appreciation of healthy lifestyles that promote lifelong wellness.

Though a lot more work needs to be done to understand the complex relationship between physical, social and emotional functioning in later life of the overweight or obese elderly, we hope that our integrated analysis would improve geriatric assessment and may be used in health service evaluation.

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Hyokyoung Grace Hong
Department of Statistics and Probability
Michigan State University
East Lansing, MI 48824
USA
E-mail address: hhong@stt.msu.edu

Satrajit Roychoudhury
BDM Oncology
Novartis Pharmaceutical Company
Florham Park, NJ
USA
E-mail address: satrajit.roychoudhury@novartis.com

Pulak Ghosh
Department of QM & IS
Indian Institute of Management
Bangalore
India
E-mail address: pulakghoshc@gmail.com