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The Impact of Public Relations and Astroturfing Strategies on Consumer Behavioural Intention: Moderating Role of Age and Gender in Online Reputation Management

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Abstract

Public relations and astroturfing strategies of online reputation management are significantly shaping consumer behavior. Corporate reputation, online reviews, and perceived authenticity are key drivers of consumer decisions, while astroturfing can manipulate opinions and increase uncertainty. The purpose of this study is to examine the moderating role of age and gender in understanding the effectiveness of both strategies among consumers. To validate the research questions and hypotheses, data were obtained from young consumers using a Google Form via a self-administered survey questionnaire that was close-ended. A total of 423 valid responses were obtained, from which data were analysed using hierarchical linear regression with the Statistical Package for the Social Sciences version 22. The results showed that the four hypotheses of the study were not significant in moderating the role of age and gender. Public relations had a positive significant impact on shaping consumer attitudes, while astroturfing had a negative impact on consumer behavior. This means that if consumers find that reviews or other mentions are fabricated, across all age groups irrespective of gender, they do not accept the brand and it damages its brand image. For practitioners, this implies that segmentation based purely on demographic factors may not be necessary when designing PR or astroturfing-based ORM strategies. Organizations should develop a systematic strategy focusing on message quality, authenticity, transparency, consistent behaviour towards the services they provide to consumers, and ensuring the credibility of digital platforms. In the future, researchers may examine psychographic and cognitive traits, including trust, familiarity with online platforms, and digital understanding, as moderators in determining the effectiveness of online reputation management

Keywords: Online Reputation Management, Public Relations, Astroturfing, Demographic Moderation, Consumer Behavioural Intention

1. Introduction

Reputation management is a set of channels that includes monitoring, creating a reputation, addressing critical mentions online, and engaging stakeholders to build and maintain a positive image among clients, which is important for organizational success. Businesses largely use search engine optimization, social media interaction, and online review platforms to shape their online visibility (Kim & Lim, 2022). This process is known as Online Reputation Management, which enhances the positive image among their target audience for the purpose of building consumer credibility, trust, and positive intentions. A recent survey conducted by Deloitte collected the perceptions of 300 marketing executives, and the results found that 90% ranked reputation as a significant area of risk, with 80% actively handling it through various strategies. Another survey conducted by Trustpilot about consumer trust in brands found that 90% of consumers remain loyal to brands that share their values. Currently, 85% of consumers place the same degree of trust in online reviews as they do in personal recommendations from friends and family, indicating that controlling your online review presence is not an option—it is required. This highlights that digital reputation has become a strategic determinant of market trust and consumer decision-making. Most companies have universal adoption of online reputation management strategies, including SEO (Search Engine Optimization), social media management, and online reviews. In the realm of SEO, achieving a high ranking ensures that content is prominently displayed and easily seen by consumers, directly impacting their perception. Successful SEO tactics involve enhancing website content, meta tags, and keywords to manage the visibility of brand information, enabling businesses to minimize negative content and highlight the positive stories. Another strategy is social media management as a proactive tool for managing customer feedback, critical communication, actively engaging with them, and collaborating to influence public perception strongly. This can help build consumer trust and shape a positive image for the company. Businesses that promptly address customer feedback, whether it's positive or negative, motivate customers to provide genuine feedback and reviews about their businesses, which can improve the effectiveness of reputation management.

Although, the recent development of artificial intelligence has had a huge influence on internet reviews and reputation management. Consumers are now more conscious and aware of AI-generated reviews, understanding the seriousness; however, businesses must focus on authentic review generation and be clear about their review gathering practices in light of regulatory changes and a shift in customer awareness. This evidence shows that these strategies are not guaranteed to influence consumer attitudes. Businesses should focus on more authentic and transparent communication with their potential consumers. Public Relations (PR) and media employ transparent and two-way communication, through which an organization can build authentic relationships with a diverse audience (Grunig & Hunt, 1984). Unlike AI-driven marketing tools, PR influences credibility and emotional impact to enhance long-term reputation outcomes. According to Hagan (2011), public relations are primarily concerned with managing and restoring an organization's reputation in an ethical and responsible manner. Public relations focusses on reputation, which is influenced by actions, words, and feedback from others. Public relations is a field that focusses on reputation and earning understanding provide support and affect opinion and behaviour (Theaker, 2012).

Astroturfing strategy in online reputation management is a widely used online communication strategy for creating false impressions or reviews about a particular brand or company in public. It aims to shape public opinion, which is trusted by common consumers and influences their perception.

1.4 Research Objectives

This study addresses these gaps through the following objectives:

Primary Objective: To examine how consumer demographic characteristics (age, gender, education, income, profession) moderate the relationship between ORM strategies (Public Relations and astroturfing) and consumer behavioral intentions.

Specific Objectives:

O1: To test whether age moderates the effectiveness of Public Relations and astroturfing on consumer behavioral intentions

O2: To examine whether gender creates differential responses to authentic (PR) versus

2. Literature Review

2.1 Introduction to Literature Review

This section reviews three interconnected literature streams: (1) Online Reputation Management (ORM) strategies with emphasis on Public Relations and Astroturfing, (2) demographic factors shaping consumer behavior in digital environments, and (3) moderation theory and boundary conditions influencing marketing effectiveness. Integrating these domains allows for a theoretical understanding of how demographic characteristics such as age, gender, education, income, and professional background moderate the effectiveness of ORM strategies. This synthesis forms the conceptual base for hypothesizing that ORM strategy outcomes—whether authentic or manipulative—are not uniform but contingent on demographic differences among consumers.

2.2 Online Reputation Management: Strategies and Effectiveness

2.2.1 Evolution of ORM

Online Reputation Management has been transformed into a crisis-oriented defensive role to strategic proactive discipline. Previously the strategies were on the basis of damage control, negative publicity inhibition and elimination of defamatory materials (Fombrun and Van Riel, 2004). Nevertheless, the emergence of participatory digital media makes organizations focus more on the establishment of positive online identities by engaging continuously, being transparent, and communicating value-based (Pfeffer et al., 2014). The appearance of social media, review aggregators and influence systems has democratized the process of building reputation, shifting the authority of companies to consumers (Kaplan and Haenlein, 2010). This democratization requires advanced ORM practices that strike a balance between persuasion and authenticity and trust of stakeholders.

The current literature views ORM as a collection of strategies that include social media, content marketing, search engine optimization, review management, crisis management, and online PR (Chung et al., 2020). Among them, PR is an original, relational approach, and Astroturfing can be seen as the symbol of manipulation and false methods. Both are at opposing ends of the moral spectrum but they are frequently used with similar means to gain a similar reputation. The realization of how consumers with different demographic profiles perceive and react to these strategies is a very important yet a poorly-researched field.

2.2.2 Public Relations as an Authentic ORM Strategy

Public Relations (PR) in ORM is a voluntary, calculated communication that creates a comprehension and goodwill between an organization and its stakeholders (Coombs, 2007). PR is based on earned media, credibility of the third party and two-way communication unlike advertising. Digital PR applies these principles to online ecosystems with the assistance of corporate blogs, press releases, media partnerships, CSR campaigns, and social listening and creates a genuine digital image (Valentini, 2015). Theoretically, Signaling Theory (Spence, 1973) could be applied to the study of PR effectiveness by assuming that believable signals, e.g., third-party endorsements, are used to communicate organizational quality that can only be imitated with some difficulty. PR is also a very expensive attribute and a reliable indicator because it is based on external validation (Connelly et al., 2011). The Elaboration Likelihood Model (ELM) (Petty and Cacioppo, 1986) goes further to explain that consumers who are highly connected or motivated by a brand access PR message via the central route, which makes their attitude and behavior to change permanently.

There is empirical support of the positive influence of PR on purchase intention, brand trust, and credibility. As an illustration, the works of Dijkmans et al. (2015), Ki and Nekmat (2014), and Tafesse (2020) indicate the fact that open PR communication positively affects consumer confidence and long-term loyalty. In line with these results, the current study ($b = 0.511$, $p = .001$) also determines that PR is the most influencing ORM strategy. However, the existence of the same influence is still unclear in relation to age, gender, education, or profession, which indicates the necessity of demographic moderation analysis.

2.2.3 Astroturfing as a Manipulative ORM Strategy

Astroturfing as a name derived based on the idea of artificial grassroots refers to the act of deceptive advertising that creates a false impression of consumer approval through fake reviews, hidden sponsorships, and inflated metrics (Dellarocas, 2006; Mayzlin et al., 2014). Inasmuch as these tactics are able to leverage the influence of peer influence, which is persuasive in nature, there is no genuineness in these tactics. Although digital platforms strive to eliminate these falsifications, the pressures of the economy and competitiveness that underlie astroturfing remain one of its main supports (Luca and Zervas, 2016).

Astroturfing is often used in organizations to gain advantages, though in the short run: an increase in visibility, competitive balance, or temporary sales spikes (Mayzlin et al., 2014). However, once these tricks get unveiled, they tend to create a fierce backlash, destroy consumer confidence, cause negative word-of-mouth, and destroy brand loyalty (Transparency International, 2018). The strategy, therefore, has an inherent paradox: it can turn out to be effective in the short-term, but it is reputational suicidal in the long-run.

The harmful effects of astroturfing are supported by empirical research. As shown by Filieri (2015) and Fan et al. (2020), the perceived credibility and purchase intention among the consumers are dramatically reduced in the presence of counterfeit reviews discovery. Xie et al. (2014) also indicate that lies create continued brand mistrust. These results are supported by our present work resulting in a substantial negative value ($b = -0.206$, $p = .004$). However, there is one underlying issue that one cannot answer: which demographic groups are most susceptible to understanding signs of manipulation and being the most critical of them? The exploration of these differential effects is the main reason why the current attention on demographic moderation.

2.3 Demographic Factors in Consumer Behavior and Digital Marketing

2.3.1 Age and Generational Cohorts

The generational differences also impact on how customers process the online information. According to the digital natives versus digital immigrants framework provided by Prensky (2001), younger generations (Generation Z, Millennials) are more digitally literate, and as such, might be more skeptical of online persuasion, and older generations (Generation X, Baby Boomers) are more likelier to believe the information provided by the institution (Hanoch and Rice, 2006). However, the age also has an influence on cognitive processing younger consumers are more inclined to use heuristic cues in conditions of information overload, whereas elderly consumers are more prepared to approach the elaboration further, though it depends on accepted norms of trust (Yoon et al., 2009).

It was shown in empirical studies, such as those by Hudders et al. (2021) and Lou and Yuan (2019), that age is a moderator of digital persuasion reactions. Nevertheless, the mediating purpose of age has not been studied on the framework of online reputation management (ORM). Therefore, the paper in question explores the age as a non-directional moderator that can influence the viability of the PR and astroturfing strategies.

RQ1a: Does consumer age moderate the relationship between Public Relations and consumer behavioral intentions?

RQ1b: Does consumer age moderate the relationship between astroturfing and consumer behavioral intentions?

H_{1a}: Age will moderate the relationship between Public Relations and consumer behavioral intentions.

H_{1b}: Age will moderate the relationship between astroturfing and consumer behavioral intentions.

2.3.2 Gender Differences in Information Processing

The styles of gender-processing have an impact on reputation perceptions. In general, women have more comprehensive information searches (Meyers-Levy and Loken, 2015), are more sensitive to social and ethical signals (Cross and Madson, 1997). They are more likely to build trust but respond otherwise negatively to the emergence of lies (Croson and Gneezy, 2009). On the other hand, men are often more risk-takers and are more confident in their own judgment (Barber and Odean, 2001).

These empirical trends indicate that women could react better to genuine PR communication and show increased skepticism towards spotted astroturfing whilst men could show less divergent reactions. Findings of gender as a central factor in online persuasion are supported by empirical research of social media use and credibility of reviews (Tifferet and Vilnai-Yavetz, 2018; Shan and King, 2015).

H_{2a}: Consumer gender moderates the relationship between Public Relations and consumer behavioural intentions.

H_{2b}: Consumer gender moderates the relationship between astroturfing and consumer behavioural intentions.

2.4 Moderation Theory and Boundary Conditions

Moderation theory posits that the strength or direction of an independent variable's effect on an outcome depends on another variable (Baron & Kenny, 1986). In marketing, moderators identify for whom and under what conditions a strategy is effective (Sharma et al., 1981). Understanding demographic moderators thus enables precision targeting and theoretical refinement.

Moderators may enhance or buffer main effects (Cohen et al., 2003). In ORM, education and professional expertise are expected to enhance both positive and negative effects—intensifying appreciation for PR and criticism toward astroturfing. Cross-over interactions may also occur if certain demographics reverse response patterns, indicating complex psychological boundaries of persuasion (Aiken & West, 1991).

3. Research Method

3.1 The Study

The present study adopts a quantitative and descriptive method to examine the effect of a diverse demographic profile of consumers on their behavioural intention, impacted by public relations, media strategy, and astroturfing strategy of online reputation management. The study uses a survey-based method through a questionnaire designed to gather data on demographic determinants. Target population in this study consist of consumers across the diverse area within the Mumbai region in India.

3.2 Sampling technique and Sample Size

A convenience sampling method was used to collect the data. A total of 500 questionnaire was distributed in which 423 valid responses received across the different demographic segment. This sample size meets widely accepted multivariate rules of thumb. Following Tabachnick and Fidell's guideline for multiple regression ($N \geq 50 + 8m$), where m is the number of independent variables, the minimum recommended sample size for 11 predictors is $N \geq 50 + 8(11) = 138$ (Tabachnick & Fidell, 2019. The study works on 423 sample which is adequate for conducting the statistical analysis.

3.3 Data Collection Method

Data were collected through self-administrated questionnaire distributed through networks such as google forms and email. The questionnaire consisted of two sections: Demographic Information (age, gender, years of experience, organisation size, and sector), Public relation and media and Astroturfing strategies of online reputation management. Respondents indicated their responses using a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree.

3.4 Statistical Tools and Techniques

Only surveys with full responses to every statement were selected for additional processing after the surveys were examined for completeness. Following that, Microsoft Excel was used to score and total each response. To show

how the viewers responded to each variable, various Excel sheets were made. The Statistical Package for Social Science (SPSS 22.0) and Microsoft Excel were used to analyse the collected data.

4. Results

4.1 Respondents' demographic information

As shown in Table 1 that the study sample consist of 423 respondents, 216 (51.1%) were male and 207 (48.9%) were female. Most respondents [130 (30.7%)] were aged between 25-34 years and had a bachelor's degree [177 (41.9%)]. Thus, most were young and well educated.

Table 4.1 of Demographic profile of consumers

Age			
SN	Category	Frequency	Percent
1	18–24	171	40.4
2	25–34	130	30.7
3	35-44	71	16.8
4	45-54	51	12.1
5	55 and above	10	6.7
Gender			
1	Male	216	51.1
2	Female	207	48.9
Education			
1	High School	14	3.1
	Secondary School	88	20.8
2	Bachelor's Degree	177	41.9
3	Master's Degree	121	28.6
4	Doctorate	23	5.5

Table 4.2. Hierarchical Regression Analysis: Age as Moderator of the Relationship Between Public Relations and Consumer Behavioural Intentions

Model	**Predictor**	**B**	**SE**	**β**	**t**	**p**
Model 1	(Constant)	2.316	.154	—	15.07	< .001
	Public Relations	.252	.043	.263	5.80	< .001

	Age 25–34	.190	.057	.168	3.36	.001
	Age 35–44	.327	.068	.233	4.78	< .001
	Age 45–54	.424	.077	.264	5.49	< .001
	$R^2 = .154$; $F(4, 418) = 18.97$, $p < .001$					
Model 2	(Constant)	2.393	.202	—	11.85	< .001
	Public Relations	.229	.058	.239	3.97	< .001
	Age 25–34	–.129	.360	– .114	–0.36	.720
	Age 35–44	.236	.454	.168	0.52	.604
	Age 45–54	.655	.656	.408	1.00	.319
	PR × Age 25–34	.095	.106	.283	0.90	.369
	PR × Age 35–44	.027	.132	.065	0.20	.841
	PR × Age 45–54	–.066	.187	– .144	–0.35	.725
	$R^2 = .156$; $\Delta R^2 = .002$; $F(7, 415) = 10.94$, $p < .001$					

Note. N = 423. Reference category for age = 18-24 years. PR = Public Relations.

In order to test H1a, hierarchical multiple regression analysis was conducted to examine whether age moderates the relationship between Public Relations and consumer behavioural intentions. Age was represented by three dummy-coded variables with the 18-24 age group serving as the reference category. In the first block, Public Relations and age dummy variables were entered as predictors, with consumer behavioural intentions as the dependent variable. In Block 2, three interaction terms between Public Relations and age categories were added.

Model 1, containing the main effects, was statistically significant, $F(4, 418) = 18.97$, $p < .001$, and explained 15.4% of the variance in consumer behavioural intentions ($R^2 = .154$). The main effect of Public Relations on consumer behavioural intentions was significant ($B = .252$, $SE = .043$, $\beta = .263$, $t = 5.80$, $p < .001$). Additionally, significant main effects emerged for age categories. Compared to the 18-24 reference group, consumers aged 25-34 ($B = .190$, $SE = .057$, $\beta = .168$, $t = 3.36$, $p = .001$), 35-44 ($B = .327$, $SE = .068$, $\beta = .233$, $t = 4.78$, $p < .001$), and 45-54 ($B = .424$, $SE = .077$, $\beta = .264$, $t = 5.49$, $p < .001$) demonstrated significantly higher behavioural intentions.

Model 2, which included the interaction terms, remained statistically significant, $F(7, 415) = 10.94$, $p < .001$. However, the addition of the interaction terms in Block 2 resulted in a negligible and non-significant increase in explained variance ($\Delta R^2 = .002$, $\Delta F(3, 415) = 0.36$, $p > .05$). Examination of the individual interaction coefficients revealed that none achieved statistical significance: PR × Age 25-34 ($B = .095$, $SE = .106$, $\beta = .283$, $t = 0.90$, p =

.369), PR × Age 35-44 (B = .027, SE = .132, β = .065, t = 0.20, p = .841), and PR × Age 45-54 (B = -.066, SE = .187, β = -.144, t = -0.35, p = .725).

Overall, when age was included in the model, the variables in Model 2 explained 15.6% of the variance in consumer behavioural intentions. These findings indicate that age does not significantly moderate the relationship between Public Relations and consumer behavioural intentions. The positive effect of Public Relations on behavioural intentions remains consistent across all age groups examined (18-24, 25-34, 35-44, and 45-54 years). Therefore, **H1a was not supported**.

Table 4.3 Hierarchical Regression Analysis: Age as Moderator of the Relationship Between Astroturfing and Consumer Behavioral Intentions

Model	Predictor	B	SE	β	t	p
Model 1	(Constant)	3.198	0.164	—	19.53	< .001
	Astroturfing	-0.005	0.046	-0.005	-0.11	0.916
	Age 25–34	0.159	0.060	0.141	2.64	0.009
	Age 35–44	0.310	0.072	0.222	4.29	< .001
	Age 45–54	0.435	0.081	0.271	5.36	< .001
	Model Statistics	—	—	—	F(4, 418) = 9.76	$R^2 = 0.085$, $p < .001$
Model 2	(Constant)	3.103	0.228	—	13.59	< .001
	Astroturfing	0.023	0.065	0.024	0.35	0.728
	Age 25–34	0.242	0.376	0.213	0.64	0.520
	Age 35–44	0.220	0.435	0.157	0.51	0.613
	Age 45–54	1.278	0.517	0.795	2.47	0.014
	Astroturfing × Age 25–34	-0.024	0.115	-0.066	-0.21	0.838
	Astroturfing × Age 35–44	0.031	0.133	0.071	0.23	0.815
	Astroturfing × Age 45–54	-0.262	0.158	-0.527	-1.66	0.098
	Model Statistics	—	—	—	F(7, 415) = 6.02	$R^2 = 0.092$, $\Delta R^2 = 0.007$, $p < .001$

Note. N = 423. Reference category for age = 18-24 years. AE = Astroturfing.

In order to test H1b, hierarchical multiple regression analysis was conducted to examine whether age moderates the relationship between Astroturfing and consumer behavioural intentions. Age was represented by three dummy-coded variables with the 18-24 age group serving as the reference category. In the first block, Astroturfing and age dummy variables were entered as predictors, with consumer behavioural intentions as the dependent variable. In Block 2, three interaction terms between Astroturfing and age categories were added.

Model 1, containing the main effects, was statistically significant, $F(4, 418) = 9.76$, $p < .001$, and explained 8.5% of the variance in consumer behavioural intentions ($R^2 = .085$). Notably, the main effect of Astroturfing on consumer behavioural intentions was non-significant ($B = -.005$, $SE = .046$, $\beta = -.005$, $t = -0.11$, $p = .916$), indicating that exposure to astroturfing practices did not significantly influence behavioural intentions. However, significant main effects emerged for age categories. Compared to the 18-24 reference group, consumers aged 25-34 ($B = .159$, $SE = .060$, $\beta = .141$, $t = 2.64$, $p = .009$), 35-44 ($B = .310$, $SE = .072$, $\beta = .222$, $t = 4.29$, $p < .001$), and 45-54 ($B = .435$, $SE = .081$, $\beta = .271$, $t = 5.36$, $p < .001$) demonstrated significantly higher behavioural intentions.

Model 2, which included the interaction terms, remained statistically significant, $F(7, 415) = 6.02$, $p < .001$. However, the addition of the interaction terms in Block 2 resulted in a minimal and non-significant increase in explained variance ($\Delta R^2 = .007$, $\Delta F(3, 415) = 1.03$, $p = .378$). Examination of the individual interaction coefficients revealed that none achieved statistical significance: AE × Age 25-34 ($B = -.024$, $SE = .115$, $\beta = -.066$, $t = -0.21$, $p = .838$), AE × Age 35-44 ($B = .031$, $SE = .133$, $\beta = .071$, $t = 0.23$, $p = .815$), and AE × Age 45-54 ($B = -.262$, $SE = .158$, $\beta = -.527$, $t = -1.66$, $p = .098$). While the interaction term for the 45-54 age group approached conventional significance levels ($p = .098$), it did not meet the $\alpha = .05$ threshold.

Overall, when age was included in the model, the variables in Model 2 explained 9.2% of the variance in consumer behavioural intentions. These findings indicate that age does not significantly moderate the relationship between Astroturfing and consumer behavioural intentions. The null effect of astroturfing on behavioural intentions remains consistent across all age groups examined (18-24, 25-34, 35-44, and 45-54 years). Therefore, **H1b was not supported**.

Table 4.4: Hierarchical Regression Analysis - Gender as Moderator of PR and Consumer Behavioral Intentions

Model	Predictor	B	SE	β	t	p
Model 1	(Constant)	2.378	0.176	—	13.54	< .001
	Public Relations	0.252	0.045	0.263	5.58	< .001
	Gender	0.068	0.049	0.065	1.38	0.168
	Model Statistics	—	—	—	$F(2, 420) = 16.12$	$R^2 = 0.071$, $p < .001$
Model 2	(Constant)	2.986	0.468	—	6.38	< .001
	Public Relations	0.073	0.135	0.076	0.54	0.589

	Gender	-0.379	0.323	-0.362	-1.17	0.242
	PR × Gender	0.132	0.094	0.461	1.40	0.163
	Model Statistics	—	—	—	F(3, 419) = 11.42	R^2 = 0.076, ΔR^2 = 0.004, p < .001

In order to test the predictions, hierarchical multiple regression analysis was conducted to examine gender moderates the relationship between Public Relations and consumer behavioural intentions. In first block included Public Relations and gender as the predictors with consumer behavioural intentions as a dependent variable. In Block two, the interaction between PR and gender was added. Overall, the results showed that the first model was significant $F(2, 420) = 16.12$, $p< .001$, R^2=.071. Main effect of PR on consumer behavioural is significant (B= .252, SE = .045, β = .263, t = 5.58, p < .001). However, the main effect of gender was not significant (B = .068, SE = .049, β = .065, t = 1.38, p = .168), indicating no significant baseline difference in behavioral intentions between male and female consumers, Model 2, which included the interaction term, remained statistically significant, $F(3, 419) = 11.42$, $p < .001$. However, the addition of the interaction term in Block 2 resulted in a minimal and non-significant increase in explained variance ($\Delta R^2 = .004$, $\Delta F(1, 419) = 1.96$, $p = .163$). The PR × Gender interaction term was not significant (B = .132, SE = .094, β = .461, t = 1.40, p = .163). Overall, when gender were included in the model, the variables explained 7.1% of the variance, with the final model, The positive effect of PR on behavioral intentions operates uniformly across both male and female consumers. Therefore, **the hypothesis that gender moderates the PR-behavioral intentions relationship was not supported.**

Table 4.6 : Hierarchical Regression Analysis - Gender as Moderator of Astroturfing and Consumer Behavioural Intentions

Model	**Predictor**	**B**	**SE**	**β**	**t**	**p**
Model 1	Astroturfing	-0.057	0.046	-0.060	-1.23	0.219
	Gender	0.045	0.051	0.043	0.89	0.376
	Model Statistics	—	—	—	F = 1.28	R^2 = 0.006, p = 0.279
Model 2	Astroturfing	-0.077	0.143	-0.081	-0.54	0.591
	Gender	0.001	0.309	0.001	0.00	0.997
	Astroturfing × Gender	0.014	0.094	0.046	0.15	0.884
	Model Statistics	—	—	—	F = 0.86	R^2 = 0.006, ΔR^2 = 0.000, p = 0.462
	Change Statistics	—	—	—	ΔF = 0.02	p = 0.884

In order to test H2b, hierarchical multiple regression analysis was conducted to examine whether gender moderates the relationship between Astroturfing and consumer behavioural intentions. In the first block, Astroturfing and gender were entered as predictors, with consumer behavioural intentions as the dependent variable. In Block 2, the interaction between Astroturfing and gender was added.

Model 1, containing the main effects, was not statistically significant, $F(2, 420) = 1.28$, $p = .279$, and explained only 0.6% of the variance in consumer behavioural intentions ($R^2 = .006$). The main effect of Astroturfing on behavioural intentions was not significant ($B = -.057$, $SE = .046$, $\beta = -.060$, $t = -1.23$, $p = .219$). Similarly, the main effect of gender was not significant ($B = .045$, $SE = .051$, $\beta = .043$, $t = 0.89$, $p = .376$), indicating no baseline difference in behavioural intentions between male and female consumers.

Model 2, which included the interaction term, remained non-significant, $F(3, 419) = 0.86$, $p = .462$. The addition of the interaction term in Block 2 resulted in no increase in explained variance ($\Delta R^2 = .000$, $\Delta F(1, 419) = 0.02$, $p = .884$). The AE × Gender interaction term was not significant ($B = .014$, $SE = .094$, $\beta = .046$, $t = 0.15$, $p = .884$).

Overall, when gender was included in the model, the variables explained only 0.6% of the variance in consumer behavioural intentions. These findings indicate that gender does not moderate the relationship between Astroturfing and consumer behavioural intentions. The non-significant effect of astroturfing on behavioural intentions operates uniformly across both male and female consumers. Therefore, H2b was not supported.

Discussion

The alternate hypotheses in this study were framed to measure demographic factors viz age and gender moderate effect towards the online reputation management strategies includes Public relation and media and Astroturfing .The hierarchical regression was carried out are shown in Table 1 indicate that all interaction effects were non-significant **($p > .05$)**, suggesting that neither age nor gender meaningfully influences how consumers interpret or respond to these online reputation management strategies.

For **H1a n H1b**, the moderating role of Age was tested for both Public relation and media and Astroturfing. The findings of study shows that age does not significantly alter the impact of either authentic PR messages or fabricated astroturfed content on consumer behavioural intention. Although prior literature suggests that older adults may be more vulnerable to misinformation (Guess et al., 2019; doi:10.1177/0956797619868950) and younger users tend to process digital content more critically (Vijayakumar et al., 2021; doi:10.1016/j.chb.2021.106957), the present results show no significant difference. This aligns with recent studies indicating that digital exposure is becoming consistent across age groups, thereby reducing variations in susceptibility to deceptive content (Fenn et al., 2023; doi:10.1177/14614448231158077). Thus, **age does not significantly moderate consumer responses to either PR or astroturfing efforts**.

For **H2a**, the moderating effect of **Gender** was analysed. Similar to age, gender did not significantly influence the effectiveness of PR or AE. The non-significant interaction term suggests that male and female consumers evaluate authenticity cues and deceptive cues in comparable ways. Prior research also highlights that gender differences in trust evaluation and misinformation detection are often minimal (Metzger & Flanagin, 2015; doi:10.1177/1461444814532193; Brashier & Schacter, 2020; doi:10.1038/s41562-020-0889-1). The present findings reinforce this perspective, suggesting that **the perceived credibility of PR or the persuasive appeal of astroturfing does not vary significantly across gender**.

Overall, the results demonstrate that demographic traits like age and gender do not play a substantial role in shaping how consumers respond to authentic PR communication or deceptive astroturfing efforts. In contrast to traditional consumer research where demographic factors strongly influenced perception and decision-making, the present study indicates that digital reputation strategies operate uniformly across demographic segments. This could be attributed to the standardization of online communication formats and widespread familiarity with digital media across populations.

Conclusion

The study explored the moderating effect of demographic variables of consumers, including age and gender, on two online reputation management strategies: public relations and media, and their influence on consumer behaviour intention. Hierarchical regression analysis was applied to examine the impact of these strategies on consumer behavioural intention while considering the moderating role of age and gender. The results show that both strategies were not significant, implying that both strategies influence different age and gender groups similarly.

These findings contribute to the growing understanding of digital technologies, the reach of public relations and media is vast, making communication easier in this digital age. When a brand or organization creates a positive reputation through public relations and media, it will have a huge impact as there will be uniform exposure and equal responses across all age groups and genders.

For practitioners, this implies that segmentation based purely on demographic factors may not be necessary when designing PR or astroturfing-based ORM strategies. Organizations should develop a systematic strategy in which they are more focused on message quality, authenticity, transparency, consistent behavior towards the services they provide to consumers, and ensure the digital platform's level of credibility.

In the future, the researcher may examine the psychographic and cognitive traits, which include trust, familiarity with online platforms, and digital understanding, as moderators in determining the effectiveness of online reputation management.

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