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Behavioral Biases and Financial Decision-Making in Digital Entrepreneurial Ecosystems: Strategic Insights for Prospective Entrepreneurs

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KEYWORDS

Behavioral Finance; Overconfidence Bias; Anchoring Bias; Loss Aversion; Financial Decision-Making; Digital Entrepreneurial Ecosystems.

ABSTRACT

Background: The rapid expansion of digital financial services and fintech platforms has increased decision-making complexity, leaving prospective entrepreneurs within university startup ecosystems vulnerable to cognitive biases that alter managerial judgment and strategic resource allocation. Objective: This study aims to examine the simultaneous influence of overconfidence bias, anchoring bias, and loss aversion on financial decision-making among undergraduate students as prospective digital entrepreneurs, while controlling for their field of study. Methods: A quantitative explanatory design was adopted using a cross-sectional survey of 143 undergraduate students selected through purposive sampling based on their personal financial and digital service management experience. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4. Results: The structural model demonstrates that overconfidence bias exerts the strongest positive effect on financial decision-making, followed by loss aversion and anchoring bias, whereas field of study shows no statistically significant effect, revealing that cognitive psychological biases override formal academic specialization in financial choices. Conclusion: These findings highlight that enhancing managerial capability in entrepreneurial ecosystems requires moving beyond conventional technical financial education. Incubators and higher education institutions must implement structured behavioral finance interventions, including cognitive debiasing toolkits and evidence-based decision-making frameworks, to mitigate excessive overconfidence, prevent risk-averse innovation inertia, and foster sustainable digital venture performance.

ABSTRAK

Latar Belakang: Ekspansi pesat layanan keuangan digital dan platform fintech telah meningkatkan kompleksitas pengambilan keputusan, membuat calon wirausahawan dalam ekosistem startup universitas rentan terhadap bias kognitif yang mengubah penilaian manajerial dan alokasi sumber daya strategis. Tujuan: Studi ini bertujuan untuk meneliti pengaruh simultan dari bias kepercayaan diri yang berlebihan, bias penjangkaran, dan penghindaran kerugian terhadap pengambilan keputusan keuangan di kalangan mahasiswa sarjana sebagai calon wirausahawan digital, dengan mengontrol bidang studi mereka. Metode: Desain penjelasan kuantitatif diadopsi menggunakan survei lintas sektoral terhadap 143 mahasiswa sarjana yang dipilih melalui pengambilan sampel bertujuan berdasarkan pengalaman pribadi mereka dalam pengelolaan keuangan dan layanan digital. Data dianalisis menggunakan Partial Least Squares Structural Equation Modeling (PLS-SEM) melalui SmartPLS 4. Hasil: Model struktural menunjukkan bahwa bias terlalu percaya diri memberikan pengaruh positif terkuat pada pengambilan keputusan keuangan, diikuti oleh penghindaran kerugian dan bias penjangkaran, sedangkan bidang studi tidak menunjukkan pengaruh yang signifikan secara statistik, mengungkapkan bahwa bias psikologis kognitif mengesampingkan spesialisasi akademis formal dalam pilihan keuangan. Kesimpulan: Temuan ini menyoroti bahwa peningkatan kemampuan manajerial dalam ekosistem kewirausahaan membutuhkan langkah lebih jauh dari pendidikan keuangan teknis konvensional. Inkubator dan lembaga pendidikan tinggi harus menerapkan intervensi keuangan perilaku terstruktur, termasuk perangkat penghilang bias kognitif dan kerangka kerja pengambilan keputusan berbasis bukti, untuk mengurangi terlalu percaya diri, mencegah inersia inovasi yang menghindari risiko, dan mendorong kinerja usaha digital yang berkelanjutan.

1. INTRODUCTION

The advancement of digital technology has transformed how individuals—particularly university students—manage their finances and make financial decisions through various digital financial services, such as mobile banking, e-wallets, online investment platforms, and "buy now, pay later" (BNPL) services (Bagchi et al., 2025; Doucefleur, 2023) . The diversity of these financial instruments offers more alternatives for decision-making, yet simultaneously increases the complexity of the decisions individuals must face (Sathya & Gayathiri, 2024). On the other hand, the abundance of available choices and information actually increases the complexity of the financial decision-making process, meaning individuals are not always able to select the most rational alternative (Kartini & Nahda, 2021). This situation demonstrates that financial decisions are influenced not only by analytical ability but also by psychological factors that shape how an individual evaluates information, perceives risk, and makes choices.

Beyond influencing individual financial behavior, the rapid advancement of financial technology (FinTech), artificial intelligence, and digital entrepreneurship has fundamentally transformed the entrepreneurial ecosystem by reshaping how startups create value, access financial resources, and sustain innovation (Hidayat-ur-Rehman & Hossain, 2025). Startup ecosystems increasingly depend on digital financial platforms, AI-enabled financial services, digital payment systems, crowdfunding mechanisms, and data-driven financial decision support to strengthen business competitiveness and accelerate innovation (Fenwick et al., n.d.; Kanojia et al., 2024). Consequently, financial decision-making is no longer merely an individual capability but has become a strategic organizational capability that influences firms' adaptability, innovation performance, and long-term sustainability in increasingly digital business environments (Chen et al., 2024). Recent studies further highlight that digital innovation capability constitutes one of the most critical determinants of startup resilience and sustainable entrepreneurial growth in technology-driven ecosystems (Kim & Cho, 2024).

Although substantial progress has been achieved in developing digital financial infrastructures, the success of entrepreneurial ecosystems depends not only on technological capability but also on the quality of human decision-making .Behavioral biases may distort entrepreneurs' and future entrepreneurs' evaluations of financial opportunities, investment risks, and resource allocation, thereby weakening innovation capability despite the availability of sophisticated digital technologies (Roundy & Im, 2025). Recent literature published between 2024 and 2026 argues that sustainable entrepreneurial ecosystems require the integration of behavioral finance perspectives with digital innovation management to better understand how psychological factors shape financial decisions in rapidly evolving digital environments (Sholihah et al., 2025). However, empirical evidence examining these behavioral mechanisms among university students—as prospective entrepreneurs and future participants in digital startup ecosystems—remains limited (Indira et al., 2024).

University students represent an interesting group to study in the context of financial decision-making, as they are in a transitional phase toward financial independence. At this stage, students begin managing allowances, making online purchases, and utilizing financial technology services, while also becoming acquainted with investment activities and other financial instruments. Although financial literacy levels continue to rise, various studies indicate that students frequently make suboptimal financial decisions due to limited experience and the dominance of emotional factors over rational considerations (Istiana & Nur, 2020; Wayan Sri Wahyuni & Made Oka Candra Andreana, 2025).

Traditional financial theory posits that individuals are rational decision-makers capable of utilizing all available information objectively to maximize utility. However, empirical evidence indicates that this assumption often does not hold true in practice, thereby driving the development of the behavioral finance approach (Sathya & Gayathiri, 2024; Singh, Malik, Jain, et al., 2024). Behavioral finance integrates financial theory and psychology to explain how emotions, perceptions, and cognitive biases influence financial decision-making processes. This approach explains that individuals tend to employ heuristics—or mental shortcuts—when facing uncertainty, causing the resulting decisions to often deviate from the principles of rationality.

One of the key concepts in behavioral finance is behavioral bias—defined as a systematic deviation in the decision-making process resulting from psychological and cognitive factors. Among the various forms of behavioral bias, overconfidence bias, anchoring bias, and loss aversion are the most widely studied, as they have been shown to influence financial and investment decisions. Overconfidence bias leads individuals to overestimate their own abilities and the information they possess, causing them to make decisions with excessive confidence. Anchoring bias causes individuals to rely too heavily on initial information when evaluating subsequent decisions. Meanwhile, loss aversion explains that individuals are more sensitive to potential losses than to opportunities for gains of equal value (Brown et al., 2021).

Various previous studies have confirmed that behavioral biases influence financial decisions, affecting both investors and young people (Sathya & Gayathiri, 2024). These three biases have a significant relationship with financial decisions. Research on novice investors indicates that overconfidence, anchoring, and loss aversion influence the investment decision-making process (*Sigit Dwi Handoyo*, n.d.). Another study on Generation Z also found that psychological factors are important determinants in explaining variations in investment decisions, compared to relying solely on a rational economic approach (Gufron & Wibowo, 2024; Miftahul Zanah et al., 2026; Pramuditya Nugraha et al., n.d.). Anchoring bias and overconfidence bias significantly influence Generation Z's investment decisions, whereas loss aversion does not show a significant influence (Gufron & Wibowo, 2024). Other research also indicates that overconfidence bias is one of the biases that most consistently influences financial behavior, as it drives individuals to engage in excessive risk-taking (Singh, Malik, Jain, et al., 2024). Overconfidence bias consistently affects the quality of financial decisions. Individuals with excessive self-confidence tend to overestimate their ability to analyze information, thereby overlooking actual risks (Singh, Malik, & Jha, 2024). These findings indicate that financial behavior is influenced not only by analytical ability but also by an individual's psychological characteristics.

Recent studies have further demonstrated that behavioral biases extend beyond individual financial choices and increasingly influence organizational capabilities and managerial outcomes in digital business environments (Roundy & Im, 2025; Singh, Malik, Jain, et al., 2024). Overconfidence, anchoring, and loss aversion may affect strategic judgment, innovation investment, opportunity evaluation, and resource allocation, thereby shaping firms' digital innovation capability and managerial performance (Chen et al., 2024). In technology-intensive entrepreneurial ecosystems, managers and future entrepreneurs are expected to make rapid financial decisions under conditions of uncertainty; consequently, psychological biases may reduce organizational adaptability despite the availability of advanced digital technologies (Roundy & Im, 2025). These findings indicate that behavioral finance should be integrated with digital innovation and strategic management perspectives to better explain organizational decision-making in contemporary entrepreneurial ecosystems.

Although research on behavioral finance has expanded considerably, three important gaps remain. First, most previous studies primarily examine behavioral biases in the contexts of stock market investors or Generation Z, with limited attention to university students as prospective entrepreneurs operating within increasingly digitalized entrepreneurial ecosystems. Second, prior research generally investigates individual behavioral biases separately, providing limited evidence regarding the simultaneous influence of overconfidence bias, anchoring bias, and loss aversion on financial decision-making. Third, contemporary discussions on digital innovation capability and startup ecosystem readiness have largely emphasized technological and institutional factors while paying insufficient attention to the behavioral dimensions underlying financial decision-making. Consequently, empirical evidence explaining how behavioral biases may influence future entrepreneurial capability in digital ecosystems remains limited.

Addressing this research gap, this study aims to analyze the influence of overconfidence bias, anchoring bias, and loss aversion on students' financial decision-making, while also examining the field of study as a control variable. The study is expected to enrich the behavioral finance literature within the student context and offer implications for higher education institutions in designing financial literacy education that focuses not only on enhancing knowledge but also on managing various behavioral biases in the financial decision-making process.

2. METHODS

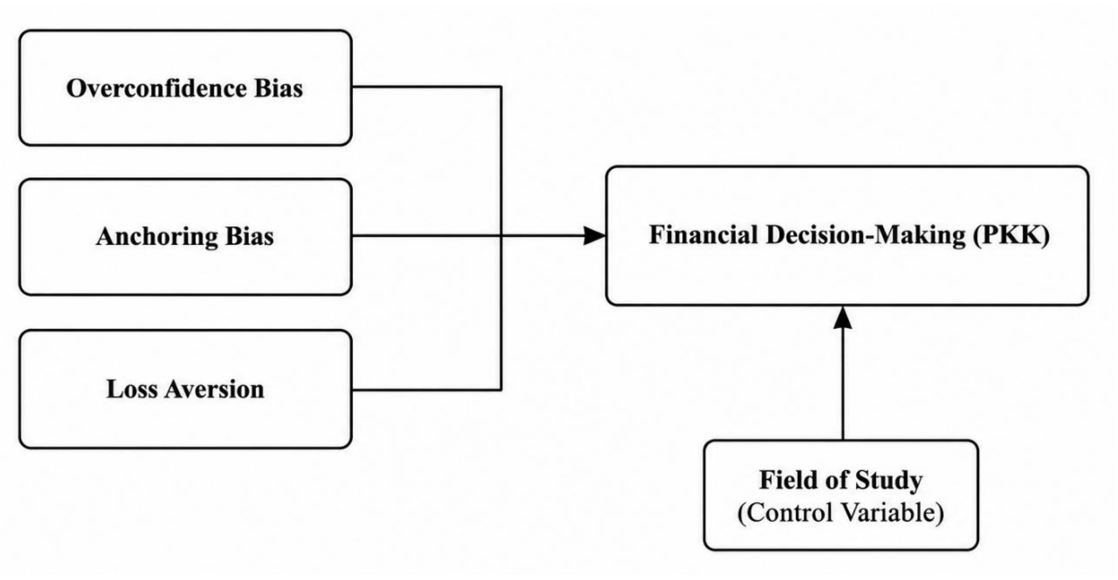
The methodology of this study is structured to rigorously test the empirical interactions between behavioral cognitive biases and financial decision-making within digital entrepreneurial ecosystems. To capture how prospective entrepreneurs navigate complex financial choices in technology-driven environments, a systematically organized research design was deployed. The following sub-sections delineate the step-by-step procedures, ranging from conceptual framework development and sampling protocols to instrument validation and structural equation modeling.

2.1 Research Design

This study adopts a quantitative approach utilizing an explanatory cross-sectional survey design to systematically evaluate the impact of overconfidence bias, anchoring bias, and loss aversion on financial decision-making, while controlling for respondents' academic major. Explanatory designs are particularly appropriate for establishing structural relationships and validating behavioral theories under real-world uncertainty (Hair et al., 2021). Drawing upon behavioral finance theory and recent digital entrepreneurship literature, the conceptual framework posits that heuristic shortcuts significantly drive financial judgments among prospective startup founders (Bagchi et al., 2025; Sathya & Gayathiri, 2024). Specifically, overconfidence bias (H_1) is hypothesized to induce subjective overestimation of venture success, anchoring bias (H_2) leads to over-reliance on initial baseline values, and loss aversion (H_3) heightens risk sensitivity during capital allocation (Brown et al., 2021; Singh, Malik, Jain, et al., 2024). To visually map these structural interactions, the conceptual framework of the study is illustrated in Figure 1 below.

Figure 1. Research Model

Figure 1 illustrates the conceptual framework linking three independent behavioral bias constructs—Overconfidence Bias, Anchoring Bias, and Loss Aversion—to the primary target construct, Financial Decision-Making, alongside Field of Study as a control variable. As shown in the model, cognitive



heuristics directly drive financial judgment outcomes, whereas academic specialization acts as a contextual control to verify whether formal technical education buffers against irrational decision-making (Gufron & Wibowo, 2024; Roundy & Im, 2025). This structural arrangement enables a clear separation between cognitive psychological influences and formal educational background in digital business environments (Chen et al., 2024; Sholihah et al., 2025).

2.2 Research Questions and Analytical Alignment

To bridge the theoretical hypotheses with empirical testing, specific research questions were formulated to guide the statistical evaluation of each behavioral construct. Aligning research questions with explicit analytical methods ensures that the empirical findings directly address the core research gaps in digital entrepreneurial ecosystems (Hidayat-ur-Rehman & Hossain, 2025; Kim & Cho, 2024). The structured relationship between research questions and analytical techniques is summarized in Table 1 below.

Table 1. research questions and analytical techniques

No.	Research Question	Type of Analysis
RQ1	Does overconfidence bias significantly influence prospective entrepreneurs' financial decision-making?	PLS-SEM Path Coefficients (β), t-statistics, p-values
RQ2	Does anchoring bias significantly influence prospective entrepreneurs' financial decision-making?	PLS-SEM Path Coefficients (β), t-statistics, p-values
RQ3	Does loss aversion significantly influence prospective entrepreneurs' financial decision-making?	PLS-SEM Path Coefficients (β), t-statistics, p-values
RQ4	Does the field of study (academic major) significantly control variations in financial decision-making quality?	PLS-SEM Control Variable Path Coefficient Evaluation
RQ5	How much variance in financial decision-making is collectively explained by behavioral biases and field of study?	Coefficient of Determination (R^2, Adjusted R^2)

Table 1 details the analytical alignment between each research question and its statistical execution within the Partial Least Squares (PLS-SEM) framework. This structural alignment guarantees that hypothesis testing directly corresponds to specific path coefficient estimates, significance tests ($t \geq 1.96, p < 0.05$), and overall model explanatory power (R^2) (Hair et al., 2019, 2021). Following this analytical mapping, the study defined its target population, sampling criteria, and geographic location.

2.3 Subject, Target Population, and Research Location

The research was conducted across higher education institutions in Indonesia, focusing on undergraduate students acting as prospective entrepreneurs within university startup incubation networks. University students in this setting represent an ideal subject group as they navigate the transition toward financial independence, managing personal funds, e-wallets, buy-now-pay-later (BNPL) services, and early-stage business capital (Bagchi et al., 2025; Istiana & Nur, 2020). A purposive sampling technique was employed to select 143 undergraduate students based on two explicit inclusion criteria: active management of personal finances and direct operational experience with digital financial services (Campbell et al., 2020; Etikan, 2017). Table 2 outlines the demographic profile and contextual background of the research subjects.

Table 2. Profile of Research Subjects and Contextual Demographics

Profile Dimension	Category / Parameter	Sample Count (N)	Percentage (%)
Academic Major	Economics, Business & Management	82	57.3%
	Non-Economics / Technical Majors	61	42.7%

Digital Fintech Experience	Active user of E-Wallets & Digital Banking	143	100.0%
	Experience with BNPL / Micro-Investment Platforms	98	68.5%
Sampling Technique	Purposive Non-Probability Sampling	143	100.0%
Geographic Context	Higher Education Incubators, Indonesia	143	100.0%

Table 2 presents the compositional makeup of the 143 undergraduate respondents who participated in this investigation. The sample contains a balanced distribution between business-related and non-business majors, allowing for a robust empirical evaluation of field of study as a control variable. Having established the sample demographics, data collection proceeded via structured digital instruments.

2.4 Data Collection Procedures

Primary data were gathered using a self-administered, structured electronic questionnaire created and distributed online via Google Forms. To eliminate response bias and non-response errors, data collection followed a multi-stage process involving screening, ethical consent, self-pacing, and data auditing (Etikan, 2017). The survey utilized a standardized 5-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree") to evaluate respondent agreement across all latent construct indicators. The sequential execution of data collection steps is outlined in Figure 2 below.

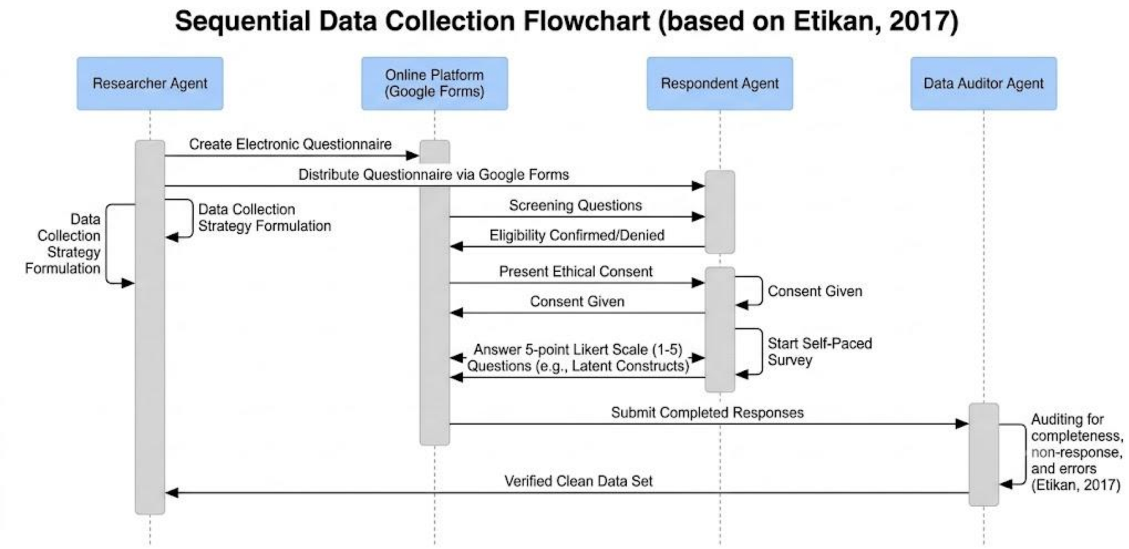


Figure 2. Sequential Data Collection Flowchart

Figure 2 illustrates the chronological operational workflow used to acquire empirical data from the respondents. The process began with instrument development and screening verification to ensure that every participant satisfied the predefined criteria regarding fintech usage and financial independence (Campbell et al., 2020). Upon closing the online survey, 143 completed responses underwent systematic data cleaning, formatting, and preparation for measurement evaluation.

2.5 Research Instrument and Operationalization

The survey instrument was adapted from validated behavioral finance scales and tailored specifically to the context of university students and digital entrepreneurial environments (Brown et al., 2021; Sathya & Gayathiri, 2024). Construct indicators were structured to measure cognitive overconfidence, anchoring effects, loss aversion sensitivity, financial decision quality, and academic major background. The structural breakdown of construct indicators, statement counts, and measurement sources is provided in Table 3 below.

Table 3. Research Instrument Operational Matrix

Latent Construct	Indicator Code	Measured Dimension / Sub-Indicator	Items Count	Scale / Source
Overconfidence Bias	OB1 – OB5	Excessive confidence in financial knowledge, overestimation of investment success, underestimation of market risk.	5 items	5-point Likert (Singh, Malik, & Jha, 2024)
Anchoring Bias	AB1 – AB5	Reliance on initial reference price points, fixation on historical financial trends during decision-making.	5 items	5-point Likert (Gufron & Wibowo, 2024)
Loss Aversion	LA1 – LA5	Asymmetric fear of monetary loss, risk avoidance during uncertainty, preference for capital preservation.	5 items	5-point Likert (Brown et al., 2021)
Financial Decision-Making	PKK1 – PKK5	Rationality in digital budgeting, risk-return evaluation quality, effectiveness of capital allocation in startup contexts.	5 items	5-point Likert (Kartini & Nahda, 2021)
Field of Study	JP	Educational major background (Finance/Economics vs. Non-Finance).	1 item	Single-indicator categorical scale

Table 3 details the operationalization of latent constructs into observable indicators. Each item captures a behavioral nuance, ensuring that the complex psychological dimensions of financial judgment are accurately reflected in the survey responses (Sathya & Gayathiri, 2024). Following operationalization, data quality was evaluated via rigorous validity and reliability protocols.

2.6 Validity and Reliability Testing Procedures

Prior to structural path analysis, the measurement model (outer model) was evaluated to establish indicator reliability, internal consistency, convergent validity, and discriminant validity following the two-stage PLS-SEM procedure (Hair et al., 2019, 2021). Indicator reliability was evaluated using outer loadings, where values ≥ 0.60 were retained given the explanatory, prediction-oriented nature of behavioral finance models (Chin, 1998; Hair et al., 2021). Construct internal consistency was verified via Cronbach's Alpha (≥ 0.70) and Composite Reliability ($\rho_c \geq 0.70$), while convergent validity was confirmed using Average Variance Extracted ($AVE \geq 0.50$) (Hair et al., 2021). The standard evaluation thresholds for outer model testing are summarized in Table 4 below.

Table 4. Outer Model Measurement Evaluation Criteria

Assessment Dimension	Statistical Criteria / Parameter	Established Threshold	Methodological Reference
Indicator Reliability	Outer Loading Value (λ)	≥ 0.60 (acceptable for behavioral studies)	Chin (1998); Hair et al. (2021)
Internal Consistency	Cronbach's Alpha (α)	≥ 0.70	Hair et al. (2019)
Composite Reliability	Composite Reliability (ρ_c)	≥ 0.70	Hair et al. (2021)
Convergent Validity	Average Variance Extracted (AVE)	≥ 0.50	Hair et al. (2019, 2021)

Table 4 specifies the statistical parameters required to validate the survey metrics. All indicators and constructs met these criteria, confirming that the empirical data were robust and free from systematic measurement error before advancing to hypothesis testing (Hair et al., 2021).

2.7 Data Analysis Technique with PLS-SEM

Hypothesis testing was performed using Partial Least Squares Structural Equation Modeling (PLS-SEM) executed through SmartPLS 4 software. PLS-SEM is well-suited for behavioral finance research as it handles prediction-oriented models, complex structural paths, and moderate sample sizes ($N = 143$) without strictly requiring multivariate normality (Hair et al., 2019, 2021). The structural model (inner model) evaluation involved bootstrapping with 5,000 resamples to generate path coefficients (β), t-statistics ($|O/STDEV| \geq 1.96$), p-values ($p < 0.05$), and explanatory coefficients (R^2, Adjusted R^2). The end-to-end analytical workflow executed in SmartPLS 4 is illustrated in Figure 3 below.

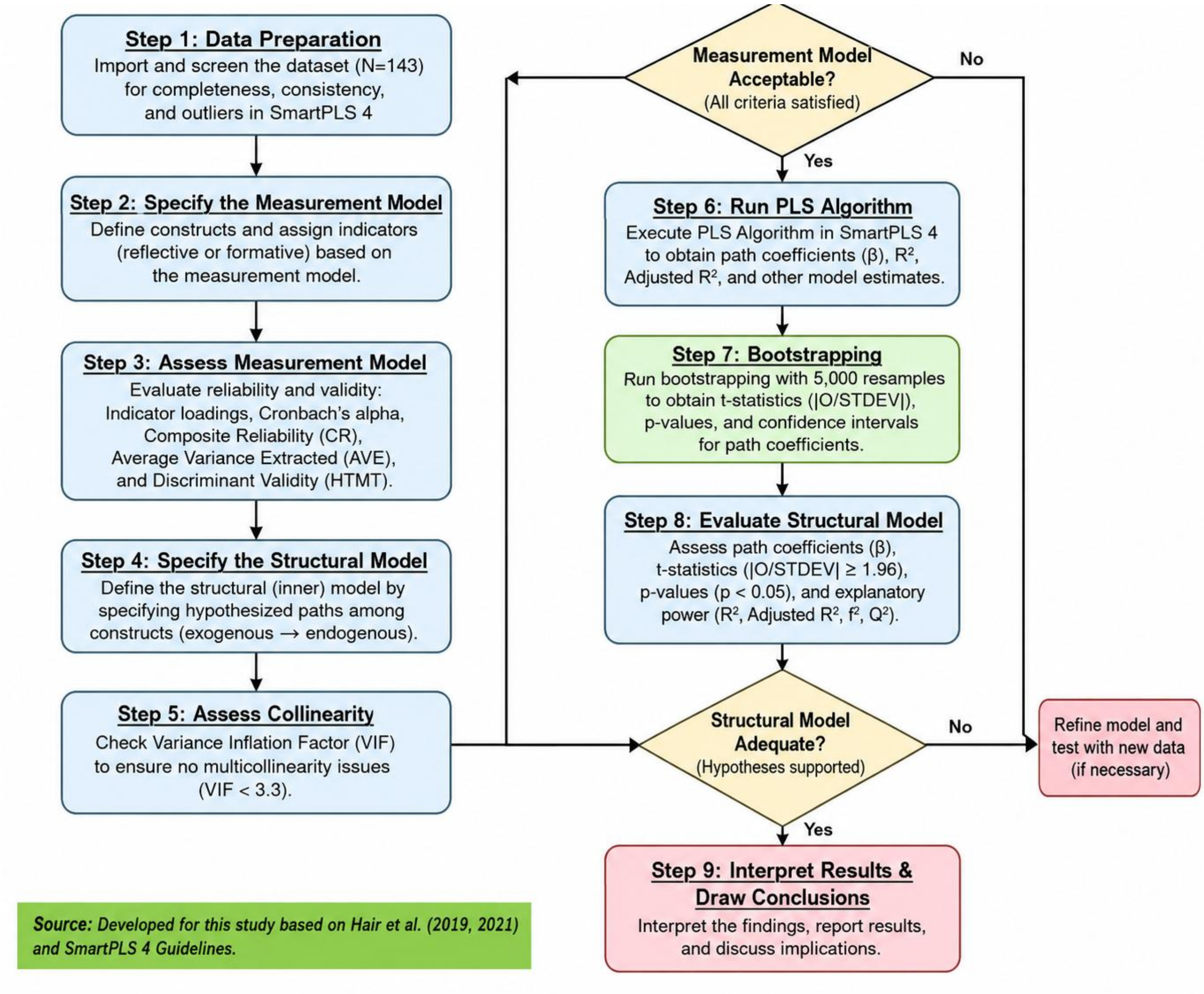


Figure 3. PLS-SEM Structural Analytical Process Flowchart

Figure 3 outlines the sequential steps performed during PLS-SEM estimation in SmartPLS 4. The process guarantees that measurement validity is confirmed prior to evaluating structural relationships, bootstrapping path estimates, and determining hypothesis acceptance (Hair et al., 2021). This analytical protocol provides a sound foundation for interpreting how psychological biases affect decision-making quality in digital business ecosystems (Roundy & Im, 2025; Sholihah et al., 2025).

3. RESULT AND DISCUSSION

3.1 Respondent Profile

Understanding the demographic and contextual characteristics of the survey respondents provides essential background for interpreting how behavioral biases operate within university startup incubators and digital entrepreneurial networks. The sample comprises 143 undergraduate students who actively manage personal finances and routinely utilize digital financial services, such as mobile banking, e-wallets, micro-investment platforms, and Buy-Now-Pay-Later (BNPL) schemes. Selecting subjects with direct exposure to digital transaction platforms guarantees that the empirical responses reflect actual behavioral decision-making under modern fintech conditions. Table 1 summarizes the demographic composition of the sample.

Table 1. Respondent Demographic Profile

Profile Dimension	Category / Operational Parameter	Sample Count (N)	Percentage (%)
Academic Major (Field of Study)	Economics, Business & Management	82	57.3%
	Non-Economics / Technical Majors	61	42.7%
Fintech Service Experience	E-Money / E-Wallets / Digital Banking	143	100.0%
	BNPL / Digital Investment Services	98	68.5%
Academic Standing	Active Undergraduate Students ($N = 143$)	143	100.0%

As shown in Table 1, 57.3% of the respondents originate from business and economics disciplines, while 42.7% represent non-finance majors. This balanced distribution enables a robust statistical test of whether formal financial education acts as a structural buffer against cognitive biases in digital business contexts.

3.2 Measurement Model Assessment (Outer Model)

3.2.1 Convergent Validity (Outer Loadings)

Before evaluating the structural model, the measurement model (outer model) was evaluated to verify indicator reliability and convergent validity. Indicator reliability was assessed via outer loading factors. In accordance with PLS-SEM standards for prediction-oriented behavioral models, outer loadings ≥ 0.60 are deemed acceptable, provided the construct satisfies composite reliability and Average Variance Extracted (AVE) thresholds (Chin, 1998; Hair et al., 2019, 2021). Table 2 presents the item loadings across all latent constructs.

Table 2. Measurement Model Validity Test (Outer Loadings)

Construct	Indicator Code	Outer Loading Factor (λ)	Assessment Result
Anchoring Bias (AB)	AB1	0.818	Valid
	AB2	0.728	Valid
	AB4	0.652	Valid
	AB5	0.750	Valid
Education Major (JP)	JP	1.000	Valid (Single Indicator)
Loss Aversion (LA)	LA1	0.705	Valid
	LA2	0.775	Valid
	LA3	0.679	Valid
	LA4	0.729	Valid
Overconfidence Bias (OB)	OB1	0.844	Valid
	OB2	0.908	Valid
	OB4	0.736	Valid
Financial Decision-Making (PKK)	PKK1	0.831	Valid
	PKK2	0.763	Valid
	PKK3	0.848	Valid
	PKK4	0.701	Valid
	PKK5	0.813	Valid

The results in Table 2 confirm that all outer loadings exceed the minimum threshold of 0.60, ranging from 0.652 to 1.000. Overconfidence Bias exhibits the highest indicator loadings (0.736 to 0.908), demonstrating strong measurement stability. The single-indicator control variable, Field of Study (JP), yields a standard value of 1.000. Thus, all measurement items successfully satisfy the convergent validity criteria.

Reliability and Construct Validity (Cronbach's Alpha, CR, AVE)

To establish construct validity and internal consistency, Cronbach's Alpha (α), Composite Reliability (ρ_a, ρ_c), and Average Variance Extracted (AVE) were calculated. Constructs achieve satisfactory internal consistency when Composite Reliability (ρ_c) is ≥ 0.70, and adequate convergent validity when AVE is ≥ 0.50 (Hair et al., 2019, 2021). The statistical outputs for construct reliability and validity are detailed in Table 3.

Table 3. Construct Reliability and Validity Evaluation

Latent Construct	Cronbach's Alpha (α)	Composite Reliability (ρa)	Composite Reliability (ρc)	Average Variance Extracted (AVE)
Anchoring Bias	0.740	0.811	0.827	0.547
Loss Aversion	0.706	0.723	0.814	0.522
Overconfidence Bias	0.778	0.823	0.870	0.693
Financial Decision-Making	0.851	0.857	0.894	0.629

As shown in Table 3, all constructs demonstrate robust internal consistency, with Composite Reliability (ρ_c) values ranging from 0.814 to 0.894, well above the 0.70 threshold. Furthermore, AVE values range from 0.522 to 0.693, confirming that each construct explains more than 50% of its indicator variance. These metrics confirm that the outer model possesses high reliability and valid measurement properties.

3.3 Structural Model Assessment (Inner Model)

Coefficient of Determination (R^2)

The structural model was evaluated to determine the proportion of variance in Financial Decision-Making explained by the behavioral bias constructs and the control variable. The Coefficient of Determination (R^2) results are presented in Table 4.

Table 4. Coefficient of Determination (R^2)

Endogenous Latent Construct	R-Square (R2)	R-Square Adjusted (Radj2)	Explanatory Power
Financial Decision-Making (PKK)	0.358	0.339	Moderate

The R^2 value of 0.358 indicates that Overconfidence Bias, Anchoring Bias, Loss Aversion, and Field of Study collectively account for 35.8% of the total variance in students' financial decision-making. According to Hair et al. (2021), an R^2 of approximately 0.35 reflects moderate explanatory power in behavioral studies. The remaining 64.2% of the variance is attributable to external psychological, environmental, or institutional determinants, such as digital financial literacy, risk tolerance, and fintech governance.

Hypothesis Testing (Path Coefficients, t-statistics, p-values)

Hypothesis testing was executed using a bootstrapping procedure with 5,000 subsamples in SmartPLS 4. Direct path coefficients (β), sample means (M), standard deviations ($STDEV$), t-statistics ($|O/STDEV|$), and p-values were computed to evaluate structural significance ($\alpha = 0.05, t \geq 1.96$). The structural path estimation results are summarized in Table 5.

Table 5. Structural Path Coefficients and Hypothesis Testing

Structural Path Relationship	Original Sample (β)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Empirical Decision
Anchoring Bias → Financial Decision-Making	0.201	0.207	0.099	2.017	0.044	Supported (H_2)
Field of Study → Financial Decision-Making	-0.134	-0.133	0.069	1.935	0.053	Not Significant
Loss Aversion → Financial Decision-Making	0.237	0.249	0.092	2.575	0.010	Supported (H_3)
Overconfidence Bias → Financial Decision-Making	0.298	0.294	0.091	3.265	0.001	Supported (H_1)

3.4 Discussion

H_1: Overconfidence Bias → Financial Decision-Making

The empirical analysis confirms that Overconfidence Bias has a positive and highly significant effect on prospective entrepreneurs' financial decision-making ($\beta = 0.298, t = 3.265, p = 0.001$), supporting H_1. This represents the largest path coefficient in the structural model, establishing overconfidence as the primary psychological driver of financial judgment among university-based startup founders. Individuals exhibiting high overconfidence tend to overrate their analytical capabilities, underestimate financial volatility, and make active financial choices based on subjective intuition rather than objective data (Singh, Malik, & Jha, 2024). Within digital entrepreneurial ecosystems, this dominant overconfidence exerts a dual effect. On one hand, moderate confidence fosters entrepreneurial alertness, proactive opportunity recognition, and decisive capital commitment necessary for startup initiation (Roundy & Im, 2025). On the other hand, unmitigated overconfidence leads to severe managerial vulnerabilities, including premature scaling, overinvestment in unvalidated technologies, and resistance to executive pivoting during strategy changes.

To counteract these vulnerabilities, startup incubators and venture support programs must establish structured "debiasing toolkits". Implementing mandatory peer reviews, scenario-based financial stress testing, and structured decision journals can help founders distinguish genuine market signals from cognitive overconfidence. The findings indicate that Overconfidence Bias exerts the strongest influence on financial decision-making among prospective entrepreneurs. Individuals who possess higher confidence in their financial abilities tend to make decisions more assertively and rely heavily on their personal judgment. This result suggests that excessive confidence can become a dominant behavioral mechanism influencing financial choices within entrepreneurial ecosystems.

H_2: Anchoring Bias → Financial Decision-Making

The path coefficient for Anchoring Bias demonstrates a positive and statistically significant impact on financial decision-making ($\beta = 0.201, t = 2.017, p = 0.044$), validating H_2. This indicates that prospective digital entrepreneurs frequently anchor their financial evaluations to initial reference points, baseline pricing, or historical performance metrics when navigating complex capital allocation choices. In technology-intensive environments characterized by rapid pricing fluctuations and volatile asset values, anchoring bias can lead to rigid capital structures and flawed valuation assessments. Startup founders who anchor their operational expectations to early revenue figures or initial venture valuations often fail to adjust budget allocations dynamically when market conditions shift. To address this issue, incubators must incorporate adaptive financial forecasting models that rely on dynamic real-time analytics rather than static historical baselines (Hidayat-ur-Rehman & Hossain, 2025). Teaching prospective entrepreneurs to decouple strategic resource allocation from initial reference points enhances venture agility and preserves capital efficiency. Anchoring Bias was found to positively and significantly affect financial decision-making. This finding implies that respondents frequently rely on initial information or reference points when evaluating financial alternatives. Consequently, financial decisions are often shaped by the first available information rather than by a comprehensive assessment of all relevant evidence

H_3: Loss Aversion → Financial Decision-Making

Loss Aversion exerts a strong positive and statistically significant influence on financial decision-making ($\beta = 0.237, t = 2.575, p = 0.010$), confirming H_3. In accordance with Prospect Theory, prospective entrepreneurs exhibit heightened sensitivity to potential financial losses relative to equivalent monetary gains (Brown et al., 2021). This psychological asymmetry leads individuals to prioritize capital preservation and defensive risk management during uncertain periods. While loss aversion protects early-stage ventures against catastrophic downside risks, excessive loss aversion creates strategic inertia. Founders impacted by high loss aversion frequently underinvest in essential research and development (R&D), delay digital technology integration, and resist necessary business model pivots out of fear of sunk cost realization. To optimize venture resilience, entrepreneurship development programs should balance loss aversion with experimental risk-taking frameworks. Utilizing agile prototyping, milestone-based funding release, and sandbox testing environments allows prospective founders to test innovative concepts while keeping monetary exposure within acceptable thresholds.

Loss Aversion also demonstrated a significant positive effect on financial decision-making. Respondents who exhibit stronger concerns about potential losses tend to behave more cautiously when making financial choices. This result supports Prospect Theory, which argues that individuals generally place greater weight on potential losses than equivalent gains.

Control Variable: Field of Study → Financial Decision-Making

The control variable, Field of Study, demonstrates a negative but non-significant effect on financial decision-making ($\beta = -0.134, t = 1.935, p = 0.053$). This counterintuitive finding indicates that formal academic specialization in finance or business administration does not inherently yield superior financial decision-making quality when behavioral cognitive biases are present. This finding reinforces a core behavioral finance principle: technical knowledge does not automatically protect decision-makers from psychological heuristics. While business students acquire superior theoretical financial literacy, they remain equally susceptible to overconfidence, anchoring, and loss aversion when operating under real-world uncertainty. Conversely, non-finance students often manage personal funds and digital transactions based on practical experience, developing heuristic behaviors similar to their business school peers.

From a strategic perspective, this non-significant effect highlights that cognitive self-regulation and behavioral adaptability serve as universal microfoundations for digital innovation capabilities (Chen et al., 2024; Roundy & Im, 2025). Venture capital firms, incubators, and higher education leaders should not rely solely on academic credentials as a proxy for financial rationality. Instead, entrepreneurship curricula must combine technical financial training with cognitive behavioral interventions, ensuring that future venture leaders can manage psychological biases while driving sustainable innovation in digital business ecosystems. The control variable, Field of Study, did not significantly influence financial decision-making. This finding suggests that students from finance-related and non-finance-related disciplines display relatively similar decision-making patterns once behavioral biases are considered. The result highlights that psychological factors may play a more influential role than formal academic specialization in shaping financial decisions.

Managerial and Entrepreneurial Implications

The results emphasize that behavioral biases constitute critical determinants of financial decision-making within digital entrepreneurial ecosystems. Since Overconfidence Bias emerged as the strongest predictor, universities, startup incubators, and entrepreneurship support institutions should integrate behavioral finance training, cognitive debiasing programs, evidence-based decision frameworks, and reflective decision-making practices into entrepreneurial development initiatives. Such interventions may improve managerial judgment, strengthen innovation capability, and enhance the sustainability of digital ventures.

4. CONCLUSION

This study examined the influence of overconfidence bias, anchoring bias, and loss aversion on financial decision-making among undergraduate students as prospective digital entrepreneurs while controlling for field of study. Using Partial Least Squares Structural Equation Modeling (PLS-SEM) with 143 valid responses, the findings demonstrate that all three behavioral biases significantly affect financial decision-making. Among the examined predictors, overconfidence bias emerged as the strongest determinant, followed by loss aversion and anchoring bias. These results confirm that psychological factors play a substantial role in shaping how individuals evaluate financial alternatives and make financial decisions within digital entrepreneurial environments.

The study further reveals that field of study does not significantly influence financial decision-making. This finding suggests that students from finance-related and non-finance-related disciplines exhibit relatively similar decision-making patterns when behavioral biases are considered. Therefore, formal academic specialization alone is insufficient to explain differences in financial decision quality, as cognitive and psychological factors appear to exert a stronger influence on individual financial behavior.

From a theoretical perspective, the findings extend behavioral finance literature by demonstrating that behavioral biases remain significant predictors of financial decision-making among prospective entrepreneurs in digital entrepreneurial ecosystems. Practically, the results suggest that universities, startup incubators, and entrepreneurship support institutions should complement conventional financial education with behavioral finance interventions, including cognitive debiasing strategies, evidence-based decision-making frameworks, and reflective learning approaches. Such initiatives may help prospective entrepreneurs improve managerial judgment, reduce bias-driven errors, and strengthen the sustainability and competitiveness of digital ventures.

Despite its contributions, this study explains 35.8% of the variance in financial decision-making, indicating that other factors beyond behavioral biases may also influence financial behavior. Future research is therefore encouraged to incorporate additional variables such as financial literacy, entrepreneurial orientation, digital innovation capability, risk tolerance, and investment experience to provide a more comprehensive understanding of financial decision-making in entrepreneurial contexts.

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