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Multiple indicators multiple causes modeling of socio-demographic disparity effects on word-of-mouth consumer behavior towards healthcare purchasing

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Abstract

Word-of-mouth (WOM) expressed as basic face-to-face WOM (bWOM) and electronic or internet-based WOM (eWOM) is the most common form of communication among consumers. The impact of socio-demographic characteristics on WOM preferences among consumers of pharmaceutical products is a largely unexplored area. The study aimed to examine the role of socio-demographic attributes or covariates (gender, age, educational status, and employment status) on preference for WOM behavior, and also, to determine the comparative impact of bWOM and eWOM on purchase intentions among consumers. A cross-sectional study of 1,118 randomly selected customers of community pharmacies in Nigeria with online questionnaires for data collection. Based on latent variable modeling and cognitive dissonance theory, hypotheses were developed and tested using the Multiple-Indicators Multiple-Causes (MIMIC) co-variance-based structural equation modeling technique. Results revealed that the developed measurement model for the study was adequately fitted and valid. The two-factor structure of WOM was confirmed. Positive correlations were found among exogenous covariates such as age, gender, employment, and educational status. Gender and educational status covariates did not influence respondents' preferences. Younger customers had a higher preference for bPOM. Unemployed respondents had higher tendency to use bWOM and eWOM compared to employed respondents. Also, eWOM had a stronger influence on purchase intentions compared to bWOM. Policymakers and regulators in the pharmaceutical industry should use knowledge of consumers' demographic disparities and communication preferences in formulating consumer awareness and education programs about proper drug use on social media platforms. The study adds to the literature by developing an integrated model to examine the effects of demographic disparities on consumer preferences using the MIMIC framework.

Keywords: Word-of-Mouth, Consumer Behavior, Preferences, Multiple Indicators Multiple Causes, Demographics, Structural Equation Modeling

INTRODUCTION

Globally, due to the advent of the internet, social media platforms have redefined person-to-person interactions as the predominant information-sharing avenues among consumers of products and services including pharmaceutical products (Pasternak et al., 2017; Bartschat et al., 2022). Word of mouth (WOM) entails the exchange of information between persons about their perceptions and opinions about goods and services through verbal in-person interaction and electronic media. WOM (expressed as basic- bWOM and electronic-eWOM) is recognized as the most frequently used medium of interaction among patrons of businesses including community pharmacies in the healthcare sector.

Apart from the conventional or basic WOM (that is, bWOM), technology growth has supported the rapid increase in the use of eWOM channels among consumers generally. This is evidenced in the vast use of online and website platforms such as WhatsApp, Google, Instagram, YouTube, Twitter, etc., among consumers of goods and services. In marketing, WOM is an increasingly important construct for assessing consumer satisfaction, engagement, and goodwill advertising at the least possible cost (Martin, 2017; Schall et al, 2019; Albarq & Doghan, 2020).

Extant literature has established that consumer attitudes and subsequent behavior are influenced by information from social media platforms, in particular from WOM (Abzari et al., 2014). This influence on attitude and behavior is associated with purchase intentions (willingness or unwillingness to buy a product or service)

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(Abzari et al., 2014). This presupposes that WOM may either generate positive or negative feedback that may influence current or future use of the product or service (Pena-García et al, 2020; Shastry & Anupama, 2021).

The WOM phenomenon potentially affects consumers of healthcare products such as medicines, who avail themselves of WOM avenues (bWOM and eWOM) to share their experiences about medicines, prescribed by physicians or recommended by pharmacists or even by important others (close friends and family). This scenario requires investigation, and hence, should be studied. Empirical evidence of the influence of consumers' demographic variables on WOM behavior is scanty. Previous research had focussed on WOM in medical tourism (Gurcu & Korkmaz, 2018), choice of healthcare facilities, and physician choice (Soare et al., 2022). But modeling the causal effects of demographic covariates on latent variables is difficult due to the nominal and ordinal nature of demographic attributes (Teo & Milutinovic, 2015: Chen & Jiang, 2019). To resolve this challenge, the use of Multiple Indicator Multiple Causes (MIMIC) modeling is appropriate to test the effects of demographic covariates on WOM of patrons of healthcare products.

To the best of the author's knowledge, no known study has addressed the influence of demographic factors on WOM (decomposed to bWOM and eWOM), and the consequent impact of WOM on purchase intentions among consumers of pharmaceutical products using an integrated model based on the framework of MIMIC modeling.

Justification of the study

The justification of examining the effect of demographic variables on the main dependent variable-WOM is actually hinged on providing more information about general consumer behavior with WOM based on their demographic differences, and the consequent effect of WOM domains (basic- bWOM and electronic-eWOM) on purchase intentions. These differences, if any, would enable healthcare practitioners and policy makers to adapt how drug related information is shared and coordinated among consumers of healthcare products. The use of latent variable modeling (LVN) and multiple indicators multiple causes modeling (MIMIC) techniques is essential to achieving the analysis of the study.

Relevance of latent variable modeling to the present study

Latent variable modeling (LVM) is an aspect of structural equation modeling that relates observed or manifest variables to latent or unobserved variables. In the context of this study, LVM involves 3 key elements- firstly, observed or manifest variables such as gender, sex, employment status, and socioeconomic status, secondly, unobserved or latent variables that cannot be directly measured, but are measured by measurement items or indicators e.g. WOM construct which is measured by different items. Thirdly, measurement error which accounts for bias in measurement or unexplained variance; which is referred to as disturbance or error term in structural equation modeling (Chang et al., 2020). The ability of SEM to account for measurement error differentiates it from regression models that assume error-free estimates which can cause bias path estimates. LVM involving demographic variables is scanty, especially in studies in which demographic information or variables are used to test hypotheses or provide some form of explanation for a phenomenon under consideration (Wunsch & Gourbin, 2020). The rationale for the use of the MIMIC model compared to the basic t-test for group comparison to test the hypotheses of the study rests in the fact that it ensures simultaneous estimation of measurement and structural models with better levels of item reliability (Teo & Milutinovic, 2015).

Basis for the use of Multiple-Indicator Multiple-Causes (MIMC) modeling to the present study

MIMIC models or factor analysis with covariates or exogenous covariates with confirmatory factor analysis, are structural equation models which simultaneously estimate path relationships in the structural model and factor loadings in the measurement model. MIMIC models advanced by researchers- Jöreskog & Goldberger (1975); Jöreskog & Sörbom, (1996); and Schumacker & Lomax (2016), are used to contextualize latent variables of statistical interest using demographic variables which are assumed to be measured without measurement error. It is composed of two models- the measurement model and the structural model (Jöreskog & Goldberger, 1975; Chang et al., 2020).

For the current study, the measurement model is composed of the latent variables- eWOM and bWOM with their respective indicators or measurement items. The structural model aspect relates to the predictive or cause-effect of the observed variables (exogenous covariates) on the latent variables- eWOM and bWOM (Brown, 2015). Therefore, MIMIC models provide a working template to estimate the effect of covariates (demographic variables) to explain possible differences in a latent variable or phenomenon (in this case, WOM construct which was broken into 2 sub-constructs- eWOM and bWOM). According to Frazier et al (2004), in measurement and evaluation, MIMIC models are a form of moderation in which the dependent variable is examined at different levels of the exogenous covariate (usually dichotomized). These exogenous covariates serve as independent or predictor variables and include age, gender, socioeconomic status, employment and educational status.

Literature review

Word of mouth (WOM)

Basic POM (bWOM) is the basic oldest, and traditional form of communication between persons (interpersonal) about goods and services received. Huete-Alcocer (2017), Luo et al, (2013), Cheung & Thadani (2012), and Hussain et al (2017) highlighted succinct differences between both forms, whilst, bWOM is typified a private person-to-person interaction, a source of information or sender is known, spreads slowly, and less accessible. On the other hand, for eWOM, the sender is often unknown (anonymous), information is made public once sent, spreads rapidly, and is easily accessible (Albarq & Doghan, 2020).

Electronic WOM (eWOM) refers to communication between individuals in a social interactive context by use of social media for consuming, commenting, posting, and sharing information (Pasternak et al., 2017; Bartschat et al., 2022). This informal form of communication is commonplace due to the increased technology-influenced consumption and purchase among consumers of pharmaceutical products through online platforms such as WhatsApp, Google, Instagram, YouTube, Twitter, etc., to relay their experiences about medicine use and effects. This has been shown to have a potential influence on consumer behavior and changing attitudes towards the product (Huete-Alcocer, 2017). Due to access to social media, people tend to rely on the posted comments and reviews about products used thereby underscoring its influence on behavior (Nieto et al., 2014).

In hospital settings, WOM tends to influence the attitude and behavior of consumers towards patronizing hospitals due to perceived quality and satisfaction derived or obtained from previous encounters (Islam & Farooqi, 2014). However, Frazier et al (2004) and Mladenovic et al (2020) argued that to expand the interpretability of studies on WOM, it is important to explore them under different contexts such as exploring significant differences in WOM based on the influence of demographic attributes (age, gender, employment status, educational status, income) among a population.

Demographic factors or covariates

Demographic information such as age, gender, education lifestyle, income, and socioeconomic status, has been shown to influence behavior among populations (Frasquet et al., 2015). For instance, a health survey conducted among individuals in Malaysia by Yanuar & Ibrahim (2010), affirmed the effects of demographic factors of the population on health index. In the same vein, a study situated in Malaysia provided empirical evidence of the impact of age, place of residence, and education on the fertility of women (Islam et al., 2016). In the area of health policy development, demographic data enables policymakers and healthcare managers to formulate policies that would be beneficial to specific subgroups within a general populace (Wirayuda et al., 2022).

According to Guan (2017), demographic attributes like socioeconomic factors such as age, gender, ethnicity, income, and employment status have been shown to influence health outcomes as well. Furthermore, studies have established the use of demographic variables or covariates as predictors or independent variables to influence research outcomes (Alrehili, et al, 2022; Nagamani & Katyayani, 2013; Aydin & Baju, 2016; Dharmashree et al., 2020).

Demographic data has been subject to descriptive statistics which tends to obscure some salient inferences that may be required to enhance interpretability (Sifers et al., 2002; Connelly, 2013). Hammer (2011) highlighted that inadequate reporting and use of demographic information in research tend to yield skewed results by assuming universal conclusions that may not reflect the actual reality of the study. Thus, nuanced differences that may occur or exist at subgroup levels of demographic data may be jettisoned or ignored.

Purchase intention

Purchase Intention refers to the willingness or unwillingness of a person to buy or procure a good or service (Zhang et al., 2022). Purchase intention is a measure of how well a customer or customer enjoys or perceives a product or service, thereby influencing consumer behavior (Morwitz, 2012; Montano & Kasprzyk, 2015; Shastry & Anupama, 2021). Several studies have been done in the area of consumer behavior to ascertain the factors that may influence a customer to re-purchase or for a new customer to purchase a product (Pena-García et al, 2020). Literature has shown that online reviews and WOM are prominent channels that may influence the eventual intention to purchase a product. In the context of healthcare especially medicines, purchase intention supposes the willingness of a consumer to purchase a product or medicine prescribed by the physician or recommended by the pharmacist, which may be influenced by WOM (both bWOM and eWOM). These influences may be triggered by the sociodemographic characteristics of the consumers themselves, which should be considered in the context of age, gender, educational status, and employment status.

Theoretical framework of the study

Theory of cognitive dissonance

To understand the context of WOM as it affects purchase intentions, the theory of cognitive dissonance plays an integral part, Cognitive dissonance theory was propounded by Festinger (1957) which surmises that there is some discomfort or tension or unease when an individual's beliefs do not align (different from) with their actions or behavior. Cognitive dissonance is the outcome of discomfort arising from an individual having a ‘misalignment’ (dissonance) when one‘s action contradicts one’s cognition or thoughts. WOM is the step taken by the individual to resolve the dissonance. For instance, in the case of healthcare, when a patient who is on a drug A and gets positive benefits from it, tries to convince other persons by recommending and gaining positive purchase from other persons. By this action (WOM), the individual assures himself or herself that the drug or service obtained was the right one. (Wangenheim, 2005; Pauli et al, 2023). Also, if a person fails to comply with the advice (against smoking) given by important others, he or she resolves this failure (dissonance) by taking steps to quit smoking or convince himself about the positive aspects of the habit (Wangenheim, 2005; Pauli et al, 2023).

Research questions

Based on the literature review and theoretical framework of the study, the following questions were asked:

1. Do demographic variables influence domains of WOM behavior (bWOM and eWOM) among patrons of pharmaceutical products?

2. Does bWOM positively influence purchase intention?

3. Does eWOM positively influence purchase intention?

4. What is the comparative effect of bWOM and eWOM on the purchase intentions of consumers of pharmaceutical products?

Hypotheses of the study

Based on the literature review, the following hypotheses according to the model were proposed for testing

MIMIC Model (Model 1)

H1a- Age [0-≤35 years. 1-≥36 years] has a positive influence on bWOM

H1b- Age [0-≤35 years. 1-≥36 years] has a positive influence on eWOM

H2a- Gender [0-female. 1-male] has a positive influence on bWOM

H2b- Gender [0-female. 1-male] has a positive influence on eWOM

H3a- Employment status [0-unemployed. 1-employed] has a positive influence on bWOM

H3b- Employment status [0-unemployed. 1-employed] has a positive influence on eWOM

H4a- Educational status [0-basic education. 1-postgraduate] has a positive influence on bWOM

H4b- Educational status [0-basic education. 1-postgraduate] has a positive influence on eWOM

Path Model (Model 2)

H5- eWOM has a positive effect on purchase intentions

H6- bWOM has a positive effect on purchase intentions

H7- eWOM has a stronger effect on purchase intentions compared to bWOM

METHOD

Participants and procedure

A Large adult sample (N=1,118) who visited community pharmacies at least thrice in the last year for their over-the-counter and prescription medication needs were randomly selected from the six geopolitical zones (southwest, south-south, southeast, northeast, northcentral, and northwest) in Nigeria. Nigeria has a population of over 200 million people and has a fast-developing pharmaceutical market according to McKinsey (2017). Participants were randomly selected from across different sectors of society- students in tertiary institutions, retirees, teachers, civil servants, and private sector workers through social media platforms, WhatsApp groups, and individual invites. Selection criteria were purposively for educated participants due to the nature of the data collection instrument (Google Forms questionnaire) used to collect information. The sample size was determined by using the inverse square root method by Kock and Hadaya (2018) based on absolute path coefficient=0.15, statistical power of 99%, and significance level at 1%, which gave 963 at a minimum number of participants required to develop reliable models. Informed consent was obtained from respondents before filling out the questionnaire. The study protocol was approved by the Health research ethics committee in the Ministry of Health, Ogun state.

Data analysis

Data was analyzed using structural equation modeling techniques (SEM) in Analysis of Moment Structures version 24 (AMOS, Arbuckle, 2016). SEM was used considering the multivariate relationships between variables to be examined using MIMIC modeling. Due to the robustness of the maximum likelihood estimation method in AMOS, issues with nonnormality of data were resolved or addressed in the analysis.

Model 1-MIMIC model

To address hypotheses H1, H2, H3, and H4, a MIMIC Model was developed using covariance-based structural equation modeling

Model 2-structural model

To address hypotheses H5, H6, and H7, a structural Model was developed using covariance-based structural equation modeling

Measurement model for WOM

The latent variable- WOM was operationalized based on theory into–eWOM and bWOM which were measured using a four-point Likert scale type ranging from never (1) to most times (4). The measurement model reflects the latent variable measured by its measurement items or indicators. The eWOM latent variable was measured by four indicators- and bWOM was measured by four measurement indicators.

Structural model for demographic covariates

For the structural model, the observed or manifest variables (demographic variables- Age, gender, employment status, and educational status) were functionally applied as predictors or causes and are operationally dichotomized into two groups (coded as 0 and 1) for ease of analysis and interpretability as depicted in Table 1. Path coefficients were used to predict the effects of demographic variables on WOM. Positive path coefficients indicate higher influence from group 1 while

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negative path coefficients depict higher influence from group 0.

For ease of computation and interpretability of regression output, the exogenous covariates or predictor or independent variables (Age, gender, education status, and employment status) were dichotomized into two categories 1 and 2 (coded 0 and 1 respectively) as shown in Table 1. For instance, Age was divided into equal and below 35 years for young adults (coded 0) and older adults for those equal and above 36 years (coded 1). This categorization was based on African youth Carter and the Nigerian Youth policy that defined youths as those between the ages of 13 and 35 years of age (African Youth Charter, 2006; National Youth Policy, 2019). The MIMC model is depicted in Figure 1.

Table 1. Operationalization of Demographic Variables for MIMIC Model

Covariates	Category 1 (coded 0)	Category 2 (coded 1)	Regression Sign (+ve and –ve)	Interpretation
Age	≤35 years	≥ 36 years	positive (+ve)	Category 2 has more impact on DV
Gender	Female	Male		
Education	Basic	Postgraduate	negative (-ve)	Category 1 has more impact on DV
Employment	Unemployed	Employed		

Table 2. Measurement of Latent Constructs

Construct	Indicator items	Code
Basic Word of Mouth (bWOM)	I rely on oral advice my friends give me on drugs	WOM1
	I buy medicines based on oral recommendations by friends and family	WOM2
	I take advice from friends and family on how to treat ailments	WOM3
	I take medications recommended by persons other than the physician or pharmacist	WOM4
Source	Huete-Alcocer, 2017; Luo et al, 2013; Cheung & Thadani, 2012; and Hussain et al., 2017	
Electronic Word of Mouth (eWOM)	I post on social media information I have about medicines	SMB1
	I readily read social media posts on drugs for knowledge sake	SMB2
	I actively share posts on social media of healthcare products with high ratings	SMB3
	Online recommendations of healthcare products are of interest to me	SMB4
Source	Pasternak et al., 2017; Bartschat et al., 2022; Huete-Alcocer, 2017	
Purchase Intention (PUI)	I am willing to purchase medicines when I am informed about them	PUI1
	I am willing to buy or request for a medicine after viewing an advert	PUI2
	I am willing to re-purchase a medicine I found useful for my health	PUI3
	I am willing to buy medicines after discussing with my friends and family	PUI4
	I tend to make better purchase decisions because of adverts and social media influences	PUI5
	I am willing to bear extra cost to get more information about drugs I intend to purchase	PUI6
	Drug adverts have a strong impact on my desire to purchase them	PUI7
Source	Zhang et al., 2022; Morwitz, 2012; Montano & Kasprzyk, 2015; Shastry & Anupama, 2021	

Table 3. Demographic Characteristics of Participants

Variables	Number	Percentage
Age		
≤ 35	646	57.8
≥ 36	472	42.2
Gender		
Male	573	51.3
Female	545	48.7
Highest Education		
High school	202	18.1
Diploma	46	4.1
Bachelor	543	48.6
Masters	240	21.5
PhD	87	7.8
Employment Status		
Unemployed	356	31.8
Employed	762	68.2
Total	1.118	100

Measurement of variables

Based on extant literature, the latent constructs for the study were measured by indicators or measurement items using a Likert-type scale. As shown in Table 2, eWOM and bWOM were measured on a scale of 1-4 ranging from never (1) to most times (4) while Purchase intentions (PUI) was measured on a 1 to 4 Likert scale type from 1 (strongly disagree) to 4 (strongly agree).

Table 6 shows that 65.3% of the teachers had a guidance.

RESULTS

Response rate and demographic characteristics of respondents

Out of 1,300 online invitations extended to the adult general public through Google forms questionnaire, 1,118 useable responses were received representing 86% return rate (Table 3) The majority of participants were male (51.3%, n=573) and the mean age of the study population was 35.85 years (SD=13.79) which reflects the mean value for youths in the African context (African Youth Charter, 2006; National Youth Policy, 2019).

In the MIMIC model, significant positive correlations ($p < 0.001$) were found between the covariates as shown in Table 4. The correlation between age and educational status had the strongest relationship. Hence, an increase in age is associated with an increase in educational qualifications. This implies that a change in one demographic variable is associated with the change in another.

Model 2- Influence of eWOM and bWOM on purchase intentions

To address hypotheses H5, H6, and H7, a path model was developed using covariance-based structural equation modeling

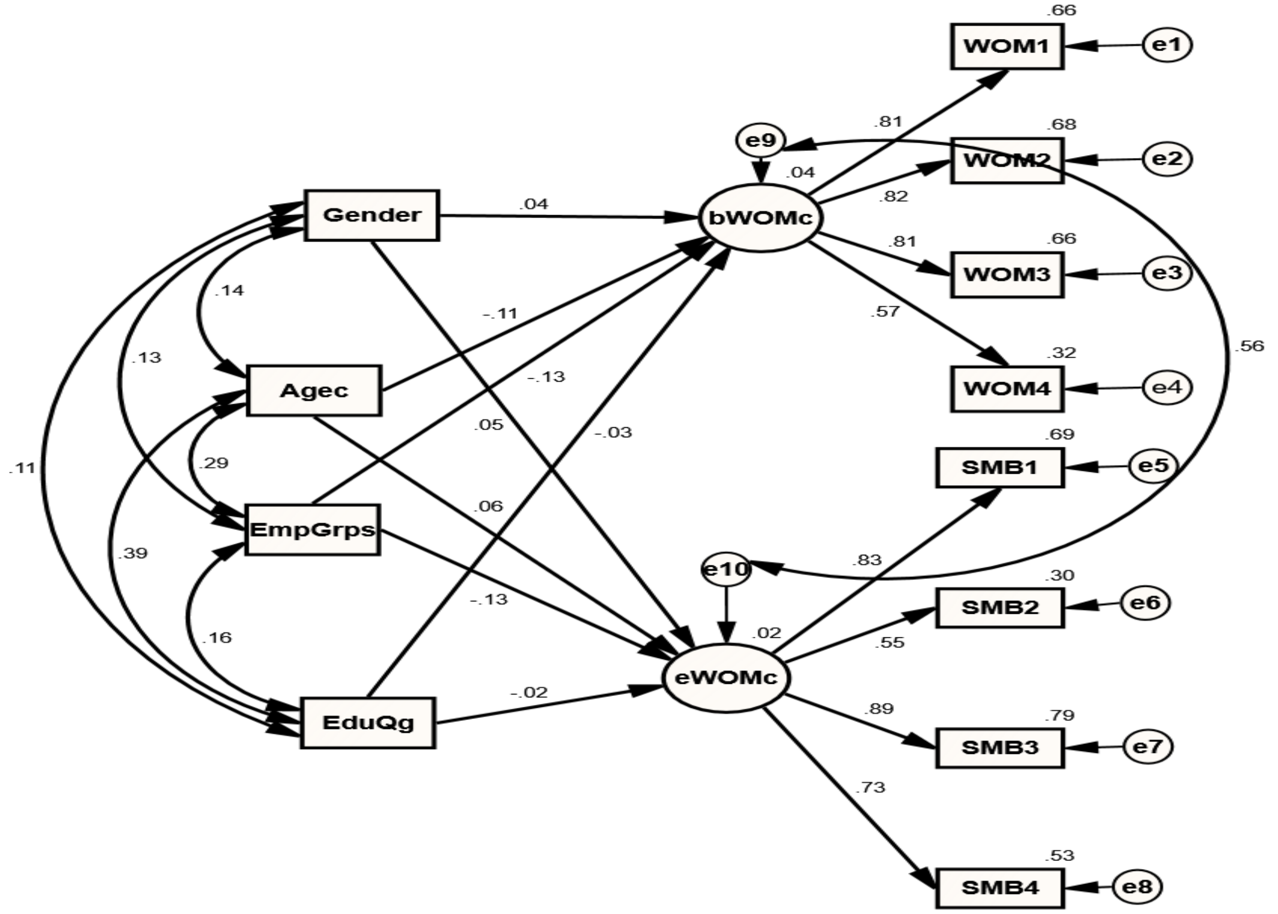

Figure 1. Path diagram showing full MIMIC Model Analysis of Covariates

To examine the Influence of eWOM and bWOM on Purchase Intentions, the factor scores of the WOM domains were obtained from the output of the MIMIC model. The advantage of using the factor scores is that they are robust factor scores controlled for demographic variables (Chang et al., 2020). Figure 2 shows the relationship using the factor scores of eWOM and bWOM on purchase intentions. The analysis showed that eWOM had a stronger effect (β=0.476, p<0.001, C.I-[0.412-0.539]) on the purchase intentions of consumers compared to bWOM (β=0.132, p<0.001, C.I-[0.069-0.199).

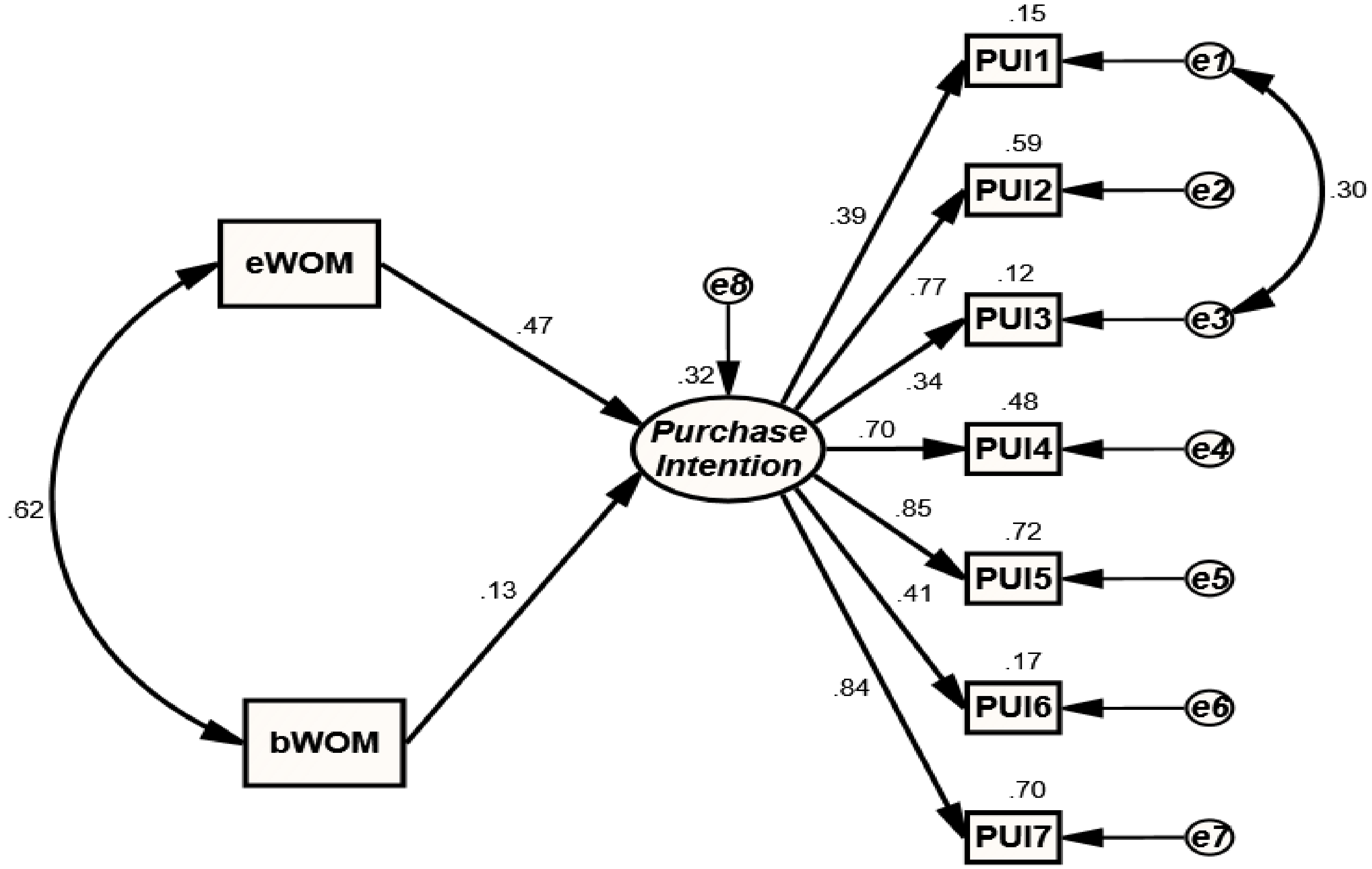

Figure 2. Path analysis showing impact of eWOM and bWOM on Purchase Intentions (controlled for covariates)

Based on the recommendation of Henseler et al (2015), the HTMT value should fall below the strict value of 0.85 to depict truly distinguishable constructs. As shown in Table 6, the values obtained were between 0.455 to 0.628; hence establishing discriminant validity or separability of the constructs.

Assessment of MIMIC model 1

The MIMIC model was assessed for model fit based on set criteria by Hu and Bentler (1999) and recommended by Byrne (2016) namely; relative fit indices such as Comparative Fit Index (CFI>0.90), Tucker Lewis Index (TLI>0.90), and absolute fit indices such as Root Mean Square Error of Approximation (RMSEA≤0.08), and Standardized Root Mean Residual (SRMR≤0.08). As presented in Table 7, the model gave parameter values as follows-CF1=0.975; TLI=0.962; RMSEA=0.048 [C.I. 0.040-0.057], SRMR=0.039.

Table 4. Correlation Relationship between Covariates

Parameter Relationships			coefficient	Lower	Upper	p-value
Gender	<----->	Age	0.138	0.081	0.195	0.001
Gender	<---->	Employment status	0.132	0.073	0.189	0.001
Age	<---->	Employment status	0.293	0.240	0.345	0.001
Age	<---->	Educational status	0.390	0.337	0.443	0.001
Employment status	<---->	Educational status	0.161	0.109	0.215	0.001
Gender	<---->	Educational status	0.112	0.055	0.168	0.001
e9	**<---->**	**e10**	0.561	0.505	0.615	0.001

Table 5. Assessment of Latent Variables					
Constructs	**Indicators**	**Factor loading**	**Cronbach**	**CR**	**AVE**
Word of Mouth (bWOM)	WOM1	0.825	0.833	0.845	0.581
	WOM2	0.813			
	WOM3	0.567			
	WOM4	0.813			
Electronic Word of Mouth (eWOM)	SMB1	0.831	0.834	0.842	0.578
	SMB2	0.549			
	SMB3	0.889			
	SMB4	0.728			
Purchase Intention (PUI)	PUI1	0.392	0.824	0.820	0.420
	PUI2	0.771			
	PUI3	0.341			
	PUI4	0.695			
	PUI5	0.850			
	PUI6	0.410			
	PUI7	0.839			

Assessment of Structural Model (Model 2)

The structural model as presented in Table 8 was assessed for model fit based on a set of criteria by Hu and Bentler (1993) namely; CFI, TLI, RMSEA, and SRMR. The values obtained were within acceptable range; CF1=0.936; TLI=0.908, RMSEA=0.094 [C.I. 0.084-0.104]; and SRMR=0.04. In Table 8, the results showed that eWOM had significantly stronger influence on purchase intentions compared to eWOM.

Table 6. Heterotrait Monotrait Measures			
Constructs	**bWOM**	**eWOM**	**PUI**
bWOM	-		
eWOM	0.628	-	
PUI	0.455	0.538	-

Note. HTMT=Heterotrait Monotrait

DISCUSSION

Using two models developed from the framework of latent variable modeling and cognitive dissonance theory, the study attempts to answer the research questions by exploring the effects of demographic covariates on WOM behavior and the comparative impact of bWOM and eWOM on purchase intentions among consumers of pharmaceutical products. The study is relevant as it provides evidence for policy development for regulatory organizations and insights into consumer information utilization behavior in the healthcare industry.

In the study, the MIMIC Model was used to examine significant differences that existed at the subgroup level (e.g. young vs. older consumers; male vs. female; basic vs.

Table 7. Test of Hypotheses for MIMIC Model							
Parameter Relationships			**path coefficient**	**t-value**	**p-value**	**hypothesis**	**Inference**
Age	----->	bWOM	-0.108	0.081	0.002	**H1a**: supported	younger adults
Age	---->	eWOM	0.065	0.073	0.068	**H1b**: supported	n/a
Gender	---->	bWOM	0.041	0.240	0.203	**H2a**: not supported	n/a
Gender	---->	eWOM	0.054	0.337	0.091	**H2b**: not supported	n/a
Employment status	---->	bWOM	-0.135	0.109	0.001	**H3a**: supported	Unemployed
Employment status	---->	eWOM	-0.131	0.055	0.001	**H3b**: supported	Unemployed
Basic Education	---->	bWOM	-0.031	0.505	0.366	**H4a**: not supported	n/a
Postgraduate Education	---->	eWOM	-0.025		0.475	**H4b**: not supported	n/a

Note. *p* < 0.001, set at t-value greater than 2.560; n/a =not applicable

postgraduate education; employed vs. unemployed) regarding the level of the influence of WOM. From the results of the MIMIC Model in Table 7 (Model 1), the findings of the study showed that gender did not influence WOM; this outcome is in sync with a similar MIMIC study which found no impact of gender on behavioral intention to use technology among teachers in Serbia (Teo & Milutinovic, 2015). This implies that the global trend in technology use marked by increased use of the internet and online social media platforms for interaction by people does not depend on gender disparities (Teo & Milutinovic, 2015). The findings of the study revealed that higher tendency to exhibit bWOM among young adults compared to older consumers with a higher affinity for eWOM albeit not statistically significant. This outcome is corroborated in a study by Frasquet et al (2015) which showed that younger people have a higher tendency to use bWOM compared to eWOM.

Table 8. Test of Hypothesis for Model 2

Direct effects			coefficient	Lower C.1	Upper C.1	p-value	Hypothesis	Inference
bWOM	----->	Purchase İntention	0.132	0.630	0.199	0.001**	H5: supported	positive and significant
eWOM	----->	Purchase İntention	0.476	0.412	0.539	0.001**	H6: supported	positive and significant
Difference in Effects			0.344	0.076	0.177	0.001**	H7: supported	eWOM is stronger

Note. *p* < 0.01, ***p* < 0.001, C.I=confidence interval

Furthermore, the results of the study showed that consumers of pharmaceutical products based on age, and employment status agree on influence of WOM behavior. From the findings of the study, with respect to age, apparently, younger adults are more prone or likely to justify their use of medications by exhibiting WOM behaviors (e.g. sharing experiences about drugs with colleagues more in person than through electronic media) as a way of resolving any form of cognitive dissonance. (Pauli et al, 2023). This approach is similar to MIMIC model used by Teo & Milutinovic (2015) to assess the influence of age and gender on technology use among teachers in Malaysia which found no significant effect. However, in this study, the structural model approach used aligns with the dyadic approach adopted by Kristor et al (2012) on evaluating shared decision-making measures between two groups of patients and physicians.

In the same vein, unemployed participants were more prone to share drug related information through both bWOM and eWOM compared to employed participants. This is probably due to more time available to them to readily share experiences compared to working adults. This finding aligns with the assertion of Hoang & Knabe (2021) that free, non-work time for the unemployed is related to more levels of enjoyment compared to employed persons who had significantly lower levels of enjoyment (Hoang & Knabe, 2021).

In the study, Education level (basic education and postgraduate) did not yield any significant impact on eWOM and bWOM. This is contrary to the findings by Rogers (2003) and Willis and Tranter (2006) who found more educated people to be easy adopters of internet use compared to less educated people. Therefore, the absence of any significant disparity based on education is probably because the study sample was purposively restricted to literate adults.

Therefore, the MIMIC approach used in the study provided more insight into salient sub-group differences in level of perception, among respondents which otherwise would have been missed or ignored (Frazier et al, 2004; Frasquet et al., 2015).

From the structural model (Model 2) in Table 8, it is observed that eWOM had a stronger impact on purchase intentions compared to bWOM. This finding is corroborated by See-To & Ho (2014) and Nieto et al (2014) who asserted that people tend to rely more on eWOM for information and reviews about products or services consumed by others than bWOM. This outcome is apparently due to greater exposure to readily accessible online and social media platforms (Huete-Alcocer, 2017; Luo et al, 2013). Another reason for the higher impact of eWOM on purchase intentions is attributable to the widespread adoption of online social media for communication and preferred exchange of information (Cheung & Thadani, 2012; Hussain et al 2017) compared to direct face to face interaction among individuals.

Furthermore, since purchase intentions leaned more towards eWOM, this finding presents an opportunity for pharmaceutical regulators and marketing firms to use social media platforms to gauge, influence, guide, and support objective assessment of consumers' behavior based on knowledge and perception about medicines (Cantallops & Salvi 2014). Professional groups for community pharmacists should consider piloting ‘online comment websites’ that are accessible and available to the general public. This approach is vastly adopted by hospitality firms to manage public opinion about their goods and services (Vallejo et al., 2015; Huete-Alcocer, 2017). From the professional angle, this strategy would serve as a means of tracking possible trends of drug misinformation and misuse from the general public. These pre-emptive measures are important because (negative and positive feedback and information) resulting from eWOM is rather more difficult to contain or manage in terms of spread and impact than bWOM (Cheung & Thadani, 2012).

Implications of the study

The findings of the study are useful to both researchers and policymakers as it enables them to use demographic information to identify, assess, and address the problems associated with misinformation, and disinformation about drug use through WOM channels. Therefore, MIMIC modeling ensures that researchers ensure that group-specific considerations are prioritized over making universal or blanket policies that do not address specific group interests.

From the perspective of healthcare delivery, consumer behavior as influenced by WOM mechanisms, may impact on how patients' (consumers') adherence to medications prescribed by the physician or recommended by the pharmacist. Social media has great potential to negatively influence consumer attitude and behavior towards medication use as prescribed or tend to try other medications not recommended by authorized health professionals. Therefore, educational measures by local health authorities to provide guidance the general public on medicines or drugs use should be used to public opinion.

Limitations of the study

The focus of this study was principally to examine the effects of demographic variables on WOM; hence, it did not consider measurement invariance of the model based on demographic variables using the differential item functioning approach. The study was restricted to literate respondents, and as a result, the non-literate respondents were not captured in the study. Therefore, extrapolation of findings to the general population should be done with caution. Although the outcome variable-purchase intention was positively influenced by WOM, it does not necessarily predict actual purchase behavior, and hence the gap should be considered in future research studies. Lastly, the study population was mainly accessed through social media and online platforms which may introduce some bias to the sampling process. Hence, generalization of findings should be done with caution.

Conclusion

This study using an integrated model addressed the effects of demographic attributes or covariates on WOM. Based on cognitive dissonance theory, the study provided more insights into the impact of WOM on consumer behavior and serve as a template to inform policy and censorship to support the ethical and appropriate use of information about drugs on social media among consumers of medicines. Gender and educational status covariates did not influence respondents' preferences. Younger customers had a higher preference for bWOM. Unemployed respondents had higher tendency to use bWOM and eWOM compared to employed respondents. Also, eWOM had a stronger effect on purchase intentions compared to bWOM. Policymakers and regulators in the pharmaceutical industry should use knowledge of consumers' demographic disparities and communication preferences in formulating consumer awareness and education programs about proper drug use on print and social media platforms. The study adds to the literature by examining the effects of demographic disparities on preferences by developing an integrated model of WOM among healthcare consumers.

Abbreviations

MIMIC- Multiple-Indicators Multiple-Causes

WOM- Word-of-mouth

bWOM-Face-to-face Word-of-mouth

eWOM- Internet-based Word-of-mouth

PUI- Purchase Intention

CFI- Comparative Fit Index

TLI- Tucker Lewis Index

RMSEA- Root Mean Square Error of Approximation

SRMR- Standardized Root Mean Squared Residual

SEM- Structural equation modeling

Ethical approval: The research includes human participants and the data were collected upon receiving informed consent from the participants.

Consent to participate: The participants were informed the process of research report.

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