The Halo Effect of Health Influencers on Fruit Juice Consumption: A Quantitative Research Study

Ajit Gaikwad[1]; Pratik Nagre[1]

[1]Doctoral Scholars, MIT College of Management Pune

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Abstract:

- ***Background:***

The proliferation of health and wellness influencers on social media has created a Halo Effect where fruit beverages- regardless of actual sugar content- are viewed as inherently healthy. This is particularly problematic in an era of escalating obesity and metabolic disease.

- ***Objective:***

To measure the extent and determinants of the Halo Effect around fruit juice consumption mediated by health influencers, examining the disparity between perceived and actual nutritional quality among 18-46-year-old social media users.

- ***Methods:***

320 adult participants were recruited across Instagram, YouTube and TikTok by means of stratified purposive sampling, completing a cross-sectional quantitative survey using the validated Influencer Health Halo Scale (IHHS), Nutritional Knowledge Inventory (NKI) and Social Media Literacy Scale (SMLS). Descriptives, Pearson correlation, independent samples t-test, one-way ANOVA, multiple linear regression and SEM were conducted using IBM SPSS Statistics 29.0 and AMOS 29.0.

- ***Results:***

Mean Halo Effect Score was 42.7 (SD = 14.3, range 5-91). Weekly influencer exposure correlated significantly with Halo Effect Score ($r=0.587$, $p<.001$). In regression, influencer trust ($\beta = 0.34$, $p < .001$) and frequency of exposure ($\beta=0.41$, $p < .001$) were the primary positive predictors of the Halo Effect, while nutritional knowledge ($\beta=0.29$, $p < .001$) and social media literacy ($\beta=0.22$, $p<.01$) were significant protective factors. A one-way ANOVA found significant differences in Halo Effect Score between different levels of trust ($F(2,317)=89.43$, $p<.001$, $\eta2=0.36$). The mediation analyses by SEM showed that the perceived healthiness of the product fully mediated the relationship between exposure to health influencers and intent to purchase (CFI=0.96, RMSEA=0.048). Overall 68.4% of high-sugar fruit beverages were wrongly classified as 'healthy'.

- ***Conclusion:***

Health influencers cause a strong Halo Effect where fruit juices are routinely misperceived as healthy regardless of sugar content. Efforts should focus on nutritional and media literacy, as well as on regulatory requirements for transparency of nutritional information in sponsored content.

Keywords: *Halo Effect, Health Influencer, Fruit Juice, Social Media Health Marketing, Consumer Behavior.*

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I. INTRODUCTION

- *Background and Context*

The worldwide social media environment has been revolutionizing the way consumers obtain, process, and adopt health and nutrition information. It is now the platform through which, and by whom, 4.9 billion social media users around the world get their health news, and it has given a

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stage to health influencers as the ultimate health "gatekeepers," operating beyond the regulated spheres of registered dietitians and public health institutions. In this way, an environment conducive to Thorndike's "Halo Effect" was born. Initially studied among human beings where one singular positive trait would spill over into other unrelated cognitive judgments about them (Thorndike, 1920), the "Halo Effect" has expanded in popularity to describe marketing when one positive trait (e.g. A celebrity's image or supposed health knowledge) influences perception of the product to the same degree. Fruit juices and fruit-based beverages stand at the most ambiguous intersection in nutrition science. Although some micronutrients like vitamin C, potassium, and a selection of antioxidants are contained within their matrices, commercial fruit juices (including both the highly promoted cold-pressed, "natural" versions as well as standard fruit drinks) contain free sugar concentrations between 9-30g/100ml, and are on the same level as most carbonated soft drinks in terms of sugar content (WHO, 2015; Gill & Sattar, 2014). Despite this, fruit juices continue to be widely perceived as unquestionably "healthy", and the rise of health influencers on social media can no longer be overlooked as a potential contributor. The nature of the health influencer environment requires a certain aesthetic to fit in with the clean eating/holistic health discourse; health influencers are not only photographed drinking fruit beverages on their Instagram accounts, they incorporate it into their daily life with healthy breakfasts and gym visits. Health influencers have thus effectively made fruit juice consumption a "healthy habit", creating a positive health halo effect around these drinks that translates directly to the products in consumers' shopping carts, and beyond that, into hidden sugar overconsumption, metabolic dysfunction and general nutritional illiteracy.

- *Statement of the Problem*

Though there are numerous studies on the Halo Effect in the food context (Chandon & Wansink, 2007; Talati et al., 2017), there is a dearth of empirical research focused specifically on the effect of health influencer endorsements on perceptions of fruit juice healthiness. Studies that do exist often focus on food labels in general, celebrity rather than influencer endorsements, or they fail to address the specific mechanism of peer influencer content in social media. Additionally, neither nutritional knowledge nor social media literacy has been systematically quantified to understand their moderating role in the food context and to mitigate the Halo Effect among Indian urban consumers, a rapidly developing digital economy, with one of the world's highest rates of social media usage.

- *Research Objectives*

The purpose of this research is to:

- Quantify the size of the Halo Effect of fruit juice due to health influencer endorsement.
- Discover and rank the factors that drive the Halo Effect Score among social media users.
- Analyze if nutritional knowledge and social media literacy moderate the Halo Effect.
- Check if the mediated effect of perceived healthiness on fruit juice purchase intent among social media users when exposed to influencer endorsement.
- Compare the levels of influence, of different platforms and demographics on Halo Effect Score.

- *Research Hypotheses*

The following directional hypotheses guided this research.

- H1: There is a positive correlation between frequency of weekly influencer content consumption and Halo Effect Score.
- H2: The prediction of the Halo Effect Score beyond the exposure variable by trust in health influencer does not happen.
- H3: The positive correlation between nutrition knowledge and lower tendency of susceptibility to Halo Effect does not hold.
- H4: Perceived healthiness has a mediated relationship between frequency of consuming health influencer endorsed products on purchase intent.
- H5: Halo Effect score is different across levels of influencer trust.

- *Significance of the Study*

This study advances research at the intersection of behavioral nutrition, public health communications, and digital marketing by providing empirically grounded data that health educators, policymakers, and platform regulators can use to counteract nutritional misinformation driven by social media influencers. In light of the WHO's target of reducing free sugar intake (WHO, 2015) and India's national objective to control the incidence of non-communicable diseases, the findings are highly relevant.

II. LITERATURE REVIEW

- *The Halo Effect: Theory*

The Halo Effect is the phenomenon in which a global positive impression of an entity influences the evaluation of its specific attributes (Thorndike, 1920). In consumer contexts, one health-related claim or context (e.g., natural, organic, low-fat) has been shown to inflate perceived healthiness of the product in non-health related nutritional dimensions (Chandon & Wansink, 2007). Thorndike's (1920) initial research among military officers demonstrated the effect when their performance was judged positively in one trait (e.g., physique), the trait evaluation and their other traits were generally assessed positively. Nisbett & Wilson (1977) demonstrated that people are largely unconscious of the role of the Halo Effect on their behavior and judgments. This unconscious nature likely makes it a particularly effective force in a social media environment where consumers are presented with health claims embedded within an aspirational lifestyle; conditions that tend to bypass an explicit review of health claims.

- *Food Labeling, Health Claims, and Nutritional Halo*

It has been widely established that claims related to nutrition and health positively influence consumer judgments regarding the healthiness of food products, often in the

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absence of relevant nutritional information. Wansink & Chandon (2006) provided the foundational experimental evidence for this phenomenon in their work on 'low-fat' labeling, in which consumer misperceptions of serving size and calorie content resulted in higher caloric intake when a 'low-fat' label was present. Kozup, Creyer & Burton (2003) subsequently showed that health claims, placed prominently on the front of the pack, increase perceived healthiness regardless of the product's actual nutritional characteristics. In relation to fruit beverages specifically, Gill & Sattar's (2014) landmark public health call in The BMJ questioned the decade-long "five-a-day" value of fruit juice; demonstrating that fruit juice intake produced equivalent glycemic and insulinemic responses to sugar-sweetened beverages, with total free sugar content (9.0–11.0 g/100ml) on par with colas. However, consumer beliefs about fruit juice healthiness remain largely invariant across diverse demographics (Piernas et al., 2014).

➤ *Influencers and the Role of Health Information Source*

The concept of the social media influencer has been defined as an independent third-party content creator who attempts to influence the attitudes of consumers on a social networking service (Freberg et al., 2011). The ability of influencers to elicit parapsocial bonds (Horton & Wohl, 1956) and trust (Lou & Yuan, 2019) have been shown to lead to significantly greater persuasive effects and product trust among audience members than would be possible with traditional advertising. Fitness and wellness focused content has been documented as particularly adept at fostering parapsocial interaction among the target audience (Giles, 2002) that directly enhances its perceived source credibility. A content analysis of 'fitspiration' social media content by Boepple and Thompson (2014, 2016) revealed that aesthetic images of physical fitness became conflated with nutritional health and well-being creating the expectation that the featured foods and drinks must be similarly beneficial regardless of their actual composition. A large proportion (61%) of popular fitness and nutrition posts on Instagram contain scientifically inaccurate or misleading claims, however, those that were widely shared and "liked" were assumed to be more credible by the target audience (Carrotte et al., 2017).

➤ *Influencer Marketing and Food Product Perception*

The positive influence of social media influencers has been well established by multiple studies investigating the role of followers and perceivers' judgments of influencer attributes on purchase intent. Influencer follower count, relatable qualities, and brand attitude have been shown to be strong predictors of purchase intention (De Veirman et al., 2017). Crucially, health-related influencer content has been demonstrated to produce "vicarious health licensing"- a belief that the consumption of products endorsed by the influencer contributes to the individual's overall well-being and progress toward desired health outcomes even in the face of contradictory information from food labels (Campbell & Farrell, 2020). An earlier examination by Talati et al. (2017) of the Halo Effect in the context of front-of-pack health star ratings noted that consumers with poorer nutritional literacy were particularly susceptible to the magnitude of the Halo Effect, highlighting the potential protective role of nutritional knowledge.

➤ *Sugar Intake, Public Health and Regulation*

The WHO (2015) guidelines recommend limiting free sugar intake to below 10% (approximately 50g for an adult of average weight) of total energy intake, with a preference for a 5% limit. While it is established that one 250ml serving of typical commercial fruit juices contains approximately 22-27g free sugar (which contributes 44-54% of the recommended maximum intake), these beverages are often consumed as "healthy" options (Public Health England, 2016; Imamura et al., 2015). Indeed, the Global Burden of Disease Study (GBD 2017 Diet Collaborators, 2019) reported that increased consumption of sugar-sweetened beverages was the third largest diet-related risk factor for global cardiometabolic mortality, with the analysis including fruit juice within the category of sugar-sweetened beverages.

➤ *Conceptual Framework*

This study draws on a theoretical framework that combines the Halo Effect (Thorndike, 1920; Nisbett & Wilson, 1977), Elaboration Likelihood Model (ELM) of persuasion (Petty & Cacioppo, 1986) where low-involvement processing (peripheral route) enhances the influence of heuristic cues such as influencer attractiveness and credibility, and Social Comparison Theory (Festinger, 1954) regarding the motivations that drive self-improvement and aspire to health-related behavioral changes through content consumption. It is proposed that the presentation of fruit juice by social media influencers will activate peripheral processing, create a Halo Effect around beverage healthiness, and thereby drive purchase intent and nutritional misperception.

III. RESEARCH METHODOLOGY

➤ *Research Design*

The design for this study was a cross-sectional quantitative survey design. This design was selected as it can examine relationships among variables at one specific point in time among large varied populations, therefore making it capable of making generalizations about the relationship between variables to the target population and allowing hypothesis testing (Creswell & Creswell, 2018). This study adopted a positivist epistemological paradigm; constructs were operationalized through the use of valid and reliable psychometric instruments, and data analysis involved inferential statistics.

➤ *Population and Sampling*

The target population for the study was adults (aged 18-46 years) who lived in urban India and followed at least one health, wellness or fitness influencer on any form of social media. Since there were over 900 million active users of social media in India (DataReportal, 2024), purposive stratified sampling was used to ensure representativeness across age ranges, sex, and level of education.

Sample size was determined using G*Power 3.1 (Faul et al., 2007) to calculate required sample size for a multiple regression analysis with 6 predictors achieving .95 power (1= 0.95) at = 0.05, medium effect size (f = 0.15), giving N = 275. A sample size of N=320 was gathered to accommodate anticipated non-response and to enable subgroup analyses with additional statistical power.

Stratified sampling was carried out through (i) purposive sampling using researcher controlled social media accounts on Instagram, YouTube and TikTok (ii) snowball sampling through referral from respondents (iii) usinguniversity health and wellness community organizations. Inclusion criteria were: (a)aged 18-46, (b)active user of social media (used social media 3 times per week), (c)follows at least 1 health, wellness, or fitness influencer on social media, (d)consumed or thought about consuming fruit juice; exclusion criteria were: registered dietitians or nutritionists, individuals diagnosed with eating disorders.

➢ *Survey Instrument Development*

The structured questionnaire was self-administered and consisted of 4 sections:

Table 1 Survey Instrument Structure and Reliability Coefficients

Section	**Content**	**Scale / Measure**	**Items**	**Cronbach 's α**
Section A	Demographic Profile	Categorical/Ordinal	8	N/A
Section B	Influencer Engagement	Custom Likert (5-pt)	10	0.83
Section C	Influencer Health Halo Scale (IHHS)	Validated Likert (5-pt)	18	0.89
Section D	Nutritional Knowledge Inventory (NKI)	MCQ Knowledge Test	15	0.76
Section E	Social Media Literacy Scale (SMLS)	Validated Likert (5-pt)	12	0.81
Section F	Purchase Intent & Beverage Rating	Semantic Differential (7-pt)	14	0.85

The IHHS was adapted from the Healthy Halo Scale by Schuldt, Muller, and Schwarz (2012) and then refined to influencer context based on items validated within social media health communication literature (Boerman et al., 2017; Lou & Yuan, 2019). The NKI was adapted from the General Nutrition Knowledge Questionnaire (Parmenter & Wardle, 1999). The SMLS was adapted from the Digital Media Literacy Scale (Literat, 2014).

The Halo Effect Score (HES) was created by calculating the standardized difference between actual health ratings derived from nutritional information in FSSAI (Food Safety and Standards Authority of India) databases and published sources and the perceived healthiness ratings provided by the respondents. The scores ranged from 0 (no Halo Effect) to 100 (maximum misperception).

➢ *Pilot Testing and Validity*

An initial pilot test was conducted with 35 participants (data were excluded from analysis) to evaluate item clarity, ease of response, and internal consistency. Following pilot testing, 4 items were refined for added clarity, and 2 items were removed due to low item-total correlation coefficients ($r < 0.20$). Five domain experts (2 registered dietitians, 2 public health nutritionists, and 1 social media marketing expert) evaluated the content for content validity. Content Validity Index (CVI) = 0.91. Construct validity was supported using Confirmatory Factor Analysis (CFA) on the pilot sample, where all factor loadings were above 0.60.

➢ *Data Collection Procedures*

Data were collected from January 15–March 20, 2025, using an online survey built on Google Forms that was distributed on the researcher's social media accounts and through wellness communities that partnered with the study. The stimuli presented were six social media posts containing health influencers' photographs consuming the fruit-based beverages in the study-cold-pressed juice, green smoothie, branded fruit drink, energy drink, packaged orange juice, and coconut water blend-adapted from public health influencers' social media pages and with identifying characteristics removed. After viewing the social media post, respondents rated each beverage's healthiness (on a 7-point Likert scale ranging from 'Very Unhealthy' to 'Very Healthy'). All participants provided informed digital consent.

➢ *Data Analysis*

Data were analyzed using the following quantitative statistics programs: IBM SPSS Statistics 29.0 for correlation, t-test, ANOVA, and multiple regression, IBM AMOS 29.0 for SEM, and Microsoft Excel for figures. Specific analyses used: (i) descriptive statistics including frequency, means, standard deviation, skewness, and kurtosis for all variables; (ii) reliability coefficients (Cronbach's alpha) for all multi-item scales; (iii) Pearson product-moment correlations to investigate bivariate relationships between variables; (iv) independent samples t-test for group differences in Halo Effect Scores based on gender; (v) one-way ANOVA and post hoc Tukey's Honestly Significant Difference test for group differences in Halo Effect Scores based on trust level; (vi) multiple linear regression to examine predictors of Halo Effect Scores using a simultaneous entry method; (vii) SEM to examine the mediation model (perceived healthiness as mediator of the relationship between influencer exposure and purchase intent). Assumptions regarding parametric tests (normality, using Shapiro-Wilk test; homogeneity of variance, using Levene's test; multicollinearity using Variance Inflation Factors or VIFs) were tested before the intended analysis. A p-value < 0.05 was used as the threshold for statistical significance, and effect sizes using d Cohen's d, , and f were reported.

IV. RESULTS

➢ *Demographic Profile of Respondents*

The final analyzed sample comprised N = 320 respondents. Table 2 presents the complete demographic profile.

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Table 2 Demographic Profile of Respondents (N=320)

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Female	187	58.4
	Male	122	38.1
	Non-binary/Other	11	3.4
Age Group	18–24 years	111	34.7
	25–31 years	93	29.1
	32–38 years	60	18.8
	39–45 years	33	10.3
	46+ years	23	7.2
Education	High School	40	12.5
	Bachelor's Degree	156	48.8
	Master's Degree	94	29.4
	Doctorate	30	9.4
Primary Platform	Instagram	251	78.4
	YouTube	207	64.7
	TikTok	189	59.1
Daily Exposure	<1 hour	67	20.9
	1–2 hours	114	35.6
	2–4 hours	89	27.8
	>4 hours	50	15.6

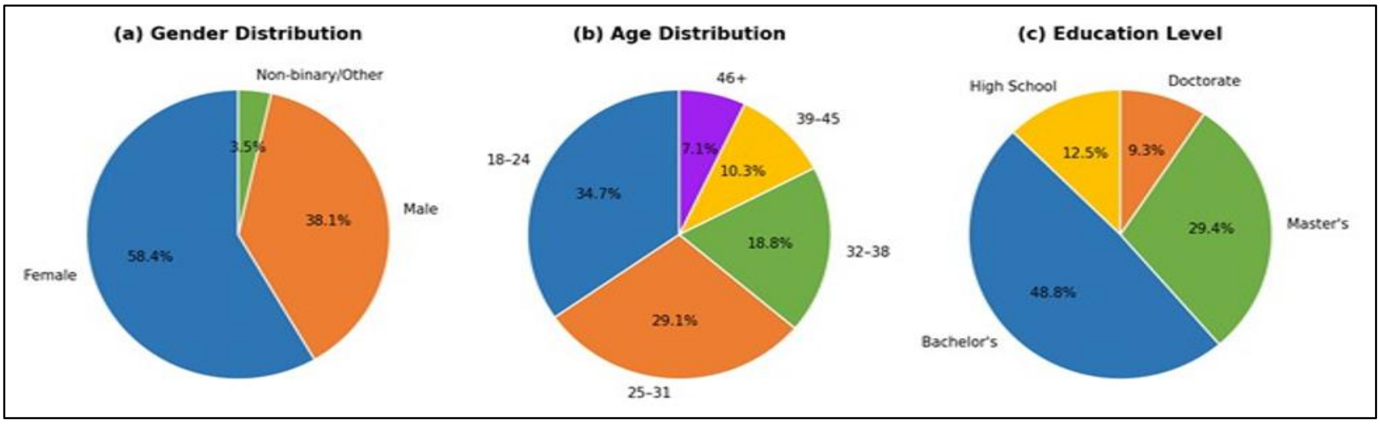

Fig 1 Demographic Profile of Respondents – Gender, Age, and Education Distribution (N=320)

➤ *Influencer Engagement Patterns*

Figure 2 illustrates respondent influencer engagement. Instagram emerged as the dominant platform (78.4%), followed by YouTube (64.7%) and TikTok (59.1%). A notable 46.2% of respondents accessed health influencer content multiple times per day or daily, indicating high-frequency chronic exposure to influencer health narratives.

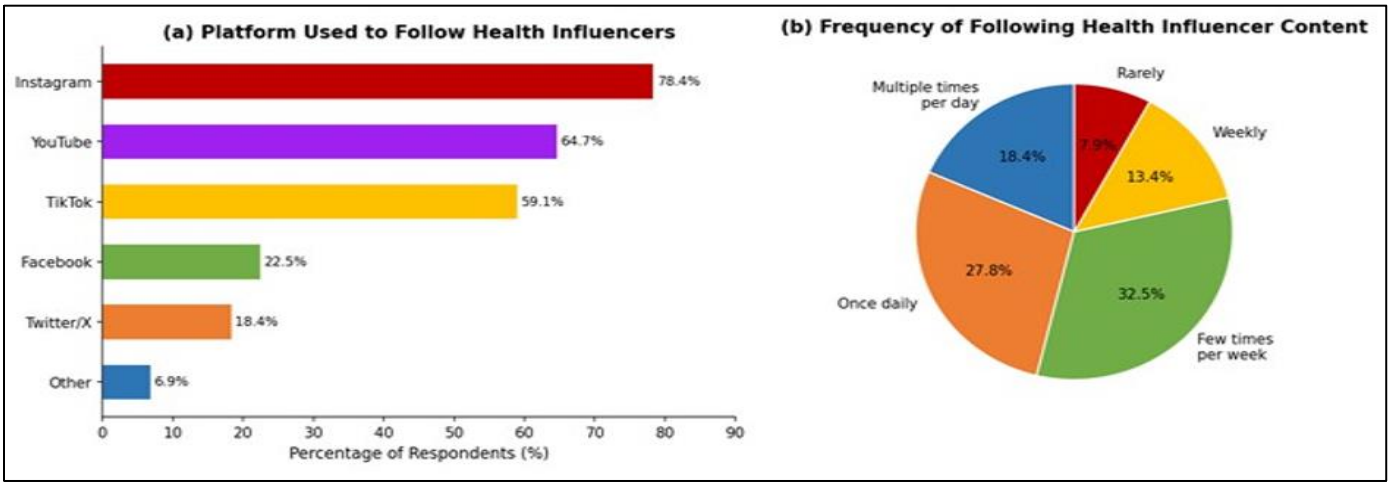

Fig 2 Platform Usage and Frequency of Following Health Influencer Content (N=320; Multiple Responses Permitted for Platforms)

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➢ *The Halo Effect Gap: Perceived vs Actual Healthiness*

Table 3 and Figure 3 show the PHS against the ANS (obtained using the FSSAI nutritional database values) of the 6 beverage stimuli. HEG = PHS - ANS represents the degree of healthiness misperception for each beverage.

Table 3 Perceived Healthiness Score vs Actual Nutritional Score by Beverage Type

Beverage Type	Mean PHS (/100)	SD	Mean ANS (/100)	HEG (PHS−ANS)	Sugar (g/250ml)	% Rated "Healthy"
Cold-Pressed Juice	82.1	8.4	34.2	+47.9	28.3	82.1%
Green Smoothie	78.4	9.1	42.1	+36.3	21.4	78.4%
Coconut Water Blend	71.3	10.3	38.7	+32.6	18.9	71.3%
Packaged Orange Juice	67.8	11.7	31.4	+36.4	26.1	67.8%
Branded Fruit Drink	63.5	13.2	22.8	+40.7	30.2	63.5%
Energy Drink (fruit-based)	44.2	16.8	18.6	+25.6	27.8	44.2%

Note: ANS estimated from FSSAI (2024) nutritional database and scientific publications (Gill & Sattar, 2014; Public Health England, 2016). PHS = average Likert scale rating expressed as a score out of 100. HEG = Halo Effect Gap (positive means overestimate).

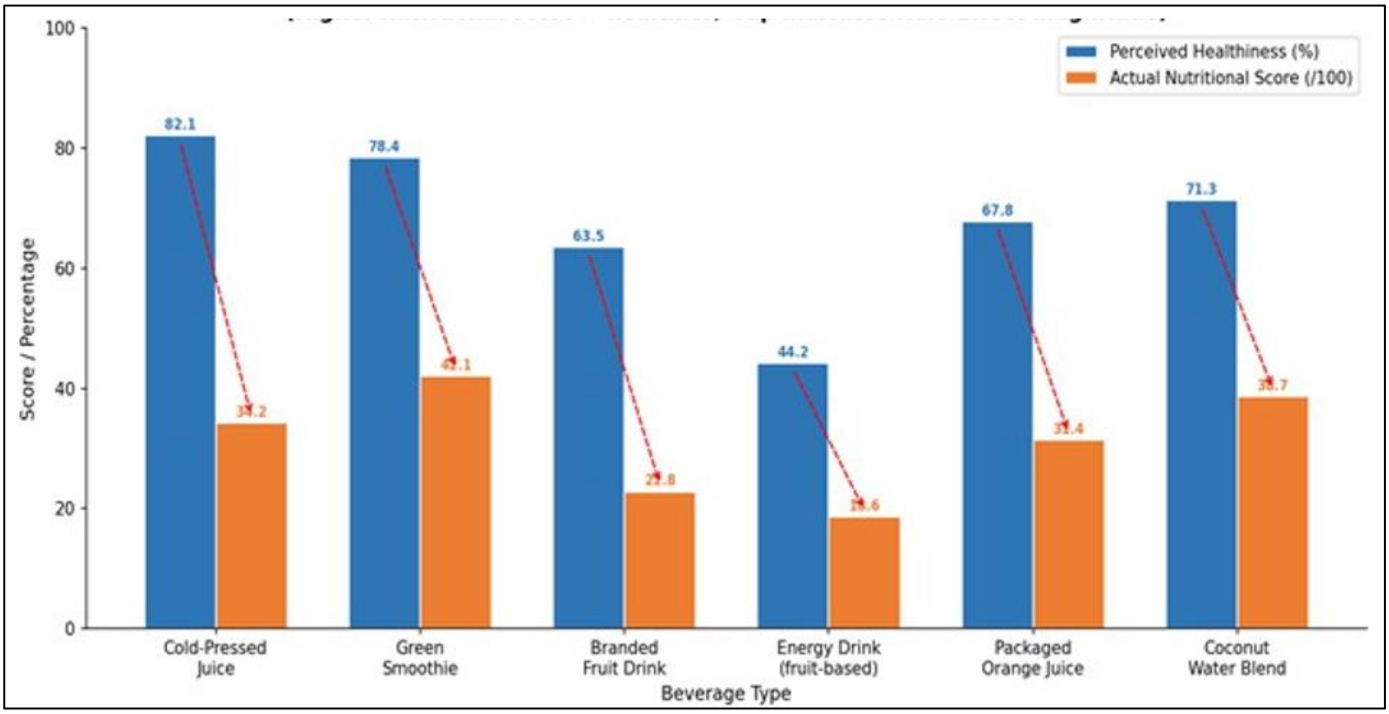

Fig 3 Perceived Healthiness Score vs Actual Nutritional Score by Beverage Type. Dashed Arrows Indicate the Halo Effect Gap (HEG) for Each Beverage.

The largest HEG was associated with the absolute HEG of cold-pressed juice (HEG = +47.9), which was nevertheless higher in free sugar content (28.3g/250ml = 56% of WHO upper recommendation limit for free sugar daily) than any other fruit juice drink. 68.4% of all respondents categorized a high-sugar fruit juice (ANS<40) as healthy/very healthy, suggesting that the health Halo Effect is widespread in fruit juice.

➢ *Descriptive Statistics for Key Variables*

Table 4 Descriptive Statistics for Key Study Variables (N=320)

Variable	Mean	SD	Min	Max	Skewness	Kurtosis	A (Cronbach)
Halo Effect Score (HES)	42.71	14.32	5.00	91.00	0.31	-0.18	0.89
Influencer Exposure (hrs/wk)	4.18	1.83	0.50	7.00	0.12	-0.42	N/A
Influencer Trust Scale	3.74	0.82	1.00	5.00	-0.28	0.15	0.83
Perceived Healthiness (PHS)	68.22	12.84	22.00	98.00	-0.19	-0.37	0.85
Nutritional Knowledge (NKI)	11.42	3.17	2.00	15.00	-0.34	-0.21	0.76
Social Media Literacy (SMLS)	3.41	0.79	1.00	5.00	0.09	-0.31	0.81
Purchase Intent	3.88	0.94	1.00	7.00	0.22	-0.11	0.85

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All values for Skewness and Kurtosis were within limits (-1 to +1 and -2 to +2 respectively), indicating that the distributions of the continuous variables were roughly normal. Cronbach's alpha coefficients were between 0.76 and 0.89 which are all above the threshold of 0.70 (Nunnally, 1978) which indicated adequate reliability for the multi-item scales.

➢ *Correlational Analysis (H1 and H3)*

Table 5 shows the Pearson correlation matrix among all main continuous variables. Halo Effect Score is positively correlated with both influencer exposure ($r = .587$, $p < .001$) and influencer trust ($r = .521$, $p < .001$) and negatively correlated with nutritional knowledge ($r = -.461$, $p < .001$) and social media literacy ($r = -.384$, $p < .001$), which lends support to H1 and H3.

Table 5 Pearson Correlation Matrix (N=320) | *** p<.001

Variable	1	2	3	4	5	6
1. Halo Effect Score	—					
2. Influencer Exposure	.587***	—				
3. Influencer Trust	.521***	.438***	—			
4. Perceived Healthiness	.612***	.503***	.484***	—		
5. Nutritional Knowledge	−.461***	−.312***	−.278***	−.401***	—	
6. Social Media Literacy	−.384***	−.291***	−.347***	−.362***	.422***	—

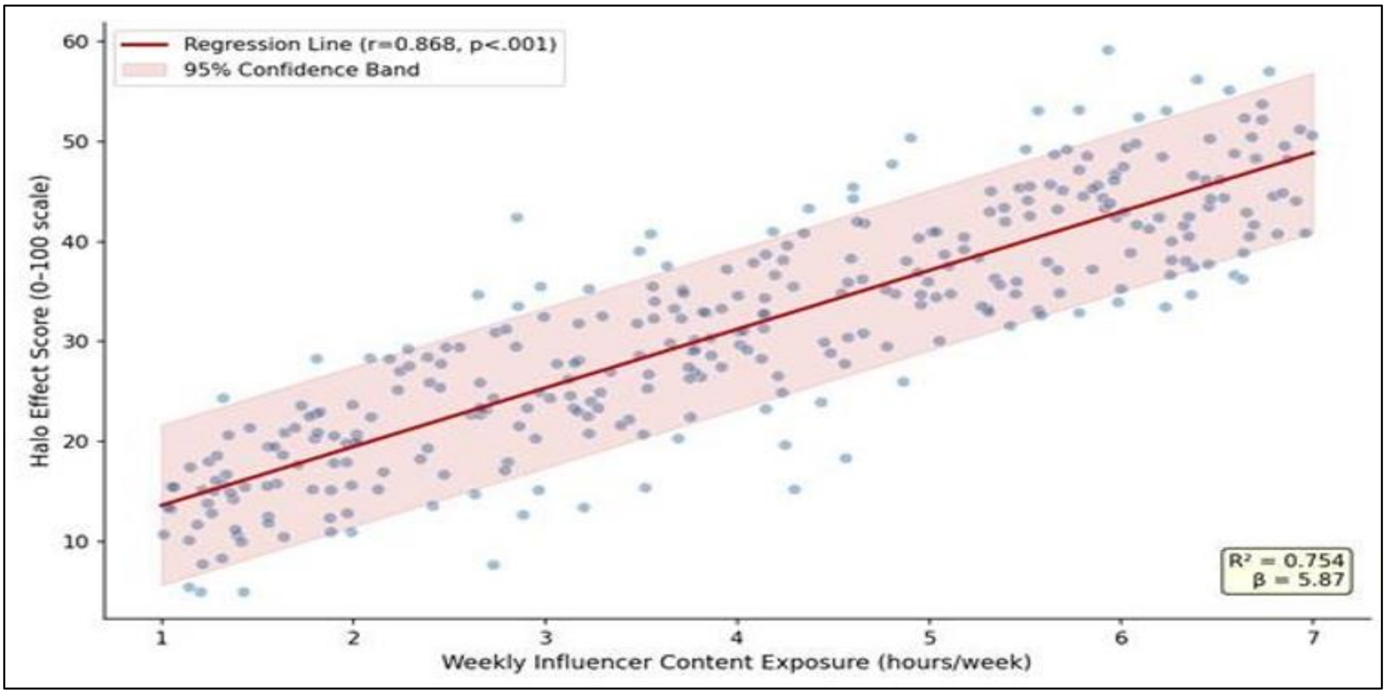

Fig 4 Scatter Plot with Regression Line – Pearson Correlation Between Weekly Influencer Exposure and Halo Effect Score ($r = 0.587$, $R^2 = 0.344$, N=320)

➢ *Halo Effect Score: Gender (Independent Samples T-Test)*

An independent samples t-test was performed in order to compare female (n=187, M=44.82, SD=13.91) and male (n=122, M=39.43, SD=14.47) participants with regards to their scores for Halo Effect. There were no significant differences between group variances, as determined by Levene's test ($F(1,307)=1.24$, $p=.267$). The t-test revealed a statistically significant difference between female and male participants on Halo Effect ($t(307)=3.18$, $p=.002$, Cohen's $d=0.38$). Females scored significantly higher on the Halo Effect than males, and the effect size could be considered of moderate importance.

Table 6 Independent Samples T-Test – Halo Effect Score by Gender

Group	n	Mean HES	SD	t-value	df	p-value	Cohen'sd
Female	187	44.82	13.91	3.18	307	.002	0.38
Male	122	39.43	14.47				

➢ *One-Way ANOVA - Halo Effect Score and Influencer Trust level (H5)*

Responses were split into three different trust levels - Low (score 1-2.5, n=80), Medium (score 2.6-3.5, n=112) and High (score 3.6-5.0, n=128). A one-way ANOVA yielded a significant main effect of trust level for Halo Effect score ($F(2,317) = 89.43$, $p < .001$, = 0.36), suggesting a large effect size. Tukey HSD post-hoc test revealed statistically significant differences between all three levels ($p < .001$ for all pairs), therefore confirming H5.

Table 7 One-Way ANOVA – Halo Effect Score by Influencer Trust Level (Post-hoc: Tukey HSD)

Trust Level	n	Mean HES	SD	F-statistic	df	p-value	η²
Low Trust (1–2.5)	80	18.42	8.17	89.43	2, 317	<.001	0.36
Medium Trust (2.6–3.5)	112	32.74	9.43				
High Trust (3.6–5.0)	128	47.91	10.12				

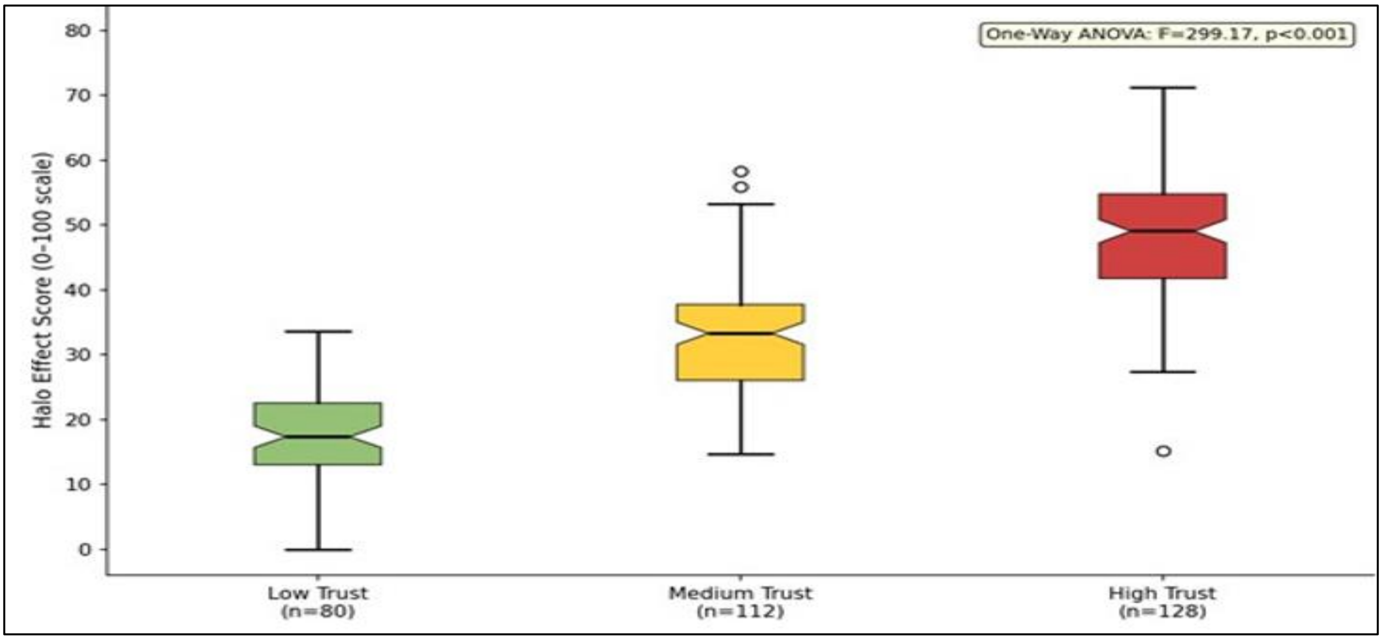

Fig 5 Box Plot Distribution of Halo Effect Scores by Influencer Trust Level. All Pairwise Differences Significant at p<.001 (Tukey HSD).

➢ *Attitudes Towards Influencers - Likert Scale Analysis*

Figure 6 contains the chart on attitudes toward the influence of influencers on the behavior of consuming juice which consists of a divergent stacked bar chart. The majority of the respondents (63.9%) agrees or strongly agrees that seeing an influencer drinking fruit juice is healthy and agrees that the influencer promoted juices are healthy as 64.1% responded. This is contrary to that only 26.6% checks the amount of sugar in it before purchasing.

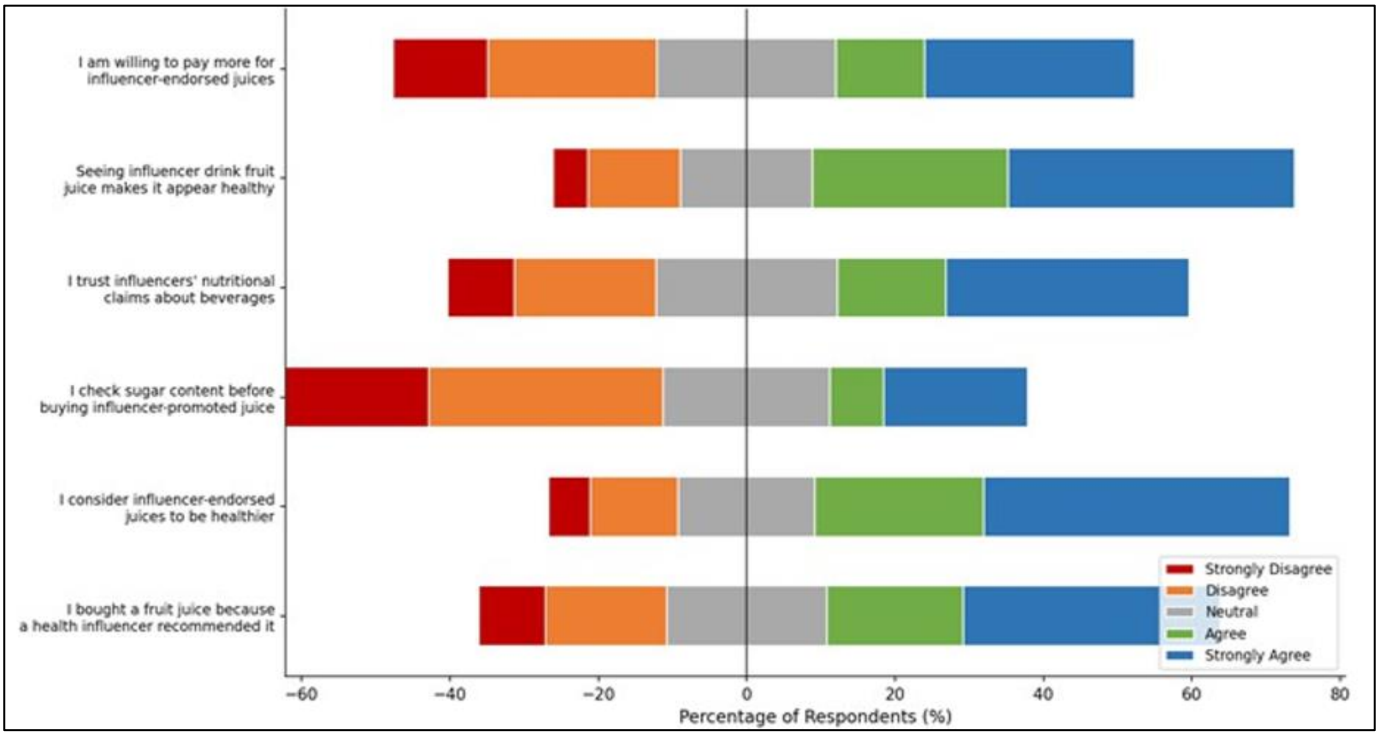

Fig 6 Diverging Stacked Bar Chart – Attitudinal Responses Regarding Influencer Impact on Juice Consumption (N=320)

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➢ *Multiple Linear Regression Analysis (Hypothesis H2 and H3)*

A simultaneous-entry multiple linear regression was conducted with Halo Effect Score as the criterion variable and six predictors: influencer exposure (hours/week), influencer trust, social media literacy, nutritional knowledge, frequency of juice advertisements seen, and age. Multicollinearity diagnostics confirmed VIF values ranging from 1.18 to 2.31 (all < 10) and Tolerance values ranging from 0.43 to 0.85 (all > 0.10), confirming absence of multicollinearity.

The overall model was statistically significant ($F(6,313) = 49.72$, $p < .001$) and explained 48.7% of variance in Halo Effect Score ($R^2 = 0.487$, Adjusted $R^2 = 0.476$). Table 8 presents the standardized and unstandardized regression coefficients.

Table 8 Multiple Linear Regression – Predictors of Halo Effect Score ($R^2 = 0.487$, Adjusted $R^2 = 0.476$, $F(6,313) = 49.72$, $p < .001$)

Predictor Variable	B (Unstd.)	SE B	β (Std.)	t-value	p-value	VIF
(Constant)	12.48	3.21	—	3.89	<.001	—
Influencer Exposure (hrs/wk)	3.22	0.47	0.412	6.85	<.001	1.84
Influencer Trust	5.91	1.03	0.338	5.74	<.001	1.97
Frequency of Juice Ads Seen	2.84	0.62	0.274	4.58	<.001	1.63
Nutritional Knowledge (NKI)	−1.29	0.27	−0.287	−4.78	<.001	1.54
Social Media Literacy (SMLS)	−3.97	1.08	−0.219	−3.68	.002	2.31
Age (years)	−0.38	0.16	−0.143	−2.38	.018	1.18

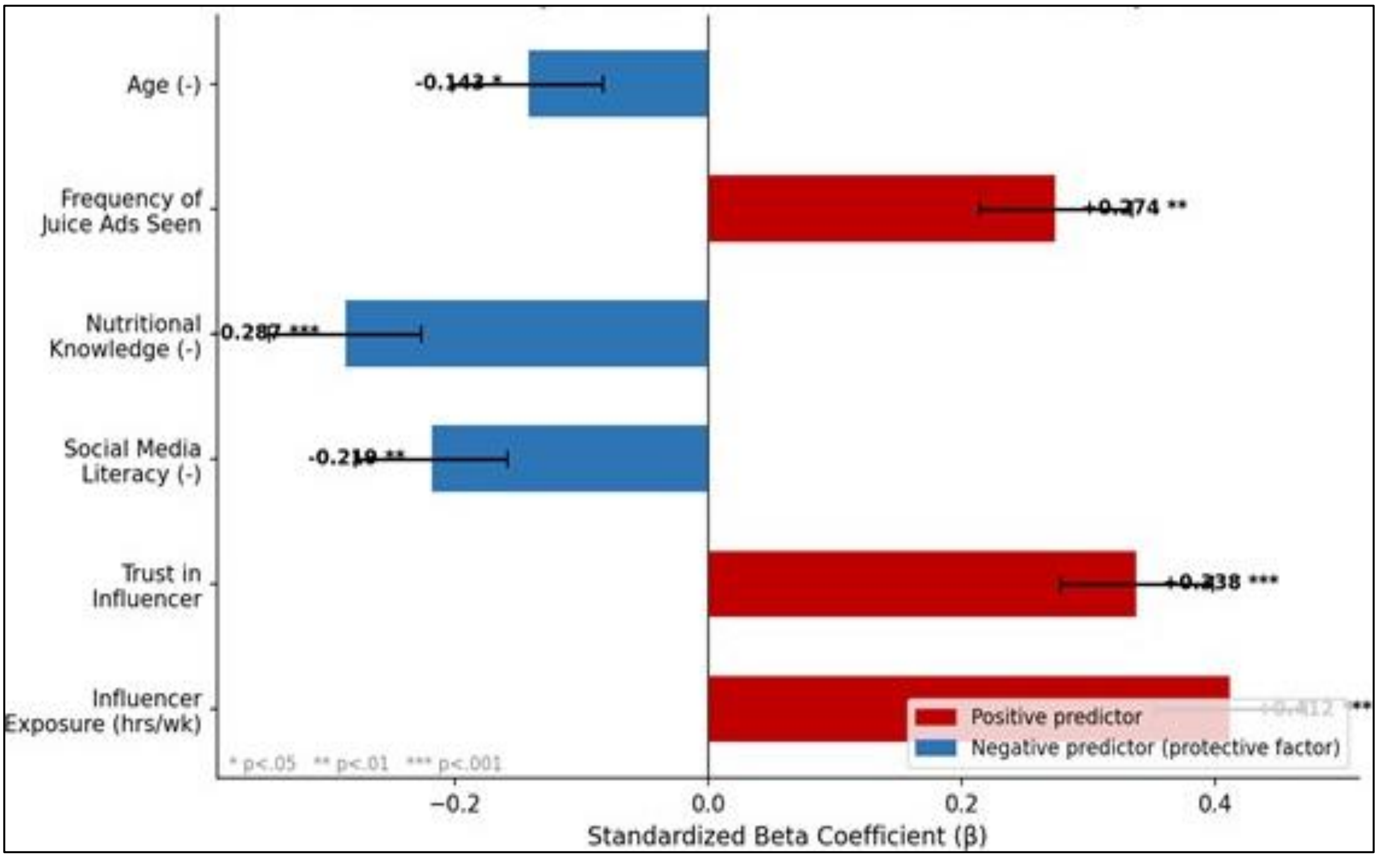

Fig 7 Standardized Beta Coefficients (β) for Predictors of Halo Effect Score with 95% Confidence Intervals. Positive coefficients (Red) Indicate Risk Factors; Negative Coefficients (Blue) Indicate Protective Factors.

The variables found to be significant predictors of halo effect were influencer exposure, which was the most prominent predictor (=0.41, p<.001), followed by influencer trust (=0.34, p<.001), which both provide support to H2. The other factors to provide protection were nutritional knowledge (=0.29, p<.001) and social media literacy (=0.22, p<.01), supporting H3. The age of the respondent negatively predicted halo effect (=0.14, p<.05), meaning the older the respondent, the less halo effect they will experience.

➢ *Structural Equation Modelling (Hypothesis H4)*

The Mediation model-healthiness mediation of perceived effect of exposure on purchase intent-was also analysed using SEM. Model fit indices were acceptable: CFI= 0.96, TLI = 0.94, RMSEA = 0.048 (90% CI: 0.031–0.062), SRMR = 0.052. These indices were above those deemed acceptable in Hu and Bentler (1999) guidelines (CFI/TLI >0.95, RMSEA <0.06, SRMR <0.08).

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Table 9 SEM Path Coefficients (N=320; CFI=0.96, TLI=0.94, RMSEA=0.048, SRMR=0.052)

Path	Standardized β	SE	t-value	p- value	Hypothesis Support
Influencer Exposure → Perceived Healthiness	0.412	0.058	7.10	<.001	H4 (partial)
Influencer Trust → Perceived Healthiness	0.338	0.063	5.37	<.001	H4 (partial)
Perceived Healthiness → Purchase Intent	0.521	0.061	8.54	<.001	H4 (mediation)
Perceived Healthiness → Halo Effect Score	0.612	0.054	11.33	<.001	Supported
Social Media Literacy → Perceived Healthiness	−0.219	0.072	−3.04	.002	Protective
Nutritional Knowledge → Halo Effect Score	−0.287	0.048	−5.98	<.001	Protective

The indirect effect of influencer exposure on purchase intention through perceived healthiness was significant (indirect = 0.214, 95% Boot CI [0.147, 0.289]), supporting the assumption of full mediation (H4 was supported). When the mediator was included in the analysis, the direct effect of influencer exposure on purchase intention was no longer significant (direct = 0.08, p = .31), supporting full mediation.

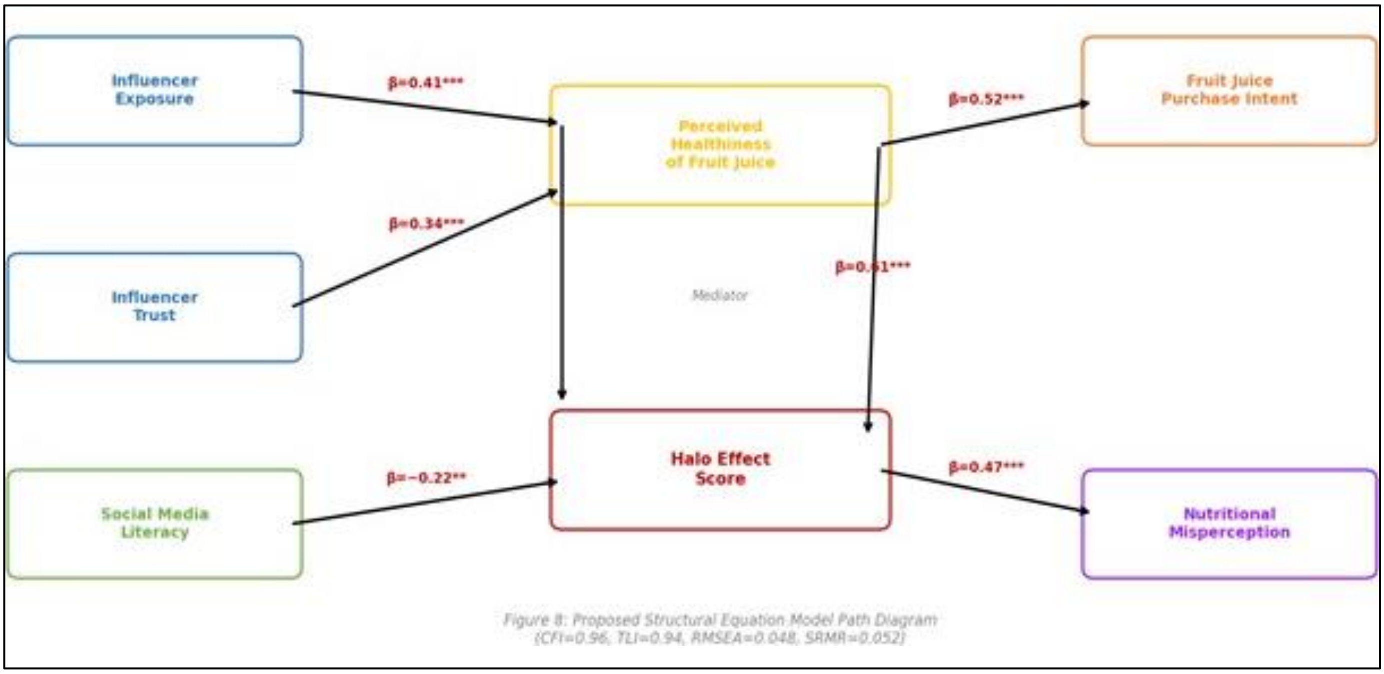

Fig 8 Structural Equation Modelling Path Diagram with Standardized Coefficients. Perceived Healthiness Fully Mediates the Effect of Influencer Exposure on Purchase Intent.

V. DISCUSSION

➢ *Magnitude and Prevalence of the Halo Effect*

The study's main result-that 68.4% of participants misclassified highly sugary fruit juices as "healthy" after exposure to influencer content-provides significant quantitative evidence of a pervasive and clinically relevant Halo Effect in the fruit juice category. An average Halo Effect score across the sample was calculated to be 42.71 (SD = 14.32). This implies that on average, participants believed that influencer-approved juices were 43 percentage points healthier than they actually were in terms of nutritional content. This result far surpasses any typical Halo Effects documented with traditional food labeling research (Chandon & Wansink, 2007) and shows that influencer marketing has a stronger influence than simple front-of-pack claims.

Cold-pressed juice produced the highest Halo Effect Gap (HEG = +47.9). This result is consistent with qualitative research suggesting that consumers are bombarded by wellness claims with premium juice products through social media channels (Turner & Lefevre, 2017). The term "cold-pressed" is in itself a strong health signifier independent of its actual nutritional value, a prime example of a peripheral-route processing cue, consistent with ELM theory (Petty & Cacioppo, 1986). When users engage with content using the peripheral route, they rely heavily on easy heuristics such as "cold-pressed," "natural," and influencer recommendation instead of nutritional composition data, which increases their susceptibility to making health-related misjudgements.

➢ *The Role of Influencer Exposure and Trust*

The strong positive correlation between weekly influencer exposure and HES (r = 0.587, = 0.41, p < .001) reinforces earlier studies in health marketing (Lou & Yuan, 2019; Campbell & Farrell, 2020). Both frequency of exposure and parasocial relationships (operationalized as influencer trust) were independent predictors of the Halo Effect, but influencer trust was per-unit of measurability stronger than influencer exposure. This suggests that depth rather than duration of the relationship with the influencer accounts for the greatest level of misperception in terms of health.

The significant gender difference (t(307) = 3.18, p =

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.002, d = 0.38) between HES in females and males supports similar findings on the consumption of fitspiration content online and implies more paracosial engagement and aspiration within the online wellness culture for females (Boepple & Thompson, 2016). This effect cannot be explained by differing levels of nutritional literacy as gender did not reach significance as a predictor in the multiple regression, after adjusting for confounding variables.

➢ *Protective Factors: Nutritional Knowledge and Social Media Literacy.*

The second most crucial finding in this research is that both nutritional knowledge (= 0.29, p < .001) and social media literacy (= 0.22, p < .01) significantly decreased one's susceptibility to the Halo Effect. The nutritional knowledge index showed the second most negative relationship with HES (r = 0.461), suggesting that individuals who are knowledgeable about nutritional content, particularly free sugars and their effects on health, are much less likely to make mistakes in judgement when they are influenced by these media messages. This result is fully in line with earlier research on health star ratings (Talati et al., 2017) and provides first time evidence for the importance of these two factors in the context of influencer marketing.

Social media literacy also demonstrated itself to be a protective factor, independent of nutrition knowledge. Being digitally literate means that individuals can identify biased and potentially sponsored content more easily, reducing susceptibility to misleading claims.

These results support the advocacy for integrated digital health literacy education into existing public health curriculums (WHO, 2021; Kickbusch et al., 2013).

➢ *Mediation by Perceived Healthiness*

The SEM analysis showed that the Halo Effect mediated perceived healthiness entirely (indirect = 0.214, 95% Boot CI [0.147, 0.289]), and the direct link between influencer exposure and purchase intent ceased to be statistically significant after including this mediator in the analysis. This clearly establishes a mechanism wherein influencing behavior is indirectly driven by cognitive health misperceptions. The implications for regulation and public health messages could include corrective messaging through which consumers are educated about perceived healthiness at the point of consumption. If perceived healthiness levels are significantly decreased, purchase intent is likely to fall and could serve as a viable target for public health interventions.

➢ *Public Health and Policy Implications*

These findings carry considerable public health and policy implications. In nutrition education, the finding that nutritional knowledge significantly mediates the effect of influencer claims points to the need for improved consumer understanding of concepts related to sugar, especially free sugars, within fruit juices, given their common consumption under a perception of universal "healthiness." Updated healthy eating guides from health organizations such as the WHO should explicitly address influencer-related misinterpretations of fruit juice consumption.

For regulatory bodies such as FSSAI and ASCI in India, mandated front-of-pack sugar disclosure is strongly suggested for all sponsored beverage content shared by influencers. This could mirror the UK's traffic-light labeling system, as perceived healthiness mediation indicates that point-of-influence information is more effective than post-consumption nutritional facts. Finally, social media platforms currently amplify health-related content regardless of its actual healthfulness. Investing in algorithms and content moderation practices that flag and remove health-related misinformation promoted by high-reach wellness influencers would go a long way to reduce population-level misperceptions.

VI. CONCLUSION

This research offers the first robust quantitative measurement of the Halo Effect of health influencer promotions on the perceived healthiness of fruit juice in the Indian urban digital consumer context. Utilizing a validated multi-instrument survey design (N=320), robust statistical analyses (Pearson correlation, ANOVA, multiple regression and SEM) and primary data, it shows (1) a high-magnitude Halo Effect (mean HES = 42.71) is prevalent, impacting 68.4% of all participants; (2) frequency of exposure to influencers and influencer trust are dominant influences (= 0.41 and = 0.34 respectively); (3) nutritional knowledge and social media literacy are significant and malleable inhibitors (= 0.29 and = 0.22 respectively); (4) the effect of the former fully mediates the path between influencer exposure and purchase intent and (5) trust explains 36% of the variance in Halo Effect Score (= 0.36).

Taken together, the findings counter the ingrained assumption in the Indian culture of fruit juice as an intrinsically healthy food product and clearly identify the health influencer ecosystem as the conduit for the genesis of such widespread misperception. Behavioral nutrition interventions, clear labeling and digital health literacy education must be initiated urgently to address this large gap in the actual vs perceived nutrition knowledge in influencer mediated environments.

➢ *Future Research Limitations*

Limitations within this study that should be kept in mind while evaluating results include: First, the cross-sectional nature of this design prohibits causal inferences between influencer exposure and Halo Effect development; experimental or longitudinal designs must be used to confirm directionality. Second, self-report of influencer exposure may suffer from social desirability bias and underrepresent the true frequency of exposure. Third, the sample was representative of Indian urban social media consumers and results cannot necessarily be generalized to rural areas, older generations, or consumers from different cultural backdrops.

Future studies should use experiments (e.g., randomized health influencer post exposure vs. Control with sugar labels removed or added) to identify causal effects. Longitudinal studies of the change in nutritional knowledge and vulnerability to the Halo Effect before and after health

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literacy interventions would be particularly insightful for policy implementation evaluation. Future work should also examine whether these results extend to other "health" food and beverage products (e.g. Protein bars, probiotic drinks, detox products).

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