

A Study of Financial Literacy in a Changing Financial Era: An Intergenerational Study of Gen X, Gen Y, and Gen Z in Bengaluru

Meena M V

Research Scholar, Department of Commerce, PSG College of Arts and Science, Civil Aerodrome Post, Coimbatore
Tamil Nadu 641014

Email-meenamv31396@gmail.com

Dr. Gowri M

Associate Professor, Department of Commerce, PSG College of Arts and Science, Civil Aerodrome Post, Coimbatore
Tamil Nadu 641014

Email-gowri_m@psgcas.ac.in

Abstract

Financial literacy has become a basic skill as more money decisions move onto phones, yet little is known about how it differs across generations in Indian cities. We surveyed 235 working adults in Bengaluru from Generation X, Generation Y and Generation Z. Literacy was scored from 0 to 100 as the mean of financial knowledge, attitude and behaviour. The analysis used descriptive statistics, one-way ANOVA, multiple regression, confirmatory factor analysis (CFA), structural equation modelling (SEM) and a comparison of structural paths across generations. Mean literacy was 50.04 (SD = 5.90), and 91.5% of respondents landed in the moderate band. Generations did not differ on composite literacy, $F(2, 232) = 1.91$, $p = .151$, $\eta^2 = .016$, or on any single dimension, although Generation X had the highest knowledge and behaviour means. A regression with demographic, economic, digital and awareness predictors explained almost nothing, $F(22, 212) = 0.65$, $p = .883$. The path from literacy to decision-making was small and non-significant ($\beta = -0.10$, $p = .884$) and did not vary by generation. Every scale had very low internal consistency ($\alpha \leq .10$) and the CFA failed to show convergent validity, so the results cannot support firm substantive conclusions. The paper gives a baseline for Bengaluru, finds no clear generational split in measured literacy, and argues that future work needs stronger multidimensional instruments.

Keywords: Financial literacy; Generational differences; Generation X; Generation Y; Generation Z; Financial decision-making; Structural equation modelling; Bengaluru

JEL Classification: D14; D91; G53; J11

1 Introduction

Financial literacy matters more than it used to, because people now make choices that employers and the state once made for them. A working employee in a city such as Bangalore could easily obtain a loan, get a credit card, get access to investment applications, and decide how to save, how much to save, and where to invest this all is accessible to a user a single phone that too within a shorter period of time. Research connects users' ability to handle these choices with financial planning, market participation, wealth, and recovery after shocks. (Lusardi and Mitchell 2014; van Rooij et al. 2011; Klapper and Lusardi 2020). As these financial services are accessible widely but the people can't use them properly.

In today's world the three main aspects that changed the finance of the world are new technology's new products and an uncertain economy. Digital payments, robo-advice and online lending have driven transaction costs down and access up (Gomber et al. 2017; D'Acunto et al. 2019); they have shrunk decision time, and introduced digital fraud risks unmentioned in long-standing financial education. The proper understanding of the interest and the inflation is the essential part but it also includes having the patience in judgements self control and proper use of digital services (Kumar et al. 2023).

Three generations work alongside each other in India. Generation X, which established its habits around branches and deposits. Millennials, or Generation Y that witnessed the move to online during their working lives, and Generation Z who began their working lives with mobile payments and online investing already in place. Life-cycle theory predicts shifts in knowledge and behaviour as people age and acquire experience (Ando and Modigliani 1963), and cohort theory argues

shared formative experiences lead to lasting heterogeneity (Parment 2013). Empirical validation is much more complex and essential than what the media is presenting to us. Lyons and Kuron (2014) found generational effects to be small, volatile and confounded by age and career.

Indian evidence on this is sparse, Bengaluru-specific even sparser. Earlier work found low, uneven literacy among young urban workers and linked attitudes and literacy to stock-market participation (Agarwalla et al. 2015; Sivaramakrishnan et al. 2017; Rai et al. 2019). We found no work comparing all three generations in a metropolitan sample with a single instrument, or examining, in a single framework, how literacy levels, generational gaps, determinants and decision-making interact. Bengaluru is a good place to begin, having both a large technology workforce, active start-up and gig economy, extensive adoption of digital finance and wide variation in income and background.

We set out four objectives: (1) to measure the level of literacy in each generation; (2) to compare knowledge, attitude and behaviour across them; (3) to discover which demographic, economic, technological and awareness factors predict literacy; and (4) to test whether literacy relates to financial decision-making and whether this association differs across generations. Each objective is addressed with a distinct statistical technique and we report measurement quality fully, an aspect often neglected in this area of enquiry. Section 2 reviews the literature and sets out the hypotheses, Section 3 describes the method, Section 4 presents results objective by objective, Section 5 discusses them and Sections 6 to 8 address implications, limitations and conclusions.

2 Review of Literature and Hypotheses Development

2.1 Conceptualising and measuring financial literacy

The concept of financial literacy has been expanded over a period of years. The original 'big three' questions on interest, inflation and diversification only captured aspects of the knowledge dimension (Lusardi and Mitchell 2014). Huston (2010) distinguished understanding and application and highlighted the diversity of different constructs that were being measured under the umbrella term. Remund (2010) highlighted competence in communicating about money, managing it, making decisions and feeling confident about the future. Hastings et al. (2013) highlighted the challenges of separating literacy from cognitive ability and income. There is also a measurement tradition that covers behavioural constructs. Dew and Xiao (2011) constructed a scale of spending, cash management, saving, investing and credit and showed that measures of practices could be reliably used as distinct from knowledge. Allgood and Walstad (2016) found that what people feel they know can be as influential as what they actually know, sometimes. We share this multidimensional view. Our literacy score captures knowledge, attitude and behaviour and we consider product awareness and digital adoption as correlates rather than components.

2.2 Generations, the life cycle and financial literacy

For age, the evidence is mixed. Agarwal et al. (2009) found that the quality of financial decisions peaks in middle age and is weaker at both ends. Finke et al. (2017) found that literacy declines in old age while confidence stays high, which is a risky pairing. Among young adults, parents, early jobs and schooling shape attitudes and habits (Shim et al. 2010).

The cohort view starts from a different place. People who grew up in the same historical and technological setting, it argues, end up with similar outlooks. Parment (2013) traced differences in shopping behaviour between Generation Y and Baby Boomers to their formative years. Yet the systematic review by Lyons and Kuron (2014) found that many reported generational effects were small, unstable or confounded with age and career stage. Taken together, these studies suggest Generation X may hold an advantage in experience, and Generation Z an advantage in digital familiarity but not in experience. How large any gap should be is unclear, which is why we test it directly.

H1: Generation X, Generation Y and Generation Z differ significantly in (a) financial knowledge, (b) financial attitude, (c) financial behaviour and (d) composite financial literacy.

2.3 Determinants of financial literacy

Studies of determinants keep returning to the same demographic variables. Chen and Volpe (1998) found that gender, major, class standing and work experience mattered among college students, and Potrich et al. (2015) found that gender, age, education and income did among Brazilian adults. Women tend to score lower on knowledge tests, mostly because they choose "do not know" more often (Bucher-Koenen et al. 2017), while male overconfidence can lead to excess trading

and poorer returns (Barber and Odean 2001). In India, Agarwalla et al. (2015) reported low and uneven literacy among the urban working young, and Sivaramakrishnan et al. (2017) tied attitudes and literacy to stock-market participation.

Technology is a newer candidate. Digital finance has changed how people get information and make choices (Gomber et al. 2017). Robo-advice can improve diversification for some users (D'Acunto et al. 2019), and digital financial literacy is linked to better decisions and wellbeing (Kumar et al. 2023). Literacy goes with greater financial inclusion across countries (Grohmann et al. 2018), and an Indian structural model found that attitude, behaviour and knowledge jointly define literacy (Rai et al. 2019). Together these results point to a multi-factor model.

H2: Demographic (age, gender, education), socio-economic (income, occupation, employment status, dependents), technological (digital adoption) and awareness factors jointly and significantly explain variation in financial literacy.

2.4 Financial literacy and financial decision-making

Households with more financial knowledge manage cash, save and invest more in the recommended ways (Hilgert et al. 2003). Low literacy goes with staying out of equity markets (van Rooij et al. 2011), borrowing at high cost (Disney and Gathergood 2013; Gathergood 2012) and costly investment mistakes (Calvet et al. 2007). Literate households absorb shocks better (Klapper and Lusardi 2020) and report higher financial wellbeing and satisfaction (Netemeyer et al. 2018; Joo and Grable 2004). Xiao and O'Neill (2016) add that education builds capability, meaning knowledge plus the opportunity and ability to act.

The link is far from automatic. Loss aversion pulls decisions away from rational benchmarks (Kahneman and Tversky 1979), well-designed defaults raise saving without any change in knowledge (Thaler and Benartzi 2004), and overconfidence weakens retirement planning (Parker et al. 2012). Evidence on financial education is split. One meta-analysis found small effects that fade (Fernandes et al. 2014), a later one of randomised trials found gains in both knowledge and behaviour (Kaiser et al. 2022), and school programmes range from no effect (Mandell and Klein 2009) to fewer delinquencies among the young (Brown et al. 2016). The strength of the link may depend on experience, product exposure and life stage, so it may differ by generation too. We therefore propose:

H3: Financial literacy has a significant positive effect on financial decision-making.

H4: The effect of financial literacy on financial decision-making differs significantly across Generation X, Generation Y and Generation Z.

2.5 Conceptual framework

The framework ties the four objectives together. Generation and the demographic, economic, technological and awareness variables are expected to shape literacy (H1 and H2). Literacy, measured through knowledge, attitude and awareness, is expected to influence decision-making, which is measured through observed management practices (H3), and the strength of that path may differ by generation (H4). To avoid circularity, behaviour is the outcome in the structural model, while the composite used for Objectives 1 to 3 includes all three dimensions.

3 Research Methodology

3.1 Research design and study area

The study is a cross-sectional survey of working adults, run with a structured questionnaire and analysed both descriptively and inferentially. We chose Bengaluru, the capital of Karnataka, for its large and varied working population, its concentration of technology and start-up jobs, and its early uptake of digital financial services.

3.2 Sample and generational classification

After removing incomplete cases, 235 responses remained, with no missing values on the study variables. Respondents were working adults reached through convenience sampling, and we deliberately sought a spread of employment statuses and occupations. The questionnaire recorded age in five bands, and generations were built from them. Respondents aged 18 to 30 were Generation Z ($n = 103$, 43.8%), those aged 31 to 40 were Generation Y ($n = 93$, 39.6%), and the top band, running to age 62, was Generation X ($n = 39$, 16.6%). These bands only roughly match the usual birth-year cut-offs for a 2026 survey (Generation X born about 1965 to 1980, Generation Y 1981 to 1996, Generation Z from 1997). Some respondents in their early forties may therefore belong to Generation Y, and we list this as a limitation.

Table 1. Generational classification of respondents (N = 235)

Generation	Age band in questionnaire (years)	Approximate birth years	n	%
Generation X	Top band, up to 62	About 1965 to 1980	39	16.6
Generation Y	31 to 40	1981 to 1996	93	39.6
Generation Z	18 to 30	From 1997	103	43.8

Note. The bands only roughly match the usual birth-year cut-offs for a 2026 survey. Some respondents in their early forties may belong to Generation Y.

3.3 Instrument and measurement of constructs

The questionnaire had demographic items and sections on product awareness and usage, financial knowledge, attitudes, management practices and the effect of economic conditions. Table 2 shows how each construct was built. Every dimension was rescaled to 0–100 with the formula $(\text{mean} - \text{minimum}) / (\text{maximum} - \text{minimum}) \times 100$, and composite financial literacy (FL) is the unweighted mean of the knowledge, attitude and behaviour scores. Scores below 40 were labelled low, 40 to 60 moderate and above 60 high, which are common cut-offs on a 0–100 scale.

Table 2. Measurement and scoring of study variables

Construct	Items	Response format and scoring	Role
Financial knowledge (KNOW)	15 statements (FK01–FK15)	Five-point agreement scale (1–5); FK14 reverse-keyed because cryptocurrency is not regulated in India	Dimension of FL
Financial attitude (ATT)	18 statements (FA01–FA18)	Five-point agreement scale (1–5); FA01, FA05, FA06, FA07, FA13, FA14 and FA15 reverse-keyed	Dimension of FL
Financial behaviour (BEH)	11 practices (FB01–FB11)	Never to Always (1–4); FB09 (running out of money) reverse-keyed	Dimension of FL; outcome (FDM) in SEM
Product awareness (AWARE)	19 products	Not aware to High (0–3)	Predictor; FL indicator in SEM
Digital adoption (DIGI)	10 digital services	Never, Occasionally, Regularly (0–2)	Predictor
Composite FL	KNOW, ATT, BEH	Mean of three 0–100 scores	Dependent variable (Objectives 1–3)

Note. All composite scores were rescaled to 0–100. In the SEM, financial literacy is indicated by KNOW, AWARE and ATT, and financial decision-making by three parcels of the financial management practices.

3.4 Reliability, validity and common-method checks

We assessed internal consistency with Cronbach's alpha, sampling adequacy with the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity, and dimensionality with an unrotated principal-component analysis set against a parallel-analysis benchmark from random data. In the CFA, convergent validity was judged from standardised loadings, composite reliability (CR) and average variance extracted (AVE), using the usual thresholds of 0.70 for loadings and CR and 0.50 for AVE (Fornell and Larcker 1981; Hair et al. 2019). Discriminant validity was planned through the Fornell–

Larcker criterion and the heterotrait–monotrait ratio (Henseler et al. 2015). Because everything came from one self-report survey, we also ran Harman's single-factor test for common-method variance (Podsakoff et al. 2003).

3.5 Statistical tools and analytical strategy

Each objective had one main technique. Objective 1 used descriptive statistics: mean, median, standard deviation, skewness, kurtosis, frequencies and percentages. Objective 2 used one-way ANOVA on the knowledge, attitude, behaviour and composite scores, with Levene's test, Tukey's HSD comparisons, a Kruskal–Wallis robustness check, and eta-squared and omega-squared as effect sizes. Objective 3 used OLS regression of composite FL on age, gender, education, employment status, occupation, monthly income, dependents, digital adoption and product awareness. Categorical predictors were dummy coded against Male, Undergraduate, Full-time Employee and IT/Software. We checked multicollinearity (variance inflation factors), autocorrelation (Durbin–Watson), heteroscedasticity (Breusch–Pagan) and residual normality (Shapiro–Wilk).

Objective 4 started with a two-factor CFA to validate the measurement model, followed by a covariance-based structural model in which latent literacy predicts latent decision-making. We chose maximum likelihood over PLS-SEM because we wanted model fit and the measurement model laid out explicitly. Fit was judged against CFI and TLI of at least 0.95 and RMSEA of at most 0.06 (Hu and Bentler 1999). For the generation comparison we estimated the structural path in each group, tested path differences with critical ratios, and tested moderation through an interaction model. Formal invariance testing relies on changes in fit between nested models (Cheung and Rensvold 2002; Chen 2007) and needs a well-defined measurement model in every group, a condition Section 4.6 shows we could not meet. We ran the analyses in Python (SciPy, statsmodels, factor_analyzer and semopy) and used a two-tailed 5% significance level.

Table 3. Objectives, hypotheses and statistical techniques

Objective	Hypothesis	Main technique	Supporting checks
1. Level of financial literacy	–	Descriptive statistics (mean, median, SD, skewness, kurtosis, frequencies, percentages)	–
2. Intergenerational differences in knowledge, attitude and behaviour	H1	One-way ANOVA	Levene's test, Tukey's HSD, Kruskal–Wallis, η^2 and ω^2
3. Factors influencing financial literacy	H2	OLS regression of composite FL	VIF, Durbin–Watson, Breusch–Pagan, Shapiro–Wilk
4. Financial literacy and financial decision-making	H3, H4	Two-factor CFA, covariance-based SEM (maximum likelihood), multi-group path comparison	CFI and TLI ≥ 0.95 , RMSEA ≤ 0.06 , critical ratios, interaction model

Note. FL = financial literacy; CFA = confirmatory factor analysis; SEM = structural equation modelling; VIF = variance inflation factor.

4 Results and Analysis

4.1 Profile of respondents

Table 4 gives the profile of the 235 respondents, who are spread evenly across gender, education, employment, occupation, income and number of dependents. Freelancers and gig workers were the largest employment group at 27.2%, followed by the self-employed at 23.0%, and no income band held more than 22% of respondents. Chi-square tests found no generational differences in gender ($\chi^2 = 4.46$, $p = .615$), education ($\chi^2 = 4.33$, $p = .826$), employment status ($\chi^2 = 10.45$, p

= .235), occupation ($\chi^2 = 11.15, p = .516$), income ($\chi^2 = 9.52, p = .301$) or dependents ($\chi^2 = 4.50, p = .810$). The three groups are therefore alike in makeup, so sample composition is unlikely to produce a generational gap.

Table 4. Demographic and socio-economic profile of respondents (N = 235)

Characteristic	Frequency	Percentage
Generation		
Gen X	39	16.6
Gen Y	93	39.6
Gen Z	103	43.8
Gender		
Male	70	29.8
Female	50	21.3
Non-binary	66	28.1
Prefer not to say	49	20.9
Educational qualification		
Diploma/ITI	47	20.0
Undergraduate	45	19.1
Postgraduate	54	23.0
Professional (CA/CFA/CFP)	51	21.7
Other	38	16.2
Employment status		
Full-time Employee	41	17.4
Freelancer/Gig Worker	64	27.2
Self-employed	54	23.0
Startup Founder	36	15.3
Remote Worker	40	17.0
Occupation		
IT/Software	27	11.5
Finance/Banking	40	17.0
Manufacturing	32	13.6

Characteristic	Frequency	Percentage
Education	32	13.6
Healthcare	41	17.4
E-commerce	31	13.2
Other	32	13.6
Monthly income (₹)		
₹20,000-40,000	50	21.3
₹40,001-60,000	40	17.0
₹60,001-100,000	50	21.3
₹100,001-150,000	51	21.7
>₹150,000	44	18.7
Number of dependents		
None	44	18.7
1	48	20.4
2	48	20.4
3	49	20.9
Above 3	46	19.6

Source: Primary data. Percentages are of the total sample.

Table 5. Chi-square tests of generational differences in sample composition

Characteristic	χ^2	p
Gender	4.46	.615
Education	4.33	.826
Employment status	10.45	.235
Occupation	11.15	.516
Monthly income	9.52	.301
Number of dependents	4.50	.810

Note. No test is significant at the 5% level.

4.2 Data screening, reliability and dimensionality

The scales were examined before any substantive analysis, because what they show changes how every later result reads. Cronbach's alpha was 0.03 for knowledge, 0.05 for attitude, 0.05 for behaviour, -0.04 for awareness and -0.03 for digital

adoption, against a customary minimum of 0.70 (Table 6). KMO values ran from 0.44 to 0.51 and no Bartlett test was significant (all $p > .50$), so the correlation matrices could not be told apart from identity matrices and item-level factor modelling has no support. Across the 44 knowledge, attitude and behaviour items, the mean inter-item correlation was 0.003 (SD = 0.063), and only 4.8% of the 946 correlations reached significance, about what chance alone produces. In Harman's test the first unrotated component explained 4.3% of variance, and its eigenvalue (1.89) fell below the mean eigenvalue from random data of the same size (1.94). Common-method variance is therefore not a worry, but the same result says the items share no common structure in this sample.

Table 6. Reliability and sampling adequacy of the scales

Scale	Items	Cronbach's α	KMO	Bartlett χ^2 (df)	Bartlett p
Financial knowledge	15	0.03	0.51	93.8 (105)	.774
Financial attitude	18	0.05	0.49	118.0 (153)	.984
Financial behaviour	11	0.05	0.44	54.0 (55)	.513
Product awareness	19	-0.04	—	—	—
Digital adoption	10	-0.03	—	—	—
Composite (KNOW, ATT, BEH)	3	0.10	—	—	—

Note. KMO = Kaiser–Meyer–Olkin measure of sampling adequacy. Reliability of 0.70 or above is conventionally required.

Table 7. Dimensionality and response-pattern diagnostics

Diagnostic	Result
Mean inter-item correlation (44 knowledge, attitude and behaviour items)	0.003 (SD = 0.063)
Correlations significant at 5% (of 946)	4.8%
Variance explained by first unrotated component (Harman's test)	4.3%
Eigenvalue of first component versus mean eigenvalue from random data	1.89 versus 1.94
Items with response distribution indistinguishable from uniform	93.2% of 44 items

Note. Chance alone would produce about 5% significant correlations.

Another 93.2% of the 44 items had response distributions that could not be told apart from a uniform spread across the answer categories. The composite scores are therefore best read as descriptive summaries of the responses given, and tests of association will have little power to find true relationships because of measurement error. Section 7 returns to this. We still report every analysis, in the order of the objectives, because that was the planned sequence.

4.3 Objective 1: Level of financial literacy

Mean composite literacy was 50.04 on the 0–100 scale (median 50.15, SD 5.90), with scores from 28.29 to 65.39 (Table 8). Knowledge averaged 49.43 (SD 9.20), attitude 49.70 (SD 8.55) and behaviour 51.00 (SD 11.64). Skewness and kurtosis sat near zero for every score, and the composite passed the Shapiro–Wilk test ($W = .994$, $p = .472$), so parametric methods are reasonable. Product awareness averaged 49.96 and digital adoption 50.77. Mean awareness ratings for the 19 products stayed between 1.43 and 1.60 on a 0–3 scale, and use of the ten digital services ranged from 0.94 to 1.09 on a 0–2 scale, so no product or service stood out as better known or more widely used.

Table 8. Descriptive statistics of financial literacy scores (N = 235)

Variable	Mean	Median	SD	Min	Max	Skewness	Kurtosis
Financial knowledge	49.43	50.00	9.20	26.67	75.00	0.01	-0.20
Financial attitude	49.70	50.00	8.55	26.39	72.22	-0.01	-0.42
Financial behaviour	51.00	51.52	11.64	15.15	78.79	-0.25	0.31
Composite financial literacy	50.04	50.15	5.90	28.29	65.39	-0.08	0.03
Product awareness	49.96	49.12	8.36	28.07	75.44	0.05	0.07
Digital adoption	50.77	50.00	12.75	20.00	85.00	0.17	-0.13

Note. All scores are on a 0–100 scale. Kurtosis is excess kurtosis.

Table 9 and Figure 1 give the split across literacy levels. Of the 235 respondents, 215 (91.5%) were in the moderate band, 10 (4.3%) in the low band and 10 (4.3%) in the high band. The clustering comes from averaging three weakly related scores, which narrows the spread. The level distribution did not differ by generation, $\chi^2(4) = 4.04$, $p = .400$. No Generation X respondent was in the low band while seven Generation Z respondents were, but the cell counts are small and the contrast should be held loosely.

Table 9. Levels of financial literacy by generation, n (row %)

Generation	Low (<40)	Moderate (40–60)	High (>60)	Total
Gen X	0 (0.0)	37 (94.9)	2 (5.1)	39
Gen Y	3 (3.2)	87 (93.5)	3 (3.2)	93
Gen Z	7 (6.8)	91 (88.3)	5 (4.9)	103
All respondents	10 (4.3)	215 (91.5)	10 (4.3)	235

Note. Pearson $\chi^2(4) = 4.04$, $p = .400$.

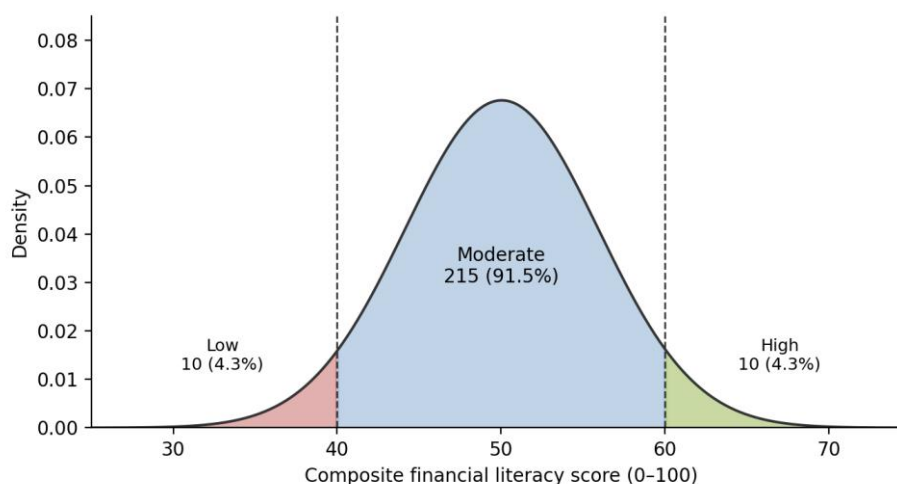


Figure 1. Distribution of composite financial literacy scores with the normal curve and the 40 and 60 cut-offs (N = 235). The curve is drawn from the reported mean and SD; counts in each band are the observed values.

4.4 Objective 2: Intergenerational differences in knowledge, attitude and behaviour

Table 10 gives the means and standard deviations by generation, and Figure 2 shows them with 95% confidence intervals. Generation X had the highest knowledge (52.35) and behaviour (54.39) means but the lowest attitude mean (47.76). Generation Y and Generation Z sat closer to the sample mean on every dimension. On composite literacy, Generation X scored 51.50, Generation Z 50.14 and Generation Y 49.32.

Table 10. Financial literacy scores by generation, mean (SD)

Variable	Gen X (<i>n</i> = 39)	Gen Y (<i>n</i> = 93)	Gen Z (<i>n</i> = 103)
Financial knowledge	52.35 (8.89)	49.28 (9.27)	48.45 (9.09)
Financial attitude	47.76 (8.67)	49.42 (8.02)	50.70 (8.90)
Financial behaviour	54.39 (9.98)	49.27 (11.48)	51.28 (12.16)
Composite financial literacy	51.50 (5.42)	49.32 (5.48)	50.14 (6.37)
Product awareness	49.21 (7.70)	50.01 (7.92)	50.20 (9.01)
Digital adoption	47.44 (12.13)	51.40 (12.67)	51.46 (12.96)

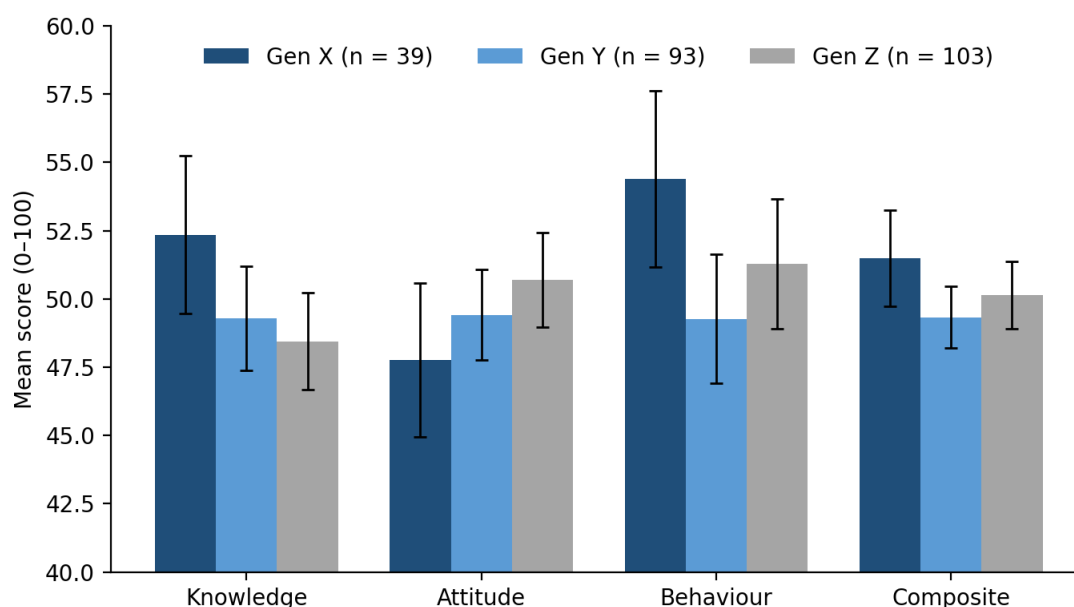


Figure 2. Mean financial knowledge, attitude, behaviour and composite literacy by generation (error bars show 95% confidence intervals)

Table 11 holds the ANOVA results. Levene's test showed equal variances for every score (all $p > .17$), and no omnibus test reached the 5% level: knowledge, $F(2, 232) = 2.60$, $p = .076$; attitude, $F(2, 232) = 1.78$, $p = .172$; behaviour, $F(2, 232) = 2.75$, $p = .066$; composite literacy, $F(2, 232) = 1.91$, $p = .151$. Effect sizes were small, with η^2 between .015 and .023, so generation accounts for roughly 1.5% to 2.3% of variance in the dimensions and 1.6% in the composite. Awareness ($F = 0.20$, $p = .821$) and digital adoption ($F = 1.60$, $p = .203$) did not differ either. Kruskal–Wallis agreed on every score except behaviour ($H = 7.19$, $p = .027$), and with six related tests that single result misses the Bonferroni threshold of .0083.

Table 11. One-way ANOVA of financial literacy scores across generations

Variable	SS between	SS within	MS between	MS within	F (2, 232)	p	η^2	ω^2
Financial knowledge	434.2	19352.1	217.1	83.4	2.60	.076	0.022	0.013
Financial attitude	258.0	16851.1	129.0	72.6	1.78	.172	0.015	0.007
Financial behaviour	735.6	30992.5	367.8	133.6	2.75	.066	0.023	0.015
Composite financial literacy	132.0	8020.6	66.0	34.6	1.91	.151	0.016	0.008
Product awareness	27.7	16317.7	13.9	70.3	0.20	.821	0.002	-0.007
Digital adoption	518.7	37493.4	259.4	161.6	1.60	.203	0.014	0.005

Note. η^2 = eta-squared; ω^2 = omega-squared. No omnibus test is significant at the 5% level.

Tukey comparisons (Table 12) show the same picture. The biggest gaps were Generation X against Generation Z on knowledge (-3.90 points, 95% CI -7.95 to 0.15, adjusted $p = .062$) and Generation X against Generation Y on behaviour (-5.12 points, 95% CI -10.32 to 0.08, adjusted $p = .055$). Both fall just short of significance. The direction, with the oldest cohort scoring highest on knowledge and practice, fits a build-up of experience over the life cycle, but the data give no reliable evidence for it. A sensitivity check shows that 235 respondents in three groups gave 80% power for Cohen's $f = 0.20$ at the 5% level, so effects smaller than small-to-medium could have gone unseen.

Table 12. Tukey HSD post-hoc comparisons between generations

Variable	Comparison	Mean difference	Adjusted p	95% CI	Sig. ($p < .05$)
Financial knowledge	Gen X vs Gen Y	-3.07	.185	[-7.18, 1.04]	No
	Gen X vs Gen Z	-3.90	.062	[-7.95, 0.15]	No
	Gen Y vs Gen Z	-0.84	.798	[-3.92, 2.25]	No
Financial behaviour	Gen X vs Gen Y	-5.12	.055	[-10.32, 0.08]	No
	Gen X vs Gen Z	-3.11	.327	[-8.24, 2.02]	No
	Gen Y vs Gen Z	2.01	.444	[-1.89, 5.91]	No
Composite financial literacy	Gen X vs Gen Y	-2.18	.130	[-4.82, 0.47]	No
	Gen X vs Gen Z	-1.36	.438	[-3.96, 1.25]	No
	Gen Y vs Gen Z	0.82	.593	[-1.16, 2.80]	No

Note. Mean difference is the second group minus the first group.

Item-level comparisons were exploratory. Of the 44 knowledge, attitude and behaviour items, four differed by generation at the 5% level: cryptocurrency regulation (FK14), systematic investment plans and volatility (FK15), keeping financial records (FB01) and comparing financial products (FB07). Among the 29 awareness and usage items, awareness of exchange-traded funds (ETFs) and use of budgeting apps differed. Table 13 lists the key means. Generation X rated the

systematic-investment statement higher (3.72) than Generation Y (3.06) or Generation Z (2.96), kept records more often than Generation Z (2.85 against 2.31), and used budgeting apps least (0.74 against 1.16 and 1.06). Six hits in 73 tests is not far above the 3.7 expected by chance, and none survives a Bonferroni correction (adjusted threshold .0007). We offer them as leads for later testing, not as findings.

Table 13. Exploratory item-level differences across generations (unadjusted ANOVA)

Item	Gen X	Gen Y	Gen Z	F	p
FK14 Cryptocurrency regulated in India (reverse-keyed)	2.49	3.03	2.60	3.39	.036
FK15 SIPs reduce volatility impact	3.72	3.06	2.96	4.52	.012
FB01 Maintain financial records	2.85	2.58	2.31	3.44	.034
FB07 Compare financial products	3.00	2.40	2.65	4.33	.014
Awareness of ETFs	1.49	1.26	1.74	4.45	.013
Usage of budget apps	0.74	1.16	1.06	3.50	.032

Note. Cell entries are item means. None of the differences remains significant after Bonferroni correction for 73 comparisons.

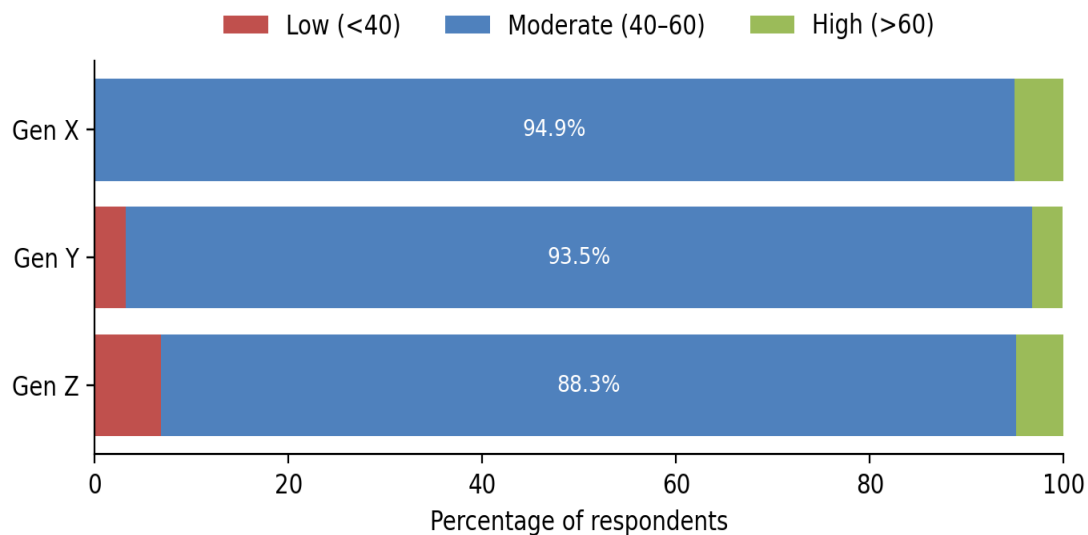


Figure 3. Distribution of financial literacy levels by generation (percentage of respondents)

On the ANOVA evidence, H1 is not supported. The three generations do not differ significantly in knowledge, attitude, behaviour or composite literacy in this sample.

4.5 Objective 3: Factors influencing financial literacy

Table 14 shows the correlations among the main variables. Composite FL correlated strongly with each of its parts ($r = .54$ to $.66$), which is built in by construction. The parts barely correlated with one another ($|r| \leq .12$), and neither awareness nor digital adoption correlated with FL ($r = -.01$ and $-.02$). The weak links among the components match the reliability results in Section 4.2.

Table 14. Pearson correlations among study variables (N = 235)

Variable	Knowledge	Attitude	Behaviour	FL	Awareness	Digital
Knowledge	1					
Attitude	.12	1				
Behaviour	-.06	.07	1			
FL	.54	.59	.66	1		
Awareness	.01	.08	-.08	-.01	1	
Digital	-.04	.05	-.03	-.02	.12	1

Note. Lower triangle shown. With N = 235, $|r| \geq .13$ is significant at $p < .05$. The correlations of FL with its components reflect part-whole overlap.

The OLS model (Table 15) regressed composite FL on age, gender, education, employment status, occupation, monthly income, dependents, digital adoption and product awareness. Diagnostics were fine: variance inflation factors ranged from 1.08 to 2.24, the Durbin–Watson statistic was 1.91, the Breusch–Pagan test showed no heteroscedasticity ($p = .492$) and residuals were normal (Shapiro–Wilk $p = .447$). The model itself explained almost nothing, $F(22, 212) = 0.65$, $p = .883$, $R^2 = .063$, adjusted $R^2 = -.034$. No coefficient was significant, and robust (HC3) standard errors changed nothing. The largest standardised coefficient belonged to dependents ($\beta = 0.11$, $p = .104$), followed by income ($\beta = -0.07$) and age ($\beta = 0.07$). Digital adoption ($\beta = -0.02$, $p = .734$) and product awareness ($\beta = -0.005$, $p = .941$) were close to zero.

Table 15. Multiple linear regression (OLS) with composite financial literacy as dependent variable

Predictor	B	SE	β	t	p	VIF
Intercept	49.15	3.69	–	13.31	<.001	–
Gender: Female (ref. Male)	0.44	1.17	–	0.38	.708	1.49
Gender: Non-binary	0.20	1.06	–	0.18	.854	1.49
Gender: Prefer not to say	0.42	1.16	–	0.36	.718	1.44
Education: Diploma/ITI (ref. Undergraduate)	-0.11	1.32	–	-0.09	.932	1.81
Education: Other	-0.48	1.34	–	-0.36	.721	1.59
Education: Postgraduate	-1.27	1.23	–	-1.04	.301	1.74
Education: Professional	-0.36	1.26	–	-0.28	.776	1.76
Employment: Freelancer/Gig (ref. Full-time)	-0.65	1.26	–	-0.52	.604	2.05
Employment: Remote worker	0.31	1.37	–	0.23	.822	1.73
Employment: Self-employed	1.48	1.28	–	1.15	.249	1.90
Employment: Startup founder	-0.12	1.47	–	-0.08	.933	1.83

Predictor	B	SE	β	t	p	VIF
Occupation: E-commerce (ref. IT/Software)	2.48	1.64	–	1.51	.132	2.01
Occupation: Education	-0.69	1.62	–	-0.42	.673	2.02
Occupation: Finance/Banking	0.91	1.54	–	0.59	.555	2.20
Occupation: Healthcare	-0.03	1.54	–	-0.02	.985	2.24
Occupation: Manufacturing	0.94	1.61	–	0.59	.558	1.98
Occupation: Other	1.80	1.61	–	1.11	.267	2.00
Age band (1–5)	0.31	0.30	0.07	1.02	.311	1.10
Monthly income band (1–5)	-0.31	0.29	-0.07	-1.08	.283	1.09
Number of dependents (0–4)	0.48	0.29	0.11	1.63	.104	1.08
Digital adoption	-0.01	0.03	-0.02	-0.34	.734	1.10
Product awareness	-0.00	0.05	-0.01	-0.07	.941	1.12

Note. $R^2 = .063$; adjusted $R^2 = -.034$; $F(22, 212) = 0.65$, $p = .883$; Durbin–Watson = 1.91; Breusch–Pagan $p = .492$. β is reported for continuous predictors only. Reference categories are shown in parentheses.

Table 16. Regression diagnostics and model summary (composite financial literacy)

Statistic	Value
$F(22, 212)$	0.65 ($p = .883$)
R^2	.063
Adjusted R^2	-.034
Variance inflation factors	1.08 to 2.24
Durbin–Watson	1.91
Breusch–Pagan p	.492
Shapiro–Wilk p (residuals)	.447
Largest standardised coefficient	Dependents, $\beta = 0.11$ ($p = .104$)
Robust (HC3) standard errors	No change in results

Note. Reference categories: Male, Undergraduate, Full-time Employee and IT/Software.

As a supplementary check, we regressed the same predictors on each dimension separately. None of the three models was significant overall (knowledge, $F = 1.28$, $p = .186$; attitude, $F = 1.09$, $p = .359$; behaviour, $F = 0.76$, $p = .773$). A few single coefficients did pass $p < .05$: female gender (+4.57, $p = .010$), age band (+1.19, $p = .010$) and e-commerce occupation (+5.90, $p = .018$) for knowledge, and dependents (+0.90, $p = .031$) for attitude. Across 66 coefficient tests about three false

positives are expected at the 5% level, so these stay exploratory. The full model could detect $f^2 = 0.10$ with 80% power, which means smaller effects of individual factors cannot be ruled out. H2 is not supported.

Table 17. Supplementary regressions on each dimension of financial literacy

Dependent variable	F	p	Coefficients with $p < .05$ (exploratory)
Financial knowledge	1.28	.186	Female gender (+4.57, $p = .010$); age band (+1.19, $p = .010$); e-commerce occupation (+5.90, $p = .018$)
Financial attitude	1.09	.359	Dependents (+0.90, $p = .031$)
Financial behaviour	0.76	.773	None reported

Note. Across 66 coefficient tests in the three models, about three false positives are expected at the 5% level.

4.6 Objective 4: Financial literacy and financial decision-making

Confirmatory factor analysis

The measurement model had two latent constructs. Financial literacy (FL) was indicated by the knowledge, awareness and attitude scores, and financial decision-making (FDM) by three parcels of the management-practice items (FB01, FB04, FB07 and FB10; FB02, FB05, FB08 and FB11; FB03, FB06 and FB09). We used parcels because the item-level data would not support item-level factor modelling (Section 4.2), and indicators were standardised before estimation.

Table 18 shows that the model did not reach convergent validity. The knowledge loading was fixed at 1.00 because its residual variance came out at zero, an improper (Heywood) solution. Awareness (0.01) and attitude (0.12) loaded negligibly and non-significantly. For FDM, only the first parcel loaded appreciably (0.76), while the other two loaded at 0.08 and 0.00. Composite reliability was 0.39 for FL and 0.23 for FDM, and AVE was 0.34 and 0.19, all under the 0.70 and 0.50 thresholds (Fornell and Larcker 1981; Hair et al. 2019). The latent correlation between FL and FDM was -0.10 ($p = .245$). Fornell–Larcker discriminant validity holds trivially, since the square roots of AVE (0.58 and 0.44) exceed the correlation between constructs, but that follows from the near-zero correlation and says nothing about well-defined constructs, so we did not interpret HTMT.

Table 18. Confirmatory factor analysis: standardised loadings, composite reliability and AVE

Construct	Indicator	Std. loading	SE	z	p	CR / AVE
Financial literacy (FL)	Knowledge	1.00†	–	–	–	0.39 / 0.34
	Awareness	0.01	0.092	0.10	.918	
	Attitude	0.12	0.841	0.15	.883	
Financial decision-making (FDM)	Parcel B1	0.76†	–	–	–	0.23 / 0.19
	Parcel B2	0.08	0.855	0.12	.907	
	Parcel B3	0.00	0.125	0.05	.960	

Note. † Loading fixed to 1.00 for scale identification (unstandardised); the knowledge indicator has an estimated residual variance of zero (Heywood case). Standard errors are for unstandardised loadings. FL–FDM correlation = -0.10 , $p = .245$.

Fit indices for the CFA were $\chi^2(8) = 8.63$, $p = .374$, RMSEA = 0.018, with CFI and TLI at or above 1.00. By the Hu and Bentler (1999) benchmarks that looks like a good fit, but it should not be read that way. The baseline (independence) model

had $\chi^2(15) = 14.44$, $p = .492$, so the null model itself was not rejected and the six indicators are essentially uncorrelated. CFI and TLI therefore carry no information, and good absolute fit is what you would expect when there is almost no covariance to explain.

Structural equation model

The structural model added a path from FL to FDM (Figure 4). Fit matched the CFA to the second decimal ($\chi^2(8) = 8.63$, $p = .375$, RMSEA = 0.018). The standardised path was $\beta = -0.10$ (unstandardised -0.076 , SE = 0.521, $z = -0.15$, $p = .884$), and FL explained only about 1% of variance in FDM ($R^2 = .010$). The sign is opposite to our prediction, and the estimate cannot be told apart from zero. A covariance-based analysis on the observed composite scores gave a similar result: standardised $\beta = -0.04$ ($p = .568$) for the effect of the three-indicator FL composite on behaviour in the pooled sample. H3 is not supported.

Table 19. Fit indices and structural path estimate for the CFA and the structural model

Statistic	CFA	Structural model
$\chi^2(8)$	8.63	8.63
p	.374	.375
RMSEA	0.018	0.018
CFI and TLI	At or above 1.00	—
Baseline (independence) model $\chi^2(15)$	14.44 ($p = .492$)	—
FL–FDM latent correlation	-0.10 ($p = .245$)	—
Standardised path, FL to FDM	—	$\beta = -0.10$ ($p = .884$)
Unstandardised path (SE)	—	-0.076 (0.521), $z = -0.15$
R^2 (FDM)	—	.010
Composite-score check: standardised β	—	-0.04 ($p = .568$)

Note. FL = financial literacy; FDM = financial decision-making. Fit is identical to the second decimal because the structural path adds no covariance to a model whose indicators are almost uncorrelated.

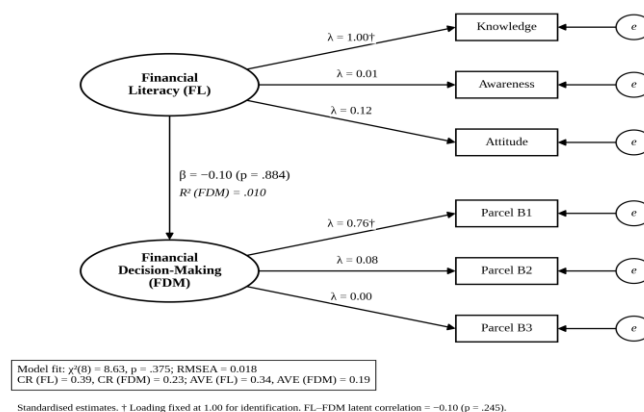


Figure 4. Structural equation model of financial literacy and financial decision-making: standardised estimates for the pooled sample

Multi-group comparison across generations

To test H4 we estimated the literacy-to-decision-making path separately for each generation (Table 20). With observed composite scores, the standardised paths were $\beta = -0.07$ ($p = .657$) for Generation X, $\beta = -0.03$ ($p = .793$) for Generation Y and $\beta = -0.04$ ($p = .702$) for Generation Z. Critical ratios for pairwise differences were small (X versus Y, $z = -0.24$, $p = .814$; X versus Z, $z = -0.18$, $p = .854$; Y versus Z, $z = 0.07$, $p = .942$), and the literacy-by-generation interaction was non-significant, $F(2, 229) = 0.01$, $p = .988$. Latent models fitted inside each generation gave non-significant paths (X: 0.59, $p = .462$; Y: -0.32 , $p = .457$; Z: -0.06 , $p = .844$), with chi-square values of 6.66, 3.96 and 8.09 (all $p > .40$). Those estimates differ widely in sign and size, but they rest on unreliable indicators and, for Generation X, on only 39 people, so they show estimation instability and not real heterogeneity.

Table 20. Path from financial literacy to financial decision-making by generation

Generation	n	Observed β	SE	p	Latent β (SEM)	p (SEM)	χ^2 (df = 8)
Gen X	39	-0.07	0.16	.657	0.59	.462	6.66 ($p = .574$)
Gen Y	93	-0.03	0.10	.793	-0.32	.457	3.96 ($p = .861$)
Gen Z	103	-0.04	0.10	.702	-0.06	.844	8.09 ($p = .425$)

Note. Observed β is the standardised slope of behaviour on the three-indicator composite of knowledge, awareness and attitude. Critical ratios for path differences: X vs Y $z = -0.24$ ($p = .814$); X vs Z $z = -0.18$ ($p = .854$); Y vs Z $z = 0.07$ ($p = .942$). Interaction test $F(2, 229) = 0.01$, $p = .988$.

We did not run formal configural, metric and scalar invariance tests in any way that could be interpreted. Metric invariance assumes loadings that are well defined within each group, but here most loadings are indistinguishable from zero and one sits on a boundary. Differences in fit between nested models (Cheung and Rensvold 2002; Chen 2007) would then reflect estimation noise. The path comparison should be read as finding no detectable difference in the literacy–decision-making link across generations, which does not support H4.

4.7 Summary of hypothesis testing

Table 21 sets each hypothesis beside its test and result.

Table 21. Summary of hypotheses and results

Hypothesis	Statistical test	Key result	Decision
H1: Generations differ in knowledge, attitude, behaviour and composite FL	One-way ANOVA	$F(2, 232) = 1.91$ to 2.75 ; $p = .066$ to $.172$; $\eta^2 \leq .023$	Not supported
H2: Demographic, socio-economic, technological and awareness factors explain FL	Multiple regression (OLS)	$F(22, 212) = 0.65$, $p = .883$; $R^2 = .063$	Not supported
H3: FL positively affects financial decision-making	CFA and SEM	$\beta = -0.10$, $p = .884$; $R^2 = .010$	Not supported
H4: The FL–decision-making effect differs across generations	Multi-group path comparison	Interaction $F(2, 229) = 0.01$, $p = .988$	Not supported

5 Discussion

We compared financial literacy across Generation X, Y and Z in Bengaluru and tested whether generation, demographic and economic traits, and digital adoption explain literacy and its link to decisions. Mean literacy sits at the scale midpoint, generations differ little, no set of predictors explains literacy, and literacy does not relate to decision-making in the

structural model. These null results have to be read next to the measurement findings in Section 4.2, so we take the two readings in turn.

Taken at face value, the missing generational gap fits Lyons and Kuron's (2014) caution that such differences are usually smaller than assumed. The direction of the point estimates is still worth noting. Generation X scored highest on knowledge and behaviour, which matches the idea that experience builds up with age (Ando and Modigliani 1963) and that the youngest adults decide less well (Agarwal et al. 2009). Generation X's lowest attitude score and Generation Z's slightly lower knowledge fit the view that digital fluency does not replace experience (Shim et al. 2010). But the gaps are 4 to 5 points on a 100-point scale with confidence intervals that include zero, so these patterns are suggestive only. The item-level contrasts, such as Generation X's record-keeping and its grasp of what systematic investment plans do, and its lower use of budgeting apps, are plausible given the literature on experience and digital adoption (Gomber et al. 2017), but they did not survive correction for multiple testing.

The lack of determinants contrasts with earlier work that tied literacy to gender, age, education and income (Chen and Volpe 1998; Potrich et al. 2015; Bucher-Koenen et al. 2017). Our convenience sample of working adults from one city may have limited variation in education and income compared with national samples. The composite also averages three weakly correlated scores, which squeezes its variance ($SD = 5.90$) and leaves predictors little to explain. The absence of a digital-adoption effect departs from work treating digital finance and literacy as complements (Kumar et al. 2023; Grohmann et al. 2018). It may simply reflect that using an app is not the same as understanding what it does. Measurement error also weakens every relationship, and reliabilities this low would hide modest true associations.

The missing link between literacy and decision-making differs from the broader evidence on saving, planning, participation and credit (Hilgert et al. 2003; van Rooij et al. 2011; Disney and Gathergood 2013; Rai et al. 2019). Overconfidence, present bias and social influence can separate knowing from doing (Parker et al. 2012; Kahneman and Tversky 1979), and the behavioural effects of education are modest and fade (Fernandes et al. 2014). Still, our estimates are not merely small. They are indeterminate, because the measurement model never defined its latent variables. The defensible reading is that these data can neither confirm nor reject the relationship.

The reliability findings deserve their own comment. Inventories spanning many product categories are heterogeneous by design, and alpha understates reliability for such formative collections. Even allowing for that, an alpha near zero, a mean inter-item correlation of 0.003, a first component no larger than random data would produce and near-uniform item distributions are not what real survey data usually look like. They fit responses given with little attention to item content, such as inattentive or patterned answering, or data that did not come from a controlled collection process. The data cannot settle which, and the source needs checking before anyone uses these results for inference or policy (see Section 7).

6 Implications

6.1 Theoretical and methodological implications

For method, the study shows that a three-part definition of literacy can be run in a generation-wise design with objectives, hypotheses and tests matched one to one, and that every inferential claim can carry an effect size and a diagnostic. It also shows why reliability and dimensionality belong before modelling, since conventional SEM fit indices can look excellent when there is no covariance structure at all, as in our CFA. And it supports treating generational labels as hypotheses about experience, technology exposure and life stage, to be tested with adequate power and measurement, not as established categories (Lyons and Kuron 2014).

6.2 Practical and policy implications

The small generational differences give no reason to build separate programmes for each cohort. A few cautious suggestions follow from the data. Workplace financial education in Bengaluru could pair basic content with digital skills, since all three generations scored near the midpoint on both. Tailoring by experience may work better than tailoring by birth year, with modules on record-keeping, product comparison and budgeting tools for less experienced people, and app training for long-experienced people who rarely use apps. Because education effects fade (Fernandes et al. 2014) and defaults can change behaviour without changing knowledge (Thaler and Benartzi 2004), programmes should be backed by features such as automatic saving. Employers and regulators who track literacy should also invest in validated instruments, since measurement quality decides whether any programme can be targeted or evaluated.

7 Limitations and Directions for Future Research

The main limitation is measurement. The scales had unacceptable internal consistency, item correlations sat at chance level, and the CFA did not establish convergent validity, so the null results are not evidence of no relationship. Before any confirmatory use, the dataset should be audited for response quality, with attention checks, response times, duplicated or patterned response strings and the origin of each record. The design is also cross-sectional, non-probability and limited to one city, so the results do not extend to Bengaluru as a whole or to India. The generation groups come from age bands that only approximate birth years, and Generation X has just 39 respondents, which limits generation-specific estimates. Decision-making was proxied by self-reported management practices that sit close to the behaviour dimension itself, so later work should use objective outcomes such as portfolio diversification, credit-card revolving balances or retirement contributions. The questionnaire also had sections on retirement planning, sources of guidance and open-ended concerns that we did not analyse, and they could enrich a later study.

Future studies should check the knowledge items against a scored test with right and wrong answers instead of agreement ratings. They should use stratified or quota sampling that puts more Generation X respondents in the sample, add digital financial literacy and fraud awareness as explicit constructs, and use longitudinal or experimental designs. Full invariance testing makes sense once a reliable measurement model exists, and PLS-SEM could complement it when prediction is the goal (Hair et al. 2019).

8 Conclusion

Average financial literacy among our Bengaluru respondents was about 50 on a 0 to 100 scale. Generation X scored higher on knowledge and behaviour, but the gaps were small and not statistically significant. Demographic, economic, digital and awareness variables did not explain literacy, and the path from literacy to decision-making was near zero in every generation. The scales were too unreliable and the measurement model too weak to support strong conclusions. What the paper offers is a transparent baseline and an analytical template for intergenerational work in an Indian city, along with a demonstration of how much instrument and data quality decide. A replication with validated measures and a larger, better-balanced sample is the next step.

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