Lifestyle Segmentation for Older Fashion Consumers using Latent Class Analysis

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Consumers 60 years of age and older are expected to dominate consumer spending in the U.S. over the next five to ten years (Best, 2020), however they are often mistakenly considered to be a homogeneous group rather than forming heterogenous segments. Brands that cater to older consumer segments' preferences and desires may have a competitive advantage (Nikitina & Vorontsova, 2015). Lifestyle, a major criterion used for market segmentation, reflects "the manner in which people conduct their lives, including activities, interests, and opinions" (AIO; Peter & Olson, 1994, p. 463). An AIO approach has provided new insights into consumer behavior towards food (Brunsø & Grunert, 1998), tourism (Konu, 2010), and museum/gallery (Todd & Lawson, 2001). Purinton-Johnson (2013) confirmed that older consumers, as well, can be segmented based on activities and these segments will include differences in consumption patterns and demographic characteristics. However, there appears to be scant literature about how lifestyle segments of older consumers differ in fashion consumption. Moreover, research in this area may be able to draw on secondary data to understand fashion consumption. The purpose of the present study was to use secondary data to (1) identify older consumer segments that share similar patterns of activities and (2) test for statistically significant differences among these segments in monthly clothing purchases (H1) and demographic characteristics (H2).

Sample and Procedure. Secondary data from the 2017 Consumption and Activities Mail Survey (CAMS), mailed to a sub-sample of respondents from the Health and Retirement Study (HRS), were used. HRS is a longitudinal panel study with a representative sample of about 37,000 individuals over the age of 50 in the U.S (Sonnega et al., 2014). The HRS provides researchers with multidisciplinary data to address issues of aging. The sample for the present study consisted of 4782 individuals (1950 men and 2832 women) ranging in age from 52 to 99 years ($mean_{age}$ = 68.8). Caucasians comprised 73% of the sample. We employed latent class analysis (LCA), a person-centered approach for identifying unobserved subgroups based on similarity in responses to observed categorical items (Collins & Lanza, 2010; McCutcheon, 1987). Essentially, LCA segments a heterogeneous population of individuals into groups/classes based on common characteristics, resulting in distinct response patterns (Jung & Wickrama, 2008). Item probabilities specify the likelihood of an individual being placed into a specific class.

Measures. Within AIO, activities denote the behavioral portion of lifestyle that is related to the way individuals allocate their time (Gonzalez & Bello, 2002). CAMS data contained 35 activity items. Sixteen items were selected based on Glass et al.'s (1999) leisure/social activities (e.g., playing games, attending religious services) and productive activities (e.g., shopping, volunteer work). Respondents were asked how much time they spent on a given activity. The items were dichotomized (0 = no time spent on activity; 1 = time spent on the activity) prior to data analysis to handle high skewness (Macia & Wickham, 2019).

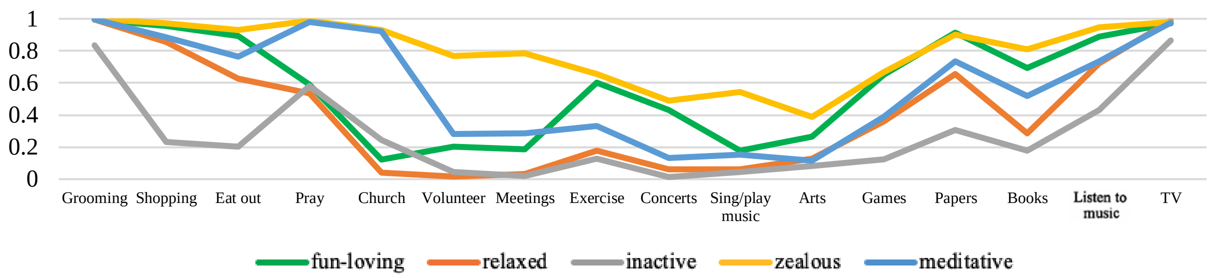
Analyses. LCA was conducted to identify whether consumer groups could be formed based on lifestyle characteristics (i.e., activities). LCA has become increasingly popular in recent psychology literature (Nylund-Gibson & Choi, 2018). The advantage of LCA over other clustering techniques is that it is a model-based clustering that provides fit indices. The optimal number of groups was determined using the sample size-adjusted Bayesian information criteria (sBIC), which is the most widely used and trusted fit index for model comparison (Nylund et al., 2007). We tentatively selected the five-class solution according to its lowest sBIC value (72441.169) and highest entropy value (0.68) indicating superior fit (Nylund-Gibson & Choi, 2018). To test the hypotheses, Analysis of variance (ANOVA) with Scheffe's post hoc test assessed mean differences in monthly clothing purchase behavior and demographics.
Results and Discussion. Five lifestyle groups (i.e., *fun-loving*, *relaxed*, *inactive*, *zealous*, and *meditative*) were identified through LCA (Table 1 and Figure 1). Comparing the five lifestyle groups in ANOVA, there were significant differences in monthly clothing spending, supporting H1. The results (Table 1) indicate that the *fun-loving* group spent significantly more on clothing compared to all other groups with the exception of the *zealous* group. The *relaxed* and *meditative* groups spent significantly more compared to the *inactive* group. The *inactive* group spent significantly less compared to all other groups. Our findings indicate support for H1; there was a positive association between the level of activities and spending on clothing. In particular, social activities and outdoor activities (e.g., dining out, attending meetings, or exercising) are the most distinctive attributes for *fun-loving* and *zealous* groups who had significantly higher scores on monthly clothing purchases. This result, regarding older consumers, supports previous finding that clothing selection is an essential means of expressing an individual's personal and social identities (Roach-Higgins & Eicher, 1992). In addition, there were significant demographic differences in age and gender, supporting H2. The results (Table 1) showed that *fun-loving* and *zealous* groups, the two most socially active groups, were relatively younger than *inactive* and *meditative* groups. However, it is notable that the *relaxed* group, those not as socially active as *fun-loving* and *zealous* groups, was significantly younger than *inactive* and *meditative* groups, indicating that older adults across the age spectrum engage in heterogeneous lifestyle activities. In addition, groups with a higher ratio of women (i.e., *zealous* and *meditative*) were more likely to participate in religious activities.

Table 1. *Older Consumers' Profile based on ANOVA with Scheffe's Post-Hoc Test*

	Fun-loving (N=925)	Relaxed (N=1125)	Inactive (N=275)	Zealous (N=982)	Meditative (N=1475)	Total (N=4782)	F-value
Clothing Purchase ($)	80.23[a]	59.55[b]	24.77[c]	77.60[a]	62.80[b]	65.97	59.98***
Age	67.5[a]	67.7[a]	71.7[b]	68.0[a]	70.4[b]	68.8	24.04***
Gender (M/F)	44.1/55.9[a]	46.4/53.6[ab]	45.5/54.5[a]	33.6/66.4[c]	38.3/61.7[ac]	40.8/59.2	11.63***

Note. Different superscripts denote significant differences. M/F= male/female. *** p<.001.

Figure 1. *Activities Item Probabilities*



Implications. This was a person-centered approach for classifying individuals into lifestyle groups. All five lifestyle groups scored highly on personal grooming, which supports that older consumers pay attention to their appearance. Given their high spending power, beauty and apparel markets should acknowledge older consumers as an important segment of the market. The findings will provide richer insights for apparel businesses to develop appropriate products and marketing strategies to reach each older consumer segment. A limitation is that we assessed one phase of data from a longitudinal study (i.e., ninth phase of CAMS data) to explore older fashion consumer lifestyle segments. Future studies using multiple waves of CAMS data may address issues pertaining to the market trends over time.

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