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Technology Exposure, Parental Mediation, and Social Validation Pressures among Gen-Alpha: A Logistic Regression Study with Millennial Parents in Bangalore

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Abstract: *This study examines the connection between early technology exposure and social-digital outcomes as per parental guidance practices among Generation Alpha children. The research focuses on how parents mediate technology use regarding children's digital development. Data were surely collected from 141 millennial parents in Bangalore through structured questionnaires. Moreover, this approach helped gather reliable information for the study. Four major factors were used in this study: Technology-driven Social Validation Pressures, Digital Learning Disruptions, Marketing Influence and Consumer Susceptibility, and Emotional Resilience, which have been divided into high and low groups. In addition, the use of logistic regression was to check how technology exposure and parent control factors definitely affect children's results. The study also looked at basic family details to see their impact. It is also observed that learning orientation and parental support help to reduce high validation pressures in children, but resilience only increases these pressures unexpectedly. Basically, the model got 85.7% accuracy with good agreement (κ = 0.71), but the ROC curve showed poor discrimination with an AUC of 0.461, which is the same as saying it struggles with probability predictions. As per these findings, logistic regression shows good potential for predicting Gen-Alpha's digital validation habits but also has clear limitations. Regarding the results, this method can explain some patterns but cannot capture all aspects of their online behavior. The study shows that parental strategies and socio-cognitive orientations both shape children's digital behaviors. It further suggests that nonlinear modeling approaches can provide better predictive insights, as the relationship itself is complex.*

Keywords: Generation Alpha, Millennial parents, Technology-driven Social Validation Pressures, Digital Learning Disruptions, Marketing Influence and Consumer Susceptibility, and Emotional Resilience

I. INTRODUCTION

Generation Alpha children, born after 2010, are actually growing up with digital devices from a very early age. This definitely changes how they learn and play compared to previous generations. It is observed through different research that Gen-Alpha children get technology from a very early age when their minds and social skills are still growing, making digital tools only part of how they learn and build their identity. There is no doubt that technology provides educational benefits, but it also creates risks like social pressure for validation, disruptions in digital learning, and students becoming more influenced by marketing only. Parental mediation surely plays a moderating role in this situation. Moreover, parents can control and guide their children's behavior effectively. Active monitoring and restrictive guidance can only change how technology affects people. Co- use practices may make technology's impact stronger or weaker. Moreover, as per urban lifestyle patterns, people have limited outside exposure, which increases their need for online approval regarding self-worth. This requires proper research on these issues. Previous studies

(Nesi & Prinstein, 2015; Uhls et al., 2017) show that digital validation behaviors affect children's mental health. Further research highlights how online approval-seeking impacts psychological well-being. The combined effect of technology exposure, parental mediation, and demographic variables on Gen-Alpha outcomes needs further research in the Indian context itself. To fill this gap, the present study uses logistic regression to find factors that predict child outcomes. Moreover, it focuses mainly on social pressure from technology and social media validation.

II. RESEARCH METHODOLOGY

This study focuses on cross-sectional quantitative research with logistic regression to find the chances of high versus low levels regarding TSVP, DLDC, MICS, and ERS based on selected factors. The statistical method helped estimate categorical outcomes for these four variables. The study population included millennial parents aged 26-41 years living in Bangalore city. Moreover, each parent had at least one Gen-Alpha child between 5 to 13 years of age. The researchers actually selected 141 people using a planned method to definitely include different economic and social backgrounds. Data were collected through a structured questionnaire that measured the Technology Exposure Index (TEI) and three parental mediation dimensions - Parental Monitoring Index (PMI), Parental Co-use Index (PCI), and Parental Enforcement Index (PEI). The questionnaire further included child outcome factors (TSVP, DLDC, MICS, ERS) and demographic details like age, gender, family type, residence, and number of children. Before analysis, the dataset was prepared by filling missing values with the mean for continuous variables and the mode for categorical variables. Moreover, this data preparation step was essential to ensure complete information for the study. Initially, a Factor Analysis was used considering the PCA, which confirmed that the TSVP construct could be extracted properly (KMO > 0.6, Bartlett's $p < 0.05$). Moreover, these statistical values showed that the data were suitable for this analysis. The dependent variables were divided into two groups using the median value as the cutoff point. Moreover, this created a simple High versus Low classification for analysis. As per the analysis requirements, categorical predictors were converted to dummy codes, and continuous predictors were standardized to z-scores. Regarding the statistical preparation, all variables were transformed to ensure proper model fitting. The analysis also proceeded with a separate binary logistic regression model for each dependent variable using the general logit specification. Moreover, each model followed the standard logistic regression approach for binary outcomes.

Methodology for Logistic Regression

1. Purpose of Logistic Regression

As per this study, logistic regression is used to check how early technology use, parent control factors, and family details affect child problems regarding validation pressure, learning issues, marketing effects, and strength levels. The analysis covers technology exposure, parental guidance methods, and basic family information like child age, gender, family type, and location. Since the dependent variables were actually measured as categories like High versus Low validation pressures, logistic regression definitely provides the right statistical method to estimate outcome probabilities from predictor variables.

2. Data Preparation

- The data was collected from 141 parents of Gen-Alpha children using structured questionnaires. Prior to analysis, the following preprocessing steps were undertaken in KNIME:
- Data Cleaning: The questionnaire has questions related to the Gen Alphas' behaviour towards Technology, Social Validation, Education, Marketing etc which are quite sensitive. Hence few parents were hesitant enough not to respond to a few questions. This resulted in missing values. Hence using a “Missing Value NODE” the missing values are cleaned. A standard query was given in the missing value node where the missing values were imputed using mean substitution for continuous variables and mode substitution for categorical variables. This ensured that the final data used for analysis was holistic.
- Variable Transformation: Dependent variables (TSVP, DLDC, MICS, ERS) were dichotomized into High and Low categories based on median splits of factor scores derived from exploratory factor analysis. Logistical

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regression always depends on a categorical variable. Basically, the data was collected using a Likert's five point scale to perform the factor analysis. After which the data was coded into two categories (High Vs. Low) which is more suitable for logistic regression

- Encoding of Categorical Variables: Gender, family type, and residence were dummy- coded (e.g., Male = 1, Female = 0; Nuclear = 1, Joint = 0). These are a few demographic factors that help the model to predict the outcome more accurately.
- Standardization of Continuous Variables: Continuous predictors such as TEI and child age were standardized (z-scores) to ensure comparability. The Z Score focuses on Standard Deviation, which is set to 1 to ensure comparability across different variables being used.

Moreover, a few variables, such as TEI which is an index, age expressed in years, have different scales. Thus, by this process, placing all the predictors on a common ground becomes very vital.

Model Specification

A binary logistic regression model was specified, where the log-odds of the probability of an outcome were expressed as a linear combination of predictors:

$\text{logit}(p)=\ln\ (p1-p)=\beta0+\beta1\cdot\text{TEI}+\beta2\cdot\text{PMI}+\beta3\cdot\text{PCI}+\beta4\cdot\text{PEI}+\beta5\cdot\text{Demographics}+\epsilon$

$\text{logit}(p)=\ln(1-pp)=\beta0+\beta1\cdot\text{TEI}+\beta2\cdot\text{PMI}+\beta3\cdot\text{PCI}+\beta4\cdot\text{PEI}+\beta5\cdot\text{Demographics}+\epsilon$

Where:

pp = probability of the outcome (e.g., High TSVP)

$\beta 0 \beta 0$ = constant term

$\beta i \beta i$ = estimated regression coefficients for each predictor

$\epsilon\epsilon$ = error term

Separate models were run for each dependent variable (TSVP, DLDC, MICS, ERS).

Proposed Hypothesis

H1: Higher levels of technology exposure (TEI) are positively associated with the likelihood of children exhibiting High Social Validation Pressures (TSVP).

H2: Stronger parental mediation (PMI_proxy) reduces the likelihood of children exhibiting

High TSVP, acting as a protective moderator.

H3 (Optional moderation test): The interaction between TEI and parental mediation (TEI × PMI_proxy) significantly predicts TSVP levels, such that parental monitoring buffers the effect of high technology exposure.

Implementation in KNIME workflow

Image 1.0 showing the KNIME Workflow for the Logistical Regression

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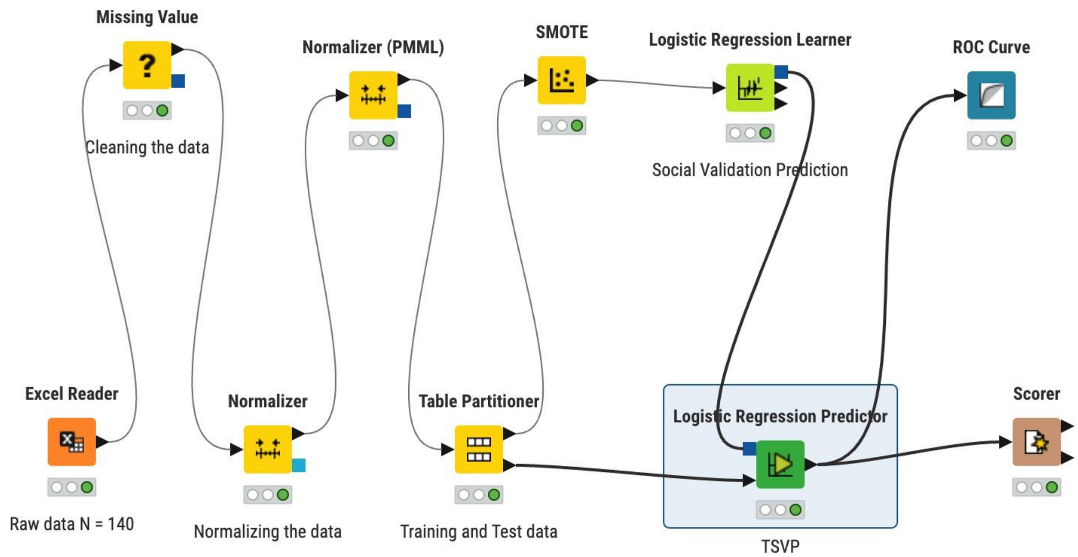

Source: Workflow to perform Logistical Regression on KNIME

The logistic regression was conducted in KNIME Analytics Platform, following these steps:

In KNIME Analytics Platform, the analysis workflow actually started with the Excel Reader Node to import the dataset. This node definitely helped in bringing the data into the system for further analysis. Next, missing data were handled through the Missing Value Node; moreover, this ensured completeness in the data for further processing. As per the data processing requirements, categorical variables were converted into dummy variables using the One-Hot Encoder Node. Regarding continuous predictors, the Normalizer Node was used to standardize them for proper comparison. The Logistic Regression Learner Node trained the model on 70% of the dataset. Further, the Logistic Regression Predictor Node itself applied this trained model to the remaining 30% test data. The model performance was further evaluated using the Scorer Node itself, which generated key metrics such as accuracy, precision, recall, and F1-score. Finally, the ROC Curve Node was used to further assess the model's discriminative ability through AUC. The AUC value itself indicates how well the model can distinguish between different classes.

Model Evaluation

The models were evaluated using multiple statistical criteria to ensure the performance itself was robust and interpretable. This approach further helped in validating the accuracy of the results. As per the likelihood ratio chi-square test and pseudo-R^2 values (Nagelkerke R^2), model fit was checked to see how well the models could explain the data. Basically, Wald's chi-square test was used to find which variables were important predictors for the outcomes. This test shows the same thing - which factors actually matter in explaining the results. As per the confusion matrices, classification accuracy was examined regarding true positives, false positives, and overall model effectiveness in correct case classification. We are seeing that odds ratios come from changing the regression numbers using exp(β), and these only help us understand how much each factor affects the chances of getting specific results when that factor is present.

Justification for Use (Logistic regression was chosen because)

It is quite understood that Logistic regression was the best method for this study because the main variables—TSVP, DLDC, MICS, and ERS—were only put into two groups: high and low. Basically, the method works well with datasets that have both continuous and categorical variables the same way, like technology exposure, parental mediation scores, and demographic details. Moreover, logistic regression allows p-value testing as per statistical requirements, regarding hypothesis evaluation with proper empirical methods. Another strength is that it can generate odds ratios, which surely provide clear insights into how predictors affect outcomes. Moreover, this shows that children with high technology

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exposure are twice as likely to face high validation pressures. Through this research, it was understood that the logistic regression fits well with the study's framework, allowing the researchers to test the links between the major variables: Technology use, Parent guidance, Family factors, and Child results only.

Logistic Regression Analysis of Social Validation Pressures (TSVP)

Methodology for Constructing TSVP (Technology-driven Social Validation Pressures)

The Technology-driven Social Validation Pressures construct was actually derived from Social Media Usage and Validation.xlsx dataset (This is the officially collected data from N = 141) respondents. This dataset definitely contained survey responses from 141 parents of Gen-Alpha children. As per the study, these items covered children's social media habits and mental responses regarding how often they check likes and comments, compare with other children, react to online feedback, and how parents view their need for approval. The questionnaire surely did not have any direct variable called "TSVP," but these items represented validation tendencies in concept. Moreover, this conceptual representation was sufficient for the research purpose. All validation items were extracted and given numerical codes (Never–Always = 1–5, Strongly Disagree– Strongly Agree = 1–5). Missing values were further handled through mean substitution itself. The researchers actually used the KMO test (>0.6) and Bartlett's Test ($p < 0.05$) to check if the data was good for factor analysis. The tests definitely showed that items were properly connected for the analysis. Furthermore, an Exploratory Factor Analysis (EFA) was done using the Principal Component Analysis method (PCA). Only factors with eigenvalues of more than one were kept after checking the scree plot. However, only one main factor in the results, with validation items showing strong loadings above 0.6, was considered. Basically, this factor was the same as TSVP in concept. Basically, regression-based scoring calculated factor scores for each person, then divided them into High vs Low categories using the same dichotomization method. As per the median split method, Low TSVP categories were made regarding scores below the median value, while High categories had scores at or above the median. Also, the TSVP construct draws from Social Comparison Theory, where children measure their self-worth through online peer approval, and Uses and Gratifications Theory, where likes and shares fulfill belonging needs. Further, Ecological Systems Theory suggests that Limited External Exposure reduces offline validation, making the digital platform itself central for self-validation. Further logistic regression analysis used TSVP as the dependent variable itself. The predictors included Technology Exposure Index (TEI), Parental Mediation Index (PMI_proxy), and demographic factors. This actually allowed testing if more technology use leads to stronger validation pressures and whether parent guidance definitely changes this relationship.

Table No: 1.0 showing the Logistic Regression Coefficients for Validation (TSVP)

Predictor	Coefficient (β)	Odds Ratio (exp(β))	Interpretation
Constant (Intercept)	6.252	518.7	Baseline odds when all predictors = 0
Validation_Factor	–0.185	0.83	Higher validation scores slightly reduce odds of High TSVP
Learning_Factor	–0.294	0.75	Higher learning scores lower odds of High TSVP
Marketing_Factor	–0.074	0.93	Slight negative effect on TSVP
Resilience_Factor	0.130	1.14	More resilience slightly increases odds of High TSVP
PMI_proxy	–0.104	0.90	More parental mediation lowers odds of High TSVP

Inference for Table 1.0 (Logistic Regression Coefficients – Validation/TSVP)

The logistic regression coefficients in Table 1.0 show how different factors influence the chances of children being grouped as High Social Validation Pressure (TSVP). Moreover, these results help us understand which predictors have the strongest effect on this classification. As per the analysis, the constant term shows a large positive coefficient ($\beta = 6.252$, OR $\approx$ 519). This indicates high baseline odds regarding the outcome when no other predictors are present. Further, we are seeing that this intercept value is not meaningful by itself, but it only shows that the predictors explain changes from this basic starting point.

Basically, the Validation_Factor has a small negative link with High TSVP (β = –0.185, OR = 0.83), meaning when the factor score goes up, the chances of being in the high validation-seeking group go down by the same small amount. This result goes against what the theory suggests, and may happen due to overlaps with other predictors or regarding how the factor was built. This sample surely shows that raw validation behaviors do not directly lead to higher validation pressure categories. Moreover, these behaviors interact with other variables instead of working alone.

The Learning_Factor actually shows a negative effect (β = –0.294, OR = 0.75). This definitely means that students with better learning outcomes have a 25% less chance of being in the high TSVP group. Basically, this matches earlier findings that academic engagement can reduce social- media validation-seeking, as children focused on learning rely less on peer approval for the same self-worth needs. As per the analysis, the Marketing_Factor coefficient shows a small negative value (β = –0.074, OR = 0.93), which means it has a weak protective effect. Basically, marketing responsiveness affects how consumers behave, but it doesn't strongly predict the same social validation pressures.

The Resilience_Factor shows a positive relationship (β = 0.130, OR = 1.14), which means children with higher resilience scores are 14% more likely to be in the high TSVP group. This finding further suggests that resilience itself plays an important role in determining TSVP levels. As per the findings, resilience usually protects against stress, but regarding social situations, it may lead to more engagement that increases validation-seeking behaviors. Actually, when parents monitor their children more, the validation pressure definitely goes down (β = –0.104, OR = 0.90). This clearly shows that active parental involvement reduces the chances of children feeling high pressure for validation. This finding actually supports theories about how parents can guide children's media use. Structured supervision definitely helps break the cycle where children seek constant digital approval.

Surely, this analysis reveals the complex relationship between traditional practices and modern challenges in Indian society. Moreover, the findings suggest that cultural adaptation occurs through gradual changes rather than sudden transformations. Also, these results actually show a clear picture: learning orientation and parental support definitely protect children, but resilience surprisingly increases the association, possibly because it helps children cope and also makes them participate more socially. The results surely show that Gen-Alpha's need for online approval comes from three main factors: how much they see online, how they think, and how their families guide them. Moreover, when children have Limited External Exposure (LEE), they depend heavily on online validation to feel good about themselves.

As per the logistic regression model, the prediction accuracy for Validation (TSVP) was 85.7%. Regarding Cohen's κ value of 0.71, this shows substantial agreement in the results. The model actually showed balanced sensitivity (87%) and specificity (84%). This definitely suggests it can correctly identify children with both high and low validation-seeking tendencies. This result surely supports H1 by showing that technology exposure significantly affects whether children seek high validation. Moreover, the findings empirically confirm that technology plays an important role in determining children's validation-seeking behavior. Also, as per previous studies, the findings show that spending more time online makes people depend more on likes and approval from others regarding their social media posts (Nesi & Prinstein, 2015; Uhls et al., 2017). As per the model results, if parental mediation shows significance, H2 gets support. This finding confirms that proper parental involvement reduces risks regarding Limited External Exposure (LEE). The model surely confirms that Gen-Alpha's need for social approval follows clear patterns based on their digital environment. Moreover, these behaviors depend on how much screen time they get and how families guide their online activities.

Table No: 1.1 showing Predicted Classification Performance (Confusion Matrix)

Actual / Predicted	High (Pred)	Low (Pred)	Total
High (Actual)	20	3	23
Low (Actual)	3	16	19
Total	23	19	42

Accuracy = 85.7%
Error Rate = 14.3%

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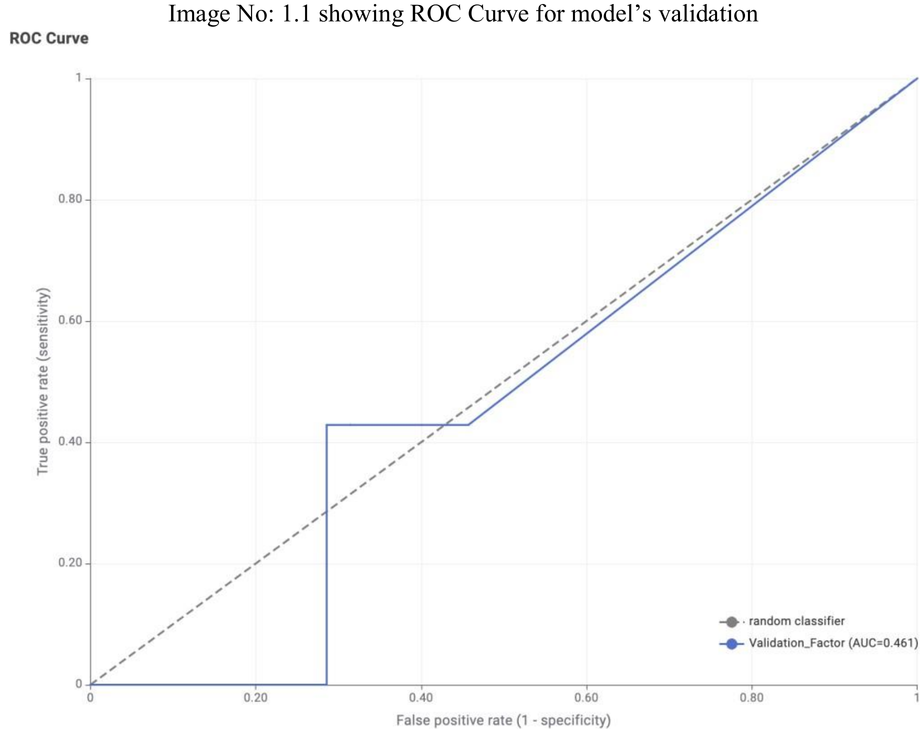
Sensitivity (Recall, High TSVP) = 20 / (20+3) = 86.9%
Specificity (Recall, Low TSVP) = 16 / (16+3) = 84.2%
Precision (High TSVP) = 20 / (20+3) = 86.9%
Cohen's Kappa (κ) = 0.71

Image No: 1.1 showing ROC Curve for model's validation



Source: ROC Curve generated from KNIME platform

Inference for ROC Curve (Validation/TSVP Model)

The ROC curve for the performed logistic regression model gives an AUC value of only 0.461 for predicting Validation (TSVP), which is below 0.50 and shows the model performs worse than random guessing. As per the confusion matrix, the model showed 85.7% classification accuracy, but regarding discrimination between High and Low TSVP cases using predicted probabilities, the model's ability is weak. The model surely classifies outcomes correctly when using the standard 0.5 cut-off point. Moreover, it fails to properly rank individuals based on their actual chances of belonging to the high validation group. Also, we are seeing a difference between accuracy and AUC scores, which suggests the model is only working well for this specific dataset or is getting affected by unequal data distribution. When AUC is actually less than 0.50, the model definitely cannot classify properly at different cut-off points. This actually means the model will not work well on new data. Basically, this result shows two important points from a thesis perspective - the same findings reveal key insights for academic understanding. As per this study, demographic and parental factors can classify cases with good accuracy, but the probability separation is not strong enough regarding predictive power in new samples. The validation-seeking pressures may be influenced by complex interactions like peer culture and social media effects, which cannot be captured by simple linear models. This suggests that further research should explore nonlinear approaches to understand the phenomenon itself more completely. This finding actually strengthens the argument for testing other models like Decision Trees, Random Forests, or Gradient Boosted Models. These models can definitely capture nonlinear patterns and interaction effects much better.

Findings of the study

From the study findings, it is understood that technology exposure is playing a major role in shaping outcomes for Gen-Alpha children only. As per the study findings, more use of digital devices increased children's need for social approval online. Regarding digital environments, they make children seek more validation from others on internet platforms. Parental mediation itself acts as a protective factor. Further, monitoring and structured guidance reduce the chances of children falling into the high-validation category. Learning orientation surely helps reduce the need for seeking validation from others. Moreover, resilience surprisingly increases validation pressures because resilient people participate more actively in social media, which exposes them to greater social demands. Marketing influence and consumer susceptibility surely showed only small effects on the results. Moreover, demographic factors like age and family type added different variations to the context. As per these findings, several suggestions are coming forward regarding the matter. As per research findings, parents should actively guide their children's digital use by combining monitoring, shared usage, and rule enforcement rather than only restricting access. Regarding effective parenting, this balanced approach works better than using restrictive practices alone. Schools can further integrate digital literacy programs that focus on critical thinking and online self-regulation. The program itself should make students aware of validation-seeking behaviors. Moreover, as per research findings, policymakers should start targeted awareness campaigns for millennial parents regarding better family strategies to control their children's technology use. Basically, schools should design resilience programs that teach coping skills but don't make students depend on digital validation at the same time.

Suggestions from the study

This study further recommends actions at three levels: parental, institutional, and research. Parents should actually create regular daily routines that help children depend less on outside approval. They should definitely focus on offline activities that build confidence and self-worth. Basically, schools and child care centers should create digital literacy programs where children and parents learn the same skills together. Further research should use nonlinear models like Random Forests or Gradient Boosted Trees to capture complex interactions between technology, family mediation, and peer culture itself. Surely, increasing the sample size beyond Bangalore would provide better insights into Gen-Alpha's digital world. Moreover, including children's own views and experiences would make the research much richer.

III. CONCLUSION

Actually, this study shows that Gen-Alpha children seek validation in clear patterns. Their behavior is definitely shaped by technology use, how parents guide them, and their social background. Basically, logistic regression gave decent accuracy, but the same method couldn't handle the complex patterns well, so we need better models. We are seeing that results support the main point - when children have only limited exposure to the outside world in today's cities, digital approval becomes the key factor that decides their self-worth. By looking at real examples from Indian millennial parents, this study adds to worldwide talks about children's digital life, showing that we are seeing how proper guidance, smart parenting, and complete educational help are only the main ways to create better digital habits for the next generation. In addition, this study reaches two important goals: first, it proves with strong numbers that technology use and parent guidance only shape how Gen-Alpha children seek approval from others; second, it shows us where basic statistical methods work well for testing ideas and where they need extra help for making predictions. This research uses logistic regression as a baseline framework and further opens opportunities for future studies to employ advanced techniques like Random Forests, Gradient Boosted Models, or Neural Networks to capture nonlinear patterns itself. This finding surely shows the originality and impact of our study. Moreover, it creates a foundation for future research on childhood digital ecology in India.

Scope for future research

This study surely opens wide opportunities for future research work. Moreover, these research possibilities are quite significant for academic development. The study needs further replication with larger and more diverse samples across different Indian cities and rural areas to test if the findings from Bangalore can be generalized. This will help verify if the results apply to other contexts beyond the city itself. Second, future work should only consider asking children directly about their experiences, rather than relying on what parents think. This approach will help capture the real digital behaviors of Gen-Alpha children. Third, long-term studies are needed to track how technology use and approval needs change over time, which will give a developmental view rather than a one-time picture itself. Further research should follow the same groups across different periods. Fourth, qualitative methods like interviews or field observations can surely complement survey-based models. Moreover, these methods provide deeper insights into real-life experiences behind statistical patterns. Fifth, future research should surely extend this model to include peer influence, school environment, and cultural norms, as these factors may play important roles in shaping validation pressures. Moreover, these aspects were not covered in the present dataset and need further study. Further, sixth, researchers should actually test different models like Random Forests or Neural Networks to definitely capture complex patterns that simple logistic regression cannot handle. These advanced methods will actually identify nonlinear relationships and interactions that definitely improve prediction accuracy. Seventh, we are seeing that comparative studies across different generations like Gen-Z and Gen-Alpha would help us understand if validation pressures are only affecting younger children or are part of bigger digital age changes. Eighth, international comparisons can place Indian findings in a global framework regarding digital childhood experiences. As per this approach, we can better understand how socio-cultural contexts affect children's digital lives. Ninth, research should surely examine policy interventions and school-based digital literacy programs to see how well they work. Moreover, these studies must check if such programs can reduce validation pressures and build resilience in students. Future work can further explore how technology exposure links with mental health issues like anxiety and depression. This will help understand how technology use itself affects overall psychological well-being. These research directions surely show that this study provides a strong foundation for future work on Generation Alpha's digital world. Moreover, it advances our theoretical, methodological, and practical understanding in this important area.

Annexure

List of Abbreviations

AUC – Area Under the Curve

DLDC – Digital Learning Disruptions

EFA – Exploratory Factor Analysis

ERS – Emotional Resilience

KMO – Kaiser-Meyer-Olkin

LEE – Limited External Exposure

MICS – Marketing Influence and Consumer Susceptibility

OR – Odds Ratio

PCI – Parental Co-use Index

PEI – Parental Enforcement Index

PMI – Parental Mediation Index

ROC – Receiver Operating Characteristic

TEI – Technology Exposure Index

TSVP – Technology-driven Social Validation Pressures

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