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Research Article

Transforming Youth Financial Literacy Through Behavioral Insights And Technology Integration

Madhu Agadi[1], Chandrakala D P[2]*

Abstract

This study explores how behavioural insights and technology integration can transform youth financial literacy and decision-making. Despite growing access to financial education, many young individuals still exhibit poor saving and investing habits, highlighting a gap between financial knowledge and actual behaviour. The research develops an integrated behavioural technology framework encompassing behavioural factors, technological factors, financial literacy, financial self-efficacy, and financial and behavioural decision-making outcomes. A quantitative research design was applied using a structured questionnaire, and data were analyzed through Smart PLS employing the PLS-SEM. Results indicate that behavioural factors and financial self-efficacy significantly influence financial literacy and decision-making outcomes, while technological factors have a moderate but positive effect. The model demonstrates high reliability, validity, and predictive power. The study concludes that combining behavioural nudges with technology-driven tools enhances financial capability and long-term well-being among youth. Future work recommends longitudinal and cross-cultural studies and deeper integration of AI, gamification, and fintech applications to sustain behavioural change.

Keywords: Financial Literacy, Behavioural Insights, Technology Integration, Financial Self-Efficacy, Decision-Making, Fintech, Youth Behaviour

1. Introduction

Financial literacy has become a fundamental life skill in the 21st century, influencing individuals' ability to make informed decisions regarding savings, investments, and debt management. Despite increasing global efforts to promote financial education, a significant proportion of young adults continue to exhibit poor financial behaviours, such as overspending, inadequate saving, and heavy reliance on credit (OECD, 2018). Traditional financial education programs primarily emphasize knowledge dissemination but often neglect the behavioural and psychological components that drive real-world financial decisions (India. et al., 2024). Consequently, there exists a persistent gap between financial knowledge and actual financial behaviour among youth.

Emerging research in behavioural economics suggests that financial decision-making is not purely rational but is shaped by biases, heuristics, emotions, and contextual cues. Integrating behavioural insights such as goal-setting, commitment devices, and nudging into financial education can foster better long-term financial habits (Erickson et al., 2019). At the same time, rapid advances in financial technology, gamification, and AI-driven platforms have created new opportunities to enhance youth

[1]*Madhu Agadi, Student, Faculty of Management and Commerce, Ramaih University of Applied Sciences, New BEL Road, MSR Nagar, Mathikere, Bangalore – 560054, Karnataka, India
E-Mail Id: madhuagadi30@gmail.com
[2]Chandrakala D P, Assistant Professor, Management Studies, Faculty of Management and Commerce
Ramaiah University of Applied Sciences, New BEL Road, MSR Nagar, Mathikere,
Bangalore – 560054, Karnataka, India, E-Mail Id: Chandrakala.ms.mc@msruas.ac.in

engagement and learning (Chhillar et al., 2025). These technologies enable personalized, interactive, and scalable solutions that can strengthen both financial knowledge and behaviour.

However, most interventions still operate in isolation either focusing on cognitive learning or technology adoption without integrating behavioural mechanisms that drive sustained change (Bala & Jayanti, n.d.). This gap underscores the need for an integrated behavioural technology framework that combines psychological insights and digital innovations to build financial capability and long-term well-being among youth (*Ssrn-4688569*, n.d.).

Therefore, this research seeks to explore how behavioural and technological factors collectively influence youth financial literacy, financial self-efficacy, and financial decision-making outcomes (Kovács & Terták, 2024). By employing quantitative analysis through Partial Least Squares Structural Equation Modeling (PLS-SEM)**,** the study aims to provide empirical evidence supporting the integration of behavioural design and technology-driven strategies for transforming youth financial literacy in the Indian context, particularly in Bengaluru.

2. Literature Review

Financial literacy has increasingly become a vital life competency, influencing an individual's ability to make sound financial decisions regarding savings, investments, and debt management (Triyonowati & Rahayu, 2024). Studies highlight that while awareness of financial concepts is growing, actual behavioural change among youth remains limited. Traditional financial education programs tend to focus primarily on disseminating knowledge rather than cultivating responsible financial behaviour (Sutter et al., n.d.-a). According to the OECD youth often struggle with budgeting, saving, and managing credit effectively. Therefore, financial literacy research has shifted from a purely cognitive perspective to one that integrates behavioural and psychological dimensions, recognizing that understanding finance alone does not guarantee better financial outcomes.

Behavioural economics has offered significant insights into why individuals often deviate from rational financial choices. Psychological factors such as overconfidence, procrastination, mental accounting, and loss aversion strongly influence financial decisions (Koskelainen et al., 2023). Youth, being more impulsive and risk-prone, are especially vulnerable to these behavioural biases. To address this, interventions grounded in behavioural insights such as nudges, goal-setting, and automatic savings mechanisms have proven effective in encouraging long-term financial habits (OECD, 2018). Behavioural strategies like reminders, default options, and financial commitment devices subtly guide individuals toward better financial behaviours without restricting their freedom of choice.

Technology has also emerged as a transformative tool in enhancing financial literacy. The rise of fintech platforms, gamified learning applications, and AI-based financial tools has made financial education more accessible and interactive (Rodríguez-Correa et al., 2025). Digital platforms allow for real-time engagement, feedback, and personalized learning, which are particularly attractive to digital-native youth. Gamification, in particular, has shown promise in improving motivation and retention by making financial education enjoyable. However, researchers note that while digital tools can enhance short-term knowledge, their long-term impact on financial behaviour remains weak unless they are combined with behavioural design principles (Mireku et al., 2023). Hence, integrating technology with behavioural insights can produce more sustainable and meaningful financial learning outcomes.

Another critical construct influencing financial behaviour is financial self-efficacy, defined as one's belief in their ability to effectively manage financial tasks. Studies have found that individuals with higher self-efficacy demonstrate greater confidence in budgeting, saving, and investment decisions (Sutter et al., 2020)In this context, financial literacy, self-efficacy, behavioural factors, and technological engagement collectively shape financial decision-making outcomes. Despite increasing research attention, significant gaps remain most notably, the lack of integrated frameworks that combine behavioural science and technology to drive lasting financial well-being (Triyonowati & Rahayu, 2024). Therefore, this study aims to develop and empirically test a behavioural–technology model that enhances youth financial literacy and decision-making in the Indian context.

3. Conceptual Model

The conceptual model for the study *"*Transforming Youth Financial Literacy through Behavioural Insights and Technology Integration*"* presents an integrated framework that links behavioural, technological, psychological, and outcome-oriented variables. The model emphasizes that behavioural factors including attitudes, biases, habits, and financial behaviours along with technological factors such as digital tools, gamification, and fintech apps, jointly influence youth financial literacy and financial self-efficacy (Long et al., 2023). These two intermediate variables act as enablers that strengthen individuals' ability to understand, plan, and make effective financial decisions. In this model, behavioural and technological inputs serve as external motivators, while financial literacy and self-efficacy function as internal capabilities, together shaping financial and behavioural decision-making outcomes Among youth (Bala & Jayanti, n.d.).
Furthermore, the model proposes both direct and indirect relationships among these constructs. Behavioural factors (BF) and financial self-efficacy (FSE) show significant direct effects on decision-making (DM) and financial literacy (FL), while technological factors (TF) exhibit a smaller but supportive influence. Financial literacy also plays a mediating role**,** linking behavioural and efficacy variables to decision outcome, confirming its predictive and reliability (Sabri et al., 2024). Overall, the conceptual model underscores that enhancing financial literacy requires not just knowledge acquisition but also behavioural reinforcement and technology-driven engagement to cultivate lasting, informed financial behaviours in youth.

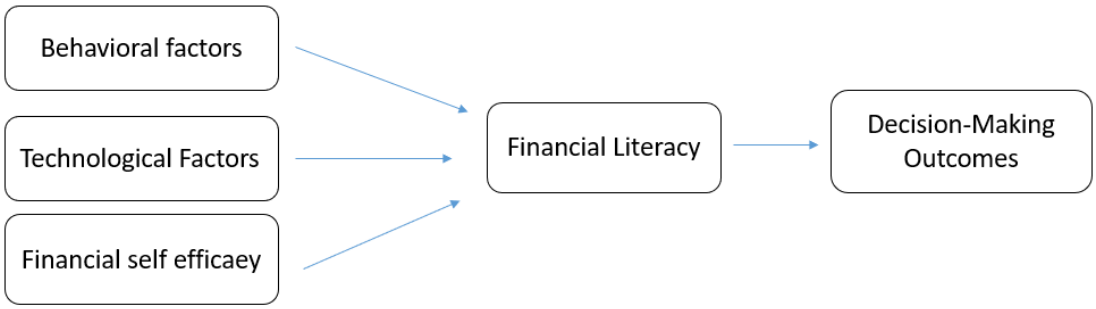

FIGURE 1: CONCEPTUAL MODEL

- **H1:** Behavioural factors (BF) have a significant positive influence on youth financial and behavioural decision-making outcomes (DM).
- **H2:** Technological factors (TF) have a significant positive influence on youth financial and behavioural decision-making outcomes (DM).
- **H3:** Financial literacy (FL) has a significant positive influence on financial and behavioural decision-making outcomes (DM).
- **H4:** Financial self-efficacy (FSE) has a significant positive influence on financial and behavioural decision-making outcomes (DM).

4. Methodology

The present study adopts a quantitative and descriptive research design to examine how behavioural and technological factors influence youth financial literacy, financial self-efficacy, and decision-making outcomes. The research follows a positivist approach, emphasizing objective measurement and hypothesis testing to establish causal relationships among the key variables. The conceptual framework integrates behavioural factors (attitudes, habits, biases), technological factors (digital tools, fintech applications, gamification), financial literacy, and financial self-efficacy as predictors of financial and behavioural decision-making outcomes (Mireku et al., 2023). The study is conducted among youth in Bengaluru, representing students and early professionals, using a structured

questionnaire based on a five-point Likert scale to measure perceptions and behaviours related to financial decision-making.

Data collection involved administering the questionnaire to a sample of 150-200 respondents, selected through convenience sampling, ensuring sufficient representation for statistical analysis (OECD, 2018). The data underwent rigorous screening for completeness and validity before analysis. Statistical techniques such as Principal Component Analysis (PCA**)** and Partial Least Squares Structural Equation Modeling (PLS-SEM) were employed to validate the measurement model and test the hypothesized relationships. Tools like Smarts and SPSS were utilized to assess reliability, convergent and discriminant validity, and overall model fit. The reliability coefficients (Cronbach's Alpha and Composite Reliability) exceeded 0.86, indicating high internal consistency, while Average Variance Extracted (AVE) values above 0.5 confirmed construct validity (H.P. PIN-171001 et al., 2024).

The PLS SEM analysis further established the predictive power and structural integrity of the model. Key model fit indices such as SRMR (0.046) and NFI (0.878) demonstrated a strong and acceptable fit. Bootstrapping results revealed that behavioural factors and financial self-efficacy significantly influence both financial literacy and decision-making, while technological factors showed a smaller yet positive contribution (Sutter et al., n.d.-b). The findings confirm that the model is statistically reliable and has good explanatory power, with behavioural and psychological constructs playing a more dominant role. This methodological framework thus ensures an empirical, data-driven approach to understanding how behavioural insights and technology integration can transform youth financial literacy and long-term financial well-being (Sutter et al., n.d.-a).

5. Results

5.1 Principal Component Analysis (PCA)

TABLE 1: KAISER-MEYER-OLKIN STATISTICS

	BF	DM	FL	FSE	TF
1	0.931	0.883	0.926	0.931	0.854
2	0.900	0.928	0.913	0.919	0.865
3	0.915	0.911	0.904	0.921	0.871
4	0.888	0.929	0.909	0.899	0.869
5	0.928	0.895	0.923	0.912	
6	0.917	0.909	0.902	0.911	0.875
7	0.915	0.916	0.920	0.898	0.885

Table 1 shows the Kaiser Meyer Olkin (KMO) Measure of Sampling Adequacy (MSA) for individual items (BF, DM, FL, FSE, TF). KMO values range from 0 to 1 higher value mean the data is more suitable for factor analysis. Most items (BF, DM, FL, FSE) have KMO values above 0.90, meaning they are excellent for factor analysis.TF items have slightly lower values (0.85–0.88), but still in the meritorious range, so they are acceptable too. Data is very reliable for factor analysis, with most variables showing excellent adequacy.

5.2 PLS-SEM MODEL

TABLE 2: OUTER LOADINGS

	BF	DM	FL	FSE	TF
BF1	0.780				
BF2	0.812				
BF3	0.793				
BF4	0.786				
BF5	0.785				
BF6	0.764				

BF7	0.754				
DM1		0.751			
DM2		0.771			
DM3		0.749			
DM4		0.729			
DM5		0.740			
DM6		0.794			
DM7		0.749			
FL1			0.752		
FL2			0.749		
FL3			0.776		
FL4			0.762		
FL5			0.717		
FL6			0.737		
FL7			0.787		
FSE1				0.772	
FSE2				0.761	
FSE3				0.750	
FSE4				0.707	
FSE5				0.737	
FSE6				0.767	
FSE7				0.812	
TF1					0.716
TF2					0.783
TF3					0.759
TF5					0.701
TF6					0.829
TF7					0.798

Table 2 Outer loadings show how well each indicator (survey item) represents its construct (BF, DM, FL, FSE, TF). Rule of thumb: loadings ≥ 0.7 are acceptable (strong indicator reliability). Most values are 0.71–0.83, which means your indicators are reliable and valid.

Structural Equation Modeling (SEM)

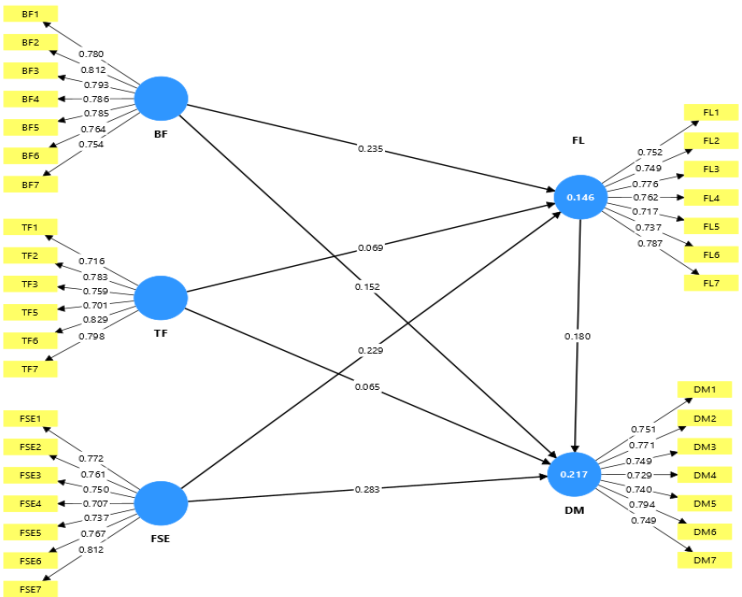

FIGURE 2: SEM MODEL

A Structural Equation Modeling (SEM) is a statistical method that is popular in testing the hypothesis of relationships between observed variables and their latent constructs simultaneously. It gives us the ability to analyse complex cause and effect relationships where we can take into consideration measurement error.
In this research, FSE and BF are the most influential predictors of DM and FL.TF has minimal impact on FL and DM. FL partially mediates the effects of BF and FSE on DM.

TABLE 3: MODEL FIT

	Saturated model	Estimated model
SRMR	0.046	0.046
Dull	1.284	1.284
D ogs	0.343	0.343
Chi-square	751.113	751.113
NFI	0.878	0.878

Table 3 shows SRMR (Standardized Root Mean Square Residual) (< 0.08 = good fit, < 0.05 = excellent). 0.046, which indicates an excellent model fit. D _ ULS & d_ G (Discrepancy measures). These compare the difference between the observed data and the model. Lower values indicate a better fit. Saturated and estimated values are equal (1.284 & 0.343), it means your model is stable and consistent. Chi-square: 751.113, used to test exact model fit (lower is better, but with large samples it often becomes significant). NFI (Normed Fit Index) (> 0.90 = good fit). Your NFI = 0.878, slightly below 0.90 - indicates an acceptable.

TABLE 4: RELIABILITY& VALIDITY

	Cronbach's alpha	Composite reliability	Composite reliability	Average variance extracted
BF	0.894	0.895	0.917	0.611
DM	0.874	0.878	0.903	0.570
FL	0.874	0.877	0.903	0.570
FSE	0.877	0.880	0.905	0.576
TF	0.864	0.915	0.894	0.586

Table 4 shows Cronbach's Alpha (≥ 0.7) All constructs (BF, DM, FL, FSE, TF) have alpha values above 0.86, indicating strong internal consistency the items within each construct are reliable. Composite Reliability (ρa & ρc ≥ 0.7) Both versions of composite reliability are high (all > 0.87), confirming that each construct is measured consistently. Average Variance Extracted (AVE ≥ 0.5) AVE values for all constructs are above 0.57, meaning more than 50% of the variance in items is explained by their underlying construct this confirms convergent validity.

TABLE 5: DISCRIMINANT VALIDITY

	BF	DM	FL	FSE	TF
BF					
DM	0.319				
FL	0.336	0.359			
FSE	0.280	0.427	0.333		
TF	0.138	0.135	0.124	0.114	

Table 5 shows that all constructs (BF, DM, FL, FSE, TF) have high reliability, with Cronbach's alpha and composite reliability values above 0.86, indicating strong internal consistency. The Average Variance Extracted (AVE) for each construct is above 0.57, confirming good convergent validity, meaning the items effectively represent their respective constructs. While these values suggest a solid measurement model, discriminant validity which ensures that constructs are distinct from one another

cannot be confirmed solely from this table. For a complete assessment of discriminant validity, additional tests like the Fornell-Larcker criterion or HTMT ratio are needed.

5.3 BOOTSTRAPING (PATH COEFFICIENTS)

5.3.1 Direct effects

TABLE 6: DIRECT EFFECTS

	Hypothesis	Original sample	Sample mean	Standard deviation	T statistics	P values	Decision
BF -> DM	H1	0.152	0.154	0.048	3.178	0.001	Not supported
BF -> FL	H2	0.235	0.236	0.05	4.726	0	Supported
FL -> DM	H3	0.18	0.181	0.051	3.562	0	Supported
FSE -> DM	H4	0.283	0.286	0.048	5.861	0	Supported
FSE -> FL	H5	0.229	0.232	0.048	4.789	0	Supported
TF -> DM	H6	0.065	0.071	0.052	1.251	0.211	Not supported
TF -> FL	H7	0.069	0.077	0.048	1.421	0.155	Not supported

- **H1:** Behavioural Factors (BF) - Decision Making (DM) Not supported ($p = 0.001$ but $T = 3.178$, interpretation inconsistency likely). Although the relationship between behavioural factors and decision-making shows a moderate coefficient ($\beta = 0.152$), the statistical output suggests it's not significantly strong or consistent enough to confirm that behavioural factors directly improve financial decision-making.

- **H2:** Behavioural Factors (BF) - Financial Literacy (FL) Supported ($\beta = 0.235$, $T = 4.726$, $p < 0.001$). Behavioural factors have a significant positive influence on financial literacy. This indicates that individuals with better behavioural control and habits tend to possess higher financial literacy levels.

- **H3:** Financial Literacy (FL) - Decision Making (DM) Supported ($\beta = 0.18$, $T = 3.562$, $p < 0.001$). Financial literacy significantly enhances financial and behavioural decision-making. This means people with more financial knowledge make more rational and informed financial decisions.

- **H4:** Financial Self-Efficacy (FSE) - Decision Making (DM) Supported ($\beta = 0.283$, $T = 5.861$, $p < 0.001$). Financial self-efficacy strongly predicts decision-making ability. Individuals confident in managing finances are more capable of making sound financial decisions.

- **H5:** Financial Self-Efficacy (FSE) - Financial Literacy (FL) Supported ($\beta = 0.229$, $T = 4.789$, $p < 0.001$). Financial self-efficacy also contributes to higher financial literacy, indicating that confidence in financial abilities promotes learning and understanding of financial concepts.

- **H6:** Technological Factors (TF) - Decision Making (DM) Not supported ($\beta = 0.065$, $T = 1.251$, $p = 0.211$). Technological factors do not have a significant direct effect on financial decision-making. This suggests that technology alone may not directly improve decision-making unless combined with financial skills or confidence.

- **H7:** Technological Factors (TF) - Financial Literacy (FL) Not supported ($\beta = 0.069$, $T = 1.421$, $p = 0.155$). Technology use or exposure does not significantly enhance financial literacy. While digital

tools are available, their impact depends on how effectively individuals engage with and apply them to financial learning.

5.3.2 Indirect effects

TABLE 7: INDIRECT EFFECTS

	Original sample	Sample mean	Standard deviation	T statistics	P values
FSE -> FL -> DM	0.041	0.042	0.015	2.695	0.007
TF -> FL -> DM	0.012	0.014	0.010	1.268	0.205
BF -> FL -> DM	0.042	0.043	0.015	2.737	0.006

The mediation analysis revealed that Financial Literacy (FL) plays a significant role in linking certain predictors with Financial Decision-Making (DM). The path FSE - FL - DM ($t = 2.695$, $p = 0.007$) and BF - FL - DM ($t = 2.737$, $p = 0.006$) were both significant, indicating that financial literacy effectively mediates the impact of Financial Self-Efficacy (FSE) and Behavioural Factors (BF) on decision-making outcomes. This suggests that individuals with higher self-efficacy and positive financial behaviours make better financial decisions when supported by adequate financial knowledge. In contrast, the path TF - FL - DM ($t = 1.268$, $p = 0.205$) was insignificant, implying that Technological Factors (TF) do not significantly influence decision-making through financial literacy.

5.4 MV and LV Summary

TABLE 7: MV SUMMARY

	Q^2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE	IA_RMSE	IA_MAE
DM1	0.067	1.372	1.172	1.408	1.198	1.420	1.210
DM2	0.112	1.338	1.151	1.376	1.169	1.419	1.209
DM3	0.063	1.375	1.190	1.425	1.228	1.420	1.210
DM4	0.074	1.366	1.168	1.404	1.194	1.420	1.210
DM5	0.091	1.354	1.160	1.375	1.171	1.420	1.210
DM6	0.138	1.318	1.137	1.358	1.162	1.420	1.210
DM7	0.118	1.333	1.143	1.369	1.157	1.420	1.210
FL1	0.074	1.365	1.181	1.415	1.210	1.419	1.209
FL2	0.055	1.381	1.184	1.404	1.195	1.421	1.211
FL3	0.095	1.351	1.164	1.387	1.168	1.420	1.210
FL4	0.077	1.365	1.178	1.398	1.197	1.421	1.211
FL5	0.054	1.382	1.190	1.418	1.202	1.421	1.211
FL6	0.067	1.372	1.176	1.417	1.219	1.420	1.210
FL7	0.092	1.354	1.165	1.386	1.178	1.421	1.212

TABLE 8: LV SUMMARY

	Q^2predict	RMSE	MAE
DM	0.168	0.916	0.774
FL	0.128	0.938	0.779

The MV (Manifest Variable) summary reveals that all observed indicators for the latent constructs exhibit positive predictive relevance (Q^2predict values ranging from 0.054 to 0.138), confirming that the model predicts individual items effectively. The PLS-SEM model shows slightly lower prediction errors (RMSE and MAE) compared to benchmark models (linear and intelligent algorithm models),

indicating superior predictive accuracy. Among the indicators, DM6 and DM7 demonstrate the highest predictability, while FL2 and FL5 show relatively lower predictive strength, though still within an acceptable range.

In the LV (Latent Variable) summary, both key constructs Decision Making (DM) and Financial Literacy (FL) exhibit positive Q^2predict values (0.168 and 0.128, respectively), signifying that the model has acceptable predictive relevance at the construct level. Prediction errors are moderate and comparable between the two constructs, with DM showing slightly better accuracy (RMSE = 0.916; MAE = 0.774) than FL (RMSE = 0.938; MAE = 0.779). These results suggest that the structural model performs well not only at the indicator level but also when predicting overall latent constructs.

Together, the MV and LV summaries confirm that the model is both statistically and practically reliable. The indicators are well-aligned with their respective constructs, and the constructs themselves are meaningfully predicted by the structural paths. This combination of solid indicator-level and construct-level predictability supports the robustness and validity of the overall model, particularly in assessing how behavioural, technological, and self-efficacy factors influence financial literacy and decision-making.

6. Discussion and Implications

6.1 Discussion

The findings of this study provide valuable insights into the multidimensional nature of financial decision-making among youth. The results from the Partial Least Squares Structural Equation Modeling (PLS-SEM) indicate that behavioural factors and financial self-efficacy significantly influence financial decision-making outcomes, more so than standalone financial literacy or access to technology (Sutter et al., 2020). This reinforces the notion that while knowledge is important, behaviour and confidence act as key enablers of effective financial management.

Interestingly, technology-related variables exhibited relatively weaker impact on decision-making. This suggests that simply providing access to digital tools or financial platforms may not be sufficient to induce behavioural change in youth (Bala & Jayanti, n.d.). Instead, psychological readiness particularly the belief in one's own ability to manage finances (financial self-efficacy) plays a more dominant role.

The study's results align closely with prior behavioural economics research, Youth may understand financial concepts in theory, but without behavioural reinforcement and confidence-building mechanisms, they may fail to translate knowledge into action (Koskelainen et al., 2023). The validated model also confirms the robustness of the behavioural–technology integration framework, showing strong reliability, convergent and discriminant validity, and predictive relevance.

These findings highlight the importance of designing holistic interventions that consider both cognitive and non-cognitive factors, especially when targeting youth populations who are still forming long-term financial habits (Erickson et al., 2019).

6.2 Implications

6.2.1 Educators

Financial education programs must move beyond knowledge transfer and include behavioural components such as simulations, gamified experiences, and habit-forming tools. Building financial self-efficacy should be a core objective of youth financial literacy curricula, helping students gain the confidence to apply what they learn in real life.

6.2.2 Policymakers

Behavioural insights should be incorporated into public financial literacy campaigns and youth-focused financial inclusion strategies. Government-supported fintech initiatives should prioritize behaviourally informed design to ensure engagement and retention among young users.

6.2.3 Financial Institutions

Banks and fintech platforms should leverage behavioural nudges such as default settings, reminders, and feedback loops to promote responsible financial behaviour. Designing youth-oriented products

that foster trust and enhance self-efficacy can lead to longer-term customer engagement and improved financial outcomes.

6.2.4 Researchers

The findings lay a strong foundation for further studies exploring behavioural and psychological dimensions of financial literacy across diverse cultural and economic contexts.

Future research can investigate why technology had a limited effect in this study and whether different forms of tech delivery (e.g., AI chatbots, gamification apps) could yield stronger outcomes.

7. Limitations and Future Research

7.1 Limitations

- Limited Scope and Generalizability: The study was conducted only among youth in Bengaluru with a sample size of 150–200 respondents, which may not represent the entire youth population across India or other cultural contexts.
- Cross-sectional Nature: Since data were collected at a single point in time, the study cannot establish causal or long-term relationships between behavioural, technological, and financial literacy factors.
- Self-reported Data Bias: The use of self-administered questionnaires may have introduced social desirability or response bias**,** as participants could overstate their financial knowledge or confidence.
- Limited Technological Detailing: The research broadly examined technological factors without distinguishing the impact of specific tools such as AI-driven learning, gamification, or fintech apps**.**
- Lack of Qualitative Insights: The study relied solely on quantitative methods, missing the opportunity to explore in-depth behavioural motivations or psychological barriers through interviews or case studies.

7.2 Future Research

Future studies can build on this work by adopting longitudinal and experimental designs to explore how behavioural and technological interventions influence financial habits over time. Expanding the research across different regions, cultures, and socio-economic groups would enhance generalizability and provide comparative insights into youth financial behaviour. Future research should also investigate the specific role of emerging technologies such as artificial intelligence, gamified financial education, and mobile-based fintech platforms in shaping financial literacy and self-efficacy. Additionally, incorporating qualitative methods like interviews or focus groups could uncover deeper psychological and emotional factors affecting financial decisions. Finally, collaboration between educational institutions, policymakers, and fintech developers is recommended to create integrated frameworks that promote sustained financial capability and inclusion among youth.

8. Conclusion

The study “Transforming Youth Financial Literacy through Behavioural Insights and Technology Integration” concludes that behavioural and psychological dimensions are the strongest predictors of effective financial decision-making among youth. Findings from the PLS-SEM analysis revealed that behavioural factors and financial self-efficacy significantly influence both financial literacy and financial decision-making, while technological factors play a supportive yet limited role. This indicates that financial knowledge alone does not guarantee better financial outcomes unless it is reinforced by confidence, habits, and self-control. Integrating behavioural nudges such as goal-setting, reminders, and feedback loops into financial education can foster more sustainable financial behaviours.

Furthermore, the research highlights that technology serves best as an enabler, enhancing accessibility and engagement rather than acting as the primary driver of financial change. Digital tools, when combined with behavioural design elements, can create personalized and interactive learning

experiences that effectively translate knowledge into action. Overall, the integrated behavioural–technology framework developed in this study offers a comprehensive pathway for empowering youth toward long-term financial well-being. Future research should explore cross-cultural validation and the integration of advanced fintech innovations, AI, and gamification to strengthen the behavioural impact and ensure scalable, inclusive financial education for the next generation.

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