Techniques for Creating and Preserving a Positive Brand Image in Online Reputation Management

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Abstract

Online reputation management, or ORM, is essential in the current digital world. Success may be harmed by a tarnished reputation, whilst credibility and trust are increased by a good brand image. With a focus on social media involvement, content production, monitoring, and proactive crisis management, this article examines ORM tactics for building a favorable brand image. While a damaged internet reputation can have negative effects, a well-designed brand identity can help a business succeed. This article looks at ORM tactics for building and maintaining a favorable brand image, with a focus on proactive crisis management, social media participation, strategic content development, and diligent monitoring. ORM is essential for building and preserving a positive reputation, which in turn affects success in today's digital environment when businesses' online presence is continuously examined and subject to change.

Keywords

Online Reputation Management (ORM), Protecting Brand, Brand Image, Digital

Introduction

Online Reputation Management (ORM) has become a crucial tactic for both individuals and businesses in today's digital environment. A favorable brand image may be established and maintained with the help of effective ORM, which has a big impact on success. The quick spread of information on the internet has made brand perception more important, affecting target consumers' perceptions of legitimacy and dependability. While a damaged internet reputation can cause significant harm, a well-designed brand identity can have positive effects. This article looks at the strategies for using ORM to create and preserve a positive brand reputation. Adopting these fundamental procedures is crucial at a time when digital traces are continuously examined and subject to modification. People and businesses may protect their online reputation, build trust, and succeed in the long run by giving ORM top priority.I reorganised sentences for improved flow, used more exact wording (e.g., "emerged" instead of "holds significant importance"), emphasized essential themes using bullet points, and condensed repeated material in order to improve readability, coherence, and clarity.

Online Reputation Management

Initial impressions are permanent. Take charge of your brand's story by anticipating problems and keeping an eye on internet mentions. Every company wants to be seen favorably online, but simply having a unique website or social media presence is insufficient. Everyone has an opinion on almost anything these days, and consumers are wise enough to recognize when a business is being sincere and

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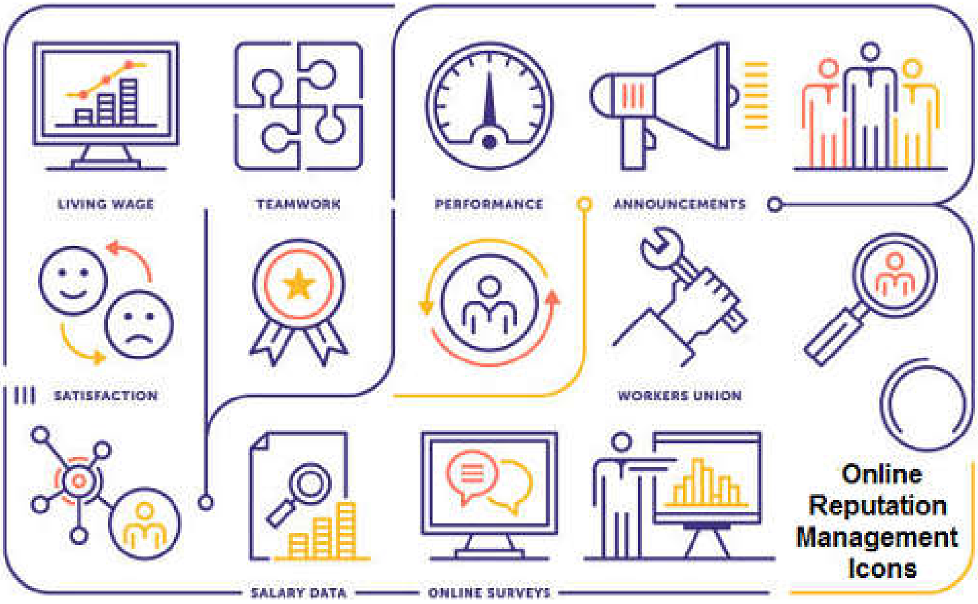
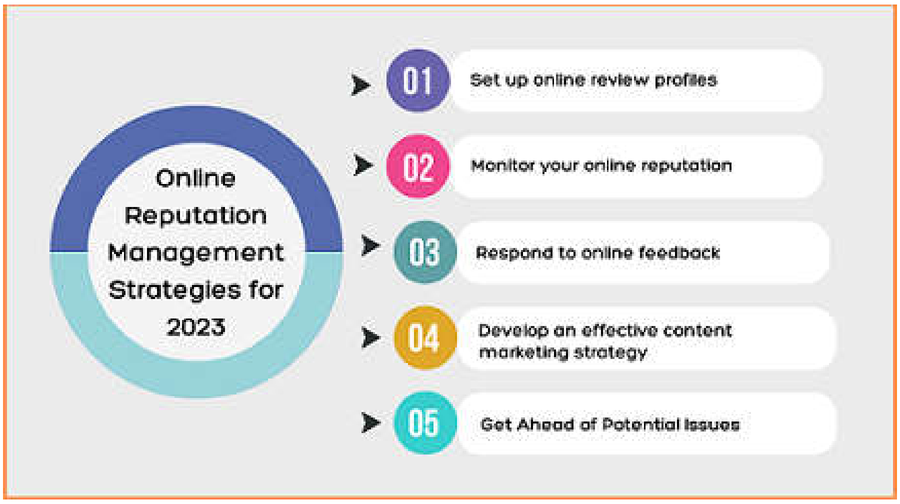
when it is concealing a negative reality. It might seem like the end of the world if your company receives a bad review or unfavorable press coverage.



Building a favorable image of a company or brand is the main goal of online reputation management, or ORM. Each and every action a brand performs should be tracked and controlled to assist influence the perceptions of current and potential clients, thereby presenting the company as dependable and trustworthy.



Factors That Contribute To ORM

Each company will employ a different combination to preserve its online reputation, but ORM should include some of the following:

Owned media – Employee and customer stories, user-generated content (UGC), reviews, webinars, and brand-created content.

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Paid media – Sponsored social posts, lead generation, affiliate programs, and native advertising.

Earned media – Media relations, influencer marketing, and PR.

Shared media – Community service and partnerships, co-branding campaigns, and organic social media posts.

Why is managing one's online reputation important?

Many businesses wait until the harm has been done before taking action, even though reputation management ought to be a continuous strategy for creating a strong online brand.

It's quite difficult to get your reputation back online.

Not only may a terrible customer experience deter future business, but it can also result in a decline in revenue if the consumer decides to post a negative review on Google, Facebook, or another platform.

If you don't keep an eye on the internet reviews and brand mentions that are being made about your business, you may lose the chance to alter the perception before it becomes permanent.

A 2023 report by Khoros found that 83% of customers say they feel more loyal to brands that respond to and resolve their complaints. So, not only can swift action prevent turning off new customers, but you may even be able to retain unhappy existing customers too.

Knowing Your Clients

You can be spending thousands of dollars on new marketing strategies that fail at the first hurdle because you didn't address more pressing problems sooner if you don't keep an eye on the online conversation about your company. Instead of having the beneficial effect you hoped for, your messaging may be in direct opposition to the concerns voiced by customers, coming across as rude and even offensive.

You combined the 7 most effective ways to build your online reputation. Of course, you can adjust them so the methods suit your business needs most.

1. Monitor the Web

2. Design a user-friendly website

3. Write a blog

4. Be active on social media

5. Reply to every request or opinion

6. Share your achievements and awards

7. Keep your content simple

Objective of the Study

1. To understand the strategies for building and protecting brand image for the sampled companies dealing online.
2. To explore quantitively the strategies that influence & support building and protecting brand image.

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Hypothesis of the study

H01: There is no significant relation between online reputation management & brand image of the sampled companies.

H01: There is no significant relationship between socio economic profile and level of perceptions.

Research Methodology

The observed results of this primary study were gathered from 100 respondents who were top management experts and company executives. The researcher contacted two tiny segment companies that deal with products online for the purpose of the study. The goal of the study is to comprehend and investigate the methods used by the tested internet businesses to establish and preserve their brand image. The outcomes of the current study were analyzed using SPSS and AMOS. The secondary data is gathered from a variety of online sources, including websites, theses, journals, and more.

Structural Equation Modelling

One multivariate statistical analysis method for examining structural links is structural equation modelling. This method, which combines multiple regression analysis with component analysis, is used to examine the structural link between latent constructs and measurable variables. Because it estimates the various and connected dependencies in a single analysis, the researcher prefers this method.

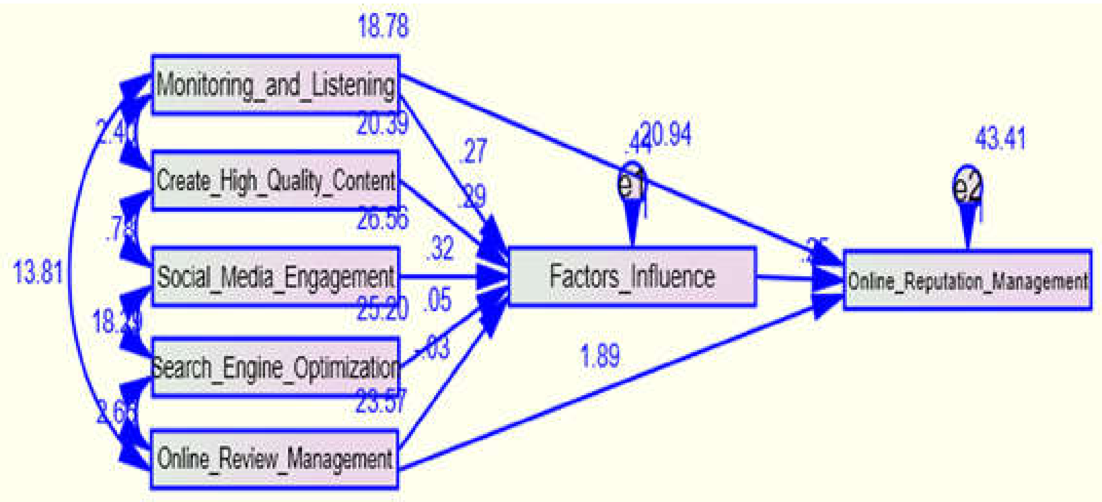

Figure 1 Online Reputation Management

Table 1 - Results of Goodness of Fit Test for Confirmatory Factor Analysis

Model fit	RMSEA	GFI	AGFI	CFI	NFI	IFI
Recommended Value	<0.08	>0.90	>0.090	>0.090	>0.090	>0.090
Study Model	0.079	0.974	0.954	0.937	0.983	0.987

Source: Computed Data

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Endogenous and exogenous variables are the two categories of variables employed in this analysis. The independent variable and dependent variables are equal to endogenous variables. The CFA or measuring model findings are highlighted in the above table. The aforementioned table suggests that the values of the different goodness of fit indices fall well within the intended ranges. The GFI, AGFI, CFI, NFI, IFI, and RMSEA are 0.974, 0.983, 0.954, and 0.987, respectively.

More significantly, the factor loadings for every item in the model are greater than 0.5 and highly significant at the 0.05 level of significance. Therefore, these findings imply that no changes to the model are required. Figure 2 shows an example structural equation model after estimation.

Latent variables are sometimes indicated with ovals while observed variables are shown in rectangles. Residuals and variances are sometimes drawn as double-headed arrows (shown here) or single arrows and a circle (as in Figure 3). The latent IQ variance is fixed at 1 to provide scale to the model.

Figure 2 depicts measurement errors influencing each indicator of latent intelligence and each indicator of latent achievement. Neither the indicators nor the measurement errors of the indicators are modeled as influencing the latent variables.

Figure 3 shows an example structural equation model before estimation. Similar to Figure 2 but without standardized values and fewer items.

Because intelligence and academic performance are merely imagined or theory-postulated variables, their precise scale values are unknown, though the model specifies that each latent variable's values must fall somewhere along the observable scale possessed by one of the indicators.

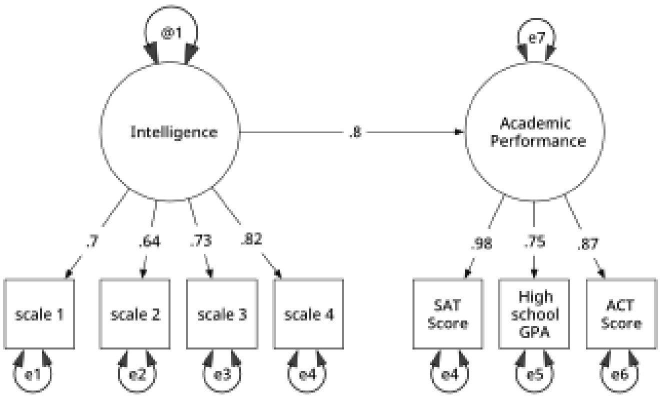

Figure 2 shows an example structural equation model after estimation

The 1.0 effect connecting a latent to an indicator specifies that each real unit increase or decrease in the latent variable's value results in a corresponding unit increase or decrease in the indicator's value.

It is hoped a good indicator has been chosen for each latent, but the 1.0 value do not signal perfect measurement because this model also postulates that there are other unspecified entities causally impacting the observed indicator measurements, thereby introducing measurement error.

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This model postulates that separate measurement errors influence each of the two indicators of latent intelligence, and each indicator of latent achievement.

The unlabeled arrow pointing to academic performance acknowledges that things other than intelligence can also influence academic performance.

- **Uses of structural equation modeling for Researchers**

When examining intricate multivariate connections, statistical methods such as regression and correlation are ineffective. Complex, multiple entities that are measured with inaccuracy can be effectively modelled using SEM. Additionally; it is helpful in defining a system of relationships.

We can investigate a collection of predictors and an independent variable with the aid of traditional approaches.

SEM enables us to comprehend the causal link between the observed variable and latent constructs, even though correlation is not causation.

Among the uses for SEM are the following:

Social Science: The impact of cultural values on human conduct in various civilisations may be investigated using SEM.

Education: Students' experiences in graduate school may be examined using SEM. For instance, to simulate US PhD student dropout rates.

Disease Risk Modeling: To calculate the risk of conditions like diabetes or heart disease, SEM can be used in disease risk modelling.

- **Structural equation modeling core concepts**

Here are some of the core concepts in structural equation modeling:

Observed Variables: Observed variables are directly measured from the study. Examples are responses to questionnaire fields.

Latent Variables: Latent variables are inferred from the observed variables in the study. For example, the level of intelligence in a student's academic performance rating.

Endogenous Variables: They are also known as dependent variables.

For example, in $y = x1 + x2 + x3$, y is the endogenous variable as it depends on the values of $x1, x2, \ldots, xn$.

Exogenous Variables: They are independent variables. For example, an athlete's sleep time is independent of the type of racing bike.

Measurement Model: measures the relationships between latent constructs and observed variables. The confirmatory factor analysis framework tests the underlying hypothesis of the measurement model.

Structural Model: This model investigates causal relationships between latent constructs. It is diagrammatically represented using path analysis.

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- **Structural equation modeling statistical assumptions**

SEM contains some underlying assumptions about the data, even if it's excellent for modelling casual connections. Among the presumptions are:

Linearity: SEM assumes linear relationships between the latent constructs and the observed variables. It is not suitable for non-linear datasets as it can give incorrect results.

Multicollinearity: SEM assumes minimal multicollinearity between the observed variables. For example, a competitor's sleep time and nutrition might be highly correlated. SEM assumes little correlation between these variables.

Sampling Assumptions: For SEM tasks, you need a sufficient sample size of at least 200 for good results. While you don't need large datasets like LLMs, a smaller sample size can give inaccurate results.

Multivariate Normality: SEM assumes the data is a multivariate normal distribution. It is not suitable for non-normal data. You can perform tests to check for normality.

Missing Data: SEM assumes that the data is complete. **One way SEM approaches missing data** is to assume that the data is missing at random. Missing data might interfere with the model's estimate.

Specification Error: SEM assumes that the defined model is specified correctly. It assumes that the measurement and structural models are assumed to contain at least all the relevant variables.

- **Types of structural equation models**

There are different types of structural equation modeling. In no particular order, they are:

Path Analysis: It is a type of SEM and an extension of regression models that deals only with observed variables (also known as predictors).

Path diagrams visually represent these relationships using arrows to show directionality.

Confirmatory Factor Analysis (CFA): It is a type of SEM used to test the validity of measurement models. It verifies whether the observed data fits a pre-specified model.

Latent Variable Structural Models (LVSM): It models the relationships between latent constructs and observed variables.

It also models the relationship between the latent constructs themselves.

Latent Growth Models: Latent Growth Models are a specialized type of SEM that focuses on modeling change over time. They are used to study the trajectories of latent variables.

(e.g., psychological traits or behaviors) and how they evolve, considering individual and group-level changes.

Structural Equation Modeling Example in Python

Developing an SEM model in Python only requires a few steps; we can use the semopy library to make it easy. The following tutorial assumes that you are familiar with Python syntax.

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Installing necessary libraries

```
pip install semopy
```

Note: For macOS users. If you encounter this error while installing the package:

```
ExecutableNotFound: failed to execute PosixPath('dot'), make sure the Graphviz executables are on your systems' PATH
```

Install graphviz through homebrew in your terminal

```
brew install graphviz
```

Defining constructs

Let's take a moment to define all of our constructs before downloading our dataset and building our model. In other words, we must determine which variables are latent and which are observable. The observed variables in our dataset, which are x1 to x3 and y1 to y8, have been given to us as labelled features. We shall describe the names of the latent variables we wish to examine: ind60, dem60, and dem65.

Observed variables

y1: freedom of the press, 1960

y2: freedom of political opposition, 1960

y3: fairness of elections, 1960

y4: effectiveness of elected legislature, 1960

y5 -y8: are the same variables as y1-y4, respectively, measured in 1965

x1: the GNP per capita, 1960

x2: the energy consumption per capita, 1960

x3: the percentage of labor force in industry, 1960

Latent Variables

ind60: exogenous latent variable on industralization.

dem60: endogenous latent variable on democracy at 1960.

dem65: endogenous latent variable on democracy at 1965.

Developing the measurement model

The goal is to define a theoretical model to specify the relationship between the latent constructs and observed variables.

```
# Measurement model
ind60 =~ x1 + x2 + x3
demo60 =~ y1 + y2 + y3 + y4
dem65 =~ y5 + y6 + y7 + y8
```

Specifying the structural model

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Here, we will specify the relationships between the latent constructs themselves.

```
# regressions
dem60 ~ ind60
dem65 ~ ind60 + dem60
```

Specifying the correlations

Here, we want to specify variables that are highly correlated with each other.

```
# Correlations
y1 ~~ y5
y2 ~~ y4
y2 ~~ y6
y3 ~~ y7
y4 ~~ y8
y6 ~~ y5
```

Preparing the dataset

For this tutorial, we will use the PoliticalDemocracy.csv dataset provided by semopy. You can download it by visiting **this GitHub repository**.

```
Import pandas as pd
data = pd.read_csv('PoliticalDemocracy.csv')
```

Defining the SEM model

We need to combine the structural and measurement definitions into a model specification.

```
# Define the SEM model specification
model_spec = """
# Measurement model
ind60 =~ x1 + x2 + x3
dem60 =~ y1 + y2 + y3 + y4
dem65 =~ y5 + y6 + y7 + y8

# regressions
dem60 ~ ind60
dem65 ~ ind60 + dem60

# Correlations
y1 ~~ y5
y2 ~~ y4
```

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```
y2 ~~ y6
y3 ~~ y7
y4 ~~ y8
y6 ~~ y5
"""
```

Next, we define the model and fit the data

```
import semopy
# Define the model
model = semopy.Model(model_spec)
#Fit the model
model.fit(data)
# Inspect the results
print(model.inspect())
```

Interpreting the results

We will plot the model's result to understand the path representation. The plot will be saved as political_sem_model.png.

```
semopy.semplot(model, 'political_sem_model.png')
print("SEM Model diagram saved as 'political_sem_model.png'.")
img = plt.imread('political_sem_model.png')
plt.imshow(img)
plt.axis('off')
plt.show()
```

The graphic illustrates the relationship between the observable variables and the latent constructs (in circles). Strong links between variables are shown by path coefficients that are closer to 1 or -1, whereas weak relationships are indicated by those that are closer to 0.

The table's standard deviations are within the acceptable range. Greater values might be a sign of model misspecification or multicollinearity. The path coefficients' statistical significance is established by the p-values. The route is typically considered statistically significant if the p-value is less than 0.05. We see 2 cases where the p-value is greater than 0.05.

Overall, the findings indicate that ind60 has a large impact on dem60, which in turn has a significant impact on dem65.

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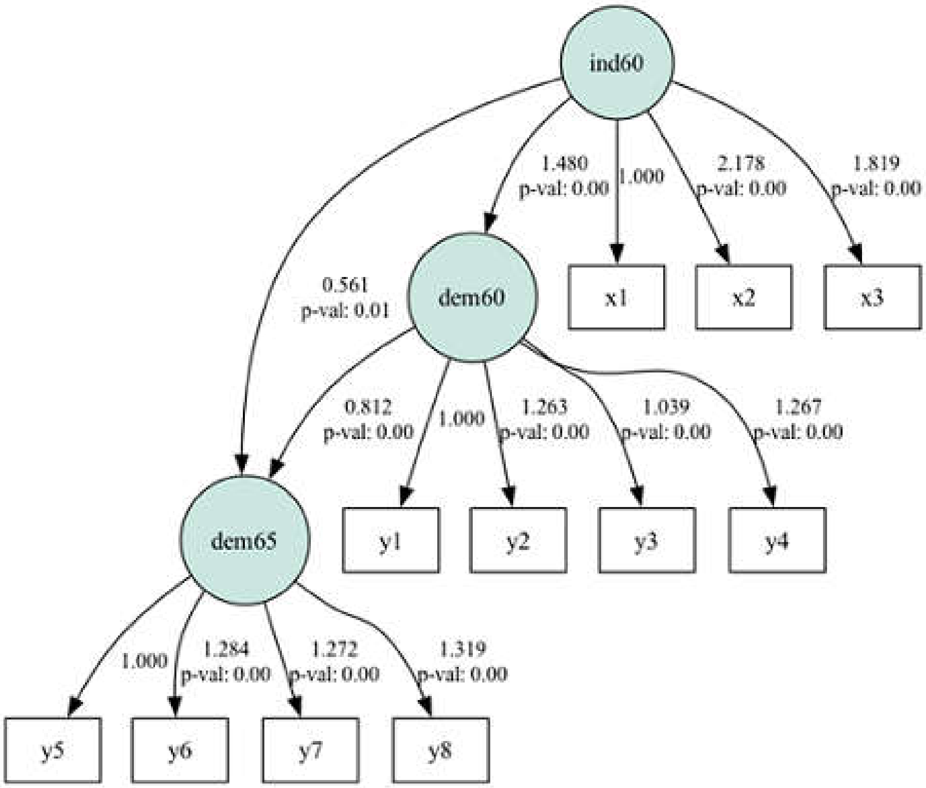

Figure 3 *SEM path diagram for political democracy dataset.*

- **Assessing model fit**

The hypothesized model should match the observed relationships to assess SEM model fit. Various fit indices are used to assess how well the model fits the data. Here are commonly used ones:

Chi-Square Test: Compares the observed covariance matrix with the model-implied covariance matrix. A non-significant chi-square indicates a good fit.

Root Mean Square Error of Approximation: It evaluates how well the model approximates the data, adjusting for model complexity. Values below 0.05 and up to 0.08 are acceptable.

Common Challenges and Solutions in SEM

Some common challenges of the structural equation modeling technique include the following:

Non-Normality of Data: SEM generally assumes the data follows a **normal distribution**. Using non-normal data might affect the standard errors, p-values, and fit indices, leading to unreliable estimates. Data transformation techniques can be applied to normalize the data.

Missing Data: Complete data is needed for SEM. Missing data can lead to biased results. You can leverage likelihood estimation methods like full information maximum likelihood (FIML) to tackle this.

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Model Fit: When the hypothesized model does not fit the observed data, it leads to misleading interpretations about the relationship between variables. You can make **theory-driven adjustments to the model or use modification indices**.

Level of Perception

To ascertain the correlation between the respondents' socioeconomic profile and degree of perception.

The null hypothesis is to be tested. The two groups' opinions are unchanged, and the "F" test has been used.

The levels of perception	Roads		Nodes	
	Group1(%)	Group2 (%)	Group1(%)	Group2 (%)
% 0-24	20	7,0	54,3	21,1
% 25-49	60	36,8	34,3	47,4
% 50-74	20	38,6	8,6	21,1
% 75-100	-	17,5	2,9	10,5

Table 2

ANOVA						
		Sum of Squares	df	Mean Square	F	Sig.
Age	Between Groups	16.809	26	.647	.636	.019
	Within Groups	74.151	73	1.016		
	Total	90.960	99			
Gender	Between Groups	10.718	26	.412	2.113	.007
	Within Groups	14.242	73	.195		
	Total	24.960	99			
Marital Status	Between Groups	32.844	26	1.263	1.156	.030
	Within Groups	79.746	73	1.092		
	Total	112.590	99			
Educational Qualification	Between Groups	39.728	26	1.528	.554	.953
	Within Groups	201.262	73	2.757		
	Total	240.990	99			
Monthly Income	Between Groups	29.187	26	1.123	.913	.045
	Within Groups	89.773	73	1.230		
	Total	118.960	99			

Source: Primary Data

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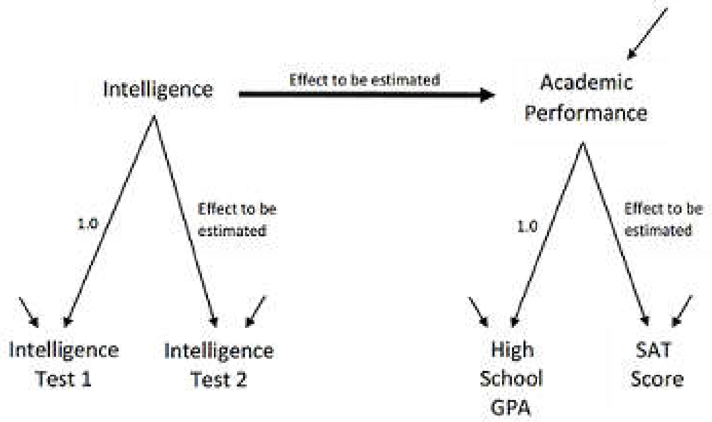

Figure 4 An example structural equation model before estimation

It's clear from the table above that the "P" value (Sig. 0.019) is below 0.05 (the 5% level of significance). It is decided to accept the null hypothesis. Therefore, the respondents' age and perception level do not significantly differ from one another. From the above table, it is evident that the "P" value (Sig. 0.007) is less than 0.05 (5% level of significance). So the null hypothesis is accepted. Thus there is no significant difference between the gender and level ofperception of the respondents.

From the above table, it is evident that the "P" value (Sig. 0.030) is less than 0.05 (5% level of significance). So the null hypothesis is accepted. Thus there is no significant difference between the Marital and level of perception of the respondents.

From the above table, it is evident that the "P" value (Sig. 0.953) is greater than 0.05 (5% level of significance). So the null hypothesis is rejected. Thus there is a significant difference between the educational qualification and level of perception of the respondents.

From the above table, it is evident that the "P" value (Sig. 0.045) is less than 0.05 (5% level of significance). So the null hypothesis is accepted. Thus there is no significant difference between the Monthly Income and level of perception of the respondents.

Conclusion

Maintaining a positive online reputation demands continuous effort. With the internet's vast reach and constant information flow, reputations can change rapidly. Effective online reputation management requires proactive vigilance, prompt issue resolution, and strategic planning to uphold a favorable digital image. Online businesses recognize the critical importance of cultivating a strong brand image, leveraging efficient methods and data-driven assessments to enhance online presence, trust, and loyalty among their target audience.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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