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Exploring the Social Media Health Information Seeking Patterns of Rural Residents to Provide Communication Strategies for Extension

Abstract

Communication capacity development is critical for Extension professionals, who work to bring agricultural and health research to the public. With social media being an almost ubiquitous communication channel, it has immense potential as a health communication resource for diverse and rural audiences. The current study, guided by an audience segmentation framework, explored the health communication patterns on social media of rural Georgia residents across demographic characteristics through a non-probability opt-in sampling online survey. Cluster analyses of social media users revealed three distinct groups: low, medium, and high users. Descriptive characteristics of each cluster were presented, to guide Extension health communication practices in rural Georgia. Additionally, inferential statistics revealed a relationship between cluster membership and perceptions of health information on social media: high frequency users were more likely to positively perceive the health information, while low users were more likely to negatively perceive the information. Implications for health promotion and Extension practitioners include using audience segmentation strategies to increase the effectiveness of tailored messages to enhance the success of social media communication for rural residents.

Keywords

cluster analysis, health communication, audience segmentation, Extension, rural outreach

Cover Page Footnote/Acknowledgements

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Authors

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Introduction

Cooperative Extension has intensified its efforts to contribute to the health and well-being of rural communities (Buys & Rennekamp, 2020). With its long-standing history of impacting rural agricultural systems, Extension also has great potential to leverage their social ties in rural areas to enhance public health promotion efforts (Buys & Rennekamp, 2020). However, with the health issues and needs varying immensely across regions in the U.S. (Strayer et al., 2020), communicating with diverse audiences in ways that are relevant and meaningful to their sociocultural realities is paramount. Health communication efforts primarily focus on the transmission and exchange of health information across interpersonal and mass communication channels, with a strong focus on the prevention of health issues related to human behavioral patterns, including diet-related chronic disease (Ishikawa & Kiuchi, 2010; Rimal & Lapinski, 2009; Snyder, 2006). Extension's reputation and history of facilitating behavior change positions it as a key institution to impact rural health (Strayer et al., 2020); however, more research is needed to understand the health communication preferences and information-seeking patterns of rural audiences to promote effective behavior change interventions.

Community-based health promotion, an increasingly-used framework in rural settings, systematically involves community leaders and their social networks, mass communication strategies, and direct education efforts to improve rural health and well-being through preventative interventions (Blackburn, 1983; Merzel & D'Afflitti, 2003). Social media has become a primary communication channel used to access health information (Chen & Wang, 2021), and previous studies have demonstrated the potential for digital and social media strategies to enhance health promotion efforts (Mehmet et al., 2020). Social media is operationalized for the current study as online resources, such as Facebook, Instagram, or Twitter (now known as "X"), designed to facilitate engagement between users (Bishop, 2019). Health promotion communication in community settings has become complex in the wake of COVID-19 (Chen & Wang, 2021; Rains et al., 2020); and increased focus on rural food security in health promotion and communication requires creative campaigns for addressing food insecurity in these regions (Ramadurai et al., 2012). Institutional use of social media for health communication (Thaker et al., 2011; Thackeray et al., 2012) and public perceptions of digital health communication (Reed et al., 2014) vary by population density along the rural-urban continuum, requiring focused research into the development of social media communication strategies to meet the health information needs of rural populations.

Health information-seeking behaviors and desired information varies respectively to the type of health issues and needs demonstrated by the consumer (Zhao & Zhang, 2017). Additionally, consumer trust and perceptions of information and source quality impact motivations to use social media as a health information source (Zhao & Zhang, 2017). Trust for health information frequently refers to cognitive trust, or an individual's belief that a certain media service is trustworthy and dependable, which has been shown to positively impact health-information seeking behavior (Pang & Liu, 2023)Motivation related to specific health issues, such as obesity, and an individual's response to the issue will further help predict health information seeking patterns for health communication (Choi & Noh, 2021). Additionally, health literacy issues complicate the landscape of health communication. Health literacy is the ability with which individuals can obtain and understand health information needed to make informed health decisions (Ratzan & Parker, 2000). Health literacy can have a large impact on health behaviors and outcomes (Ishikawa & Kiuchi, 2010), making it an important consideration for Extension's digital health communication efforts.

The strategic use of social media by organizations, such as Extension, may help increase health communication outreach with underserved and underreached populations (Wallace et al., 2021); however, more research is needed on the potential of social media campaigns among underrepresented and underreached populations to ensure the efficacy of these campaigns (Vereen et al., 2021). Social media has the potential to serve as a key component of Extension outreach, yet remains a limited aspect of rural Extension communication strategies (Son et al., 2019), leaving a gap in both literature and practice. Additionally, communication competencies for Extension agents working with rural populations are lacking and are identified as one of their top professional development needs within the literature (Berven et al., 2020). According to Das et al. (2015), Extension agents are encouraged to use internet resources as a dimension of their communication strategies for health-related information dissemination to improve community and economic development in rural areas. Due to limited research investigating the intersection of Extension outreach and social media use, as well as the Extension imperative to increase access to information for individuals' and communities' health and wellbeing (Braun, 2012), more research is needed to define strategies for rural health communication through social media.

Engaging audiences through targeted messaging strategies is one of the biggest challenges facing communication practitioners, especially due to the complexity of creating effective communication strategies, selecting the right media channels, and understanding the diverse individual and group preferences, beliefs, and values within a targeted audience (Dobbins et al., 2021; Lamm et al., 2019). Sociocultural preferences, beliefs, and norms also impact individuals' health behaviors (Savage et al., 2017) and the communication they prefer to receive surrounding health topics (Kreuter et al., 2004). Selecting the most effective communication channel for a specific audience is rife with challenges and remains understudied in the agricultural and Extension literature (Holt et al., 2015; Lamm et al., 2019).

Previous research has demonstrated the effectiveness of social media for rural health communication, specifically for adolescent mothers (Logsdon et al., 2015) and recipients of mental health services (Mehmet et al., 2020). Additionally, demographic trends for those more likely to seek health information online include more women than men (Pew Research Center, 2010) and those with higher educational attainment (Weaver et al., 2009). Health status has not been identified as a predictor for seeking online health information (Xiao et al., 2014), indicating a need for increased demographic explorations of online (specifically social media) health communication information-seeking patterns of rural residents.

Effective communication is key to successful community-university research and outreach partnerships, specifically when addressing groups with diverse characteristics (Palmer-Wackerly et al., 2020). Aspects of cultural identity impact people's interactions with science communication messages online, specifically on social media (Dobbins et al., 2021). Additionally, health communication is a social and relational process, even within digital communication channels (Anker et al., 2011). Media, including social media, does not have a direct impact on behavior - it is largely mediated by interpersonal communication factors that impact types of information sought and subsequent interpretations of that information (Anker et al., 2011). Extension is uniquely positioned to interact with the interpersonal communication pathways due to its positioning within social systems in nearly every county in the land-grant system (Seevers & Graham, 2012). Additionally, several scholars have identified interpersonal skills as a key competency for Extension agents (Harder et al., 2010; Lakai et al., 2014; Kurtzo et al., 2019). Social media, as an evolving communication channel, has changed the environment of what is considered interpersonal communication, allowing individuals to share information and social connections through digital media that would have previously been shared privately or face-to-face (Subramanian, 2017). Due to social media's potential for facilitating interpersonal communication, Extension can capitalize on its capacity for interpersonal communication and extend that capacity to the interpersonal potential of social media communication. Thus, the current study explored rural Georgia audiences' perceptions of social media as a health information source with implications for Extension health promotion efforts. The current study provides critical insights into the health communication preferences of rural audiences in order for Cooperative Extension to most effectively reach these audiences and enhance their quality of life.

Conceptual Framework

Audience segmentation (Slater, 1996) is a framework frequently used in social marketing literature to increase communication effectiveness by creating messages targeted at specific audiences (Gibson et al., 2021; Grunig, 1989; Kopfman & Smith, 1996; Lee & Kotler, 2011). Audience segmentation is a critical initial step in the creation of strategic, effective communication campaigns with intended outcomes of increased knowledge, modified attitudes, or enduring behavior changes (Slater, 1996). Tailoring messages, including communications channels used, to meet the needs of and accessibility to specific audiences is critical to ensure communication campaigns and strategies are responsive to intended audiences and their specific needs (Kopfman & Smith, 1996; Lamm et al., 2019; Slater, 1996). Tailoring of messages often occurs based upon an audience's demographics, attitudes, opinions, and psychographics (Grunig 1989; Slater, 1996) The distinctions that exist between segmented audience groups (Hine et al., 2014) allow meaningful audience clusters to form and empower social marketing practitioners to focus their campaign efforts on the audience clusters most likely to take action or change behaviors as a result of campaign influence (Andreasen, 2006). Messaging targeting and tailoring allows for personalized campaigns that can encourage behavior change within the complex realm of health behavior change, even amidst varying budgets and resources available to social marketing organizations (Schmid et al., 2008) such as Extension.

Social marketing aligns with the goals of Extension education as a tool for implementing strategic behavior change through an audience- and evaluation-centered approach (Chaudhary et al., 2017; Warner et al., 2016). As such, audience segmentation is a useful framework for Extension to strategically share scientific information with a number of diverse population segments. Byrd et al. (2023) used audience segmentation to suggest reaching international audiences with Extension science communication by featuring international scholars on platforms culturally aligned with communication preferences of diverse audiences. Findings revealed international scholars received higher engagement levels on Instagram rather than Twitter (Byrd et al., 2023). Lamm et al. (2019) determined communication preferences of opinion leaders based upon their ages, genders, education levels, organizational levels, and regions, finding dedicated web pages and blogs to be the preferred communication source for opinion leaders. Preferences for Facebook group communication saw significant differences according to age and organizational level, and LinkedIn was the preferred communication for opinion leaders under 30 and those in non-supervisory roles (Lamm et al., 2019). Using audience segmentation as a guiding framework, Carroll et al. (2022) identified the communication preferences of Extension clientele. The results indicated the best way to reach Extension clients under the age of 50 was through the internet and through social media, while preference for internet communication did tend to decrease as age increased (Carroll et al., 2022).

Additionally, several studies have broadly examined the use of social media as a communication channel for Extension agents to connect with farmers in countries like Mexico (Aguilar-Gallegos et al., 2021) and Trinidad and Tobago (Moonsammy & Moonsammy, 2020). Aguilar-Gallegos et al. (2021) conducted a social network analysis and found Twitter an effective social network for sharing and disseminating information from an agricultural research station. Moonsammy and Moonsammy (2020) found farmers had little training on social media but were still able to use the internet and technology and, therefore, social media possessed potential as an information sharing tool for Extension agents. However, few studies have empirically examined social media channel use coupled with communication channel preferences and information-seeking behaviors for U.S. rural audiences, especially related to health communication.

Purpose and Research Objectives

The purpose of the current study was to examine potential relationships between social media communication channels used, health communication information-seeking habits, and demographic characteristics of rural Georgia residents. The following research objectives guided the study:

1. Describe the social media health communication information-seeking habits of rural Georgia residents;
2. Identify distinct clusters of rural Georgia residents based on their level of social media use for health information seeking habits;
3. Examine associations between respondent demographics and levels of social media use for health information seeking habits;
4. Determine if differences exist between cluster membership and health communication information-seeking habits on social media.

Methods

The quantitative study presented here was part of a larger research endeavor to assess the Extension resource and health communication needs of rural audiences in Georgia. The research design consisted of an online survey of rural Georgia residents in which respondents self-reported health communication behaviors, including information-seeking on social media and demographic characteristics.

Data Collection

Data were collected via a non-probability opt-in sampling survey via Qualtrics, an online survey platform, in November of 2022. Public opinion research often uses non-probability sampling techniques to make population estimates that scholars have found to be greater than or equal to estimates from probability sampling (Baker et al., 2013), as well as help create targeted and effective Extension programs (Lamm & Lamm, 2019). Respondents were recruited through

Qualtrics and compensated according to the company's standard protocols. Qualtrics recruited respondents from the 120 out of the 159 Georgia counties classified as rural (Powell, 2022; State Office of Rural Health, 2021). One key limitation to surveying via an online platform is that it limits response participation to those who have access to the internet, which can increase sampling bias (Gibson et al., 2021). This limitation is important to consider in the results presented in the current study, as only rural residents with internet access could participate in the study.

Instrument

Data were collected through check-all-that-apply questions and Likert-type scale questions for health information-seeking behavior on social media. Respondents were asked to indicate which of the following social media platforms they used, including Facebook, Instagram, Snapchat, Twitter, TikTok, other, and none. Respondents who selected none were removed from the analysis. If respondents indicated they used one of the social media platforms, they were subsequently asked the frequency with which they used social media platforms on a seven-point, Likert-type scale questions with response items including 1 – *never*, 2 – *less than once a week*, 3 – *once a week*, 4 - *several times a week*, 5 – *about once a day*, 6 – *several times a day*, and 7 – *almost constantly*.

Another question asked about the use of social media for seeking health information, which was measured through a five-point, Likert-type scale ranging from 1 – *strongly disagree* to 5 – *strongly agree*. Respondents were allowed to select not applicable if an item did not apply to them. Statements included whether or not social media makes it easy to access health information, whether the respondent used social media for health information, whether social media was helpful or useful for accessing health information, whether social media provided trustworthy health information, and whether respondents used social media to communicate with others about health information. Data for demographic questions were collected through check-all-that-apply questions for race and multiple-choice questions for gender, ethnicity, age, marital status, and education level.

A panel of experts in agricultural and natural resource communication, nutrition, health promotion, Extension education, and survey design reviewed the instrument for face and content validity prior to pilot testing. The research design was then approved by the University of Georgia Institutional Review Board (PROJECT00006293). The instrument was pilot tested (n = 20) with individuals who were representative of the sample through Qualtrics. All scales in the present study were deemed reliable ($\alpha > 0.70$; Cortina, 1993), and the instrument was not changed after the pilot test, due to accuracy of the measurement scales.

Data Analysis

Data were analyzed using descriptive statistics, a cluster analysis, and inferential statistics using SPSS version 26. Specifically, hierarchical and K-means cluster analyses were used to identify distinct groups of respondents who could be categorized as low, medium, and high social media users. Cluster analyses are data reduction techniques that allow researchers to organize large data sets into smaller segments, or maximally dissimilar groups, based on response patterns in the data (Burns & Burns, 2008; Salmon et al., 2006; Yim & Ramdeen, 2015). Cluster analyses can help segment members of a sample or population into classificatory groups, reflecting audience segmentation practices, to increase the effectiveness of communication strategies and campaigns (Essary et al., 2022). Previous studies have implemented cluster analyses to determine distinct audience segments in the social sciences (Gibson et al., 2021; Warner et al., 2016) as well as health information and communication (Bennasar-Veny et al., 2020; Mackert & Walker, 2011; So et al., 2022).

A cluster analysis was conducted on the frequency of social media use items. First, a hierarchical cluster analysis (HCA) was run using Ward's method with Squared Euclidean Distance, which is used when the number of clusters should be identified, to determine how many subgroups would represent maximum dissimilarity within the data (Yim & Ramdeen, 2015). Ward's method tends to create similarly sized clusters but may be susceptible to outliers (Essary et al., 2022; Everitt et al., 2011). The number of subgroups were identified based on the largest distance between clusters, or vertical lines, on the dendrogram (Yim & Ramdeen, 2015). A K-means cluster analysis was then run, based on the subgroups/cluster identification in the HCA, using Ward's method (Burns & Burns, 2008; Gibson et al., 2021; Warner et al., 2016). Maximum iterations were adjusted from 10 to 99 to avoid early convergence (Gibson et al., 2021), and convergence was achieved after 13 iterations. Cluster descriptions (low, medium, or high frequency social media use) were determined through the means of each cluster membership category. Chi-squared tests of association were completed to test for associations between demographic characteristics and the three clusters identified (high, medium, and low frequency of social media use), using Cramer's V (Φ) to describe effect size based on degrees of freedom (Cohen, 1988). Mean scores were computed using series means for missing data in the social media for health information items followed by an Analysis of variance (ANOVA) to determine if significant differences existed between cluster membership and perceptions of social media for health information.

Respondent Demographics

A total of 780 rural Georgia residents completed the survey. Qualtrics recruited respondents from zipcodes in Georgia identified as rural (Powell, 2022; State Office of Rural Health, 2021). Table 1 presents demographic frequencies and percentages for respondents. A majority of respondents identified as White (75.6%) and female (69.6%), were between 30 and 59 years old (59.7%), and either received a high school degree/GED or completed some college (61.2%; see Table 1).

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Table 1

*Demographic Characteristics of Respondents (*N *= 780)*

Demographic Characteristic		***F***	**%**
Gender	Female	543	69.6
	Male	237	30.4
Ethnicity (Hispanic/Latinx/ Chicanx)	No	748	95.9
	Yes	32	4.1
Race	White	590	75.6
	Black/African American	179	22.9
	American Indian or Alaskan Native	17	2.2
	Other	8	1.0
	Asian or Pacific Islander	6	0.8
Age	18-19	17	2.2
	20-29	99	12.7
	30-39	207	26.5
	40-49	132	16.9
	50-59	127	16.3
	60-69	131	16.8
	70-79	54	6.9
	80+	13	1.7
Marital Status	Married	308	39.5
	Single	200	25.6
	Divorced	99	12.7
	Living with a partner, not married	91	11.7
	Widowed	47	6.0
	Separated	35	4.5
Employment	Full-time	274	26.2
	Part-time	69	8.8
	Retired	146	18.7
	Self-employed	71	9.1
	Student	19	2.4
	Unemployed, looking for work	87	11.2

	Unemployed, not looking for work	114	14.6
Income	Less than $19,000	204	26.2
	$20,000 - $39,999	224	28.7
	$40,000 - $59,999	142	18.2
	$60,000 - $79,999	54	6.9
	$80,000 - $99,999	59	7.6
	$100,000 - $119,999	45	5.8
	$120,000 or more	52	6.7
Receives SNAP Benefits	Yes	319	40.9
	No	441	56.5
	Unsure	20	2.6
Receives WIC Benefits	Yes	107	13.7
	No	668	85.6
	Unsure	5	0.6
Educational Level	Less than high school	41	5.3
	High school or GED	283	36.3
	Some college	194	24.9
	Associate's degree	93	11.9
	Bachelor's degree	99	12.7
	Graduate degree (master's, doctorate)	70	9.0

Note. SNAP = Supplemental Nutrition Assistance Program; WIC = SNAP Women, Infant, Children.

Results

Findings are presented below according to each of the four research objectives. First, descriptive statistics are presented, followed by the cluster analysis, addressing research objectives one and two. Then, non-parametric and parametric inferential statistics are presented to address research objectives three and four.

Social Media Health Communication Habits

Respondents who indicated they used social media (n = 722) and therefore addressed the frequency of social media items in the survey were clustered based on frequency of using social media. The platforms included: Facebook, Instagram, Snapchat, Twitter, and TikTok (Table 2). The majority of respondents used Facebook at least once per day (66.2%). Facebook use also had the highest mean score, while Twitter use had the lowest mean score (Table 2). Almost half of respondents indicated they used Instagram (45.1%) and TikTok (47.3%) at least once per week. A majority of respondents indicated they never used Snapchat (50.9%) or Twitter (55.8%).

Table 2

*Respondents Self-Reported Frequency of Social Media Use (*N *= 722)*

Social Media Platform	Never %	Less than Once a Week %	Once a Week %	Several Times a Week %	About Once a Day %	Several Times a Day %	Almost Constantly %	*M(SD)*
Facebook	4.5	4.5	6.0	11.4	15.4	34.9	15.9	5.13(1.63)
TikTok	37.4	7.8	3.7	7.8	8.2	17.3	10.3	3.37(2.34)
Instagram	39.7	7.8	7.1	8.2	8.5	14.2	7.1	3.09(2.20)
Snapchat	50.9	5.5	4.4	7.7	7.4	10.8	5.9	2.69(2.15)
Twitter	55.8	7.8	5.4	5.3	6.0	7.2	5.1	2.35(2.00)

Note. Scale ranged from 1 = *never* to 7 = *almost constantly*.

Respondents were asked to indicate their level of agreement or disagreement with several statements related to using social media for accessing health information (Table 3). The largest level of agreement for all response items was neither agree nor disagree. A total of 51.1% of respondents agreed or strongly agreed social media made it easy to access health information, while 50.2% agreed or strongly agreed social media was useful for accessing health information. A total of 36.6% of respondents agreed or strongly agreed they used social media to stay informed of health information, and 37.6% used social media to learn about health information. Response items with which more respondents disagreed or strongly disagreed than agreed or strongly agreed included relying on social media to get the majority of their health information (44.0%) and learning about health information on social media impacts their health decisions (35.4%). A total of 32.3% of respondents disagreed or strongly disagreed they trusted health information on social media, compared to 29.5% who agreed or strongly agreed. Finally, roughly equal percentages of respondents disagreed or strongly disagreed (33.8%) and agreed or strongly agreed (33.5%) that they used social media to communicate with others about health information. Respondents could select “not applicable” if they did not use social media. Items with the highest mean score included “social media makes it easy to access health information” and “social media is useful for accessing health information” (Table 3). Items with the lowest mean score included “I rely on social media to get the majority of my health information”, followed by “what I learn on social media about health information impacts the decisions I make in my life” (Table 3).

Table 3

*Respondents' Level of Agreement with Use of Social Media for Accessing Health Information (*N *= 722)*

Social Media Platform	Strongly Disagree %	Disagree %	Neither Agree nor Disagree %	Agree %	Strongly Agree %	N/A %	*M*(*SD*)*
Social media makes it easy to access health information	5.5	9.7	31.2	29.8	21.3	2.5	3.49(1.08)
Social media is useful for accessing health information	6.8	12.6	28.5	29.1	21.1	1.9	3.42(1.14)
I use social media to stay informed of health information	12.6	20.4	27.7	21.6	15.0	2.8	3.01(1.22)
I use social media to learn more about health information	11.5	20.2	28.8	21.9	15.7	1.9	3.05(1.22)
I rely on social media to get the majority of my health information	18.7	25.3	27.6	15.5	10.5	2.4	2.69(1.21)
Social media is useful to access health information	10.2	13.9	28.7	29.9	15.5	1.8	3.21(1.18)
What I learn on social media about health information impacts the decisions I make in my life	15.7	19.7	31.9	18.4	11.6	2.8	2.87(1.19)

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I trust the information I obtain from social media sources about health information	14.8	17.5	35.6	19.3	10.2	2.6	2.88(1.17)
I use social media to communicate with others about health information	13.6	20.2	29.8	21.9	11.6	2.9	2.95(1.18)

Note. Scale used ranged from 1 = *strongly disagree* to 5 = *strongly agree*. N/A = respondents selected "not applicable". *Means and standard deviations are reported for the mean imputed items.

Cluster Analysis

Three distinct audience segments were identified through the cluster analysis (see Figure 1). Cluster one represented low frequency social media users (*n* = 334), cluster two represented medium frequency social media users (*n* = 231), and cluster three represented high frequency social media users (*n* = 157). Cluster 3 had higher means across groups for all social media channel use (Table 4).

Figure 1

Dendrogram using Ward's Linkage for Social Media Use Frequency Cluster Analysis

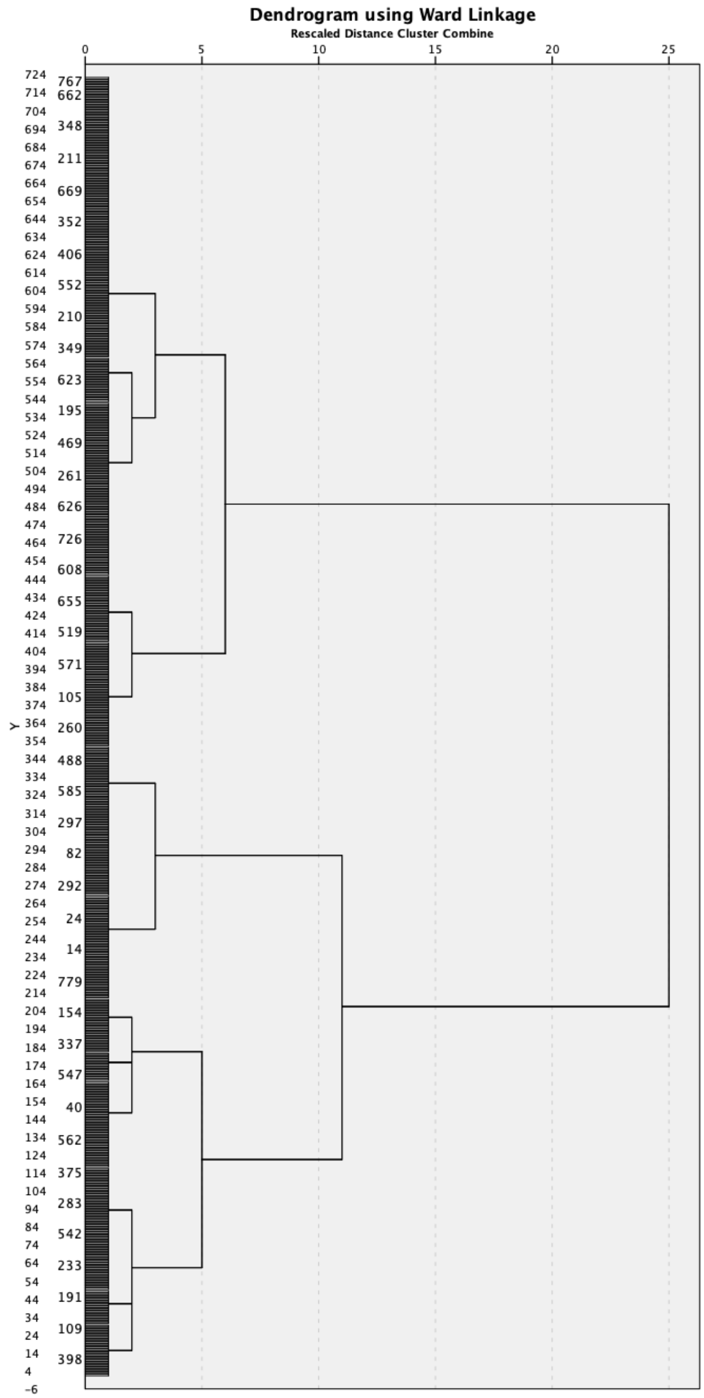

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Table 4

Mean Social Media Channel Use across Clusters

Social Media Channel	Cluster 1 (Low Users)		Cluster 2 (Medium Users)		Cluster 3 (High Users)	
	M	***SD***	***M***	***SD***	***M***	***SD***
Facebook	4.74	1.598	5.29	1.576	5.73	1.547
Instagram	1.71	1.300	2.23	1.965	5.84	1.201
Snapchat	1.25	0.782	3.12	2.058	5.13	1.782
Twitter	1.53	1.167	1.48	1.008	5.37	1.512
TikTok	1.29	0.669	4.87	1.659	5.59	1.649

Note. Scale used was 1 = *never*, 2 = *less than one a week*, 3 = *once a week*, 4 = *several times a week*, 5 = *about once a day*, 6 = *several times a day*, and 7 = *almost constantly*.

Associations between Respondent Demographics and Cluster Membership

There were observed associations between sex, ethnicity, race, age, marital status, employment, income, receives Women, Infant, Children (WIC) benefits, and education level (Tables 5, 6, and 7). Cramer’s V (Φ) effect sizes were calculated for each significant association. Several associations had a large effect size, including the associations between cluster membership and age (Table 5); employment (Table 6); marital status (Table 6); and educational level (Table 6). Medium effect sizes included associations between cluster membership and race (Table 5) and cluster membership and receiving WIC benefits (Table 7). Small effect sizes were observed for associations between cluster membership and sex and cluster membership and ethnicity (see Table 5). The only demographic characteristic for which there was no significant association with cluster membership was receiving SNAP benefits (see Table 7).

Table 5

Chi Squared Analyses of Demographic Characteristics and Cluster Membership – Sex, Ethnicity, Race, and Age

Demographic Characteristic	**Cluster 1 (Low) %**	**Cluster 2 (Medium) %**	**Cluster 3 (High) %**	$\chi2$	∪
Sex				10.731*	.12[a]
Female	68.9	77.9	63.1		
Male	31.1	22.1	36.9		
Ethnicity (Hispanic/ Latinx/Chicanx)				12.536*	.13[a]
No	97.9	96.1	91.1		
Yes	2.1	3.9	8.9		
Race				39.901***	.17[b]
White	82.3	73.7	59.2		
Black/African American	13.8	25.5	36.9		
American Indian or Alaskan Native	0.6	0	1.3		
Other	0.6	0.9	0.6		
Asian or Pacific Islander	0.3	0.3	0.0		
Mixed Race	2.4	1.7	1.9		
Age				226.077***	.40[c]
18-19	0.3	3.5	4.5		
20-29	3.3	16.9	29.3		
30-39	16.2	35.1	38.9		
40-49	15.3	21.6	17.2		
50-59	20.4	14.3	8.3		
60-69	29.0	5.6	1.3		
70-79	13.2	1.7	0.6		
80+	2.4	1.3	0.0		

Table 6

Chi Squared Analyses of Demographic Characteristics and Cluster Membership – Marital Status, Employment, Income, and Educational Level

Demographic Characteristic	Cluster 1 (Low) %	Cluster 2 (Medium) %	Cluster 3 (High) %	$\chi 2$	∪
Marital Status				58.469***	.20[c]
Single	20.1	32	29.3		
Married	41.3	29.9	45.9		
Living with a partner, not married	8.1	16.9	14.6		
Divorced	17.4	12.6	4.5		
Separated	3	5.2	4.5		
Widowed	10.2	3.5	1.3		
Employment				143.600***	.32[c]
Full-time	25.1	38.5	57.3		
Part-time	5.1	12.1	11.5		
Retired	32.3	7.8	0.6		
Self-employed	6.6	11.7	11.5		
Student	1.3	2.6	4.5		
Unemployed, looking for work	11.4	13.9	8.9		
Unemployed, not looking for work	18.3	13.4	5.7		
Income				40.399***	.17[c]
Less than $19,999	29.3	28.1	17.8		
$20,000-39,999	29.3	29.4	24.2		
$40,000-59,999	17.1	23.4	15.3		
$60,000-79,000	6.9	5.2	8.9		
$80,000-99,999	6.9	6.5	28.3		
$100,000-119,999	4.2	3	13.4		
$120,000 or more	6.3	4.3	10.8		
Educational Level				43.403***	.17[c]
Less than high school	5.7	6.5	2.5		
High school or GED	35.9	41.6	31.2		
Some college	26	30.3	17.8		
Associate's degree	13.5	6.9	12.1		
Bachelor's degree	9.3	10.8	21.7		
Graduate degree (master's, doctorate)	9.6	3.9	14.6		

Table 7

Chi Squared Analyses of Demographic Characteristics and Cluster Membership – Receives SNAP Benefits and Receives WIC Benefits

Demographic Characteristic	Cluster 1 (Low) %	Cluster 2 (Medium) %	Cluster 3 (High) %	$\chi 2$	◡
Receives SNAP Benefits				14.348	
Yes	35.3	47.6	47.8		
No	62.9	49.8	48.4		
Unsure	1.8	2.6	3.8		
Receives WIC Benefits				47.390***	.18[b]
Yes	6.3	14.7	29.3		
No	93.1	84.4	70.1		
Unsure	0.6	0.9	0.6		

Audience Cluster Demographic Profiles

The cluster analyses revealed demographic trends for low, medium, and high social media users. All clusters were predominantly female and White, due to the sample characteristics. Cluster 1 (low users) members were least likely to identify as Hispanic/Latinx/Chicanx and Black/African American; however, they were the most likely to identify as Mixed Race. Members of Cluster 1 mostly ranged in age between 50 to 69 and predominantly had either high school/GED or had completed some college. Additionally, members of Cluster 1 were least likely to be employed full time with the majority having an income below $40,000 while being least likely to receive WIC benefits. While all clusters predominantly consisted of respondents who were married, respondents in Cluster 1 were most likely to be divorced or widowed.

Members of Cluster 2 (medium users) were most likely to identify as female and most likely to identify their race as “Other.” Cluster 2 members were most likely to be between 30 to 49 years old, most likely to be single, and most likely to work part-time/unemployed but looking for work. A majority of cluster members made between $19,999 and $39,999, were most likely to have completed either less than high school, high school/GED, or some college.

Cluster 3 (high users) members were least likely to identify as female, most likely to identify as Hispanic/Latinx/Chicanx, and most likely to identify as Black/African American (Table 4). The majority of members of Cluster 3 were between 20 and 39 years old. Cluster 3 members were most likely to be married, least likely to be divorced, and most likely to have a full-time job. A majority of cluster members made between $20,000 and $39,999 or $80,000 and $99,999, and were most likely to receive WIC benefits. Finally, members of Cluster 3 were least likely overall to have a high school degree/GED and most likely overall to have received either a Bachelor’s or Graduate degree.

Cluster Membership and Perceptions of Social Media for Health Information

A one-way ANOVA was run to determine if differences existed between cluster membership and perceptions of social media for health information (n = 722). The social media for health information scale was created into a construct of the associated items, creating an approximately continuous variable. Respondents who selected not applicable for any social media health information items received a mean score. The one-way ANOVA demonstrated that cluster membership was significant for perceptions of social media for health information, $F(2, 721) = 46.92$, $p < .001$. Eta-squared equaled .115, indicating a small effect size. Post-hoc analyses through Bonferroni tests revealed differences between cluster membership group means. Cluster 1 (low; n = 334, M = 2.83, SD = .95) had a lower mean than Clusters 2 (medium; n = 231, M = 3.11, SD = .88) and 3 (high; n = 157, M = 3.69, SD = .91), indicating members of Cluster 1 had an overall more negative perception of social media for health information. Cluster 3 had a higher mean than Clusters 1 and 2, indicating members of Cluster 3 had a more positive perception of social media for health information. Cluster 2 had a higher mean than Cluster 1 and a lower mean than Cluster 3, indicating members of Cluster 2 had a more positive perception of social media for health information than Cluster 1 but a more negative perception than Cluster 3.

Conclusions, Implications, and Recommendations

A majority of respondents indicated they primarily used Facebook as a social media channel. Most respondents agreed or strongly agreed social media made it easier to access health information; thus, social media may increase access to health information for underreached rural audiences, which supports previous research (Wallace et al., 2021). However, fewer respondents agreed social media information impacted their health decisions or was a major resource for accessing health information. Thus, while social media may increase the accessibility of health information, the utilization and distribution of social media health information for personal use and across social networks remains limited in this study. Additionally, respondents on average indicated they neither agreed nor disagreed with the statement “What I learn on social media about health information impacts the decisions I make in my life,” indicating a need for more research about the impacts of health information campaigns on social media and their relationship to behavior change in rural areas.

Demographic profiles for low, medium, and high social media users were revealed through the Chi Square analyses. All but one demographic characteristic (receives SNAP benefits) demonstrated significant associations within each cluster. Important to note for the current analyses is that respondents were asked to select if they used social media channels, and if they said no, they were excluded from the social media frequency analyses. Members of all three clusters were only respondents who reported using at least some social media, not those who do not use social media and should be recognized as a limitation to the study. Thus, demographic profiles should be considered as those who use at least some social media, not those who do not use social media at all. The exclusion of non-users of social media is a limitation to the study both from an instrument perspective as well as a research design perspective due to being an online survey. However, audience segmentation strategies are important for all communication campaigns (Slater, 1996; Lamm et al., 2019), both on and offline. Thus, understanding the demographic characteristics of those who use the selected communication channel is important for creating strategic and targeted messaging strategies.

Members of Cluster 3 were the most likely to have a positive perception of social media for health information, which included the information being more accessible, more trustworthy, and making it easier to communicate with others about health information. Cluster 3 members were high frequency users of social media, indicating those who use social media the most in rural areas were the most likely to positively perceive health information on social media. Cluster 1 members were low frequency social media users, indicating low users have the most negative perceptions of health information on social media. Cluster 2 members were medium frequency users, and had more positive perceptions of social media health information than Cluster 1 and a more negative perception than Cluster 3. Thus, findings indicated that increased use of social media in rural areas increased potential positive perceptions of health information on social media. These findings support previous research indicating women and those with higher education attainment are more likely to seek health information online (Pew Research Center, 2010; Weaver et al., 2009), with members of Cluster 2 more likely to be women and and Cluster 3 members being more likely to have obtained advanced educational degrees, both having more positive perceptions of social media health information. Social media health communication campaigns in rural areas should target high social media users for the most effective campaigns, but also communicate to women specifically who may have the most positive perceptions of social media health information despite being a lower frequency user. Low users (Cluster 1) may need more evidence of source credibility to enhance trustworthiness of information on social media. Low users of social media may also experience limited access to the internet, which could limit the usability of social media for accessing health information. Future research should explore the components of social media perceptions across low, medium, and high users of social media to increase evidence for communication campaigns using social media in rural areas. Additionally, health literacy, while not directly assessed in the current study, may impact low, medium, and high cluster members' perceptions of digital health communication messages, serving as a confounding variable. Future studies should incorporate health literacy scales to model its relationship with cluster membership.

Understanding the demographic characteristics of those who use selected communication channels and their perceived trust in those sources is important for creating strategic and targeted messaging strategies for Extension aligning with audience segmentation techniques. In addition to the perception of social media health information, demographic characteristics can also impact the interpretation and perceptions of the messaging strategies. For example, people are drawn to those with similar identity characteristics on social media (Dobbins et al., 2021); thus, using messaging strategies that use personas more aligned with cluster member demographics may increase message uptake. Tailored messaging strategies using audience segmentation is critical to ensure health communication campaigns meet intended objectives and resonate with target audiences (Kopfman & Smith, 1996; Lamm et al., 2019; Slater, 1996).

Targeted campaigns could be used to reach Cluster 3, high social media users, while considering their additional demographic characteristics. For example, communications professionals should consider the racial makeup of high social media users who were most likely to identify as Hispanic/Latinx/Chicanx and most likely to identify as Black/African American. Though rural audiences may be predominantly White in Georgia, it is important to consider the health communication nuances associated with race. For example, targeted communication considering elements of religion, pride in one's race, collectivism, and perception of time were considered effective in reaching African American women with cancer prevention information (Kreuter et al., 2004). Therefore, strategic campaigns could tailor culturally appropriate social media messages for Cluster 3 members based on racial background factors. Individuals from Hispanic/Latinx/Chicanx cultures tend to be more concerned with the good of the group or the family because of collectivistic cultural values. Therefore, social media health information targeted at the Hispanic/Latinx/Chicanx audiences in Cluster 3 may use appeals that focus on how healthy practices can benefit the entire family, rather than just individuals. Yet another factor to consider in strategic campaign creation is the employment status. Cluster 3 also contained the youngest grouping of respondents. Previous research demonstrated that younger generations are more likely to trust health information online (Lin et al., 2016), indicating digital campaigns may be more effective with this group. However, trust is not always correlated with health literacy, with relationships between health literacy and trust in online social media health information can vary across demographic groups and communication channels (Paige et al., 2017). Thus, increased research is needed to more fully explore the relationship between trust, health literacy, and social media health communication within each cluster.

Because Cluster 3 respondents were most likely to be employed full-time , social media campaigns could focus on posting on social media during lunch hours or after the close of a business day while additionally incorporating suggestions for health behavior change that are tailored to those with a lack of free time during the day. Perhaps messaging such as, “It’s okay to take your sick leave to have an annual checkup. Your family will thank you for taking care of your health,” would be appropriate given the stated demographic characteristics if the campaign was based around keeping medical appointments amidst a busy work schedule. Because Cluster 3 was most likely to have received both a Bachelor’s or Graduate degree, targeted messaging to this group could use more advanced or technical language than for the other clusters. Finally, some members of this group were most likely to receive WIC benefits, indicating campaign communications should also consider audience members who may benefit from additional knowledge about social services available to help achieve health goals.

The findings of the current study should be interpreted in light of potential limitations. The sampling frame of the study only included the state of Georgia, so results should not be generalized beyond the target population. However, results may be informative for states with similar demographics as Georgia, and replication studies are encouraged to further test and refine the findings and broader implications. Definitions of rural audiences vary, and some participants may have lived in rural areas that might be considered peri-urban and thus have different lived experiences and influential factors than more geographically isolated rural areas. The use of Powell’s (2022) operationalization of rural counties in the state was meant to mitigate any sampling areas to the greatest extent possible.

Future research should explore more than just social media use, but rather the values, beliefs, and attitudes toward health information and communication across demographic segments of rural residents in Georgia and other states/countries to assist in the development of tailored Extension messages. Qualitative studies, either through interviews or focus groups, could help explore the nuances related to social media message reception according to audience members' cultural values, beliefs, and attitudes toward health information on social media. Additionally, social media analytics could assist in accessing real-time data of actual, rather than self-reported, information-seeking behaviors on social media. Social media analytics could provide a framework for measuring engagement and the type of posts that encourage social media users who fit the profile of Cluster 3 to not only respond to social media content but ask questions in comments, reply via messaging, and share with their personal networks.

Extension is uniquely positioned within rural communities to deliver health information over social media because of the various rural locations within the land-grant system (Seevers & Graham, 2012) and may be trusted to strategically explore dynamics of interpersonal communication over social media (Subramanian, 2017). Therefore, future research should explore Cluster 3 members' likelihood to interact with Extension through two-way communication and engagement over each platform. To better understand these dynamics, researchers could include experimental design questions in a survey in which respondents are delivered Facebook health messaging targeted to their racial identity, while control group members would receive standard messaging with no customization. Subsequently asking respondents their likelihood to indicate their level of engagement with the content (commenting, replying through messaging, sharing with their audiences, etc.) could inform message development going forward. In practice, Extension communication professionals could also start community Facebook groups in which two-way conversations are encouraged. Researchers could then perform thematic analyses to determine the types of conversations and engagement that happen around certain health topics within the groups and among different clientele in various demographic categories. Overall, the profiles presented in the current study can serve as baseline profiles for message testing strategies among rural residents.

Buys and Rennekamp (2020) posited that Cooperative Extension had unprecedently positive impact on agriculture in the 20th century, and that it is positioned to "do for [rural public health] in the [21st] century what it did for agriculture in the [20th] century" (p. 1300). Extension's leadership in public health and health promotion with rural audiences is imperative to enhance both health literacy and the adoption of health behavior changes, especially in the wake of COVID-19 (Chen & Wang, 2021; Rains et al., 2020). The current study provides insights into the communication preferences and health information-seeking habits of rural Georgia audiences to catalyze Extension's health promotion and communication efforts aiming to improve the livelihoods, health, and well-being of rural populations.

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