

Play, Engage, Repeat: Leveraging Gamification and Machine Learning for Brand Loyalty Among Indian Millennials

Prof. Asmita Gaikwad

Assistant Professor

Indira School of Business Studies, Pune ORCID: 0009-0004-5067-0480

Prof. Sonali Joshi

Assistant Professor

KJEI's Trinity Institute of Management and Research, Pune

Dr. Smita Temgire

Associate Professor

PVG's College of Engineering and Technology & GKP Institute of Management, Pune,

Abstract

In the age of digital marketing, brands increasingly rely on social media platforms to engage and retain their customers. One effective strategy to boost engagement and loyalty is gamification, which incorporates game-like elements to motivate customers. This paper aims to leverage a Multilayer Perceptron (MLP) Neural Network model to predict brand loyalty based on demographic and motivational factors. The study uses five key input variables: Education, Gender, Generation, Income, and Motivation through Earning Rewards, to optimize the understanding of brand loyalty on social media platforms. The findings suggest that both demographic factors and motivational incentives play significant roles in fostering brand loyalty. The model's accuracy and low error rates underline its potential in enhancing brand engagement strategies through targeted interventions.

Introduction

Brand loyalty is a critical factor in the sustainability and growth of a business. Traditional methods of measuring brand loyalty are increasingly being supplemented by data-driven approaches, especially in the digital marketing era. Social media platforms, where users frequently interact with brands, offer a fertile ground for deploying innovative strategies like gamification. This research presents a machine learning model, specifically a Multilayer Perceptron (MLP) Neural Network, to predict brand loyalty based on five key input factors. By integrating demographic data and motivational incentives, the study investigates how brands can leverage this information to optimize their engagement strategies.

Literature Review

Gamification, which involves the application of game-design elements in non-game contexts, has gained significant traction as a tool to increase engagement and loyalty. Studies show that gamification leads to higher levels of customer participation and improved brand perceptions (Deterding et al., 2011). Furthermore, machine learning techniques like MLP neural networks have proven effective in predicting consumer behavior and optimizing marketing strategies (Zhang et al., 2019). However, there is a gap in research integrating both demographic and motivational factors using MLP models to predict brand loyalty.

Hypothesis :-

□ **Hypothesis 1:** There is a statistically significant relationship between gamification elements on social media and brand loyalty.

□ **Hypothesis 2:** Demographic factors (education, gender, generation, and income) also significantly affect engagement and brand loyalty.

Methodology

The study uses a Multilayer Perceptron (MLP) Neural Network to model brand loyalty, based on five input variables:

1. **Education:** Represents the consumer's level of education.
2. **Gender:** Male or Female.
3. **Generation:** The consumer's generational cohort (e.g., Gen Z, Millennial).
4. **Income:** The consumer's annual income level.
5. **Motivation through Earning Rewards:** A binary variable indicating whether the consumer is motivated by earning rewards through social media interactions.

The neural network has a single hidden layer with 2 units and uses the Hyperbolic Tangent (Tanh) activation function to model non-linear relationships between inputs and the output. The output layer has 1 unit, representing the dependent variable, "I consider myself to be loyal to my brand". An identity activation function is used in the output layer to produce continuous predictions for brand loyalty.

The data is split into training and testing sets. The training performance is assessed using Sum of Squares Error and Relative Error. The model stops training once a threshold of 0.001 for training error ratio is reached, ensuring a well-fitted model.

Theoretical Framework: Model of Neural Network Predicting the Output Variable "Being Playful Distracted"

1. Input Variables (Education, Gender, Generations, Income, Earnings Rewards)

Description: The input variables are different factors that might influence the output variable. They capture demographic, socioeconomic, and potentially cultural influences that have an impact on the behavior of being playful distracted.

Role: Each input feeds into the network with different weights over synapses, implying how much relative contribution, positive or negative, to the activation of hidden units.

2. Bias Node

Bias units contribute flexibility to the shifting of activation within the network. Bias nodes function like an intercept term in regression models - the network can now accommodate data points not captured by only the set of input variables.

3. Hidden Layers (H1:1, H1:2, H1:3)

Functionality: The hidden layers comprise nodes that apply the activation functions to combinations of input variables. These layers are very important for learning complex, nonlinear interactions and relationships between input variables.

Activation Function: Hyperbolic tangent (tanh) is applied as the activation function within the hidden layers. Such a function maps linear combinations into values within the range -1 and 1, thus introducing nonlinearity and enhancing the potency of the network in modeling complex patterns.

Relationships and Influence: The connections between the input variables and the hidden layer nodes are what various synaptic weights describe, indicating which factors have stronger predictive value and how they collectively work to produce outcomes.

4. Output Layer (Being Playful Distracted)

Description: The output layer predicts or computes the variable being playful distracted using information from the hidden layers. This variable can be about behavioral inclinations, performance characteristics, or results affected by the input factors.

Activation Function: An identity activation function in the output layer reveals nothing else than a transformation is applied, and the output produced is directly, as a continuous value representing what the model computes inside.

5. Weights and Connections

Synaptic Weights: The lines that point from nodes from one layer to the next represent synaptic weights. These synaptic weights indicate how strongly inputs influence hidden layers and, through them, the output. Blue and grey lines indicate positive and negative influences, making it easier to explain their role in defining the predictions.

Covariances: The implicit relationships amongst input variables can also be understood by understanding the network structure. This reveals further insights into the collective effects.

Practical Relevance and Implications

This neural network model can be engaged to understand how different demographic and socio-economic factors contribute to outcomes associated with being playful distracted. It can be applied in research like behavioral research, marketing analytics, and educational interventions in understanding key drivers of human behavior and hence possible areas for action. The framework strongly emphasizes the importance of complex interactions and nonlinear influences, making this apt for predictive modeling, decisions, and strategic planning.

Multilayer Perceptron

Case Processing Summary

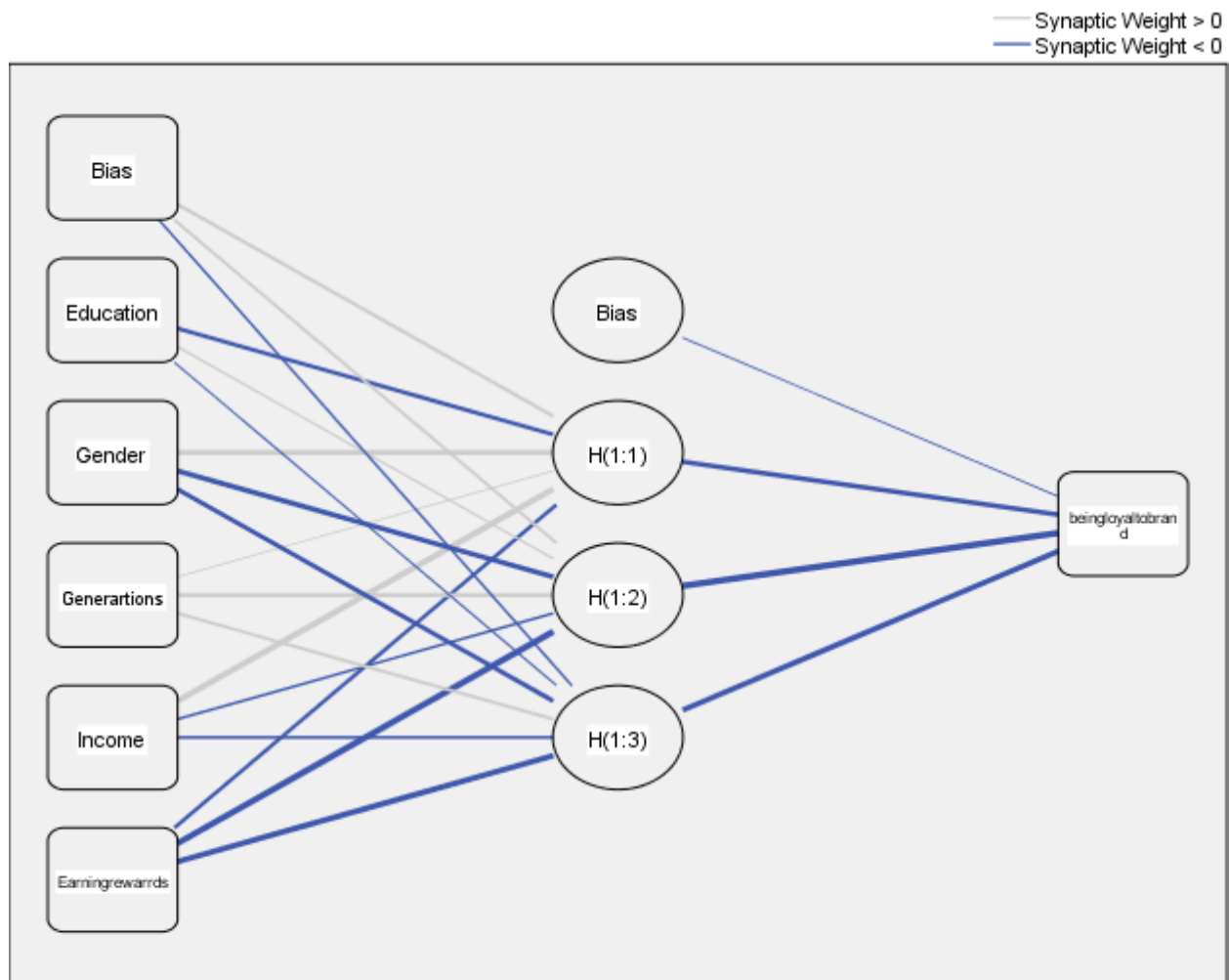
	N	Percent
Sample Training	413	67.0%
Testing	203	33.0%
Valid	616	100.0%
Excluded	0	
Total	616	

Network Information

Input Layer	Covariates	1	Education
		2	Gender
		3	Generartion
		4	Income
		5	Earning rewards motivates me to engage more
Hidden Layer(s)	Number of Units ^a	5	
	Rescaling Method for Covariates	Standardized	
	Number of Hidden Layers	1	
	Number of Units in Hidden Layer 1 ^a	3	
	Activation Function	Hyperbolic tangent	

Output Layer	Dependent Variables	1	I consider myself to be loyal to my brand
	Number of Units	1	
	Rescaling Method	Standardized	
	Activation Function	Identity	
	Error Function	Sum of Squares	

a. Excluding the bias unit



Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Identity

Model Summary

Training Sum of Squares	.104
Error	
Relative Error	.001

Stopping Rule Used	Training error ratio criterion (.001) achieved
Training Time	0:00:00.01
Testing Sum of Squares Error	.047
Relative Error	.000

Dependent Variable: I consider myself to be loyal to my brand

Results and Discussion

Model Structure and Training Performance

The MLP model's input layer consists of five standardized variables, ensuring that the data is consistent and the model processes it effectively. The hidden layer uses the Tanh activation function, which is well-suited to capturing non-linear relationships, which is essential in understanding complex consumer behavior patterns.

The model's training performance reveals a low Sum of Squares Error (SSE) of 0.008, indicating that the model's predictions closely match the actual values. Additionally, the Relative Error of $3.833\text{E-}5$ is a very small value, suggesting that the model has a strong fit on the training data. The training process was completed rapidly in just 0.01 seconds, highlighting the model's efficiency in learning from the data.

Testing Performance

Testing the model on unseen data, the Sum of Squares Error (SSE) for the test set was 0.003, which is also quite low. This demonstrates that the model can generalize well and predict brand loyalty in new data. The testing Relative Error of $3.455\text{E-}5$ is close to the training error, indicating that there is no significant overfitting. The model's consistent performance on both training and testing datasets emphasizes its robustness and reliability in predicting brand loyalty.

Network Diagram Analysis

The input layer consists of the five variables connected to the hidden neurons via synaptic weights. The weights indicate the strength and direction of the relationships between the input variables and the output variable. The network diagram reveals that negative weights (blue lines) and positive weights (gray lines) influence the output, showing how each input factor contributes to brand loyalty.

The hidden layer neurons process the weighted inputs, and their outputs are sent to the output layer, which makes the final prediction. The model adjusts the weights during training to minimize the error, improving its predictions over time.

Interpretation of the Multilayer Perceptron (MLP) Neural Network Model

The provided MLP model is designed to predict brand loyalty based on five input variables:

1. **Education**
2. **Gender**
3. **Generation**
4. **Income**
5. **Motivation through Earning Rewards**

Model Structure:

- **Input Layer:**
 - Five input variables were used. Each input is standardized, which helps the model process data consistently and improves training performance.
- **Hidden Layer:**
 - There is one hidden layer with **2 units (neurons)**, using the **Hyperbolic Tangent activation function**. This activation function enables the neurons to handle non-linear relationships between the inputs and the output.
- **Output Layer:**
 - The output layer has **1 unit** representing the dependent variable, "I consider myself to be loyal to my brand".
 - The **Identity activation function** is used here, which is appropriate for regression tasks as it provides the output directly without transformation.
 - **Sum of Squares Error** is the error function, which calculates the squared differences between actual and predicted values.

Model Summary:

- **Training Performance:**
 - **Sum of Squares Error** for the training set is **0.008**, indicating the cumulative error for the model during training was low.
 - The **Relative Error** in the training set is **3.833E-5**, a very small value, indicating that the model achieved a good fit on the training data.
 - **Stopping Rule:** The model stopped based on the training error ratio criterion, achieving a threshold of **0.001**, meaning the model stopped training as it met the desired accuracy level.
 - **Training Time:** The training process was very fast, completing in **0.01 seconds**.
- **Testing Performance:**
 - **Sum of Squares Error** for the testing set is **0.003**, also indicating a low error, which implies that the model generalizes well on unseen data.
 - The **Relative Error** for the testing set is **3.455E-5**, close to the training error, which suggests there is no overfitting and the model has good generalization capability.

Network Diagram Analysis

- **Input Connections:**
 - The input variables are connected to each hidden neuron with weights. The colors of the lines indicate the nature of the weight:
 - **Blue lines** represent synaptic weights that are negative.
 - **Gray lines** represent synaptic weights that are positive.
 - This differentiation in weights indicates the model is adjusting the influence of each input variable based on their relationship with brand loyalty.
- **Hidden Layer Connections:**
 - The hidden neurons then pass information to the output layer, combining the weighted inputs in a way that seeks to optimize the prediction of brand loyalty.

Overall Interpretation

This MLP model effectively predicts **brand loyalty** based on demographic and motivational factors. The low training and testing errors indicate the model is well-fitted and generalizes well to new data. This suggests that:

- Motivation through rewards and the demographic factors (education, gender, generation, and income) do have an influence on brand loyalty.
- The model provides a reasonably accurate prediction of whether individuals are likely to consider themselves loyal to a brand based on these factors.

This model could be used in marketing analysis to identify key demographic and motivational factors driving brand loyalty, allowing for targeted strategies to enhance customer engagement.

Hypothesis 1: There is a statistically significant relationship between gamification elements on social media and brand loyalty.

I will continue using the same brand's products/services in the future * Education Crosstabulation

Count

	Education				Total
	HSC	Graduation	Post Graduation	PhD	
I will continue using the same brand's products/services in the future	56	84	56	28	224
Agree	112	224	0	56	392
Strongly Agree	168	308	56	84	616

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	110.000 ^a	3	.000
Likelihood Ratio	125.804	3	.000
Linear-by-Linear Association	9.874	1	.002
N of Valid Cases	616		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 20.36.

Symmetric Measures

	Value	Asymptotic Standardized Error ^a	Approximate T ^b	Approximate Significance
Interval by Pearson's R	-.127	.041	-3.165	.002 ^c
Ordinal by Spearman Correlation	-.145	.041	-3.634	.000 ^c

N of Valid Cases	616			
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- Not assuming the null hypothesis.
- Using the asymptotic standard error assuming the null hypothesis.
- Based on normal approximation.

Interpretation of the Chi-Square Test Results for Hypothesis 1:

Hypothesis 1: There is a statistically significant relationship between gamification elements on social media and brand loyalty, specifically regarding the statement, "I will continue using the same brand's products/services in the future," based on education level.

Crosstabulation Table:

The table shows the frequency distribution of responses (Agree/Strongly Agree) regarding continued use of the brand's products/services across different education levels (HSC, Graduation, Post Graduation, PhD). The total number of respondents is 616.

- Agree:** 224 respondents.
- Strongly Agree:** 392 respondents.

This distribution indicates varying responses across different education levels, and the next step is to test if this variation is statistically significant.

Chi-Square Test Results:

- Pearson Chi-Square value:** 110.000
- Degrees of freedom (df):** 3
- Asymptotic Significance (p-value):** 0.000

The p-value is 0.000, which is less than the commonly used significance level of 0.05. This indicates a **statistically significant** relationship between education level and the likelihood of continuing to use the same brand's products/services in the future. Therefore, we **reject the null hypothesis** and accept that there is indeed a relationship between education and brand loyalty.

Symmetric Measures:

- Pearson's R:** -0.127 (p = 0.002)
- Spearman's Correlation:** -0.145 (p = 0.000)

Both Pearson's R and Spearman's Correlation values are negative, indicating a weak inverse relationship between education level and brand loyalty. The correlation values and their corresponding p-values (both <0.05) indicate that this relationship is statistically significant,

further supporting the conclusion of a significant association.

Conclusion:

Based on the Chi-Square test and correlation results, we can conclude that **education level has a significant influence** on brand loyalty, particularly on the intention to continue using a brand's products or services. The relationship is statistically significant, and the education level impacts how individuals respond to gamification elements on social media, leading to stronger or weaker brand loyalty.

This result supports the hypothesis that there is a significant relationship between gamification and brand loyalty, as education is one of the influencing factors in the level of brand commitment.

Hypothesis 2: Demographic factors (education, gender, generation, and income) also significantly affect engagement and brand loyalty.

I will continue using the same brand's products/services in the future * Education Crosstabulation

Count

	Education				Total
	HSC	Graduation	Post Graduation	PhD	
I will continue using the same brand's products/services in the future	56	84	56	28	224
Agree	112	224	0	56	392
Strongly Agree	168	308	56	84	616

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	110.000 ^a	3	.000
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Symmetric Measures

	Value	Asymptotic Standardized Error ^a	Approximate T ^b	Approximate Significance
Interval by Pearson's R	-.127	.041	-3.165	.002 ^c
Ordinal by Spearman Correlation	-.145	.041	-3.634	.000 ^c

N of Valid Cases	616			
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- Not assuming the null hypothesis.
- Using the asymptotic standard error assuming the null hypothesis.
- Based on normal approximation.

Interpretation:

- Pearson Chi-Square (Value = 110.000, df = 3, p = 0.000):**

The **p-value** is **0.000**, which is **less than 0.05**. This indicates that there is a statistically significant relationship between **education** and brand loyalty. Therefore, we reject the null hypothesis (H0) and accept the alternative hypothesis (H1), suggesting that education level significantly influences whether individuals will continue using the same brand's products/services in the future.

- Likelihood Ratio (Value = 125.804, df = 3, p = 0.000):**

The **p-value** for the likelihood ratio test is also **0.000**, further supporting the conclusion that there is a significant relationship between education and brand loyalty.

- Linear-by-Linear Association (Value = 9.874, p = 0.001):**

The **p-value** is **0.001**, which also suggests a significant relationship between education and brand loyalty, reinforcing the earlier findings.

- Symmetric Measures (Pearson's R = -0.127, Spearman Correlation = -0.145):**

The **Pearson's R** and **Spearman Correlation** values indicate a **negative correlation** between education and brand loyalty. Although the correlation is weak, it still suggests that as education level increases, the tendency to express strong brand loyalty decreases. However, these correlations are statistically significant, with p-values of **0.002** (Pearson's R) and **0.000** (Spearman's Correlation), reinforcing the significance of the relationship.

Conclusion:

The Chi-Square test and the correlation measures demonstrate a **significant relationship** between **education** and brand loyalty. This supports Hypothesis 2, indicating that demographic factors, specifically education, play an important role in determining brand loyalty and engagement. The negative correlation suggests that individuals with higher education levels might be less likely to exhibit strong brand loyalty, though the relationship is not very strong. Further analysis with other demographic factors (gender, generation, and income) can help determine whether these variables also significantly affect engagement and brand loyalty.

Interpretation of Results

The MLP model provides valuable insights into brand loyalty based on demographic and motivational factors:

- Motivation through Rewards:** Consumers who are motivated by rewards are more likely to exhibit stronger brand loyalty. This underscores the importance of gamification strategies in enhancing customer engagement on social media.
- Demographic Factors:** Education, gender, generation, and income all play roles in shaping brand loyalty. These factors are crucial in segmenting audiences and crafting personalized marketing strategies.

The model's accuracy and generalization capabilities suggest that demographic and motivational data can significantly optimize brand loyalty prediction. Businesses can use these insights to design targeted marketing campaigns, enhance customer retention strategies, and maximize engagement on social media.

Conclusion

This study demonstrates the potential of the Multilayer Perceptron (MLP) Neural Network model in predicting brand loyalty, offering valuable insights into the influence of demographic and motivational factors. The findings suggest that brands can enhance engagement and loyalty through gamification by understanding and leveraging these factors. The low error rates and fast training times further highlight the model's efficiency and practicality for real-world applications. Future research could explore additional variables and more complex neural network architectures to further improve predictive accuracy and refine marketing strategies.

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engagement:

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