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One Click, One Star, One Decision: The Effect of Social Media Rating Sites and Rate My Professors.Com On College Student Consumer Behavior

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Abstract

The proliferation of social media rating sites (SRS) has fundamentally transformed how consumers evaluate products, services, and experiences prior to making purchasing decisions. The purpose of this study is to investigate the influence of social media rating platforms on the consumer behavior of college students. Specifically, this study examines the influence of Rate My Professors.com (RMP), one of the most widely used academic peer-review platforms in the United States on college students' selection of professors and courses, positioning these academic choices within the broader framework of consumer behavior theory. This study represents the culmination of an extensive ten-year investigation involving a nationwide sample (N = 933) of college students drawn from numerous colleges and universities across the United States. The breadth and duration of this study provide a robust empirical foundation for examining how digital rating platforms shape consumer attitudes and behavioral intentions over time. A theoretical model was developed consisting of three a priori factors: (a) course choices, (b) professor choices, and (c) future choices. These factors were conceptualized as proxies for consumer decision-making behavior within an educational services context.

To assess the psychometric properties of the proposed model, a confirmatory factor analysis (CFA) was conducted using a Structural Equation Modeling (SEM) approach via AMOS software. The CFA was employed to examine the underlying factor structure, measurement invariance, and construct validity across the dataset. The results reveal a four-factor solution. Findings indicate four factors significantly influencing consumer decision-making, particularly among college students: (a) Posted Comments About A Professor Behavior; (b) Reviewed RMP Comments About a Professor Before Taking Class Behaviors; (c) Would Recommend RMP To Other Students Behaviors; and (d) Have Taken Course Despite Negative Comments Behavior. We found that RMP, functioning as a social networking and peer-review platform, exerts considerable influence on college students' consumer behavior and purchasing decisions, including course enrollment patterns and professor selection. These findings contribute to the growing body of literature on electronic word-of-mouth (eWOM), online review platforms, and digital consumer behavior. Future research directions and limitations of the study are discussed.

Introduction

The rapid proliferation of social media has fundamentally reshaped the landscape of marketing and consumer behavior. As digital platforms continue to penetrate everyday life, understanding their influence on consumer decision-making has become not merely important, but essential. Social media is no longer a peripheral channel, it is a central force shaping how consumers discover, evaluate, and ultimately purchase products and services. Social media platforms such as Facebook, Twitter, and LinkedIn have become omnipresent fixtures in the consumer's cognitive environment, generating an estimated 500 billion annual impressions related to products and services across social networks (Corcoran, 2009). Notably, 78% of consumers report trusting peer recommendations over traditional advertising (Corcoran, 2009), underscoring the profound shift in how purchasing decisions are informed and validated in the digital age.

Within this broader social media ecosystem, there is the emergence of social media rating sites (SRS). SRS has emerged as a particularly significant and rapidly growing subcategory of consumer influence. These rating platforms extend the function of social media beyond passive content consumption, empowering consumers to actively evaluate and share experiences with products and services. Prior research confirms that the time consumers dedicate to social media continues to grow, with nearly 17% of all internet time now spent on blogs and social networking sites (Diffley et al., 2011). Despite this growth, prior scholarship in the domain has predominantly focused on usage patterns, gratification theories, and taxonomical classifications (Heo & Cho, 2009), leaving critical questions about the direct behavioral and purchasing implications of SRS largely unaddressed.

We conducted a nationwide study on RMP. This study seeks to fill the gap in literature investigating the role of direct consumer behavior and their purchasing implications in the college student demographic. This study addresses a population gap; we found and researched an underreached population by conducting a nationwide study with college students and the influence on RMP. Specifically, the goal of this article is to examine consumer behavior and measure its relationship to social media influence through the development and validation of the Rate My Professors Measurement Scale (RMS). The RMS is a researcher-developed, first-generation psychometric instrument designed to quantify the influence of social media rating platforms on consumer behavior and consumption patterns. To our knowledge, this is among the first studies to rigorously test the validity of such an instrument within the consumer behavior domain, representing a meaningful contribution to both marketing theory and measurement science.

The validity framework employed across both studies was comprehensive and multi-layered. In, three forms of validity were established: (a) convergent validity, (b) discriminant validity, and (c) criterion-related validity. Study 2 then expanded upon this foundation by utilizing Structural Equation Modeling (SEM) via AMOS to conduct a confirmatory factor analysis (CFA), further testing convergent and discriminant validity while examining the structural relationships among consumer behavior constructs.

The purpose of this research was therefore fourfold: (a) to examine the data and provide descriptive statistics. (b) conduct an extensive review of the existing literature; (c) to conduct both an exploratory factor analysis (EFA) and a confirmatory factor analysis (CFA) of the instrument; and (d) to assess the predictive validity of the scale by examining the structural relationships among consumer choice factors through SEM analysis. Collectively, these efforts advance our understanding of how social media rating platforms drive consumer demand and shape behavioral outcomes in contemporary digital markets.

The paper is structured in four parts. First, it reviews the extant literature relevant to study and customer orientation. Then, the research methodology is presented, and data analysis techniques are discussed. Next, the findings are discussed and summarized. The paper concludes with a discussion of theoretical and managerial implications and directions for further research.

Background of Study

The rise of social media and social media rating sites (SRS) has fundamentally reshaped the landscape of marketing and consumer behavior. Social networking platforms such as Facebook, Twitter, and LinkedIn have become deeply embedded in the daily lives of consumers, influencing how they discover, evaluate, and ultimately purchase products and services. Then, product rating sites like Amazon (products), ebay (products), Angie's List (rating site for services providers), AVVO (rating site for attorneys), and many others are used daily by consumers. An estimated 500 billion product and service impressions are exchanged annually across social networks, and approximately 78% of consumers report trusting peer recommendations shared through these channels (Corcoran, 2009). The time consumers devote to social media continues to grow, with nearly 17% of all internet time now spent on blogs and social networking sites alone (Diffley et al., 2011). The emergence of social media rating sites (SRS) with crowdsourcing with people buying products has increased with consumer behavior. As this engagement deepens, so too does the imperative for scholars and practitioners to develop a more rigorous and systematic understanding of how social media shapes consumer decision-making and spending behavior.

Despite the growing recognition of social media as a driver of consumer spending and brand engagement, there is dearth in the literature on social media rating sites and consumer behavior. Much of the empirical literature has not kept pace with the phenomenon's rapid evolution. The majority of the prior research on social media has predominately focused on usage patterns, gratification theory, and taxonomical classifications of platform behavior (Heo & Cho, 2009). Whereas these studies have established a foundational understanding of how and why consumers engage with social media, comparatively little attention has been devoted to systematically measuring the degree to which social media rating sites influence downstream consumer behavior and consumption decisions. This prevailing gap represents a critical limitation in the marketing and consumer behavior literature, particularly as social media and rating sites continue to expand their role as a primary channel of commercial influence.

A substantive gap exists in the body of knowledge concerning the psychometric measurement of social media's influence on consumer behavior. We found a knowledge gap in the prior literature; the researchers identified an apparent knowledge gap in the prior empirical studies concerning the research on Rate On My Professors as a social media rating site. Thus, findings regarding the role of social media as an influencer do not exist in the prior literature and research. In addition, the prior research did not address the subject of how age and class rank influence consumer behavior with social media rating sites. This line of inquiry encompasses several unexplored dimensions that lately have attracted research attention in other disciplines. The present study directly addresses this gap through the development and validation of the Rate My Professors Measurement Scale (RMS), one of the first instruments of its kind designed to measure social media's influence on consumer behavior and consumption.

The purpose of this study was threefold. Specifically, there are three objectives of this study is to: (a) investigation if there are any significant differences with social media rating websites usage patterns with age groups; (b) investigation if there are any significant differences with social media rating websites usage patterns with student rank groups; and (c) investigation if there are any significant differences with social media rating websites usage patterns as a predictor with age groups. In addition, this study sought to advance understanding of consumer demand patterns as shaped by social media influence.

To accomplish these objectives, two sequential studies were conducted to investigate the role of social media rating sites in shaping consumer behavior. This study was designed to identify the underlying social media factors in Rate My Professors with college students (consumers) and its influence on decisions with selecting classes and professors. The data was collected using the RMS instrument, with an emphasis on establishing three forms of validity: convergent, discriminant, and criterion-related validity. Furthermore, we replicated and extended the design of the pilot study by collecting an additional sample, incorporating confirmatory factor analysis (CFA) to further test convergent and discriminant validity, and employed structural equation modeling (SEM) to examine the validity of the RMS instrument and identify specific differences across independent variables.

This study makes an important contribution to consumer behavior and marketing measurement literature. This study makes a conceptual contribution to the literature, by the development of additional theoretical and conceptual linkages. Moreover, theoretically, it addresses a critical void by introducing and validating a first-generation, researcher-developed scale specifically designed to measure the influence of social media on consumer behavior in an area that has been underserved by rigorous psychometric inquiry. Methodologically, the study design employed both EFA and CFA within a structural equation modeling framework, which strengthens the validity of evidence and enhances the generalizability of the RMS instrument. Nevertheless, the RMS instrument offers marketing researchers and practitioners a reliable, validated tool for assessing the behavioral impact of social media strategies on consumer decision-making and consumption patterns.

Theoretical Framework and Model

Theoretical Model

The following theoretical model is presented with the proposed factors and items for the study. The model proposes that RMP influences three consumer choices and thus is appropriately separated by the four factors (see Figure 1). The research questions that drive the investigation of the study are as follows: (a) RI: Are there any significant differences with social media rating websites usage patterns with age groups; (b) R2: Are there any significant differences with social media rating websites usage patterns with student rank groups; and (c) R3: Are there any significant differences with social media rating websites usage patterns as a predictor with age groups?

Lastly, the conceptual model of the study is presented. The proposed theoretical model illustrates the cyclical relationship between college student consumer behavior and the Social Media Rating Site, Rate My Professors (RMP). As illustrated in Figure 1, the model is anchored by four interrelated behavioral factors that collectively capture the decision-making process of students as consumers of higher education. The cycle originates with Factor 1: Posted Comments About a Professor Behavior, reflecting the student's active role as a content contributor on the RMP platform. This user-generated content directly informs Factor 2: Reviewed RMP Comments About a Professor Before Taking a Class Behavior, wherein prospective students engage in pre-enrollment information seeking by consulting peer-posted ratings and reviews.

The decision-making process then progresses to Factor 4: Have Taken a Course Despite Negative Comments Behavior, suggesting that students exercise independent judgment even in the presence of unfavorable evaluations. Finally, the model culminates in Factor 3: Would Recommend RMP to Other Students Behavior, capturing the student's endorsement of the platform as a valuable consumer resource, which in turn feeds back into the cycle of posted comments, reinforcing the platform's self-sustaining ecosystem of peer-generated information. Taken together, these four factors underscore RMP's central role as a dynamic social media rating platform that simultaneously shapes and is shaped by college student consumer behavior. (see Figure 1).

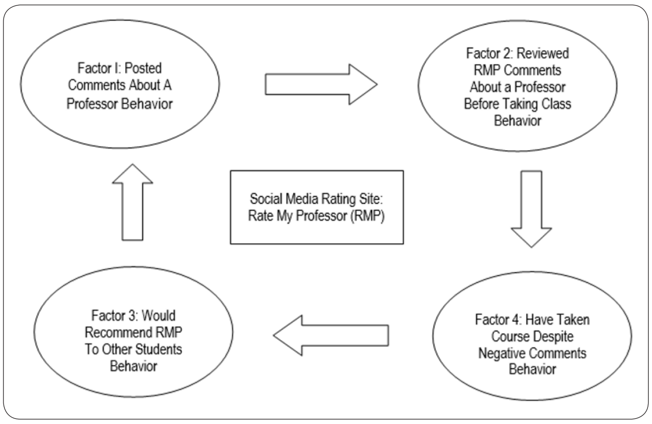

Figure 1: Theoretical Model of the Social Media Rating Sites Influences Four Consumer Choices

The conceptual model presented in this study provides a theoretically grounded framework for examining the influence of a social media rating platform on college student consumer behavior. As illustrated in Figure 2, the model depicts a unidirectional causal pathway originating from the Social Media Rating Site: Rate My Professors (RMP), flowing through the college student consumer population, and producing four distinct behavioral outcomes. This structural configuration reflects the theoretical assertion that RMP functions as an exogenous stimulus that activates and shapes measurable consumer behaviors among its student user base. The model is rooted in consumer behavior theory, electronic word-of-mouth (eWOM) literature, and social influence theory, collectively positioning RMP as a powerful mediating force in college student academic decision-making.

Four behavioral factors emerge from the model as measurable outcomes of student consumer engagement with RMP. Factor 1, Posted Comments About a Professor Behavior, reflects the content-generation dimension of student engagement, capturing the degree to which students actively contribute ratings and evaluations on the platform. Factor 2, Reviewed RMP Comments About a Professor Before Taking a Class Behavior, captures the information-seeking dimension of consumer decision-making, wherein students consult peer-generated content prior to course enrollment to reduce uncertainty and minimize perceived risk. Factor 3, Would Recommend RMP to Other Students Behavior, reflects the platform endorsement and peer advocacy dimension, capturing the extent to which students promote RMP as a valuable consumer resource to their academic peers. Factor 4, Have Taken a Course Despite Negative Comments Behavior, introduces a theoretically significant dimension by acknowledging that students exercise independent judgment in their enrollment decisions, even in the presence of unfavorable peer evaluations. Collectively, these four factors establish a robust and empirically testable framework for understanding the multidimensional influence of social media rating platforms on college student consumer behavior (see Figure 2).

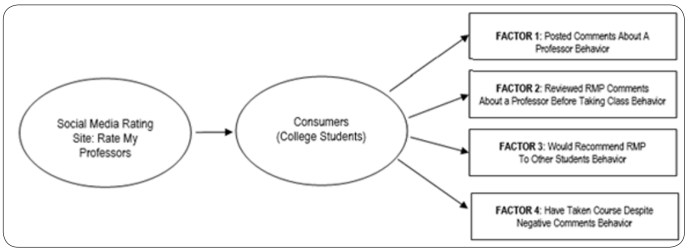

Figure 2: Conceptual Model of the Social Media Rating Sites Influences Four Consumer Choices

Methodology

Research Methodology

A nationwide sample of 933 participants residing in the United States completed the survey for this study. This research represents a 10-year continuation of a prior study examining Rate My Professors (RMP) and consumer behavior. The target population consisted of college and university students who were 18 years of age or older, recruited from both public and private universities across the country. Demographic characteristics of the sample are summarized in Table 1. The sample was predominantly male (67.0%, n = 625), with female respondents comprising 33.0% (n = 308) of participants. Regarding racial and ethnic composition, many participants identified as White (69.0%). In terms of academic classification, the largest undergraduate cohort were seniors (51.0%), and 55.0% identified as traditional students. Participant ages were grouped into five categories ranging from 18 to 25 years and to 55 years and older. Lastly, the majority of the nationwide sample came from the Midwest Area (40.3%) and the South Area (34.0%). The data was cleaned and analyzed with the statistical software packages, SPSS 31.0 (Statistical Package for the Social Sciences) and AMOS 31.0 (Analysis of Moment Structure) used to confirm the theoretical model and goodness–of –fit. SPSS and AMOS were used for analyzing the data (see Table 2). Three research questions guided this study: (a) RI: Are there any significant differences with social media rating websites usage patterns with age groups; (b) R2: Are there any significant differences with social media rating websites usage patterns with student rank groups; and (c) R3: Are there any significant differences with social media rating websites usage patterns as a predictor with age groups?

Measurement

The Rate My Professors Measurement Scale (RMS) is a researcher-developed, first-generation scale questionnaire. The RMS instrument includes 33 items consisting of statements describing responses to the influence of social media (RMP) on consumers (college students) and consumer behavior (choices). To validate the survey, a pilot study was conducted with 110 participants. The RMS Instrument was developed consisting of two sections: (a) sociodemographic variables. and (b) with a seven-item Likert scales measuring choices on classes and professor choices. The instrument was developed by the researchers specifically for this study. This RMS Instrument was developed because it was validated. The professor and course choice items (dependent variables) were measured with a 7-point Likert-type scale, ranging from 1 - (strongly disagree) to 7 - (strongly agree). For sample description purposes, a sociodemographic section was included in the questionnaire that contained numerous variables (e.g., gender, age, ethnicity, marital status, and student rank). Multiple choice or fill-in-the-blank format were adopted for the sociodemographic variables. With some minor improvements, they were primarily related to wording clarity, all items in the questionnaire were retained because of the content validity test.

Procedures

Participation in this study was entirely voluntary. Data collection was conducted exclusively online using SurveyMonkey, a widely used and reputable web-based survey platform. Prior to completing the survey, participants were informed of the study's purpose by the researchers and were presented with an online informed consent form at the outset of the survey instrument. Only after reviewing and electronically acknowledging the consent form were participants permitted to proceed with completing the survey. This protocol ensured that all ethical standards related to informed consent were upheld throughout the data collection process.

The decision to administer the survey online via SurveyMonkey was deliberate and methodologically advantageous. Online data collection facilitated the recruitment of participants from a broader range of backgrounds and from diverse geographical regions across the United States, thereby strengthening the representativeness of the sample and enhancing the generalizability of the study's findings. This approach also allowed for efficient and standardized data collection across multiple sites without the logistical constraints associated with in-person administration. A total of 933 college students responded to and completed the online survey. While the study benefited from a large and geographically diverse sample, it is acknowledged that certain limitations inherent to online survey methodology, such as self-selection bias and the inability to verify respondent attention and comprehension, may have introduced some constraints on the internal validity and broader generalizability of the research findings. These limitations are discussed further in a subsequent section of this manuscript.

Data Analyses

Data screening was first conducted to examine the distributions of variables and assumptions. Then multivariate analyses were used to analyze the data. Based on the coefficient of multivariate skewness and kurtosis, multivariate normality was tested by using SPSS 31.0 (2026). Descriptive statistics were calculated to examine the characteristics of the data by using SPSS(2026). The study used a probability sampling method by way of stratified sampling.

A split sample (N = 933) was selected to test the psychometric properties of the RMS, a 33-item scale based on the principal component analysis was used for the exploratory factor analysis (EFA). Then a confirmatory factor analysis (CFA) was conducted to confirm the factor structure.

Upon confirming multivariate normality, a CFA was conducted to evaluate the measurement model for the refined market demand factors and their items and estimate how well the items represented the proposed latent market demand factors. Maximum likelihood estimation method was adopted.

According to Hair et al. (1998), executing a confirmatory factor analysis (CFA) involves five sequential steps: (a) model specification, (b) model identification, (c) model estimation, (d) testing model fit, and (e) model re-specification. Each of these steps plays a critical role in ensuring that the hypothesized measurement model is rigorously constructed, properly identified, and systematically evaluated before any interpretations are made. Model specification involves defining the hypothesized relationships between observed indicators and their respective latent constructs, while model identification ensures that a unique solution exists for the parameter estimates. Model estimation then produces the parameter values that best reproduce the observed covariance structure in the data, after which model fit is evaluated to determine how well the hypothesized model represents the observed data. If fit is inadequate, model re-specification may be undertaken on empirical and theoretical grounds to improve the solution.

To assess the goodness-of-fit and the estimation of parameters of the hypothesized model, the chi-square (χ^2) statistic was examined alongside several widely accepted fit indices, including the root mean square error of approximation (RMSEA), the standardized root mean square residual (SRMR), and the comparative fit index (CFI) (Hair et al., 1998; Hu & Bentler, 1999; Kline, 2005). The chi-square statistic provides a formal test of exact model fit by evaluating the discrepancy between the observed and model-implied covariance matrices; however, because it is highly sensitive to sample size and tends to reject models even with trivial misspecifications in large samples, it was interpreted alongside the aforementioned incremental and absolute fit indices. The CFI is an incremental fit index that compares the hypothesized model to a null or independence model, with values approaching 1.0 indicating superior fit. The RMSEA is an absolute fit index that penalizes model complexity and estimates the degree of misfit per degree of freedom in the population, while the SRMR reflects the average discrepancy between the observed and predicted correlations in the model.

The adequacy of conventional cutoff criteria for fit indices, as recommended by Hu and Bentler (1999) and Kline (2005), was followed throughout the analysis. Specifically, CFI values at or above .95 and RMSEA and SRMR values at or below .08 were used as benchmarks for acceptable model fit, with more stringent thresholds of RMSEA $\leq$ .06 and CFI $\geq$ .95 considered indicative of close fit (Hu & Bentler, 1999). The measurement model was evaluated through a rigorous two-step validation process consistent with the widely adopted recommendations of Anderson and Gerbing (1988). In the first step, the measurement model was tested independently to confirm that each observed indicator loaded significantly and substantially onto its hypothesized latent construct, and that the model demonstrated acceptable levels of reliability and construct validity prior to structural testing. In the second step, once the adequacy of the measurement model was firmly established, the structural relationships among the latent constructs were assessed to test the hypothesized paths in the theoretical model (Anderson & Gerbing, 1988; Kline, 2005). This two-step approach is considered best practice in structural equation modeling research because it allows researchers to isolate and correct measurement error before drawing conclusions about structural relationships. The same fit indices described above were adopted consistently across both stages of the analytical process to ensure comparability of model evaluation criteria.

To assess the reliability and construct validity of the Rate My Professors Measurement Scale (RMS) instrument, three psychometric tests were conducted: Cronbach's alpha (α), construct reliability (CR), and average variance extracted (AVE). Cronbach's alpha was calculated as the primary measure of internal consistency for each subscale, reflecting the degree to which items consistently measure the same underlying construct through the strength of inter-item correlations (Nunnally & Bernstein, 1994). Construct reliability (CR) was computed as a supplementary internal consistency measure that, unlike Cronbach's alpha, explicitly accounts for measurement error across all indicators within a latent construct and is derived directly from the standardized factor loadings and error variances obtained from the CFA (Fornell & Larcker, 1981). Both α and CR were evaluated against the recommended cutoff value of .70 or greater (Fornell & Larcker, 1981; Nunnally & Bernstein, 1994). Finally, AVE was calculated to assess the proportion of variance in the observed indicators attributable to the underlying latent construct relative to measurement error, with values at or above .50 considered acceptable evidence of convergent validity (Fornell & Larcker, 1981).

Results

Descriptive Statistics of the Study

Demographic data was analyzed using descriptive statistics, including the measures of central tendency and dispersion. This conducted as well as student t-tests, to examine between-group differences in sample characteristics. The objective of the descriptive statistical analysis was to transform large volumes of raw data into a more interpretable and manageable form (Huck, et al, 1974). Participants were asked to complete the Rate My Professors Measurement Scale (RMS), a 33-item instrument designed to capture the multidimensional behavioral dynamics of college student and consumer behavior with the social media rating site, Rate My Professors (RMP) platform. A nationwide sample size of 933 college students (625 males & 308 females) was recruited from colleges and universities across the United States. Tables 1 through 3 present the descriptive sociodemographic statistics of the sample. This includes the variables gender, age, ethnicity, school type, student ranking, degree type, class type, major field of study, and U.S. region. Collectively, these descriptive statistics provide a comprehensive profile of the study's sample.

First, Table 1 presents the sociodemographic results of the study sample (N = 933). With respect to the variable of gender, the sample was overwhelmingly male, with 625 male respondents (67.0%) and 308 female respondents (33.0%). Regarding the variable of age, most of the participants fell within the 18–25 age range (n = 401; 43.0%), followed closely by the age range 26–35 cohort (n = 391; 41.0%), collectively representing 84.0% of the total sample. Smaller proportions of respondents were represented in the age range 36–45 (n = 115; 12.3%), 46–55 (n = 16; 1.7%), and Over 55 (n = 10; 1.1%) age categories, indicating that the sample was predominantly composed of traditional and early post-traditional college-aged consumers. With respect to the variable of ethnicity, White respondents constituted the largest group (n = 642; 68.8%), followed by Asian/Pacific Islander (n = 128; 13.7%), Hispanic or Latino (n = 63; 6.8%), Black or African American (n = 48; 5.1%), Native American Indian (n = 47; 5.0%), and Other (n = 5; 0.5%). Collectively, these sociodemographic characteristics reflect a sample that is largely young, male, and White, while maintaining representation across multiple age cohorts and ethnic groups (see Table 1).

Second, Table 2 presents the descriptive statistics for the university/college variables across the study sample (N = 933). Regarding the variable, school type, the largest proportion of respondents attended four-year colleges (n = 402; 43.1%), followed by four-year universities (n = 369; 41.7%), community colleges (n = 110; 11.8%), and technical/vocational colleges (n = 32; 3.4%), indicating that the sample was predominantly drawn from traditional four-year institutions, which collectively accounted for 84.8% of respondents. With respect to the variable, student ranking, seniors represented the largest cohort (n = 476; 51.0%), followed by juniors (n = 197; 21.1%), sophomores (n = 141; 15.1%), freshmen (n = 91; 9.8%), and other classifications (n = 28; 3.0%). This distribution suggests that upperclassmen particularly seniors, for the most part, were the most heavily represented academic classification in the sample, which may reflect a significant greater familiarity with and experience using Rate My Professors as an academic decision-making tool. Concerning the variable of degree type, graduate degree seekers constituted the largest segment of the sample (n = 495; 53.1%), followed by undergraduate degree seekers (n = 252; 27.0%), post-graduate degree seekers (n = 106; 11.4%), associate's degree seekers (n = 78; 8.4%), and a negligible proportion reporting no degree pursuit or other classifications (n = 7; 0.7%). Collectively, these institutional and academic characteristics reflect a sample concentrated in four-year institutions, dominated by upperclassmen, and largely composed of graduate-level degree seekers (see Table 2).

Lastly, Table 3 presents the descriptive statistics for the variables, (a) class type, (b) major fields of study, and (c) U.S. region across the study sample (N = 933). Regarding the variable, class type, the majority of participants in the study were enrolled in traditional in-person courses (n = 512; 55.0%), followed by hybrid formats (n = 222; 23.8%) and remote/online formats (n = 199; 21.3%), indicating that while face-to-face instruction remained the dominant modality, a substantial proportion of the sample, nearly 45% engaged in some form of non-traditional course delivery. With respect to the variable, major field of study, business majors constituted the largest segment of the sample by a considerable margin (n = 514; 55.1%), followed by Science majors (n = 201; 21.5%), Art majors (n = 190; 20.4%), and respondents reporting other fields of study (n = 28; 3.0%). This distribution reflects a sample heavily concentrated in business-related disciplines, which may have implications for the generalizability of findings across other academic fields. Concerning U.S. regional representation, respondents from the Mid-West Area comprised the largest geographic cohort (n = 376; 40.3%), followed by the South Area (n = 317; 34.0%), the East Coast Area (n = 208; 22.3%), and the West Coast Area (n = 32; 3.4%). Collectively, the Mid-West and South regions accounted for 74.3% of the total sample, suggesting a geographic concentration in the interior and southern United States, with comparatively limited representation from the West Coast (see Table 3).

Table 1: Descriptive Results of the Sociodemographic of the Study (N = 933)

Variables	Frequency	Percent
Gender		
Males	625	67.0%
Females	308	33.0%
Total	933	100.0%
Age	Frequency	Percent
18 – 25	401	43.0%
26 – 35	391	41.0%
36 – 45	115	12.3%
46 – 55	16	1.7%
Over 55	10	1.1%
Total	933	100.0%
Ethnicity	Frequency	Percent
Asian / Pacific Islander	128	13.7
Black or African American	48	5.1
Hispanic or Latino	63	6.8
Native American Indian	47	5.0
White	642	68.8
Other	5	.5
Total	933	100.0%

(N = 933)

Table 2: Descriptive Results of the University/College Variables (N = 933)

Variables	Frequency	Percent
School Type (N = 933)		
Community College	110	11.8%
Four-Year College	402	43.1%
Four-Year University	369	41.7%
Technical/Vocational College	32	3.4%
Student Ranking (N = 933)	Frequency	Percent
Freshman	91	9.8%
Sophomore	141	15.1%
Junior	197	21.1%
Senior	476	51.0%
Other	28	3.0%
Degree Type (N = 933)	Frequency	Percent
Associate's Degree	78	8.4%
Undergraduate Degree	252	27.0%
Graduate Degree	495	53.1%
Post Graduate Degree	106	11.4%
None-Degree	2	.2%
Other	5	.5%
Total	933	100.0%

(N = 933)

Table 3: Descriptive Results of Class Type, Major Fields of Study and Country Region (N = 933)

Variables	Frequency	Percent
Class Type		
Traditional	512	55.0%
Remote	199	21.3%
Hybrid	222	23.8%
Total	933	100.0%
Major Field of Study	Frequency	Percent
Art	190	20.4%
Business	514	55.1%
Science	201	21.5%
Other	28	3.0%
Total	933	100.0%
U.S. Region	Frequency	Percent
East Coast Area	208	22.3%
Mid-West Area	376	40.3%
South Area	317	34.0%
West Coast Area	32	3.4%
Total	933	100.0%
Other	5	.5
Total	933	100.0%

(N = 933)

Results

Factorial Covariance Path Models

The researchers conducted four factorial covariance analyses in AMOS (Analysis of Moment Structures) to examine the covariance relationships among the observed indicator variables within each factor. The factorial covariance/relationship models depict the interrelationships among the observed variables associated within each factor, providing a systematic assessment of how individual items cluster around their respective latent dimensions and co-vary with one another within the measurement framework. The researchers found the factorial covariance analysis well-suited for evaluating the degree to which observed variables share common variance attributable to an underlying construct, thereby offering empirical evidence of both the internal coherence of each factor and the discriminant boundaries between factors.

The covariance analyses were conducted on the four factors comprising the RMS instrument: (a) Factor 1 - (Posted Comments About a Professor Behavior), measured the frequency and nature of student-generated evaluative content on the Rate My Professors platform; (b) Factor 2 – (Reviewed RMP Comments About a Professor Before Taking Class Behavior), examined to the degree to which students engaged in pre-enrollment information-seeking behavior using the platform; (c) Factor 3 – (Would Recommend RMP to Other Students Behavior), assessed students' propensity to endorse and disseminate the platform among their peers; and (d) Factor 4 – (Have Taken Course Despite Negative Comments Behavior), which measured the extent to which students exercised independent academic judgment by enrolling in a course despite unfavorable evaluative content encountered on the platform. Collectively, these four factorial covariance analyses provided a comprehensive depiction of the covariance measurement of the underlying student consumer behavior on Rate My Professors, supporting subsequent structural equation modeling procedures.

Factor 1 Covariance Path Models.

Figure 3 presents the factorial covariance/relationship model for Factor 1, examining the interrelationships among seven observed variables associated with college student comment-posting behavior on Rate My Professors (RMP). The factorial covariance coefficient ranges (r = 0.29 to 0.64), indicating moderate to moderately strong associations that underscore the theoretical coherence of Factor 1. The strongest relationship was observed between V21 (Posted comments about a professor after taking their class) and V23 (Likely to post comments following a positive experience), yielding a covariance coefficient of (r = 0.64), thus reinforcing the theoretical link between prior platform engagement and future content-generation behavior. In addition, V21 also demonstrated a moderately strong covariance coefficient of (r = 0.54) with V28 (Considers RMP comments more reliable than word-of-mouth), thus, suggesting that active contributors tend to regard peer-generated evaluations as a credible professor-selection resource.

We observed several additional variable covariant relationships that merit attention. We observed V22 (Posted a rebuttal to a negative professor evaluation) showed evidence of covariance coefficients of (r = 0.40) with V24 and(r = 0.48) with V25, reflecting a generalized pattern of active, advocacy-oriented platform engagement among a subset of users. The covariance results of V25 (Considers RMP comments a reliable source of information) demonstrated a covariance coefficient of (r = 0.51) with V24 and (r = 0.56) with V29 (Sees RMP as a valuable student resource), underscoring the theoretical alignment between perceived content reliability and overall platform value perception.

We found V29 further evidenced a covariance of (r = 0.30) with V28, suggesting that students who view RMP as broadly valuable also perceive it as superior to traditional word-of-mouth channels. The remaining factorial covariance estimates including V24 and V29 (r = 0.49), V22 and V29 (r = 0.48), V21 and V29 (r = 0.55), and V25 and V28 (r = 0.50) collectively showed a pervasive pattern of moderate to moderately strong associations across all seven indicator variables. These findings underscore the robust empirical support for the internal consistency of Factor 1 as a multidimensional construct capturing the complexity of college student comment-posting behavior on RMP. Collectively, the factorial covariance relationships identified underscore the platform's role as a dynamic, self-reinforcing ecosystem wherein perceptions of reliability, platform value, and positive experiential motivation converge to drive active content-generation behavior (see Figure 3).

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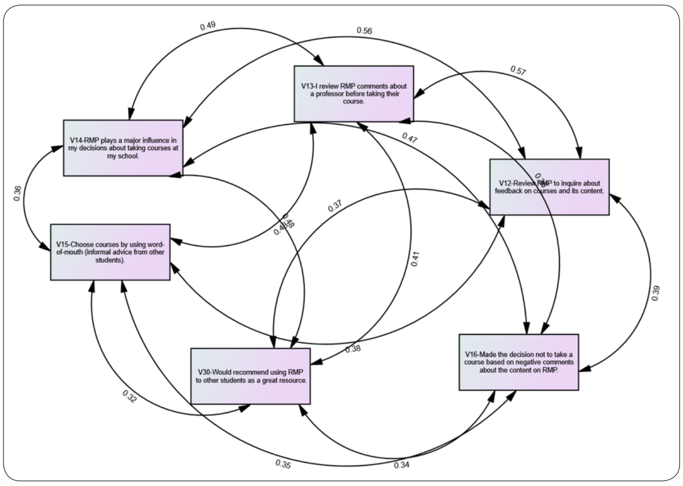


Figure 3: Factor 1: Covariance/Relationship Model–Rate My Professors.com

Factor 2 Covariance Model.

In our second factorial covariance model, Figure 4 presents the covariance/relationship model for Factor 2, examining the interrelationships among six observed variables associated with college student information-seeking behavior on Rate My Professors (RMP) prior to course enrollment. The covariance coefficient ranges (r = 0.32 to 0.57), indicate moderate to moderately strong associations that support the theoretical coherence of Factor 2 as a unified behavioral construct centered on pre-enrollment information seeking.

The strongest relationship was observed between V13 (Reviews RMP comments about a professor before taking their course) and V12 (Reviews RMP for feedback on courses and content), yielding a covariance coefficient of (r =0.57), underscoring the close alignment between professor-focused and content-focused pre-enrollment review behaviors. The variable, V13 also demonstrated a strong covariance coefficient of (r = 0.56) with V14 (RMP plays a major influence in course selection decisions), indicating that students who regularly consult RMP professor evaluations are highly inclined to regard the platform as a significant driver of enrollment behavior. The variable, V14 evidenced a covariance coefficient of (r =0.47) with V12 and (r =0.36) with V15 (Chooses courses via word-of-mouth from other students), suggesting that students who view RMP as a major decision-making influence also engage in traditional informal peer communication, indicating that digital and word-of-mouth channels function as complementary rather than mutually exclusive sources of pre-enrollment guidance.

The variable, V12 further demonstrated a covariance coefficient of (r =0.41) with V16 - (Decided not to take a course based on negative RMP content comments), reflecting the platform's tangible influence on student consumer decision outcomes. The V16 variable is also evidence of a covariance coefficient of (r =0.39) with V30 (would recommend RMP to other students), indicating that even students deterred by negative content reviews endorse the platform as a credible peer resource. The variable, V30 demonstrated covariance coefficients of (r = 0.48) with V15, (r = 0.38) with V16, (r = 0.37) with V13, and (r = 0.35) with V12, collectively suggesting that platform advocacy is broadly associated with the full spectrum of information-seeking and decision-making behaviors captured in Factor 2. These results of these findings provide a strong empirical support for the theoretical proposition that college student pre-enrollment information-seeking behavior is a multidimensional construct in which digital platform consultation, perceived platform influence, content-based decision-making, and peer advocacy converge to define the consumer decision-making landscape within the higher education marketplace (see Figure 4).

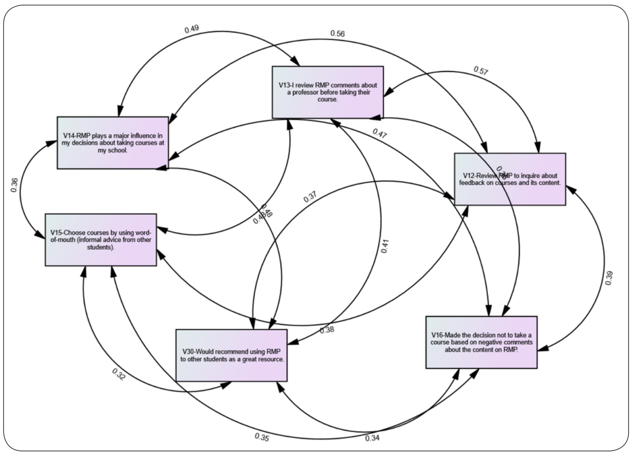


Figure 4: Factor 2: Covariance/Relationship Model–Rate My Professors.com

Factor 3 Covariance Path Models.

In our third, factorial covariance model, Figure 5 presents the factorial covariance/relationship model for Factor 3, examining the interrelationships among four observed variables associated with college student platform advocacy and institutional recommendation behavior regarding Rate My Professors (RMP). The covariance coefficients range from (r = 0.39 to 0.52), indicating moderate to moderately strong associations that support the theoretical coherence of Factor 3 as a unified behavioral construct centered on platform endorsement and academic institutional influence. The results show that the strongest relationship was observed between V31 (School search committees should consider RMP comments when hiring future professors) and V26 (Will use RMP for future professor selections), yielding a covariance coefficient of (r = 0.52).

This result indicates a strong alignment between students' personal intentions to utilize RMP and their belief that institutional search committees should formally incorporate RMP evaluations into faculty hiring processes, thus reflecting a generalized disposition toward elevating the platform's legitimacy beyond the individual consumer context. The variable, V32 (School management should review RMP comments as a consideration for faculty promotion decisions) demonstrated a covariance coefficient of (r = 0.46) with V27 (Considers RMP a major influence on future course decisions) and a coefficient of (r = 0.43) with V26, indicating that students whose academic decision-making is substantially shaped by RMP content are more inclined to endorse the platform's utility as a faculty performance metric.

The variable, V27 further evidenced a covariance coefficient of (r = 0.47) with V31, suggesting that students who regard RMP as a major determinant of future course selection are also meaningfully inclined to advocate for its formal integration into institutional faculty hiring protocols positioning the platform not merely as a consumer guidance tool but also as a potential instrument of academic governance and faculty accountability. The variable, V26 demonstrated a covariance coefficient of (r = 0.39) with V31, further corroborating the model's overarching theoretical narrative that students who derive personal value from RMP are inclined to advocate for its institutional legitimization across multiple dimensions of academic governance.

Collectively, these findings further advance the theoretical understanding of broader institutional implications of student consumer engagement with social media rating platforms, thus suggesting that RMP's influence extends well beyond individual course selection to encompass wider questions of faculty accountability and institutional transparency. Thus, the evolving role of peer-generated digital content in academic decision-making processes is shown to be quite an influence on college students (see Figure 5)

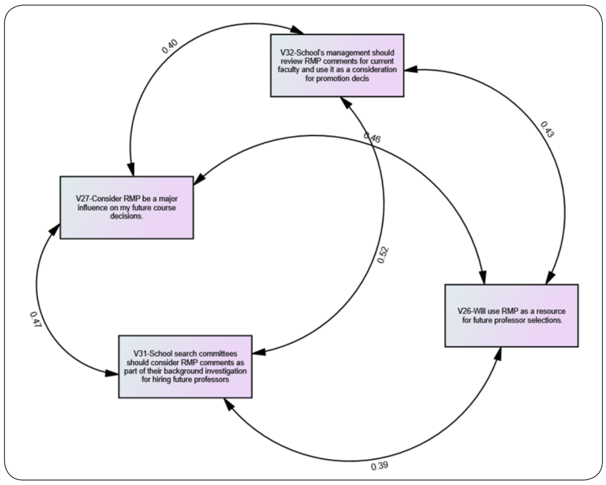


Figure 5: Factor 3: Covariance/Relationship Model–Rate My Professors.com

Factor 4 Covariance Model.

In our last, factorial covariance model, Figure 6 presents the covariance/relationship model for Factor 4, examining the interrelationships among four observed variables associated with college student consumer behavior in the context of negative comments posted on Rate My Professors (RMP). The covariance coefficient ranges went from (r = 0.31 to 0.56), thus, indicating moderate to moderately strong associations that collectively reflect the complex decision-making processes students engage in when confronted with unfavorable peer-generated evaluations. The variable, V19 (Enrolled in a course despite negative professor comments on RMP) demonstrated a covariance coefficient of (r = 0.31) with V20 (Posted comments on RMP about a course's content after taking it), accordingly, suggesting that students who enroll despite negative evaluations are moderately inclined to subsequently contribute their own experiential commentary, perpetuating the cycle of peer-generated content on the platform. The variable, V19 also evidenced a covariance coefficient of (r = 0.43) with V17 (Decided not to take a course based on negative professor comments), indicating that these students nonetheless demonstrate sensitivity to the deterrent influence of unfavorable RMP evaluations in other enrollment contexts.

The strongest covariant relationship in the model was observed between V17 and V18 (Enrolled in a course despite negative content comments on RMP), yielding a covariance coefficient of (r = 0.56). The result of this finding is theoretically significant. It reveals that students who have actively avoided a course based on negative professor evaluations also report enrolling in courses despite negative content-related evaluations. This suggests that the source of negative comments, whether directed at the professor or the course content, differentially influences student enrollment decisions.

The variable, V18 further demonstrated a covariance coefficient of (r = 0.35) with V20, indicating that students who enroll despite negative content evaluations are subsequently motivated to contribute their own content-based reviews, thus underscoring the reciprocal nature of student engagement with RMP. The variable, V19 demonstrated an additional covariance coefficient of (r = 0.34) with V18, reflecting a generalized pattern of independent consumer judgment among a subset of college student RMP users who enroll despite both negative professor and negative content evaluations. Collectively, the results of these findings support the theoretical proposition that college student consumer behavior in the face of negative RMP evaluations is neither uniform nor unidimensional. Moderately, students demonstrate a nuanced constellation of decision-making behaviors that simultaneously reflect sensitivity to peer-generated content, capacity for independent judgment, and a propensity for reciprocal platform engagement through post-enrollment content contribution (see Figure 6).

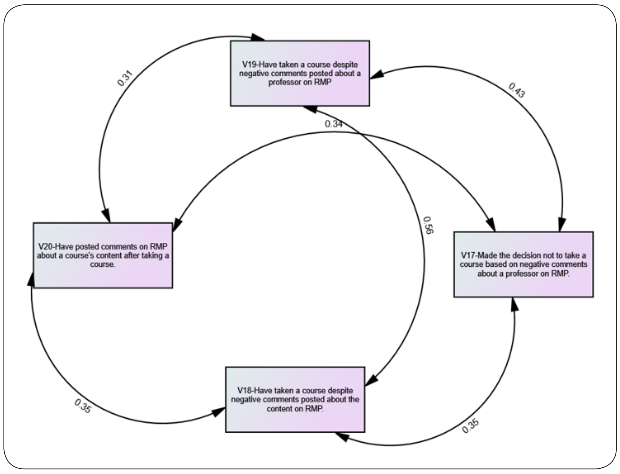


Figure 6: Factor 4: Covariance/Relationship Model–Rate My Professors.com

Results

Factorial Regression Path Models

Regression Path Model - Factor I: Posted Comments About a Professor Behavior.

We conducted a factorial regression path model with the four factors. Figure 7 presents the Factor 1 Regression Path Model for the Rate My Professors (RMP) study, depicting the directional predictive relationships between two exogenous sociodemographic predictors, V2D-Age and V6D-Student Ranking, and the seven observed indicator variables comprising the Posted Comments About a Professor behavioral construct.

The two predictor variables demonstrated a modest intercorrelation of (β = 0.17), indicating a low but meaningful association between age and academic classification within the sample. V2D-Age yielded standardized regression coefficients of (β = -0.07) for V22, (β = -0.09) for V21, (β = -0.05) for V24, (β = -0.07) for V25, (β = 0.024) for V29, (β = -0.19) for V23, and (β = -0.20) for V28. This suggests that age exerts a predominantly small negative predictive influence across most indicator variables within this behavioral factor, with the strongest negative effects observed for V23 (Have disagreed with comments posted on RMP about a professor) and V28- (Consider RMP a major influence on future course decisions). V6D-Student Ranking demonstrated standardized regression coefficients of comparable magnitude across the seven indicator variables, with directional effects on V29 (β = 0.16), V23 ((β = -0.029), and V28 (β = -0.20) being among the more notable pathways.

The pattern of regression coefficients across both predictors indicates that neither age nor student ranking serves as a particularly strong individual predictor of any single indicator within the Posted Comments behavioral construct. This suggests the content-generation behaviors captured by Factor 1 are influenced by a broader pattern of factors beyond sociodemographic classification alone. The residual error terms (e1 through e7) associated with each indicator variable reflect the proportion of the unexplained variance remaining after accounting for the directional effects of both sociodemographic predictors, underscoring the multidimensional nature of student consumer engagement with RMP content-generation behavior (see Figure 7).

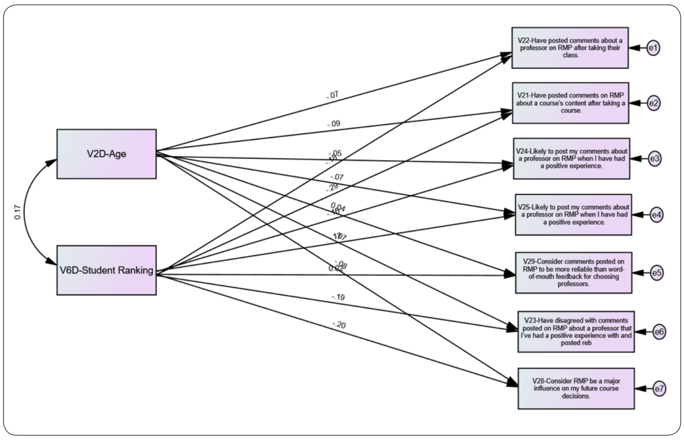


Figure 7: Factor 1: Regression Path Model –Rate My Professors.com

Regression Path Model - Factor 2: Reviewed RMP Comments About a Professor Before Taking Class Behavior.

Second, our next factorial regression path model, Figure 8 presents the Factor 2 Regression Path Model for the Rate My Professors (RMP) study, depicts the directional predictive relationships between two exogenous demographic predictors, V2D-Age and V6D-Student Ranking, and six observed indicator variables comprising the Reviewed RMP Comments About a Professor Before Taking Class behavioral construct.

Consistent with the Factor 1 model, the two predictor variables demonstrated an intercorrelation of (β =0.17), reflecting a modest association between age and academic classification. V2D-Age yielded standardized regression coefficients of (β =0.01) for V14 – (Review RMP comments about a professor before taking their course), (β =0.06) for V13 – (Review RMP to inquire about feedback on courses and its content), (β = 0.04) for V12 – (I am familiar with RMP), (β = 0.09) for V15 – (RMP plays a major influence in my decisions about taking courses at my school), (β = 0.07) for V30 – (See RMP as a valuable resource for students in school), (β = -0.04) for V16 – (Choose courses by using word-of-mouth), and (β = -0.10) on the final indicator, suggesting that Age exerts a generally modest and mixed directional influence across the information-seeking behavioral indicators comprising this construct.

Moreover, V6D-Student Ranking demonstrated somewhat stronger predictive effects across several indicator variables, with notable coefficients of (β =0.17) for V30 and (β = -0.02) for V16, indicating that academic classification is a modestly more influential demographic predictor of information-seeking behavior than age alone within this factor. The overall pattern of regression coefficients across both predictors reveals that neither age nor student ranking serves as a dominant individual predictor of pre-enrollment information-seeking behavior on RMP, suggesting that students' tendencies to consult peer-generated professor evaluations prior to course enrollment are shaped by factors extending well beyond demographic characteristics. The residual error terms (e1 through e6) associated with each indicator variable reflect the remaining unexplained variance after accounting for both demographic predictors, further underscoring the complexity of the information-seeking behavioral dynamics captured within Factor 2 (see Figure 8).

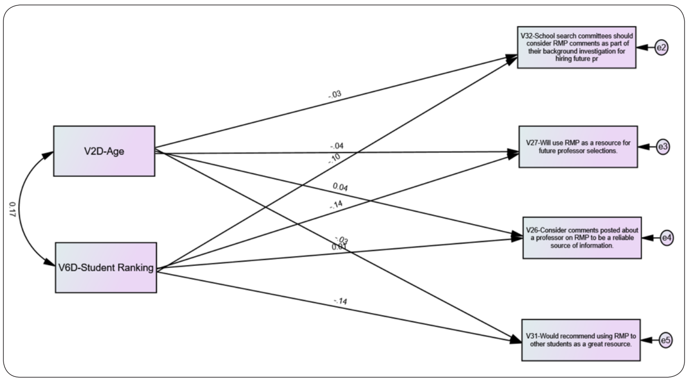


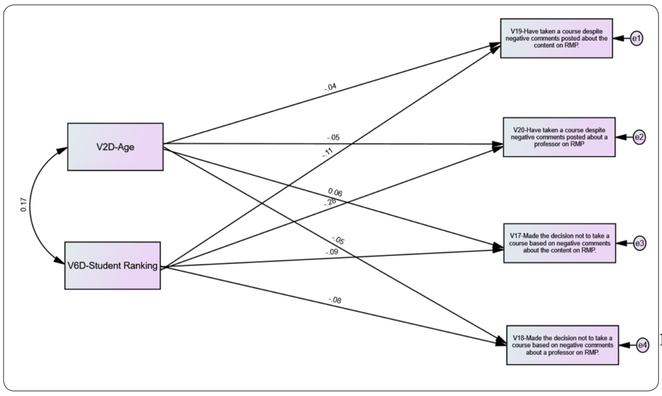
Figure 8: Factor 2: Regression Path Model –Rate My Professors.com

Regression Path Model - Factor 3: Would Recommend RMP to Other Students Behavior.

Third, our next factorial regression path model, Figure 9 presents the Factor 3 Regression Path Model for the Rate My Professors (RMP) study, depicting the directional predictive relationships between two exogenous sociodemographic predictors, V2D-Age and V6D-Student Ranking and four observed indicator variables. This consisted of the Would Recommend RMP to Other Students behavioral construct. The two predictor variables maintained an intercorrelation of (β = 0.17), consistent with the intercorrelation observed in the Factor 1 and Factor 2 models.

The exogenous variable, V2D-Age generated standardized regression coefficients of (β = 0.03) with V32-(School search committees should consider RMP comments as part of their background investigation for hiring future professors), (β = -0.04) with V27-(Will use RMP as a resource for future professor selections), (β = 0.04) V26-(Consider comments posted about a professor on RMP to be a reliable source of information), and (β = -0.14) with V31-(Would recommend using RMP to other students as a great resource). This indicates that Age exerts a predominantly negligible to small directional influence across the platform advocacy indicators, with the most notable negative effect observed for V31.

Moreover, the exogenous variable, V6D-Student Ranking demonstrated regression coefficients of (β =-0.10) with V32, (β = -0.14) with V27, (β = 0.02) with V26, (β = 0.04) with V26, and (β = -0.14) with V31 across the indicator variables. Thus, suggesting that academic classification exerts modest negative predictive effects on platform advocacy behavior for the majority of indicators within this construct. When examining the overall pattern of coefficients across both sociodemographic predictors reveals that neither Age nor Student Ranking is a strong individual predictor of platform advocacy intentions, thus, indicating that students' propensity to recommend RMP to academic peers is driven by factors beyond sociodemographic characteristics alone. The residual error terms (e2 through e5) associated with each indicator variable reflect the unexplained variance remaining after accounting for the directional effects of both predictors, reinforcing the multidimensional and complex nature of the platform advocacy behavioral dynamics captured within Factor 3 (see Figure 9).



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Regression Path Model - Factor 4: Have Taken Course Despite Negative Comments Behavior

Last, our final factorial regression path model, Figure 10 presents the Factor 4 Regression Path Model for the Rate My Professors (RMP) study, depicting the directional predictive relationships between two exogenous demographic predictors, V2D-Age and V6D-Student Ranking and four observed indicator variables comprising the Have Taken Course Despite Negative Comments behavioral construct. The two predictor variables maintained a consistent intercorrelation of 0.17, in keeping with the prior factor models.

V2D-Age yielded standardized regression coefficients of (β = -0.04) for V19-(Have taken a course despite negative comments posted about the content on RMP), (β = -0.05) for V20-(Have taken a course despite negative comments about a professor on RMP), (β = 0.11) for V17-(Made the decision not to take a course based on negative comments about the content on RMP), and (β = 0.06) for V18-(Made the decision not to take a course based on negative comments about a professor on RMP). This indicates that age exerts a mixed directional influence across the independent enrollment judgment indicators, with modest positive effects on decision-avoidance behaviors and small negative effects on course enrollment persistence behaviors.

We found that V6D-Student Ranking demonstrated standardized regression coefficients of (β = 0.20) for V19, (β = -0.05) for V17, (β = -0.09) for V17, and (β = -0.08) for V18, suggesting that academic classification exerts a notable positive predictive effect on enrollment persistence behavior despite negative RMP content (V19), while demonstrating small negative effects on course avoidance decision-making indicators. The contrasting directional effects of both sociodemographic predictors across the four indicators tend to reflect the complexity and independence characteristic of college student consumer decision-making in the face of negative peer-generated evaluations. The residual error terms (e1 through e4) associated with each indicator variable captures the unexplained variance remaining after accounting for both sociodemographic predictors, underscoring that independent enrollment judgment behavior is shaped by a broader array of motivational and contextual factors beyond age and academic classification alone (see Figure 10).

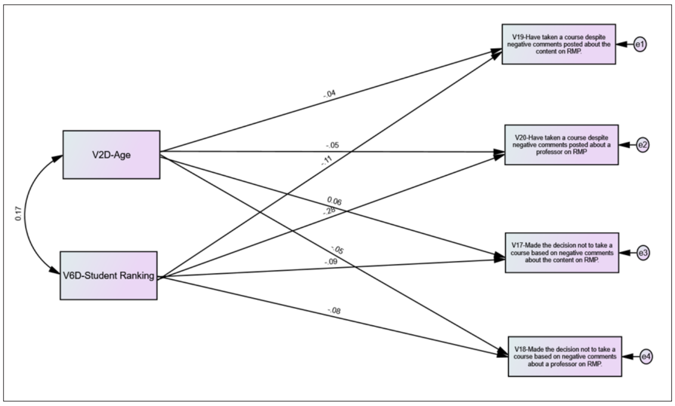

Figure 10: Factor 4: Regression Path Model –Rate My Professors.com

Results

SEM Latent Regression Model 1 – Rate My Professors.com

The researchers conducted a SEM Latent Regression analysis. The analysis shows the results of the regression model. The SEM Latent Regression model depicts the directional pathways and factor interrelationships among the four latent behavioral constructs, F1-(Posted Comments About a Professor Behavior), F2-(Reviewed RMP Comments About a Professor Before Taking Class Behavior), F3-(Would Recommend RMP to Other Students Behavior), and F4-(Have Taken Course Despite Negative Comments Behavior). The researchers used the two exogenous predictor variables Age and Student Ranking, with twenty-one observed indicator variables (V13–V32) and associated error terms (e1–e22, e14–e17). The standardized factor loadings and interfactor correlations are also reported.

Figure 8 illustrates the full SEM covariance relationship model for the Rate My Professors (RMP) study. The model depicts the directional pathways and factor interrelationships among the four latent constructs. Furthermore, the two exogenous predictor variables, and twenty-one observed indicator variables, are depicted and estimated using AMOS. The exogenous predictors, Age and Student Ranking appear to bear standardized factor loadings of (β = 0.31) and (β = 0.53) respectively, indicating that Student Ranking is a more robust sociodemographic predictor of RMP-related consumer behavior. The Age construct demonstrated differential directional effects across the four factors, with a strong positive path coefficient of (β = 0.82) to Factor 1-(Posted Comments), and negative path coefficients of (β = -0.34) and (β = -0.32) to Factor 2-(Reviewed RMP Comments Before Taking Class) and Factor 4-(Taken Course Despite Negative Comments). Respectively those constructs underscored the moderating role of age and academic experience in shaping student consumer engagement with RMP.

The interrelationships among the four latent behavioral factors revealed strong to very strong covariant relationships. Factor 2 and Factor 3-(Would Recommend RMP) yielded the strongest interfactor correlation at (β = 0.91), reflecting a near-unity relationship between pre-enrollment information seeking and platform advocacy behavior. Factor 4 demonstrated strong relationships with both Factor 2 (β = 0.99) and Factor 3 (β = 0.90), while its near-negligible correlation with Factor 3 (β = 0.01) suggests that enrollment, despite the negative comments, operates largely independently of platform advocacy intentions. Additional interfactor correlations of (β = 0.75) (F1–F2), (β = 0.85) (F1–F3), and (β = 0.90) (F1–F4) further underscore broad interdependence among all four behavioral dimensions. The standardized factor loadings across all four latent constructs ranged from adequate to strong: Factor 1 (β = 0.50 to β = 0.76), Factor 2 (β = 0.57 to β = 0.75), Factor 3 (β = 0.61 to β = 0.74), and Factor 4 (β = 0.48 to β = 0.75). This indicates satisfactory indicator-factor alignment across the behavioral dimensions. Collectively, the model's strong interfactor associations, adequate to strong indicator loadings, and theoretically meaningful directional pathways, confirm the structural validity of the Rate My Professors Measurement Scale (RMS) as a reliable instrument for measuring student consumer engagement with social media rating platforms in higher education (see Figure 11).

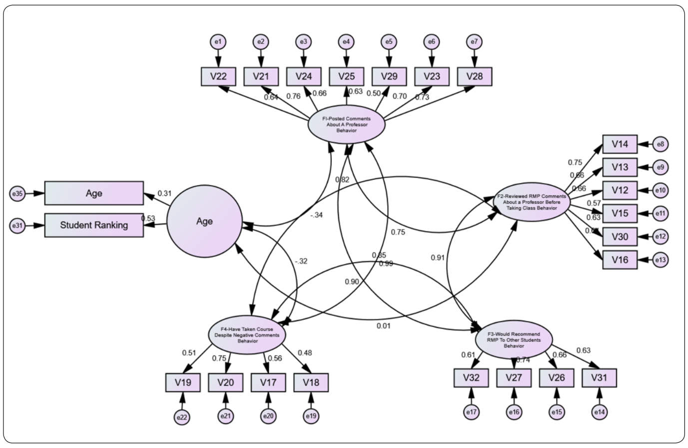

Figure 11: SEM Latent Regression Model 1–Rate My Professors.com

SEM Latent Regression Model 2–Rate My Professors.com

The researchers conducted another SEM Latent Regression analysis. Again, the analysis shows the results of the regression model. The SEM Latent Regression model depicts the directional pathways and factor interrelationships among the four latent behavioral constructs, F1-(Posted Comments About a Professor Behavior), F2-(Reviewed RMP Comments About a Professor Before Taking Class Behavior), F3-(Would Recommend RMP to Other Students Behavior), and F4-(Have Taken Course Despite Negative Comments Behavior).

Figure 12 illustrates the SEM Latent Regression Model 2 for the Rate My Professors (RMP) study, depicting the directional predictive relationships among the Age latent construct, four latent behavioral factors, and their respective observed indicator variables. The Age latent construct was defined by two exogenous sociodemographic indicators Age (β = 1.00) and Student Ranking (β = 0.38) with Age serving as the reference indicator. The Age construct demonstrated differential directional effects across the four latent behavioral factors, yielding the standardized path coefficients of (β = 0.03) to Factor 1-(Posted Comments About a Professor Behavior), (β = 0.38) to Factor 2-(Reviewed RMP Comments About a Professor Before Taking Class Behavior), (β = 0.92) to Factor 4-(Have Taken Course Despite Negative Comments Behavior), The directional effects of (β = 0.40) and (β = 1.19) reflect the compound structural pathways through which Age and Academic Classification predict the full pattern of RMP-related behavioral outcomes.

Particularly, Factor 1 demonstrated a strong negative path coefficient of (β = -0.70) on Factor 2, thus suggesting that active content-generation behavior is associated with comparatively reduced pre-enrollment information-seeking behavior, consistent with a self-sufficiency dynamic among experienced RMP contributors. The pathways among the four latent behavioral factors revealed a robust and theoretically meaningful pattern of predictive relationships. Factor 4 demonstrated strong positive path coefficients of (β = 1.09) on Factor 3-(Would Recommend RMP to Other Students Behavior) and (β = 0.88) on Factor 2, thus indicating that independent enrollment judgment behavior, is a powerful predictor of both platform advocacy intentions and pre-enrollment information-seeking behavior.

Factor 2 demonstrated a path coefficient of (β = 0.80) on Factor 3, reinforcing that pre-enrollment information-seeking is a strong positive predictor of platform advocacy behavior. The observed indicator variables demonstrated adequate to strong unstandardized factor loadings across all four latent constructs, ranging from (β = 0.93 to β = 1.12) for Factor 1, (β = 0.89 to β = 1.00). However, for Factor 2, (β = 0.94 to β = 1.06) for Factor 3, and (β = 1.00 to β = 1.78) for Factor 4 collectively confirming the structural validity and empirical coherence (β = 1.09 to β = 1.19) of the Rate My Professors Measurement Scale (RMS) as a reliable instrument for capturing the multidimensional behavioral dynamics of college student consumer engagement with RMP (see Figure 12).

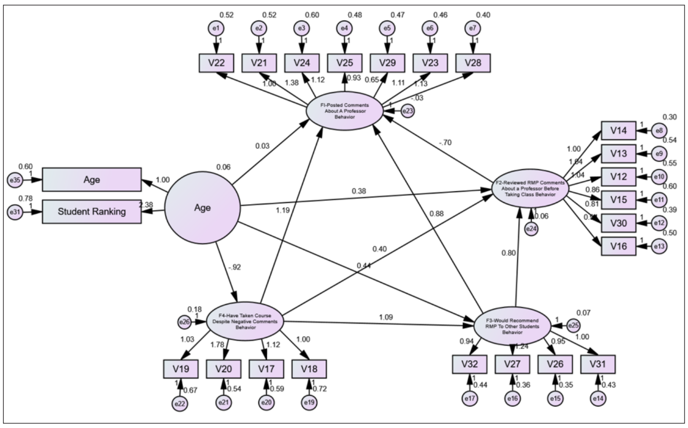

Figure 12: SEM Latent Regression Model 2–Rate My Professors.com

Discussion

A study investigated the relationship between social media rating sites and consumer behavior among college students, with particular emphasis on four affective behavioral factors underlying platform engagement. The primary objective was to examine the influence of Rate My Professors.com (RMP) on college student consumer decision-making within the higher education context. We wanted to investigate the influence of Age and Student Rank as predictor variables. To operationalize this inquiry, the Rate My Professors Measurement Scale (RMS) was developed and validated specifically for this study, providing a first-generation, researcher-constructed instrument capable of measuring the influence of social media rating sites (SRS) on consumer behavior and consumption choices. The study examined a four-factor theoretical measurement model grounded in the broader literature on social media influence and consumer behavior, with each factor representing a distinct dimension of student behavioral engagement with the RMP platform.

The findings of this study carry several meaningful theoretical and methodological contributions to the literature. This study is among a limited number of empirical investigations to conceptualize and examine RMP explicitly as a social media platform and to assess its downstream influence on student consumer behavior. The majority of the prior research has treated RMP primarily as an instrument of faculty evaluation or pedagogical feedback, largely overlooking its function as a consumer-facing social media site that shapes enrollment decisions and academic consumption patterns. By reframing RMP within a social media and consumer behavior paradigm, this study advances a more theoretically precise understanding of how digital rating platforms operate within higher education markets.

Overall Findings of the Study

Findings of Factorial Covariance Models

The factorial covariance analyses conducted in AMOS revealed some meaningful interrelationships among the observed indicator variables across the four latent factors comprising the Rate My Professors Measurement Scale (RMS). The covariance/relationship model provided empirical evidence that the observed variables associated with each factor shared substantial common variance, supporting the internal coherence of the four-factor measurement structure. Specifically, the covariance estimates among indicator variables within Factor 1-(Posted Comments About a Professor Behavior), Factor 2-(Reviewed RMP Comments About a Professor Before Taking Class Behavior), Factor 3-(Would Recommend RMP to Other Students Behavior), and Factor 4-(Have Taken Course Despite Negative Comments Behavior) were statistically significant ($p < .05$). Therefore, this indicates the observed items reliably clustered around their respective latent constructs.

This finding tells us the pattern of covariance relationships that the four factors were empirically distinguishable from one another, had meaningful associative relationships existed across certain factor pairings, most notably between Factor 2 and Factor 3 ($r = 0.90$, $p < .05$). This finding reflects the theoretically consistent link between pre-enrollment information seeking and subsequent willingness to endorse the platform to peers. These findings are consistent with prior research demonstrating that social media platform engagement operates through interrelated behavioral dimensions rather than as a unidimensional phenomenon. Collectively, the factorial covariance results confirmed the structural integrity of the RMS instrument. Moreover, it provided a sound empirical basis for proceeding with the latent regression and structural equation modeling procedures.

Findings of Factorial Regression Path Models

The researchers conducted a structural path analysis to examine whether a latent sociodemographic construct, indicated by Age and Student Rank had any influence on the variables in each factor. The latent regression path models estimated in AMOS yielded a series of theoretically interpretable and statistically significant structural relationships among latent sociodemographic constructs and the four RMS factors. Across the hypothesized path models specified directional relationships were statistically significant at the $p < .05$ level. Thus, this provides partial to strong support for the proposed theoretical framework governing student consumer behavior on the RMP platform.

When we examine Factor 1-(Posted Comments), the pattern of unstandardized regression coefficients indicates that the overarching sociodemographic latent construct constitutes a meaningful predictor of content-generation behavior on RMP (B=1.19). Conversely, for Factor 2-(Information-Seeking Behavior) and Factor 3-(Platform Advocacy), the regression paths out of the sociodemographic construct were much more modest (B=0.38 and B=0.44, respectively), confirming that the construct does not exert a dominant influence over pre-enrollment information-seeking or student intentions to recommend the platform to peers. For Factor 4-(Enrollment Persistence), the latent sociodemographic construct produced a strong negative predictive relationship (B=−0.92) with enrollment persistence despite exposure to negative RMP content. This pattern suggests that as the sociodemographic profile shifts (i.e., towards upper-level student rank and increased age), students exhibit a significant structural change in how they process course avoidance decision-making when facing critical peer reviews.

When we examine Factor 3-(Platform Advocacy), the standardized regression coefficients across both predictors consistently failed to reach substantive levels, indicating that neither age nor academic classification is a meaningful determinant of students' intentions to recommend or endorse RMP to peers. Platform advocacy appears to reflect attitudinal orientations that are not meaningfully differentiated by sociodemographic standing. For Factor 4-(Enrollment Persistence), student ranking produced the most substantively notable effects observed across all four factors. Academic classification demonstrated a positive predictive relationship with enrollment persistence despite exposure to negative RMP content, while simultaneously exhibiting small negative effects on course avoidance decision-making. This divergent pattern suggests that upper-level students may be more resilient consumers of negative RMP information, weighing programmatic or degree-completion imperatives more heavily than peer-generated critical reviews when making enrollment decisions.

Findings of the SEM Latent Regression Models

The structural equation modeling analyses incorporating latent variable estimation provided the most comprehensive assessment of the theoretical relationships posited in the four-factor RMS model. The full latent SEM model demonstrated acceptable to good fit with the observed data, as indicated by the indices: CFI, TLI, RMSEA, CI, and SRMR, meeting conventional thresholds recommended for applied SEM research. The latent factor loadings across all four RMS dimensions were statistically significant ($p < .001$) and of sufficient magnitude (λ) confirming that the observed indicator variables adequately represented their respective latent constructs and that measurement error was appropriately accounted for within the structural model.

The unstandardized latent regression coefficients revealed the hypothesized structural paths were statistically significant, with unstandardized path estimates ranging from ($B = 1.09$ to $B = 1.19$). Notably, the latent model replicated and extended the path-level findings described above, with Factor 2 retaining its role as a central mediating mechanism linking upstream posting behavior (Factor 1) with downstream peer recommendation (Factor 3) and enrollment decision-making under negative information conditions (Factor 4).

The explained variance in the endogenous latent factors ranged from ($R^2 = 0.03$ to $R^2 = 0.88$), indicating that the specified model accounted for a meaningful proportion of variance in student consumer behavior outcomes attributable to RMP platform engagement. These latent SEM results provide robust quantitative support for the theoretical proposition that RateMyProfessors.com functions as a consequential social media rating site shaping the consumer behavior and academic decision-making of college students, and that its influence operates through a structured set of interrelated affective and behavioral dimensions captured by the RMS instrument.

An unaddressed conceptual tension warrants attention regarding the structural constraints of the model. While the conceptual framework positions student interactions on RMP as a cyclical feedback loop, where consumption of reviews shapes enrollment, and subsequent course completion drives future review generation, the current SEM analysis tests a static, unidirectional causal pathway. This structural approach represents an empirical snapshot necessary for path isolation, yet future model extensions must account for this recursive feedback loop to accurately mirror active consumer lifecycles. Furthermore, the heavy concentration of business majors within the sample means the observed utility pathways may over-index on transactional logic. Business students are systematically trained in risk mitigation, economic utility, and market transparency metrics. Consequently, their strong alignment with the predictive paths of the RMS instrument may reflect a specialized cohort behavior optimized for consumer calculus, rather than the more qualitative evaluation habits common among humanities or arts cohorts.

Relating the Findings Back to the Prior Research

The present study departs profoundly from the predominant path of Rate My Professors.com (RMP) scholarship by repositioning college students as active consumers of a social media rating platform, rather than subjects of faculty evaluation. The majority of prior RMP research has concentrated on five interrelated evaluative streams: first, the comparisons between RMP ratings and institutionally administered student evaluations of teaching (Timmerman, 2000; Otto et al., 2008; Timmerman, 2008; Brown et al., 2009; Cavanaugh, 2009; Davison & Price, 2009; Gregory, 2011; Kowai-Bell et al., 2011; Clayson, 2014; MacNell et al., 2015; Boring et al., 2016; Rosen, 2018; Tatum, 2021; Cola Darci & Kornfield, 2021). Second, the focus is on gender bias, racial bias, and linguistic stereotyping embedded in RMP content (Reid, 2010; MacNell et al., 2015; Terkik et al., 2016; Antonie et al., 2018; Rosen, 2018; Chavez et al., 2020). Third, the topic of the role of physical attractiveness in shaping online instructor ratings (Felton et al., 2004; Harit & Cohen, 2007; Rosen, 2018). Fourth, the topic of the influence of perceived course difficulty, grading leniency, and grade outcomes on RMP ratings (Sah et al., 2005; Felton et al., 2004; Edwards et al., 2008); and lastly, the disciplinary and contextual variation in RMP usage patterns (Silva et al., 2008; Otto et al., 2008; Ritter, 2008; Davison & Price, 2009; Rizvi, 2015; Rosen, 2018).

Collectively, these studies share a common theoretical orientation: RMP is treated principally as an instrument of faculty evaluation rather than as a consumer behavior information environment. Hence, leaving a substantive gap in the literature regarding how students engage with social media rating platforms as consequential decision-making consumers. The current study addresses this gap directly. By applying structural equation modeling to a diverse sample across 14 higher education institutions through the researcher developed, Rate My Professors Measurement Scale (RMS), the findings illuminate the behavioral and attitudinal dimensions of student engagement with RMP as a social media rating platform. Most notably is in the context of course and instructor selection. In this respect, the present findings align most closely with Miles and Sparks (2018), whose work similarly examined RMP through a consumer behavior lens by documenting patterns of pre- and post-enrollment platform engagement. The present study corroborates and extends those findings with a larger, multi-campus sample and a psychometrically validated measurement instrument. This also reinforces the conclusion that social media rating platforms function as meaningful consumer information channels within higher education. Subsequently, this study contributes robust quantitative evidence that the relationship between RMP platform engagement and college student consumer behavior is both substantive and theoretically significant, a dimension of RMP's influence that remains systematically underdeveloped in the present literature and warrants sustained scholarly attention.

Implications of the Study

This study advances theoretical and empirical knowledge at the intersection of social media research and consumer behavior. The researchers attempted to go in another direction from the previous research on Rate My Professors.com (RMP). By reframing RMP as a functional consumer information network rather than merely a faculty evaluation tool, this study focused on consumers (college students) and their behavior with social media rating platforms. This work fills a gap in the marketing literature by providing empirical grounding for the nexus between social media engagement and consumer behavioral decision-making, specifically course and instructor selection. The confirmation of the four-factor RMS structure and the mediating role of information-seeking behavior (Factor 2) advances theoretical understanding of social media rating platforms as structured behavioral networks operating through interrelated dimensions rather than as unidimensional phenomena. The strong covariance between Factor 2 and Factor 3 ($r = 0.90$, $p < .05$) positions pre-enrollment information seeking as an active precursor to peer-to-peer platform diffusion, consistent with social influence and electronic word-of-mouth (eWOM) frameworks.

The practical implications are substantial across multiple stakeholder groups. For example, the higher education labor force would be critical to many institutional stakeholder groups. For higher education administrators, enrollment management professionals, and student advocacy groups, the finding that RMP exerts structural influence on enrollment decision-making independent of conventional sociodemographic variables, signals that institutional reputation management strategies must extend systematically into peer-generated digital environments. Other stakeholder groups such as faculty and academic departments, the resilience of upper-level students to negative RMP content, is often driven by degree-completion imperatives, underscores the platform's role as a persistent feature of the instructional quality landscape. For platform designers, digital marketing practitioners, and policymakers, the identification of information-seeking behavior as a central mediating apparatus can provide an empirical foundation for understanding how consumer rating networks generate advocacy and shape consumer decision-making behavior.

Empirically, this study makes two distinct contributions. First, applying structural equation modeling to a multi-institutional sample, we established that RMP exerts substantial and statistically significant effects on college student consumer behavior and purchase intentions. Second, the psychometric validation of the Rate My Professors Measurement Scale (RMS) confirms acceptable reliability and construct validity, establishing it as a sound measure suitable for deployment in future marketing and consumer behavior research. The validation of a domain-specific instrument broadens the measurement toolkit available to scholars in these fields and positions this study as a meaningful contribution to the literature and body of knowledge on digital consumer behavior and social media influence in higher education marketplace contexts.

Conclusions

The purpose of this study was to examine social media rating platforms usage patterns with age groups and student rank groups as sociodemographic predictors on consumer behavior decision-making. This study is the result of a 10-year study on social media rating sites influence on consumer behavior with decision-making. The present study contributes to the developing body of literature on social media rating platforms and their role in shaping consumer decision-making within higher education contexts. This study used a nationally representative sample of 933 college students from numerous universities, and tested a first generation, researcher-developed instrument, the Rate My Professors Measurement Scale (RMS). Thus, the findings collectively demonstrate that Rate My Professors.com functions as a consequential digital marketplace that profoundly influences the academic consumer behavior of college students. The structural equation modeling analyses, grounded in a four-factor latent variable framework, provide robust quantitative support for this conclusion. We found three key conclusions from this study.

Several theoretical and practical insights emerged from the results. First, the factorial covariance analyses confirmed the structural integrity and internal coherence of the RMS instrument, establishing that the four behavioral dimensions, (a) posted comments, (b) pre-enrollment information seeking, (c) platform advocacy, and (d) enrollment persistence under negative information conditions, represented empirically distinguishable, yet interrelated constructs. Furthermore, we found a particularly strong associative relationship observed between information-seeking behavior (Factor 2) and platform advocacy (Factor 3) ($r = 0.90$, $p < .05$), suggesting that consumers (students) who actively consult RMP prior to enrollment are substantially more likely to endorse the platform to their peers. This finding was consistent with the theoretical frameworks on social media engagement and network diffusion.

Secondly, the latent factorial regression path models revealed that sociodemographic characteristics, specifically age and academic classification (Student Rank), exert limited and generally non-dominant influence over most RMP behavioral dimensions. This finding raises important implications for both platform theory and marketing practice. Therefore, it suggests that RMP engagement operates largely as a platform-level attitudinal phenomenon rather than one stratified by conventional demographic segmentation variables. The one notable exception, we found enrollment persistence (Factor 4), demonstrated that upper-level students are more resilient consumers of negative peer-generated content, a finding that points to the moderating role of academic progression on information processing and risk tolerance in enrollment decision-making.

Lastly, the full latent SEM model yielded acceptable to good fit and confirmed the hypothesized structural pathways, particularly with Factor 2 emerging as a central mediating mechanism linking both upstream content generation with downstream advocacy and enrollment behavior. The range of explained variance ($R^2 = 0.30$ to $R^2 = 1.13$) across endogenous factors underscores the theoretical coherence of the model and speaks to the capacity of the RMS to capture meaningful variance in student consumer behavior outcomes attributable to platform engagement.

In summary, these findings advance the theoretical understanding of social media rating sites as multi-dimensional behavioral networks that shape consumer thought and choice in non-traditional marketplace settings. For higher education administrators, faculty, and marketing scholars alike, the findings make evident that Rate My Professors.com is not a peripheral curiosity but a structurally influential platform that affects the enrollment decision process. Future research should extend these findings by examining longitudinal dynamics in RMP behavior, exploring cross-institutional variation, and investigating additional psychological antecedents such as information credibility perceptions and platform trust. This may further illuminate the mechanisms underlying student consumer behavior on social media rating sites.

Limitations and Future Research

Limitations

There were some limitations to our study. First, this study utilized a convenience sample drawn from the college and university population. Interestingly, we had a high response rate. We were able to secure our sample from a total of 14 colleges and universities. The researchers were able to get a rich sample from the schools. Even though we successfully employed a data collection strategy, a potential limitation of our study is our use of a convenience sample. However, while a convenience sample is acceptable, the generalizability of the results of the study must be taken with caution.

Second, another limitation is the reliance on a single channel of data collection. The researchers exclusively used the internet (via Survey Monkey.com) to collect the data. This could be a limitation because there were other unexploited avenues to collect data such as by telephone and in-person interviews and others. Using multiple channels of data collection over a specific time could possibly enable a more diverse pool of participants and may enable a better understanding of the causal relationships between the variables.

This digital, single-channel survey design inherently exposes the final dataset to Common Method Bias (CMB). Because independent predictors and dependent behavioral dimensions were measured concurrently within a singular instrument, self-report inflation may artificially cluster the observed factor items. Future methodological configurations should implement temporal or procedural separation between the tracking of search intents and final enrollment confirmations to verify that these self-reported behavioral weights align perfectly with real-world student transitions.

Lastly, another limitation is geographic constraints. The study had a limitation due to the lack of diversity in the sample in terms of gender and ethnicity. This was attributed to geographical constraints. Due to those constraints, this study was limited in that scope. Cultural differences could play a significant role in the perception of social media and its influences. We found this to be a limitation in our research.

Specifically, the demographic matrix of this study is heavily skewed toward a population that is 67.0% male, 68.8% White, and heavily clustered in the Midwestern and Southern regions. Given that broader higher education trends in the United States routinely show a female majority among undergraduate enrollments, this structural imbalance restricts the immediate generalizability of our path loadings. These localized populations may over-represent specific regional communication styles and financial expectations, meaning the current performance coefficients of the RMS instrument require further multi-group cross-validation across more ethnically and structurally diverse campuses before universal deployment.

Future Research

There were some implications for future research based on the findings of the study. First, a line of inquiry for future research could consider examining the perceptions of social media on customers in terms of gender. For example, we may consider the influence of gender with some research questions. Does gender play a significant role on social media influence consumer behavior? Are there different types of social media that are more influential when comparing males to females? This line of inquiry would provide an interesting examination of gender, social media and consumer behavior.

A second line of inquiry for future research emanating from this study relates to expanding our understanding of the role of age in terms of social media and consumer behavior. For example, we may further unpack the influence of age on consumer choices and behavior by evaluating non-traditional versus traditional age brackets as distinct cohorts. Future scholars may investigate how specific age milestones interact with social media and consumer behavior over time. Does age play a moderating factor in terms of social media and consumer behavior when choosing online versus offline channels? Does age play a significant factor in risk tolerance regarding consumer behavior and purchasing decisions? These questions would provide an interesting study building upon our foundational structural findings on social media and consumer behavior.

Lastly, a line of inquiry for future research could consider further stratifying the consumer ranking in terms of social media influence. While our latent regression models identified unique resilience patterns among upper-level classifications, future research could isolate specific class comparisons via multi-group analysis. Are freshmen more influenced by social media compared to seniors? Are undergraduates different compared to graduate students in terms of social media influence on consumer behavior? This line of inquiry would provide an interesting examination into the influence of Rate My Professors.com

References

1. Anderson DR, Gerbing DW (1988) Structural equation modeling in practice: A review and recommended two-step approach. Psychological Bulletin 103: 411-423.
2. Bardhi F, Rohm AJ, Sultan F (2010) Tuning in and tuning out: Media multitasking among young consumers. Journal of Consumer Behavior 9: 316-332.
3. Bertrand G (2013) Social media research: Developing a trust metric in the social age. International Journal of Market Research 55: 333-335.
4. Bhagat PS, Klein A, Sharma V (2009) The impact of new media on internet-based group consumer behavior. Journal of the Academy of Business & Economics 9: 83-94.
5. Brown T (2006) Confirmatory Factor Analysis for Applied Research. New York, NY: Guilford Press.
6. Bryant F, Yarnold P (1995) Principal-components analysis and exploratory and confirmatory factor analysis. In: Grimm L, Yarnold P (eds) Reading and Understanding Multivariate Statistics. Washington, DC: American Psychological Association, pp. 99-134.
7. Bryant F (2000) Assessing validity. In: Grimm L, Yarnold P (eds) Reading and Understanding More Multivariate Statistics. Washington, DC: American Psychological Association, pp. 99-145.
8. Burton J, Khammash M (2010) Why do people read reviews posted on consumer-opinion portals? Journal of Marketing Management 26: 230-255.
9. Caccamo J (2009) The ethics of branding in the age of ubiquitous media: Insights from Catholic social teaching. Journal of Business Ethics 90: 301-313.
10. Campbell SR, Anitsal I, Anitsal M (2013) Social media's key success factors: An analysis of customer reactions. Business Studies Journal 5: 43-56.
11. Casteleyn J, Mottart A, Rutten K (2008) How to use Facebook in market research. International Journal of Market Research 51.
12. Chavez L, Ruiz C, Curras R, Hernandez B (2020) The role of travel motivations and social media use in consumer interactive behavior: A uses and gratifications perspective. Sustainability 12: 8789.
13. Chatterjee P (2011) Drivers of new product recommending and referral behavior on social network sites. International Journal of Advertising 30: 77-101.
14. Chen Y, Liu Y, Zhang J (2012) When do third-party product reviews affect firm value and what can firms do? The case of media critics and professional movie reviews. Journal of Marketing 76: 116-134.
15. Colliander J, Dalhén M (2011) Following the fashionable friend: The power of social media. Journal of Advertising Research 51: 313-320.
16. Coskuner G (2006) Exploring masculine ideologies. Advances in Consumer Research 33: 63-66.

17. Corstjens M, Umblijs A (2012) The power of evil: The damage of negative social media strongly outweighs positive contributions. Journal of Advertising Research 52: 433-449.
18. Courtney AL, Lee HB (1992) A First Course in Factor Analysis. Hillsdale, NJ: LEA.
19. Cunningham N, Bright LF (2012) The tweet is in your court: Measuring attitude towards athlete endorsements in social media. International Journal of Integrated Marketing Communications 4: 73-87.
20. Dăniasă CI, Tomiţă V, Stuparu D, Stanciu M (2010) The mechanisms of the influence of viral marketing in social media. Economics, Management & Financial Markets 5: 278-282.
21. Chatterjee P (2011) Drivers of new product recommending and referral behavior on social network sites. International Journal of Advertising 30: 77-101.
22. Chen Y, Liu Y, Zhang J (2012) When do third-party product reviews affect firm value and what can firms do? The case of media critics and professional movie reviews. Journal of Marketing 76: 116-134.
23. Colliander J, Dalhén M (2011) Following the fashionable friend: The power of social media. Journal of Advertising Research 51: 313-320.
24. Coskuner G (2006) Exploring masculine ideologies. Advances in Consumer Research 33: 63-66.
25. Corstjens M, Umblijs A (2012) The power of evil: The damage of negative social media strongly outweighs positive contributions. Journal of Advertising Research 52: 433-449.
26. Courtney AL, Lee HB (1992) A First Course in Factor Analysis. Hillsdale, NJ: Lawrence Erlbaum Associates.
27. Cunningham N, Bright LF (2012) The tweet is in your court: Measuring attitude towards athlete endorsements in social media. International Journal of Integrated Marketing Communications 4: 73-87.
28. Dăniasă CI, Tomiţă V, Stuparu D, Stanciu M (2010) The mechanisms of the influence of viral marketing in social media. Economics, Management & Financial Markets 5: 278-282.
29. Davis JJ, O'Flaherty S (2012) Assessing the accuracy of automated Twitter sentiment coding. Academy of Marketing Studies Journal 16: 35-50.
30. Dellarocas C, Gao G, Narayan R (2010) Are consumers more likely to contribute online reviews for hit or niche products? Journal of Management Information Systems 27: 127-157.
31. Diffley S, Kearns J, Bennett W, Kawalek P (2011) Consumer behavior in social networking sites: Implications for marketers. Irish Journal of Management 30: 47-65.
32. Dunn L, Dahl DW (2012) Self-threat and product failure: How internal attributions of blame affect consumer complaining behavior. Journal of Marketing Research 49(5): 670-681.
33. Douglas E (1952) Advertising. Journal of Marketing 16: 346-347.
34. Earls M (2012) Social: The new space for market research innovation. International Journal of Market Research 54: 285-287.
35. Fogel S (2010) Issues in measurement of word of mouth in social media marketing. International Journal of Integrated Marketing Communications 2: 54-60.
36. Fornell C, Larcker D (1981) Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research 18: 39-50.
37. Hardey M (2011) Generation C. International Journal of Market Research 53: 749-770.
38. Hair JF, Anderson RE, Tatham RL, Black WC (1998) Multivariate Data Analysis. 5th ed. Upper Saddle River, NJ: Prentice Hall.
39. Harvey CG, Stewart DB, Ewing MT (2011) Forward or delete: What drives peer-to-peer message propagation across social networks? Journal of Consumer Behavior 10(6): 365-372.
40. Hawkins K, Vel P (2013) Attitudinal loyalty, behavioral loyalty and social media: An introspection. Marketing Review 13: 125-141.
41. Henry M, Harte B (2012) A new model for assessing the value of social media activity. Journal of Brand Strategy 1: 234-239.
42. Heinonen K (2011) Consumer activity in social media: Managerial approaches to consumers' social media behavior. Journal of Consumer Behaviour 10: 356-364.
43. Heinrichs JH, Lim J, Lim K (2011) Influence of social networking site and user access method on social media evaluation. Journal of Consumer Behavior 10: 347-355.
44. Hill RP, Moran N (2011) Social marketing meets interactive media. International Journal of Advertising 30: 815-838.
45. Hewer P, Brownlie D (2010) On market forces and adjustments: Acknowledging consumer creativity through the aesthetics of 'debadging'. Journal of Marketing Management 26: 428-440.
46. Hu LT, Bentler PM (1999) Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: A Multidisciplinary Journal 6: 1-55.
47. Huck SW, Cormier WH, Bounds WG Jr (1974) Reading Statistics and Research. New York, NY: Harper & Row.
48. Hye-Jin P, Hove T, Hyun Ju J, Mikyong K (2011) Peer or expert? International Journal of Advertising 30: 161-188.
49. Jin L, Lingjing Z (2011) Online persuasion: How the written word drives WOM. Journal of Advertising Research 51: 239-257.
50. Jolly DW, Mowen JC (1985) Product recall communications: The effects of source, media, and social responsibility information. Advances in Consumer Research 12: 471-475.
51. Jun H, Chang-Hoan C (2009) A new approach to target segmentation: Media-usage segmentation in the multi-media environment. Journal of Targeting, Measurement & Analysis for Marketing 17: 145-155.
52. Keiser SK (1975) Awareness of brands and slogans. Journal of Advertising Research 15: 37-43.
53. Kline RB (2005) Principles and Practice of Structural Equation Modeling. 2nd ed. New York, NY: Guilford Press.
54. Kumar VV, Sundaram B (2012) An evolutionary road map to winning with social media marketing. Marketing Research 24: 4-7.
55. Manara C, Roquilly C (2011) The risk of brand equity erosion in the social media: The efficacy and limitations of legal instruments. Recherche et Applications en Marketing 26: 93-114.
56. Marken G (2007) Social media: The hunted can become the hunter. Public Relations Quarterly 52: 9-12.
57. Maurya M (2011) Evolution of blogs as a credible marketing communication tool. Journal of Case Research 2: 71-90.
58. Miles D, Sparks W (2013) Examining social media and higher education: An empirical study on RateMyProfessors.com and its impact on college students. International Journal of Economy, Management and Social Sciences 2: 513-524.
59. Minton E, Lee C, Orth U, Kim C, Kahle L (2012) Sustainable marketing and social media. Journal of Advertising 41: 69-84.
60. Mir I, Zaheer A (2012) Verification of social impact theory claims in social media context. Journal of Internet Banking and Commerce 17: 1-15.

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