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Determinants of Wealth Index among Online Shoppers: An Ordinal Logistic Regression Approach

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Abstract
This study examined the determinants of wealth index among online shoppers using an ordinal logistic regression (OLR) framework. Data were collected through an online survey measuring demographic characteristics, behavioral attributes, and influencing factors for online shopping, with responses assessed using Likert-scale items. The sample (N = 86) consisted predominantly of respondents aged below 25 years (36.0%) and male (66.3%), with 41.9% employed, 36.0% students, and 22.1% self-employed. Wealth index distribution indicated that 47.6% fell into the low category, 32.1% medium, and 20.2% high. Factor analysis revealed three principal dimensions influencing online shopping behavior: decision-influencing factors, attitude factors, and motivation factors. The OLR model significantly improved prediction over the intercept-only model, $\chi^2(11) = 39.64$, $p < .001$, with acceptable fit (Pearson $\chi^2(95) = 90.92$, $p = .599$; Deviance $\chi^2(95) = 69.79$, $p = .976$) and moderate explanatory power (Nagelkerke $R^2 = .599$). Age and employment status emerged as the only significant predictors: respondents under 45 years and students were substantially less likely to belong to higher wealth index categories compared to older and employed individuals. Other behavioral and attitudinal variables did not show significant effects. The findings highlight the dominance of demographic factors over behavioral traits in determining online shoppers' wealth capacity, offering valuable insights for e-commerce market segmentation and targeted marketing strategies.

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1. Introduction

The advent of the internet has significantly transformed consumer purchasing behavior, shifting shopping experiences from traditional brick-and-mortar stores to dynamic e-commerce platforms. According to Syed Meeran (2022) [6], the internet has rapidly evolved into a global phenomenon, offering companies opportunities to reduce marketing costs, disseminate product information, conduct customer satisfaction surveys, and facilitate sales transactions at reduced prices. Consumers now leverage the internet not only for purchasing goods and services but also for comparing prices, evaluating product features, and assessing after-sales service options. This evolution in consumer shopping behavior has intensified competition among e-commerce providers, leading to improved service quality, competitive pricing, and a broader array of choices for consumers.

Online shopping behavior, as defined in consumer behavior literature, encompasses the attitudes, decision-making processes, and purchasing patterns of individuals or groups acquiring goods and services for personal use (Solomon et al., 2010; Hawkins, 2007) [8, 5]. These behaviors are shaped by a complex interplay of demographic factors (such as age, income, and education), psychological influences (including perceptions and motivations), and external elements (such as website quality, social media influence, and customer reviews) (Wu & Tsai, 2017; Diop, 2012) [9, 4]. While the core principles of consumer behavior remain consistent, the online environment has enhanced accessibility, convenience, and market reach (Close, 2012) [2].

One critical socio-economic indicator influencing consumer purchasing decisions in online markets is the Wealth Index, which reflects the economic standing of individuals or households based on assets, income, and living standards. In the context of e-the Wealth Index serves as a useful segmentation tool for understanding variations in consumer purchasing power, product preferences, and shopping frequency. Despite extensive research on online consumer behavior, there is a limited empirical focus on how wealth stratification affects online shopping patterns, particularly using advanced statistical modeling.

Das and Rahman (2011) [3] critically reevaluate the application of regression techniques in malnutrition research by contrasting traditional binary logistic regression (BLR) with the more nuanced Ordinal Logistic Regression (OLR) approach. Utilizing nationally representative data from the Bangladesh Demographic and Health Survey (BDHS) 2004, their study conceptualizes child nutritional status as an ordinal outcome, categorized into three meaningful levels: severely undernourished (Z-score < –3.0), moderately undernourished (–3.0 to –2.01), and nourished (Z-score ≥ –2.0). This classification reflects both theoretical and clinical gradations in child health, advocating for modeling techniques that respect the inherent order in the response variable.

Adeleke and Adepoju (2010) [1] conducted a pioneering study in which they applied an ordinal logistic regression model to analyze pregnancy outcomes—specifically, live birth, stillbirth, and abortion—using data from Ijebu-Ode in Nigeria. Their primary aim was to model the categorical pregnancy outcome in relation to multiple predictors while ensuring model adequacy, parsimony, and validity of underlying assumption.

Wynn (2009) [10] conducted a comprehensive investigation into the factors influencing consumers' intentions to engage in apparel e-commerce shopping, focusing on the interplay between gender, shopping orientation, online experience, and the interactive features of websites. Drawing from consumer behavior theory and technology acceptance perspectives, the study examined how demographic and behavioral characteristics shape attitudes toward online apparel purchases. Gender differences were explored not only in terms of shopping preferences but also in how men and women respond to specific website features, such as personalization, interactivity, and product presentation. Shopping orientation—whether utilitarian, hedonic, or experiential—was found to interact with prior online shopping experience, affecting confidence, trust, and purchase intentions. Wynn further analyzed how the richness of a website's interactive elements, including visual tools, virtual try-ons, and responsive interfaces, contributes to perceived ease of use and enjoyment, thereby enhancing the likelihood of transaction completion. The research highlighted that effective e-commerce strategies in apparel retailing require aligning website design with consumers' motivational profiles, prior online familiarity, and gender-specific preferences. This work provides valuable insights for both academia and practitioners on optimizing the online shopping environment to maximize consumer engagement in the fashion sector.

Ordinal Logistic Regression (OLR) offers a robust framework for modeling the relationship between ordinal outcome variables such as wealth categories (low, medium, high) and multiple explanatory factors (O'Connell, A. A. (2006) [7]). Unlike binary models, OLR preserves the ordinal nature of the dependent variable, capturing the ordered relationship between categories while accounting for the effects of multiple predictors. This makes OLR particularly well-suited for investigating how demographic, psychological, and technological factors jointly influence the wealth-based segmentation of online shoppers.

The present study, therefore, aims to examine the determinants of the Wealth Index among online shoppers using Ordinal Logistic Regression. By integrating demographic profiles, behavioral attributes, and external influences into a predictive model, the research will provide valuable insights into the socio-economic segmentation of online consumers. Such insights can guide e-commerce platforms and marketers in tailoring their strategies to align with the purchasing capacities and preferences of different wealth segments, ultimately enhancing customer satisfaction and market competitiveness.

2. Methodology

2.1. Data Collection

The primary method for data collection in this study is an online survey, chosen for its wide reach and convenience for respondents. The survey consists of a series of questionairs related to the demographic, economic and factors influencing consumer loyalty and switching behaviors of online shopping attributes, with responses measured on a Likert scale (e.g., 1 to 5, ranging from "Strongly Disagree" to "Strongly Agree"). This scale enables the collection of quantifiable data on each attribute, allowing for analysis of how strongly respondents associate specific characteristics toward online shopping. The target sample from the population includes those who uses online for their shopping to ensure relevance and accuracy of perceptions.

2.2. Factor Analysis Model

In a factor analysis model, we assume that each observed variable X_i (where i=1, 2, …, p for p observed variables) is influenced by m underlying, unobserved factors $F_1, F_2, \ldots, F_m$ plus an error term. The model can be expressed as:

$$X_i = \lambda_{i1}F_1 + \lambda_{i2}F_2 + \cdots + \lambda_{im}F_m + \epsilon_t \quad (1)$$

where:

λ_{ij} are the factor loadings representing the strength of the association between observed variable X_i and factor F_j. The F_j are the latent factors (unobserved variables) common across multiple observed variables. The ϵ_t is the unique variance or error term for X_i, capturing variance not explained by the factors.

2.2.1. Factor Extraction

To determine the factors, several methods can be used, such as Principal Component Analysis (PCA), often used to initially determine the number of factors, although it's technically not a factor analysis method. It is a statistical technique used to reduce the dimensionality of data by transforming a large set of variables into a smaller set of uncorrelated variables called principal components. This is done while retaining as much of the original data's variance as possible.

Before performing PCA, it's common to standardize the data if the variables are on different scales. For an $n \times p$ data matrix X with n observations (rows) and p variables (columns), the standardized matrix Z is:

$$Z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \quad (2)$$

Where μ_j and σ_j are the mean and standard deviation of variable j, respectively. This ensures that each variable has a mean of 0 and a standard deviation of 1.

2.2.2. Principal Components

The principal components are the projections of the original data onto the eigenvectors of the covariance matrix. To get the kth principal component PC_k for each observation, we multiply the standardized data matrix Z by the eigenvector vk corresponding to the kth largest eigenvalue:

$$PC_k = Zv_k \quad (3)$$

For all principal components, we can write:

$$PC = ZV \quad (4)$$

where V is the matrix of eigenvectors (each column of V is an eigenvector v_k), and PC is the matrix of principal component scores.

2.2.3. Selecting Principal Components

To decide how many principal components to retain, we examine the eigenvalues. The proportion of variance explained by each principal component is:

$$\frac{\lambda_k}{\sum_{j=1}^{p} \lambda_j} \quad (5)$$

where λ_k is the eigenvalue for the kth component.
To determine the optimal number of components to retain in a factor analysis, three key criteria are often used. The Kaiser Criterion suggests retaining components with eigenvalues greater than 1, as these components account for more variance than a single variable. Additionally, the Scree Plot involves plotting the eigenvalues in descending order and identifying an "elbow" point, where the slope levels off, indicating the optimal number of components. Finally, the Cumulative Variance criterion recommends retaining enough components to explain a substantial percentage of the variance, such as 90%, ensuring that the model sufficiently captures the data's complexity.

2.3. Rotation of Factors

Once factors are extracted, a rotation is often applied to make interpretation easier. Two main types of rotation are Orthogonal rotation (e.g., Varimax): Assumes factors are uncorrelated and maximizes the variance of loadings within each factor and Oblique rotation (e.g., Oblimin, Promax): Allows factors to be correlated, which is often more realistic in personality and psychological research.
The rotation helps redistribute variance among factors, improving interpretability by maximizing high loadings and minimizing low loadings within each factor.

2.4. Ordinal Logistic Regression (OLR)

Since the Wealth Index is an ordered categorical variable, an Ordinal Logistic Regression model with a proportional odds assumption is employed to identify predictors of higher wealth categories.
The general OLR model is:

$$\log\left[\frac{P(Y \le j)}{P(Y > j)}\right] = \alpha_j - \beta_1 X_1 - \beta_2 X_2 - \ldots - \beta_k X_k \quad (6)$$

Where
Y is the Wealth Index category (Low, Medium and High)
$j$is the category threshold
$X_1,\ X_2, \ldots, X_k$ are the predictor variables
$\alpha_j$is the intercept for the ordered categories?
$\beta$is the regression coefficients estimating the effect of each predictor

3. Data Analysis AND Discussion OF Results

Table 1: Demography/General Information

Variable(s)	N	%
Age		
Below 25	31	36.0
25 – 34	23	26.7
35 – 44	15	17.4
45 – 54	13	15.1
55 and above	4	4.7
Gender		
Male	57	66.3
Female	29	33.3
Employment Status		
Employed	36	41.9
Self-employed	19	22.1
Student	31	36.0
Wealth Index		
Low	40	47.6
Medium	27	32.1
High	17	20.2
Loyalty toward online brands		
Loyal to specific online retailers	29	34.5
No particular loyalty to any retailer	32	38.1
Switch loyalty	23	27.4

The demographic profile in Table 1 shows that most respondents were aged below 25 (36.0%), followed by those aged 25–34 (26.7%), with smaller proportions in the 35–44 (17.4%), 45–54 (15.1%), and 55 and above (4.7%) age groups. Males constituted the majority (66.3%), while females made up 33.3% of the sample. In terms of employment status, 41.9% were employed, 36.0% were students, and 22.1% were self-employed. The wealth index distribution indicated that 47.6% fell into the low category, 32.1% into the medium category, and 20.2% into the high category. Regarding loyalty toward online brands, 38.1% reported no particular loyalty, 34.5% were loyal to specific online retailers, and 27.4% tended to switch loyalty.

Table 2a: Variables Extracted for decision-Influencing Factor for online shopping

FACTOR 1	COMPONENT		
	1	**2**	**3**
Shipping speed	.871	.218	.146
Quality of product	.836	.101	.258
Price	.832	.019	.309
Return policy	.819	.148	.097
Customer_review	.797	.247	.271
Convinience	.596	.381	.414
Avoiding crowd	.437	.362	.396

Table 2a shows variables extracted for decision-influencing factor in online shopping, categorized into three components based on factor loadings. Component 1, also identified as primary factor group captures the most significant influences on consumer decisions, as indicated by high factor loadings.

Table 2b: Variables Extracted for Attitude Factor

FACTOR 2	COMPONENT		
	1	2	3
Convenient than in-store	.108	.795	.244
I trust the security of my payment information	.105	.788	.085
I prefer online shopping over in-store shopping	-.076	.705	.406
I am likely to spend more when shopping online than in-store	.233	.644	.002
Product reviews are essential in my decision to purchase online	.423	.532	.131
Access to reviews and rating	.380	.513	.328

Table 2b identifies key attitude variables influencing consumer behavior in online shopping, categorized into three components based on factor loadings. Component 2, also identified as primary attitude factor group captures the most significant influences on consumer behavior, as indicated by high factor loadings.

Table 3c: Variables Extracted for Motivation Factor

FACTOR 3	COMPONENT		
	1	2	3
Price comparisons	.170	.229	.832
Discounts and promotions	.366	.101	.815
Product variety	.435	.302	.709

Table 3c highlights key motivational variables influencing consumer behavior in online shopping, categorized into three components based on factor loadings. Component 3, also identified as primary motivation factor is the most significant, with high factor loadings for all three variables

Table 4: Model Fitting Information for Wealth Index determinants factors

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	109.432			
Final	69.792	39.640	11	.000
Link function: Logit.				

Table 5: Goodness-of-Fit for Wealth Index determinants factors

	Chi-Square	df	Sig.
Pearson	90.918	95	.0.599
Deviance	69.792	95	0.976
Link function: Logit.			

Table 6: Pseudo R-Square for Wealth Index determinants factors

Cox and Snell	.520
Nagelkerke	.599
McFadden	.362
Link function: Logit.	

Table 7: Parameter Estimates for Wealth Index determinants factors

		Estimate	Std. Error	Wald	df	Sig.
Threshold	Low Wealth Index	-21.772	.957	517.417	1	.000
	Medium Wealth Index	-19.343	.919	443.132	1	.000
Location	Influencing Factor	.362	.396	.835	1	.361
	Attitudinal Factor	-.423	.335	1.590	1	.207
	Motivation Factor	.145	.365	.159	1	.690
	Below 25	-22.267	1.394	255.265	1	.000
	25 - 34	-21.626	1.092	392.336	1	.000
	35 - 44	-20.411	1.000	416.514	1	.000
	45 - 54	-20.264	.000	.	1	.
	55 and above	0^a	.	.	0	.
	Students	-2.626	1.263	4.327	1	.038
	Self employed	-.152	.909	.028	1	.867
	Employed	0^a	.	.	0	.
	Loyal to specific retailer	.190	.793	.057	1	.811
	Switch loyalty	1.054	.927	1.293	1	.255
	No loyalty to any retailer	0^a	.	.	0	.

An ordinal logistic regression was performed to investigate predictors of wealth index categories among respondents. The model, using the logit link function, significantly outperformed the intercept-only model, $\chi^2(11) = 39.64$, $p < .001$ as shown in Table 4, indicating that the set of predictors collectively contributed to explaining differences in wealth index levels. Model fit statistics suggested that the model adequately represented the data, as indicated by the Pearson $\chi^2(95) = 90.918$, $p > .05$, and the Deviance $\chi^2(95) = 69.792$, $p > .05$ as shown in Table 5. The pseudo R-squared values showed a moderate proportion of explained variance: Cox and Snell $R^2 = .510$, Nagelkerke $R^2 = .587$, and McFadden $R^2 = .352$.

The ordinal logistic regression results in Table 6 indicated that the thresholds for transitioning between wealth index categories were significant, with the cutpoint for moving from low to medium wealth index at B = –21.77, SE = 0.96, Wald $\chi^2(1) = 517.42$, $p < .001$, and from medium to high wealth index at B = –19.34, SE = 0.92, Wald $\chi^2(1) = 443.13$, $p < .001$. Among the predictor variables, only age and employment status showed significant effects. Specifically, respondents below 25 years (B = –22.27, SE = 1.39, Wald $\chi^2(1) = 255.27$, $p < .001$), aged 25–34 years (B = –21.63, SE = 1.09, Wald $\chi^2(1) = 392.34$, $p < .001$), and aged 35–44 years (B = –20.41, SE = 1.00, Wald $\chi^2(1) = 416.51$, $p < .001$) were significantly less likely to be in higher wealth index categories compared to the reference group aged 55 and above. Employment status also had a significant effect, with students (B = –2.63, SE = 1.26, Wald $\chi^2(1) = 4.33$, $p = .038$) being less likely to occupy higher wealth categories compared to employed respondents. Other factors including influencing factor scores (B = 0.36, p = .361), attitudinal factors (B = –0.42, p = .207), motivation (B = 0.15, p = .690), loyalty behavior (B range = 0.19 to 1.05, all $p > .05$), and being self-employed (B = –0.15, p = .867) were not statistically significant predictors of wealth index. These results suggest that age and being a student are the most critical determinants of wealth index among online shoppers.

4. Conclusion

The findings of this study underscore the pivotal role of demographic variables particularly age and employment status in determining wealth index categories among online shoppers. Younger respondents, especially those below 45 years of age, were significantly less likely to belong to higher wealth segments compared to their older counterparts, while students exhibited lower wealth index scores than employed individuals. In contrast, behavioral and attitudinal variables, such as decision-influencing factors, shopping attitudes, motivations, and loyalty patterns, did not emerge as significant predictors in the model. The overall model demonstrated good fit and explained a moderate proportion of variance in wealth index levels, indicating that while consumer decision-making traits may shape purchasing behavior, socio-demographic characteristics remain dominant in predicting wealth capacity. These insights suggest that e-commerce platforms and marketers seeking to target higher wealth segments should prioritize strategies tailored to older and employed consumers, while also exploring ways to engage younger and student shoppers whose purchasing capacity may be constrained but who represent a potential future market segment.

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