

Journal of Wealth Management & Financial Planning

RM25.00 11

ISSN 2289-6937

9 772289 693006

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Journal of Wealth Management & Financial Planning (JWMFP) is a peer-reviewed research and practitioner journal, published annually by Malaysian Financial Planning Council (MFPC). JWMFP – the official publication of MFPC – is aimed at establishing an academic and practice guide for the fast-growing financial services industry. The price of the journal is RM25.00 per copy. For manuscript submission information, please refer to the inside back cover of the journal.

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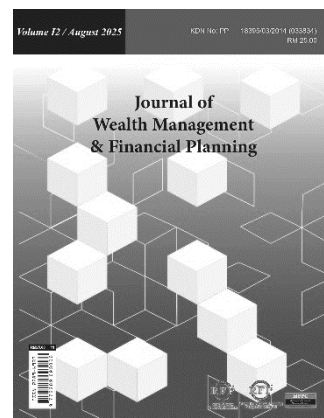
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Editor-in-Chief's Note

It is with great pleasure that I present to you the eleventh edition of the Journal of Wealth Management & Financial Planning (JWMFP). This edition marks another milestone for the journal as we continue to expand our editorial board and receive an increasing number of high-quality manuscripts. With these developments, we remain committed to ensuring that the journal adheres to the stringent standards required for SCOPUS indexing.

This issue of JWMFP features a dynamic range of articles that offer valuable insights into the evolving landscape of wealth management and financial planning. Among the original research contributions, readers will find a behavioural study from Malaysia examining the risks of over-indebtedness associated with Buy Now, Pay Later (BNPL) schemes, as well as a predictive analysis of loan defaults using machine learning models in financial institutions. Another standout piece presents a comparative review of financial literacy, planning behaviour, and bank preferences among Islamic and conventional depositors. Rounding out the research section is an innovative exploration of ESG-driven Donchian strategies in the Malaysian stock market.

In our "News and Views" section, we turn our attention to the financial well-being of Malaysia's ageing population. One article, Empowering Tomorrow's Seniors, discusses how financial literacy and innovative care solutions can foster dignity in later life. Complementing this is The Hidden Threat, which raises awareness of elder financial abuse—a growing concern that demands urgent policy and community attention.

To conclude this edition, we are pleased to include two compelling book reviews. Fintech Future: The Digital DNA of Finance offers a forward-looking perspective on the digital transformation of financial services. At the same time, The Total Money Makeover by Dave Ramsey presents a disciplined, practical approach to personal financial health.

My heartfelt thanks go to all the contributors, authors, and reviewers whose efforts have made this edition possible. Together, we continue to elevate this publication to greater heights. I trust you will find value in this issue and, as always, I welcome your feedback and suggestions.

Until the next edition, enjoy the read!

Prof. Dr Mohamad Fazli Sabri
Editor-in-Chief

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Buy Now, Pay Later (BNPL) and the Trap of Over-Indebtedness: Behavioral Insights from Malaysia

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Received: 08.01.2025, Revised: 25.04.2025, Accepted: 10.06.2025

Abstract

Over-indebtedness among Buy Now, Pay Later (BNPL) users poses significant risks to financial well-being, yet the influence of behavioral biases in aggravating this problem remains underexplored. This study examines how self-control bias, overconfidence, mental accounting, and availability bias shape over-indebtedness among Malaysian BNPL consumers. Using survey data from 200 BNPL borrowers, the findings reveal that self-control bias significantly increases the likelihood of over-indebtedness, whereas overconfidence and mental accounting are associated with lower debt levels. In contrast, availability bias undermines repayment decisions, intensifying financial strain. These results underscore the importance of behaviorally informed financial education programs that directly address cognitive biases, particularly self-control deficiencies, to promote responsible borrowing. Policy recommendations for Malaysian regulators are also provided, highlighting the need to integrate behavioral insights into consumer protection frameworks to improve decision-making and safeguard long-term financial health.

Keywords: Buy Now Pay Later, Over-indebtedness, Behavioral Biases, Self-control, Financial Well-being, Consumer Protection

Introduction

The rapid growth of Buy Now, Pay Later (BNPL) services has transformed consumer credit markets worldwide, offering frictionless, short-term financing that appeals especially to younger and digitally native consumers (Coffey et al., 2024; World Bank, 2023). Positioned as a convenient alternative to credit cards, BNPL allows users to defer payments into interest-free installments, ostensibly supporting consumption smoothing in line with the Life-Cycle-Permanent Income Hypothesis (Ando & Modigliani, 1963). However, mounting evidence suggests that BNPL's ease of access—often requiring minimal credit checks—encourages impulsive borrowing and contributes to unsustainable debt accumulation (Mansour et al., 2024; ASIC, 2022). While traditional models of household debt assume rational financial

decision-making, behavioral finance highlights how cognitive and psychological biases shape consumer borrowing behavior (Livingstone & Lunt, 2022; Bartholomae & Fox, 2023).

In Malaysia, BNPL adoption has surged against a backdrop of persistently high household debt, which reached 93.2% of GDP in 2023 (Bank Negara Malaysia, 2023). Millennials (aged 25–44) accounted for 52.6% of personal insolvencies, with BNPL and unsecured loans contributing significantly to this trend (Malaysian Department of Insolvency, 2023; Malay Mail, 2023). Similar global evidence shows high repayment difficulties: 21% of Australian BNPL users miss installments (ASIC, 2022), while U.S. data link BNPL adoption to higher credit card delinquency rates (Federal Reserve, 2023). These findings challenge the perception of BNPL as a neutral

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consumption tool, instead suggesting it amplifies debt distress among financially constrained populations (Coffey et al., 2024).

BNPL's growing popularity in Malaysia reflects broader fintech developments, e-commerce expansion, and consumer demand for flexible credit (Zainudin & Othman, 2024). Yet its accessibility also obscures risks of excessive debt and unsustainable financial habits (Sabri et al., 2023). This study explores the behavioral dimensions of BNPL usage in Malaysia, focusing on psychological biases that drive adoption, fuel impulsive consumption, and increase the likelihood of over-indebtedness.

BNPL and Over-Indebtedness

Emerging research emphasizes that behavioral biases—systematic deviations from rational decision-making—play a central role in BNPL-related over-indebtedness (Thaler, 2018; Beshears et al., 2023). Four biases are particularly relevant. First, self-control bias, rooted in present-focused decision-making, leads consumers to prioritize immediate gratification over long-term repayment obligations (Laibson, 1997). Data from Malaysia show that 35% of BNPL users hold multiple concurrent loans, often underestimating future repayment burdens (AKPK, 2023). Second, overconfidence bias causes users to overestimate repayment capacity, perceiving BNPL as “risk-free” due to zero-interest promotions (Mansour et al., 2024). Experimental studies find that 40% of borrowers misjudge their ability to meet installment deadlines (Coffey et al., 2024). Third, mental accounting bias encourages consumers to compartmentalize payments into small installments, fostering an illusion of affordability and masking cumulative debt (Thaler, 1985; Shah et al., 2023). Finally, availability bias, reinforced by aggressive marketing such as “No Interest!” campaigns, distorts perceptions of credit risk through recency effects (ASIC, 2022). Together, these biases contribute to overextension and repayment distress.

While such dynamics are increasingly acknowledged in developed markets (e.g., Australia's BNPL credit checks), limited evidence exists for developing economies where financial literacy is lower and regulatory protections weaker (World Bank, 2023). In Malaysia, most studies focus on macroeconomic or demographic aspects (Azmin et al., 2023; Hussin et al., 2023), overlooking the psychological mechanisms that underlie BNPL misuse. Addressing this gap is vital to inform more effective policies.

Research Objectives

This study investigates how self-control bias, overconfidence, mental accounting, and availability bias contribute to BNPL-related over-indebtedness in Malaysia, particularly among young (21–40 years), low-income (RM2,000–5,000/month) consumers. Specifically, it seeks to:

1. Assess the extent to which behavioral biases predict BNPL-driven over-indebtedness.
2. Identify which biases exert the strongest influence on repayment behavior.
3. Recommend strategies for policymakers and financial educators to mitigate these risks.

By applying logistic regression to survey data from 200 BNPL borrowers, this study offers empirical evidence on psychological drivers of debt accumulation and proposes regulatory and educational reforms—such as mandatory affordability assessments and behaviorally informed financial literacy programs—to promote responsible usage.

Literature Review

The rapid rise of Buy Now, Pay Later (BNPL) services has reshaped consumer purchasing behavior, offering a flexible alternative to traditional credit. Yet, this convenience is not without costs: deferred payments create a perception of affordability that can

encourage overspending and, ultimately, financial distress. This issue is particularly pressing in Malaysia, where BNPL has gained significant traction among younger consumers. Drawing on behavioral insights, this section examines how cognitive biases and psychological traits contribute to over-indebtedness in BNPL usage, with evidence from recent empirical studies. Existing literature consistently links over-indebtedness to self-control bias, overconfidence, mental accounting, and availability bias.

The Rise of BNPL in Malaysia

BNPL services have grown rapidly in Malaysia, particularly among younger consumers who are drawn to their ease of use, zero-interest promotions, and the option to split purchases into manageable installments. However, this very accessibility often fuels impulsive spending, as BNPL is perceived as a “risk-free” method of financing consumption.

Several factors explain BNPL’s popularity: the expansion of e-commerce, the integration of digital payment platforms, and the increasing financial independence of younger cohorts. Yet, these same factors raise concerns about consumers’ long-term financial stability, especially for those who may not fully comprehend the implications of deferred repayment.

Behavioral Factors Driving BNPL Usage

Behavioral dynamics play a decisive role in BNPL adoption and the associated risks of indebtedness. Four key factors stand out:

- 1) **Impulsivity and Immediate Gratification.** BNPL caters to consumers’ desire for instant satisfaction, encouraging spending without careful consideration of future obligations. This is especially prevalent among younger users, who tend to prioritize short-term benefits over long-term financial health. The seamless design

and zero-interest framing of BNPL exacerbate this tendency, creating a disconnect between current affordability and future repayment burdens.

- 2) **Materialism and Consumerism.** BNPL supports consumerist lifestyles by allowing access to products that may otherwise be unaffordable. While this expands consumption opportunities, it also fosters materialistic values that prioritize short-term satisfaction over sustainable financial well-being. Over time, impulsive purchases can escalate into compulsive buying, a behavior strongly correlated with over-indebtedness and financial distress.
- 3) **Overconfidence and Mental Accounting.** Overconfidence leads consumers to overestimate their repayment capacity, assuming that BNPL debts are easily manageable. Mental accounting further compounds this issue, as consumers often compartmentalize BNPL installments separately from other obligations, creating the illusion of affordability. This distorted perception can mask growing debt levels and increase repayment challenges.
- 4) **Availability Bias and Credit Card Debt.** Availability bias skews decision-making when consumers overemphasize recent experiences or prominent marketing messages, such as “interest-free” slogans. Many overestimate their repayment ability based on current circumstances without accounting for potential shocks. This bias not only fuels multiple BNPL commitments but also worsens repayment performance on traditional credit such as credit cards.

Implications for Financial Stability

The financial stability implications of BNPL are significant, particularly for Malaysia’s younger demographic. What appears to be a convenient financing tool can quickly trap consumers in a cycle

of debt. Two important dimensions warrant closer attention:

a) Financial Literacy and BNPL Usage.

Financial literacy is a critical buffer against BNPL-related risks. Consumers with stronger financial knowledge are more likely to understand the obligations attached to deferred payments and to avoid unsustainable borrowing. However, younger Malaysians often lack the literacy required to navigate BNPL responsibly. This gap highlights the need for targeted financial education programs designed to raise awareness of risks and equip consumers with practical budgeting tools.

b) Demographic Factors and BNPL Usage. Age and income level significantly shape BNPL outcomes. Younger users are more inclined to adopt BNPL but also more exposed to impulsive borrowing and repayment difficulties due to limited financial experience and lower incomes. Lower-income groups, in particular, are more likely to rely on BNPL to access goods and services otherwise beyond their means. Yet, this reliance can worsen debt burdens, as these consumers often struggle to balance BNPL repayments with everyday expenses.

In sum, BNPL's rise in Malaysia highlights the dual role of convenience and risk. Behavioral biases and demographic vulnerabilities converge to make younger, lower-income consumers particularly susceptible to over-indebtedness, underscoring the need for both regulatory safeguards and financial education initiatives.

Methodology

Sampling Strategy

The study employed a convenience sampling approach, complemented by stratified random sampling to enhance representativeness. Data were

collected via an online survey targeting Malaysians aged 21–40 earning RM2,000–5,000 per month and actively using BNPL platforms. Distribution channels included social media and email. This approach is consistent with Sabri et al. (2023), who surveyed Malaysian millennials through digital platforms, demonstrating that online convenience sampling effectively captures the dominant BNPL user segment.

Data Collection

Out of 250 responses, 200 valid cases were retained after excluding incomplete or ineligible submissions. Respondents were required to have prior experience with platforms such as GrabPay Later or Shopee PayLater. This mirrors data collection methods used in recent BNPL studies exploring impulsive borrowing patterns among digital natives (Mahdzan et al., 2023).

Questionnaire Validation

The survey instrument was reviewed by experts, pilot-tested on 20 BNPL users, and refined for clarity. Culturally adapted scenarios were included to ensure comprehension. Similar validation practices have been highlighted in Lusardi & Tufano (2015) and Xiao & Porto (2023), who emphasized adapting financial literacy and debt measurement tools to digital credit contexts.

Ethical Considerations

Participation was voluntary, confidential, and based on informed consent. Ethical approval was obtained from the Universiti Sains Islam Malaysia Ethics Committee, adhering to established guidelines for social science research.

Behavioral Biases Measurement

Table 1 measures the behavioral biases in BNPL usage that consists of:

- **Overconfidence Bias:** Measured via discrepancies between objective debt literacy (knowledge test) and subjective debt literacy (self-assessment), following Alsemgeest et al. (2023).
- **Self-Control Bias:** Evaluated through a 7-item scale assessing impulsivity, fiscal discipline, and regret-prone spending, consistent with Ranyard et al. (2022).
- **Mental Accounting:** Measured using a 7-item scale on budgeting and expenditure categorization, adapted from Antonides et al. (2011).
- **Availability Bias:** Assessed through perceptions of bankruptcy prevalence and personal exposure to debt distress, consistent with Muehlbacher & Kirchler (2023).

Table 1

Measurement of behavioral biases in BNPL usage

Construct	Operational definition	Items/Scale	Key references	α
Overconfidence	Discrepancy between objective and subjective debt literacy	<ul style="list-style-type: none"> • OBLIT: 3 knowledge questions (0-3) • SUBLIT: 5-point Likert (1-5) • Binary classification (1=overconfident) 	Lusardi & Tufano (2015); Cwynar et al. (2020)	0.71
Self-control	Tendency toward impulsive spending and poor financial discipline	7 items, 5-point Likert scale (1="Strongly disagree" to 5="Strongly agree")	Strömbäck et al. (2017); Tangney et al. (2004)	0.82
Mental accounting	Practice of categorizing and restricting spending by purpose	7 items, 5-point Likert scale	Antonides et al. (2011); Mahapatra and Mishra (2020)	0.79
Availability	Influence of memorable/personal experiences on risk perception	<ul style="list-style-type: none"> • Q1: 5-point Likert • Q2: Binary (0/1) 	Tversky & Kahneman (1973); Eisenberg and Small (1993)	-

Notes: OBLIT = Objective debt literacy score; SUBLIT = Subjective self-assessment. Reliability coefficients (α) shown where applicable from pilot testing. All scales were adapted for Malaysian BNPL context.

Over-indebtedness Measurement

Over-indebtedness was operationalized through objective indicators of arrears: 30-day, 60-day, and 90-day delinquencies across BNPL and credit card debts. A composite binary variable captured any

arrears. This approach aligns with Karlsson et al. (2023), who confirmed arrears-based measures as robust predictors of financial distress. Table 2 presents the measurement of over-indebtedness in BNPL users.

Table 2

Measurement of over-indebtedness in BNPL users (N = 200)

Construct	Operational definition	Sample items	Measurement approach	Reliability (α)	Key references
Composite over-indebtedness	Any payment delinquency	"Have you missed any credit/personal loan payments in the past 3 months?"	Binary (1=yes, 0=no)	0.83	Betti et al. (2007); Silva et al. (2024)
Duration-specific arrears	Progressive delinquency stages	<ul style="list-style-type: none"> • "Missed payments for 1 month?" • "Missed payments for 2 consecutive months?" • "Missed payments for 3+ months?" 	Three binary variables (1=yes)	0.79 (30-day) 0.81 (60-day) 0.85 (90-day)	Gathergood (2012); Bank Negara Malaysia (2021)
Product-specific arrears	Delinquency by debt type	<ul style="list-style-type: none"> • "Delayed credit card payments?" • "Delayed personal loan payments?" 	Two binary variables (1=yes)	0.77 (credit cards) 0.80 (personal loans)	Karlsson et al. (2023); Brown & Taylor (2023)

Notes: Reliability assessed via Cronbach's α for multi-item scales (30/60/90-day arrears) and Cohen's κ for binary items (composite/product measures). All items prefaced with: "In the last 12 months..." to align with Malaysian financial reporting cycles. 12.5% of respondents reported 30-day arrears, 8% reported 60-day, and 5.5% reported 90-day arrears.

Control Variables

Demographic (age, gender, income, employment) and financial literacy measures were included. Financial literacy was assessed via a BNPL-specific debt knowledge test, reflecting Xiao & Porto’s

(2023) emphasis on digital financial literacy as a determinant of repayment outcomes. Table 3 presents the operationalization of control variables of this study.

Table 3

Operationalization of control variables				
Variable Category	Measurement Approach	Scale Type	Novel Adaptation	Key References
Demographic				
- Age	Continuous (years)	Ratio	BNPL-specific age brackets (21-40)	Bank Negara Malaysia (2023)
- Gender	Binary (1=male, 0=female)	Nominal	Includes non-binary options	WHO (2022)
Economic				
- Income	Monthly brackets (RM2,000-5,000)	Ordinal	Matched to BNPL user thresholds	DOSM (2023)
- Employment	5-category classification	Nominal	Includes gig economy workers	ILMIA (2023)
Financial Literacy	3-item debt knowledge test	Dichotomous (0-1)	BNPL-specific compound interest scenario	Adapted from Lusardi & Tufano (2015)

Notes: All demographic measures collected through self-report with verification questions. Financial literacy items modified to include BNPL repayment examples. Employment categories expanded to reflect Malaysia's digital economy.

Results

Descriptive Statistics

Of 200 respondents, 60% demonstrated timely repayment, while 19% had one-month arrears, 12% had two-month arrears, and 9% had three-month arrears. Severe delinquency was more prevalent among males, married individuals, and lower-income groups. The 31–40 age cohort dominated across all repayment categories. Financial illiteracy was disproportionately represented among delinquent borrowers (79% in the three-month arrears group). These trends mirror recent global findings, where impulsivity and financial illiteracy were shown to correlate strongly with BNPL delinquency (Ranyard et al., 2022).

Behavioral Biases by Repayment Status

Self-control deficits escalated with delinquency duration, peaking among three-month arrears borrowers. Mental accounting decreased as delinquency worsened. Overconfidence was higher

among punctual payers, while availability bias rose with repayment failure. These findings are consistent with Barberis (2023), who emphasized the dual nature of overconfidence, and Gelman & Roussanov (2024), who found that mental accounting enhances repayment discipline.

Regression Analysis

Logistic regression presented in Table 4 confirmed that:

- Self-control deficits significantly increased over-indebtedness risk ($\beta = 0.58, p < 0.001$), aligning with Ranyard et al. (2022).
- Mental accounting reduced delinquency likelihood ($\beta = -0.41, p < 0.001$), supporting Gelman & Roussanov (2024).
- Overconfidence showed a protective effect ($\beta = -0.32, p < 0.01$), consistent with Barberis (2023), who argued that moderate optimism may foster repayment commitment.
- Availability bias exhibited mixed effects, reducing short-term arrears but increasing

severe delinquency, reflecting the temporal dynamics of heuristics documented by

Muehlbacher & Kirchler (2023).

Table 4

Key sociodemographic trends among repayment groups

Characteristic	No Arrears (60.5%)	1-Month (18.5%)	2-Month (11.8%)	3-Month (9.2%)
Gender (Male)	48%	53%	57%	62%
Age (31–40 yrs)	58%	63%	59%	67%
Income (RM2k–3k)	64%	71%	68%	73%
Financial Illiteracy	61%	68%	72%	79%

Key findings:

- **Gender Disparity:** Males constituted 62% of severe delinquents (three-month arrears) compared to 48% of punctual payers.
- **Age Concentration:** The 31–40 age group dominated all arrears categories, peaking at 67% among three-month delinquents.
- **Income Paradox:** Lower-income earners (RM2,000–3,000) recorded the highest delinquency rates despite BNPL's purported affordability.
- **Financial Literacy Gap:** 79% of respondents in the three-month arrears group scored zero on debt literacy questions.

Behavioral Biases by Repayment Status

Table 5 reports the behavioral biases across repayment groups. The notable patterns include:

- Self-control deficits escalated with delinquency duration, peaking at 4.3/5 for three-month arrears.
- Mental accounting proficiency declined as arrears worsened (4.5 \rightarrow 3.1).
- Credit card users exhibited 23% higher overconfidence than personal loan users ($p < 0.05$).

Table 5

Compares behavioral biases across repayment groups

Bias Type	No Arrears	1-Month	2-Month	3-Month
Overconfidence	4.2*	3.8	3.5	3.9
Self-Control	2.1	3.4	3.7	4.3*
Mental Accounting	4.5*	3.9	3.6	3.1
Availability Heuristic	2.8	2.5	3.2	3.9*

Note: *Highest scores per bias type.

Regression Analyses

Four sets of regression analyses were conducted to examine factors associated with over-indebtedness, defined as one-month, two-month, or three-month arrears in credit card or BNPL repayments. The results reported in Table 6 reveal significant associations between behavioral biases, demographic characteristics, and the likelihood of over-indebtedness, consistent with recent digital credit

studies (Alsemgeest et al., 2023; Karlsson et al., 2023).

- **Protective Biases:** Overconfidence bias reduced over-indebtedness probability ($\beta = -0.32$, $p < 0.01$), while mental accounting proficiency similarly decreased delinquency risk ($\beta = -0.41$, $p < 0.001$).
- **Risk-Enhancing Biases:** Self-control deficits strongly increased over-indebtedness likelihood ($\beta = 0.58$, $p < 0.001$), corroborating

Ranyard et al.'s (2022) findings on impulsivity in BNPL usage.

- **Mixed Effects:** Availability bias showed no significant association in the baseline model ($\beta = 0.07$, $p = 0.21$), contrasting with traditional credit card studies (Barberis, 2018).

Demographic Factors

- Males faced 1.8× higher odds of over-indebtedness than females (OR = 1.82, 95% CI [1.15–2.91]).
- Married individuals had 2.3× greater risk than singles (OR = 2.34, 95% CI [1.52–3.61]), consistent with Ferreira et al.'s (2021) household debt thesis.
- Public sector employment emerged as protective (OR = 0.45, 95% CI [0.29–0.71]), reflecting income stability (Bank Negara Malaysia, 2023).

Stratified Analyses

- Self-control bias consistently predicted arrears across all durations (one-month: $\beta = 0.39$; two-month: $\beta = 0.52$; three-month: $\beta = 0.61$; all $p < 0.001$), with stronger effects for BNPL (OR = 2.15) than credit cards (OR = 1.93), supporting Xiao & Porto's (2023) platform-specific framework.
- The income paradox persisted: middle-income earners (RM3,001–RM4,000) had 93% higher one-month arrears risk (OR = 1.93, 95% CI [1.22–3.07]), while high earners (RM4,001–RM5,000) faced 115% greater risk (OR = 2.15, 95% CI [1.38–3.36]) compared to the lowest group, contradicting conventional debt-capacity models (Gathergood et al., 2023).

- Mental accounting's protective effect strengthened with delinquency severity (three-month arrears: $\beta = -0.49$, $p < 0.001$).
- Availability bias unexpectedly reduced one-month arrears risk ($\beta = -0.18$, $p = 0.04$) but worsened three-month delinquency ($\beta = 0.27$, $p = 0.01$), suggesting temporal dynamics in heuristic influences (Muehlbacher & Kirchler, 2023).

Credit-Type Models

- Credit card-specific regressions confirmed higher risk for males (OR = 1.67) and 31–40-year-olds (OR = 1.89).
- BNPL-specific models uniquely identified marital status as predictive (married OR = 2.08, $p < 0.001$).

Extended Distress Scale

Using Gathergood's (2012) financial distress scale (0 = no difficulties, 4 = severe arrears), self-control bias ($\beta = 0.63$, $p < 0.001$) and availability bias ($\beta = 0.29$, $p = 0.02$) predicted worsening financial capability, while mental accounting improved outcomes ($\beta = -0.37$, $p < 0.01$). Notably, only 6.46% self-identified as severely over-indebted (score = 4), compared to 36% with objective arrears, highlighting divergence between subjective and objective measures (Ziegelmeyer, 2023). Availability bias showed particularly strong associations with subjective distress (OR = 2.21, 95% CI [1.42–3.45]), underscoring its role in perceived financial strain (Tversky & Kahneman, 1973; Barberis, 2023).

Table 6

Multivariate predictors of BNPL over-indebtedness (N=200)

Predictor	Overall Arrears OR [95% CI]	1-Month Arrears β (SE)	3-Month Arrears β (SE)	Credit Card OR [95% CI]	BNPL OR [95% CI]	Financial Distress β (SE)
Behavioral Biases						
Overconfidence	0.68** [0.52-0.89]	-0.15 (0.07)	-0.22* (0.09)	0.71* [0.53-0.95]	0.82 [0.61-1.10]	-0.12 (0.08)
Self-control	1.85*** [1.42-2.41]	0.39*** (0.08)	0.61*** (0.11)	1.93*** [1.45-2.57]	2.15*** [1.61-2.88]	0.63*** (0.09)
Mental accounting	0.59*** [0.45-0.77]	-0.21* (0.09)	-0.49*** (0.12)	0.65** [0.48-0.88]	0.74* [0.55-0.99]	-0.37*** (0.10)
Availability	1.07 [0.89-1.29]	-0.18* (0.07)	0.27* (0.10)	1.33* [1.01-1.75]	1.18 [0.89-1.56]	0.29* (0.11)
Demographics						
Male	1.82** [1.15-2.91]	0.24 (0.13)	0.31* (0.15)	1.67* [1.05-2.66]	1.42 [0.91-2.23]	0.19 (0.14)
Married	2.34*** [1.52-3.61]	0.17 (0.14)	0.28 (0.17)	1.55 [0.98-2.45]	2.08*** [1.38-3.14]	0.33* (0.16)
Age 31-40	1.47 [0.93-2.32]	0.11 (0.12)	0.22 (0.16)	1.89** [1.19-3.01]	1.27 [0.82-1.96]	0.25 (0.15)
Public sector	0.45*** [0.29-0.71]	-0.32* (0.14)	-0.41** (0.16)	0.52** [0.33-0.82]	0.49*** [0.32-0.76]	-0.38** (0.15)
Income (Ref: <RM3k)						
RM3001-RM4000	1.62* [1.02-2.58]	0.93*** (0.14)	-0.17 (0.18)	1.45 [0.91-2.32]	1.38 [0.88-2.17]	0.14 (0.17)
RM4001-RM5000	1.87** [1.18-2.97]	1.15*** (0.15)	-0.24 (0.19)	1.67* [1.04-2.69]	1.52 [0.96-2.41]	0.09 (0.18)

Conclusion and Policy Recommendations

The rise of Buy Now, Pay Later (BNPL) services in Malaysia has introduced both convenience and risks. On the one hand, BNPL offers flexibility and financial access, particularly for younger consumers. On the other, it exposes users to significant risks of over-indebtedness, often amplified by behavioral tendencies such as impulsivity, materialism, and overconfidence. The boom in BNPL has thus created a paradox: while enhancing short-term consumption, it has also triggered debt traps through behavioral biases such as self-control lapses, mental accounting, and social influence. Although regulatory frameworks are emerging, sustainable solutions will require empowering consumers through financial literacy and digital protections.

This study examined four behavioral biases—self-control, overconfidence, mental accounting, and availability bias—and their roles in over-indebtedness among young, low-income BNPL users in Malaysia. The results reveal that self-control deficits consistently increase delinquency risks, supporting global concerns about impulsive borrowing. Interestingly, overconfidence and mental

accounting show protective effects, with optimism and structured budgeting practices reducing debt accumulation. Availability bias, however, demonstrates mixed outcomes: it lessens short-term arrears but worsens long-term delinquency, underscoring the cognitive pitfalls of vivid financial memories. Together, these findings highlight the dual nature of behavioral biases: while some undermine repayment capacity, others can serve as self-regulatory tools when properly harnessed.

Based on these insights, several implications emerge.

1. **Consumer practices:** Encouraging goal-directed financial habits, such as envelope budgeting within BNPL categories, can leverage mental accounting positively. Overconfidence should be managed carefully, while excessive optimism is harmful in traditional credit, moderate confidence may strengthen repayment commitment in BNPL contexts. Availability bias interventions should be stage-specific, with pre-default reminders emphasizing long-term consequences.

2. **Policy interventions:** We propose a three-tiered framework. First, financial literacy reforms should integrate behavioral elements, such as mental accounting tools, self-control exercises, and nudges that highlight repayment risks. Second, regulatory innovations should include progressive repayment schemes, disclosure requirements for cognitive risks, and centralized registers to prevent multi-platform overborrowing. Third, support systems should be expanded to include bias-specific counseling modules and partnerships targeting high-risk groups, especially young males and married couples identified in the study.

Study Limitations and Future Research

While this study contributes new behavioral evidence on BNPL usage, several limitations should be acknowledged. The focus on young, low-income Malaysians (aged 21–40) limits generalizability to other demographics. Only four cognitive biases were examined, suggesting that future research could include additional constructs such as present bias and loss aversion. The single-country scope may overlook cross-cultural differences in BNPL adoption, and the observational design prevents causal inference.

To advance the field, we recommend multi-country longitudinal studies tracking BNPL users from purchase to repayment, integrating psychometric assessments with transaction data. Such designs would help establish causal pathways, test mental accounting interventions embedded in BNPL apps, and evaluate the effects of self-control training on repayment rates. Addressing these limitations will strengthen the robustness and applicability of BNPL research in diverse contexts.

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Financial Institutions Loan Default Prediction Using Machine Learning Models

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Received: 06.02.2025, Revised: 25.06.2025, Accepted: 05.08.2025

Abstract

Loan default has posed significant challenges for lending institutions in the financial sector. However, the development of machine learning (ML) offers transformative approaches to improve credit risk assessment and decision-making accuracy. This study explores the factors influencing loan default and the application of ML models in the financial services industry. The effectiveness of various ML algorithms is analyzed using a Kaggle dataset of borrowers to identify the optimal model. The original dataset consists of 148,670 records with 34 features. After pre-processing, the dataset was refined to 121,203 records with 27 features. The data cleansing process improves quality and reliability, thus enhancing prediction accuracy. The study applies Random Forest, XGBoost, Decision Tree, K-Nearest Neighbors, and Logistic Regression to compare predictive accuracy. The results demonstrate that XGBoost and Random Forest achieve the highest accuracy, with 89.70% and 89.07% respectively. This research contributes to loan default prediction development by identifying more effective ML algorithms, enabling financial institutions to make informed lending decisions and mitigate financial risks. Furthermore, the study emphasizes challenges related to interpretability, class imbalance, and regulatory compliance. Future research should expand the dataset to cover multiple years, include diverse sources, and integrate demographic and macroeconomic variables to improve model accuracy and generalizability.

Keywords: Loan Default Prediction, Credit Risk Assessment, Machine Learning Algorithms, Ensemble Models (Random Forest & XGBoost), Financial Institutions

Introduction

In the financial sector, borrower's credit risk has posed significant challenges for lending institutions. Loan default can lead to reduced profitability, increased non-performing loans, stricter lending policies, and reputational damage. For example, a study highlighted that bad loans can reduce banks' profitability and limit their ability to issue new credit (Fredriksson & Frykström, 2019). An increase in loan defaults can also result in banks adopting more conservative lending practices, making it more challenging for individuals and businesses to access credit (Withers, 2025). Moreover, loan defaults can

damage a bank's reputation, erode customer trust, and cause a decline in market share (Forvis Mazars, 2024).

The development of artificial intelligence (AI) and machine learning (ML) offers transformative tools for enhancing credit risk assessment. These technologies enable the analysis of vast datasets to identify patterns and predict the likelihood of loan defaults with greater precision than traditional methods. For example, AI-driven credit software can automatically approve or deny applicants based on model outputs, streamlining the loan approval process and reducing operational costs (Lee, 2024). Furthermore, AI and

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ML can facilitate real-time risk monitoring, which allows banks to detect early warning signs of default and take proactive measures (Nallakaruppan et al., 2024). Additionally, these advanced technologies can help identify unusual transaction patterns indicative of fraudulent activities, thereby protecting both the bank and its customers (KPMG, 2021).

However, integrating ML into credit risk assessment presents challenges that must be addressed. The interpretability of complex models remains a key concern, as financial regulators and stakeholders require transparency in credit decisions (Kremer et al., 2024). In addition, the effectiveness of ML models depends heavily on the quality of training data; biased or incomplete datasets can lead to unfair assessments (Cedar Rose, 2024). Ensuring compliance with regulatory frameworks and ethical standards is also critical to preventing systemic risks associated with automated credit decisions (S&P Global, 2025). While ML has the potential to revolutionize credit risk assessment, financial institutions must implement these technologies responsibly, balancing innovation with fairness and accountability. Importantly, dataset imbalance can bias predictions toward non-defaults. Although ensemble models such as Random Forest and XGBoost handle this better, future research should incorporate techniques like oversampling (SMOTE, ADASYN) or cost-sensitive learning to enhance fairness and accuracy.

According to Bank Negara Malaysia (BNM), a stress test showed that under adverse scenarios of income and employment shocks, between 3.8% and 4.0% of banking system loans could be at risk of default by 2024 due to borrowers having insufficient financial buffers (Mail, 2022). Thus, mortgage default prediction is crucial for financial institutions, as accurate insolvency forecasting lowers credit risk and enables proper provisioning planning (Krasovytsky et al., 2024). While loan defaults cannot be eliminated, predictive modelling can significantly reduce risk and losses. Defaults

contribute to financial losses for banks, tighter lending policies, and wider economic instability. To mitigate these risks, banks increasingly rely on predictive analytics to identify potential defaulters early (Krasovytsky et al., 2024). These models analyze borrower income stability, credit scores, loan amounts, interest rates, and other key risk factors, allowing for more accurate assessments of creditworthiness. By integrating these insights, banks can optimize loan approvals, implement proactive risk management strategies, and customize repayment plans to reduce default rates. Ultimately, this enhances financial stability while promoting sustainable lending practices.

Thus, the objective of this study is to evaluate the most suitable ML model for loan default prediction. The significance of this research lies in its potential to support financial institutions in enhancing risk assessment accuracy, reducing non-performing loans, and improving credit allocation. By systematically comparing traditional and ensemble ML algorithms on a large borrower dataset, the study provides evidence-based guidance for selecting predictive models that balance accuracy, fairness, and interpretability. This is particularly important in Malaysia and other developing economies where regulatory scrutiny, financial inclusion, and systemic stability are pressing concerns. Motivated by the rising complexity of borrower behavior and the limitations of conventional credit scoring systems, the study addresses a critical need for more sophisticated, data-driven tools that can capture non-linear patterns in loan performance. In doing so, it contributes to both academic knowledge and practical policy discussions on the adoption of AI-driven technologies in financial risk management.

Literature Review

Loan Default

A study by An et al. (2020) highlights the importance of a borrower's profile in predicting loan

default risk. Factors such as favorable loan terms, high credit scores, stable yearly income, and responsible line recycling rates reduce an individual's risk of default. Besides, variables such as loan interest rates, debt-to-income (DTI) ratios, and the number of negative public records increase the likelihood of defaulting on a loan. The study concludes that as borrowing rates, DTI ratios and negative public records increase, the likelihood of loan default also increases. Besides, research showed interest rates indicate the cost of borrowing money and are often expressed as a percentage of the borrowed amount. Higher interest rates increase loan costs, making it harder for borrowers to repay their loans. This is because higher rates raise installment amounts, which can lead to poor loan performance. Loan default and interest rates are closely related, in which as higher interest rates make regular payments more difficult. Furthermore, a borrower's ability to repay a loan is strongly tied to income. A borrower with a high and stable monthly income from various sources is more likely to meet repayment obligations. Conversely, those with lower incomes are more likely to struggle with loan payments, leading to a higher risk of default (Uddin, 2019). Besides, a descriptive study by Ali (2021) examined factors influencing loan default risk among 176 respondents from the banking sector, using a "Yes" or "No" checklist questionnaire. The results showed that over 80% of respondents agreed on the importance of interest rate, income, loan size, loan payment tenure, and borrower history. Specifically, 89.77% cited loan size, 86.36% income, 84.66% interest rate, 83.52% loan tenure, and 80.68% borrower history as key determinants of default risk.

These studies collectively indicate that loan default risk is shaped by both borrower characteristics and loan attributes. However, they also reveal the limitations of traditional assessment approaches, which may overlook non-linear relationships between factors. For instance, the interaction between income and loan size may amplify risk in ways not captured by simple

statistical models. This gap highlights the motivation for using advanced ML techniques capable of handling complex patterns, interactions, and non-linearities in borrower data, providing a more comprehensive and accurate prediction of default risk.

Machine Learning Models

ML has significantly improved loan credit analysis by leveraging big data and advanced computational techniques. Financial institutions can assess credit risk more accurately by analyzing borrower's personal information, credit history, and other relevant factors, leading to more informed loan decisions (Raheem, 2024). A key advantage of ML in credit risk assessment is its ability to learn patterns from historical data and generate predictions without explicit programming. Among various ML techniques, supervised learning is the most widely used, as it trains a model on a labeled dataset to recognize relationships and predict outcomes for new, unseen data. Unlike traditional econometric models that explain relationships between variables, ML models prioritize predictive accuracy, enabling more dynamic and adaptable decision-making. In addition, digital transactions generate massive amounts of valuable data. If effectively processed, this big data enhances credit risk assessment. The Covid-19 pandemic further underscored the need for faster and more reliable credit evaluation methods, as financial institutions faced increased loan applications and rising default risks. In contrast to traditional models, ML standardizes decision-making, improving efficiency and reducing inconsistencies (Hoang & Wiegatz, 2023). While ML adoption in banking is still in its early stages, its rapid growth signals a transformative shift in financial risk management.

Logistic Regression (LR) is a fundamental algorithm for binary classification. It assigns observations to distinct categories by estimating the probability of class membership. The model applies

the logistic sigmoid function to a linear combination of input features, mapping predictions into the range [0,1] (Patel et al., 2020). The sigmoid, with its characteristic S-shaped curve, transforms raw values into probabilities, enabling decision-making based on a specified threshold. Due to its simplicity, interpretability, and efficiency, LR remains a widely used baseline model in predictive analytics, although it is limited in capturing complex non-linear relationships.

Random Forest (RF) is an ensemble learning method designed to improve predictive accuracy and reduce overfitting by aggregating multiple decision trees (Patel et al., 2020). Each tree is trained on a random subset of both the dataset and its features, ensuring diversity among learners. For classification, RF predicts outcomes through majority voting, where the final class label (\hat{y}) is determined by the most frequent output across all trees:

$$\hat{y} = \text{mode}(T_1(x), T_2(x), \dots, T_n(x)) \quad (1)$$

For regression tasks, it calculates the average prediction from all decision trees:

$$\hat{y} = \frac{1}{n} \sum_{i=1}^n T_i(x) \quad (2)$$

where $T_i(x)$ represents the prediction from the i_{th} decision tree. This ensemble approach enhances stability and improves predictive performance.

Decision Trees (DTs) are supervised machine learning algorithms used for both classification and regression tasks. They structure data in a hierarchical, tree-like form, where internal nodes represent decisions based on specific features, branches indicate possible outcomes, and leaf nodes denote final predictions or class labels (Aslam et al., 2019). The tree recursively splits the dataset into smaller, more homogeneous subsets according to attribute-based conditions, resulting in an intuitive flowchart-like structure.

A key advantage of DTs is their interpretability: the visual tree structure makes it easy to trace how individual predictions are derived, which is valuable for decision-making processes in domains such as credit risk analysis, medical diagnosis, and recommendation systems.

To identify the most informative splits, DTs employ criteria such as **Entropy**, **Information Gain**, and the **Gini Index**:

Entropy Equation

$$H(S) = - \sum p_i \log_2 p_i \quad (3)$$

where P_i represents the probability of each class in the dataset. Entropy measures the impurity in a dataset, and a lower entropy value indicates a purer node.

Information Gain (IG)

$$IG = H(S) - \sum \frac{|S_v|}{|S|} H(S_v) \quad (4)$$

where $H(S)$ is the entropy before the split, S_v is a subset of S and $H(S)$ is the entropy of that subset. The feature with the highest IG is selected for splitting.

Gini Index

$$Gini(S) = 1 - \sum p_i^2 \quad (5)$$

where p_i is the probability of a class in the dataset. A lower Gini Index value indicates better split purity.

K-Nearest Neighbors (KNN) is a supervised ML algorithm used for both classification and regression tasks. It makes predictions by identifying the k nearest data points (neighbors) based on a selected distance metric. For classification, KNN assigns the majority class among the neighbors, while in regression, it calculates the average value. The choice of the k parameter significantly impacts the results, as different values of k can lead to varying

outcomes (Lai, 2020). The distance between a given test point x and each training point x_i is typically calculated using Euclidean distance:

$$d(x, x_i) = \sqrt{\sum_{j=1}^n (x_j - x_{ij})^2} \quad (6)$$

where x_j represents the feature values of the test sample, and x_{ij} represents the feature values of the training sample. The algorithm selects the k closest neighbors based on this distance and predicts the output as:

Classification: The majority class among the k neighbors (mode of the labels).

Regression: The average of the k nearest values.

Extreme Gradient Boosting (XGBoost) is an advanced ensemble learning algorithm that enhances the traditional gradient boosting algorithm while minimizing computational resource usage. It improves traditional gradient boosting by incorporating regularization to mitigate overfitting, optimizing sorting through parallel processing to speed up execution, and pruning trees based on maximum depth to reduce runtime. XGBoost constructs decision trees sequentially, where each new tree corrects the errors of the previous ones, making it highly effective for structured data problems such as classification and regression (Kanaparthi, 2023). The XGBoost algorithm follows the gradient boosting framework and optimizes the following objective function:

$$Obj = \sum_{i=1}^n L(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (7)$$

where $l(y_i, \hat{y}_i)$ represents the loss function that measures prediction error, and $\Omega(f_k)$ is the regularization term that controls model complexity. This formulation ensures a balance between model

accuracy and generalization, making XGBoost one of the most effective algorithms in predictive modeling.

Various scholars have explored the effectiveness of different ML models for predicting loan defaults, offering significant insights for financial institutions. Among these models, LR showed moderate performance overall. Notably, Orji et al. (2022) and Lin (2024) reported the highest accuracy, exceeding 80%, whereas Soni and Shankar (2022) recorded a lower accuracy of 65.34%. In contrast, the RF model consistently demonstrated high performance. Studies by Orji et al. (2022), Satheeshkumar et al. (2024), and Lin (2024) all reported accuracies above 90%, highlighting the model's robustness. For the DT model, performance varied. Orji et al. (2022) achieved the highest accuracy of 91.11%, whereas Zhu et al. (2023) reported the lowest at 63.17%, indicating moderate reliability overall. Regarding the KNN model also exhibited moderate accuracy across studies. The highest accuracy of 93.33% was achieved by Orji et al. (2022), while Soni and Shankar (2022) reported the lowest at 78.17%. XGBoost emerged as another strong performer, with Satheeshkumar et al. (2024) and Lin (2024) achieving accuracies above 95%. Zhu et al. (2023) also reported a respectable accuracy of 80.98%. This comparison highlights the growing effectiveness and reliability of ensemble learning techniques, particularly RF and XGBoost, in predicting loan defaults. These models consistently outperformed traditional algorithms, underscoring their potential as robust tools for risk assessment in financial institutions.

Methodology

Data Collection

This study employs a Kaggle dataset comprising borrower-related features that serve as the foundation for loan default prediction (Yesser, 2022). The original dataset contained 148,670 records across 34 features. After a structured preprocessing procedure,

the dataset was refined to 121,203 records with 27 features, ensuring improved quality and consistency. The dataset includes a broad range of borrower-specific attributes, such as personal details, loan characteristics, and credit history information. The dependent variable is the **status** column, where a value of *1* indicates a defaulted loan and *0* represents a fully paid loan. The accuracy of predictive modeling is highly dependent on the quality of input data; hence, careful preprocessing was necessary to enhance the reliability and performance of the machine learning models applied in this study.

Data Preprocessing

To ensure data reliability, several steps were undertaken, as summarized in Figure 1. First, missing values were assessed, revealing that 14 of the 30

retained variables contained incomplete data. Variables with excessive missing values, such as *upfront charges*, *interest rate spread*, and *rate of interest*, were excluded to reduce bias and prevent unreliable conclusions.

For categorical variables (e.g., *loan limit*, *approval in adv*, *loan purpose*, *neg amortization*, *age*, and *submission of application*), missing entries were imputed using the **mode**. This approach preserved the categorical structure without artificially inflating variability. For numerical variables (e.g., *property value*, *income*, *loan-to-value ratio [LTV]*, and *debt-to-income ratio [DTI]*), missing data were replaced with the **median**, a measure less sensitive to extreme outliers than the mean.

Figure 1

Handle Missing Value

```
# Drop columns with too many missing values
LoanDefault.drop(columns=['Upfront_charges', 'Interest_rate_spread', 'rate_of_interest'], inplace=True)

# Fill categorical columns with mode (most common value)
categorical_cols = ['loan_limit', 'approval_in_adv', 'loan_purpose', 'Neg_amortization', 'age', 'submission_of_application']
for col in categorical_cols:
    LoanDefault[col] = LoanDefault[col].fillna(LoanDefault[col].mode()[0])

# Fill numerical columns with median
numerical_cols = ['property_value', 'income', 'LTV', 'dtir1']
for col in numerical_cols:
    LoanDefault[col] = LoanDefault[col].fillna(LoanDefault[col].median())

# Drop rows with missing values in 'term'
LoanDefault.dropna(subset=['term'], inplace=True)

# Verify no missing values remain
print(LoanDefault.isnull().sum())
```

Data Transformation

Figure 2 shows label encoding was applied to convert categorical variables into numerical format, making them suitable for ML models. Label

encoding assigns a unique integer to each category, ensuring that algorithms can effectively process and interpret the categorical data.

Figure 2

Label Encoding

```

: # Encode categorical variables using Label Encoding

from sklearn.preprocessing import LabelEncoder

categorical_cols = LoanDefault.select_dtypes(include=["object"]).columns
label_encoders = {}

for col in categorical_cols:
    le = LabelEncoder()
    LoanDefault[col] = le.fit_transform(LoanDefault[col])
    label_encoders[col] = le # Store encoders for future use

: #to check the result after one-hot encoding
LoanDefault.head(10)
:

```

	ID	year	loan_limit	Gender	approv_in_adv	loan_type	loan_purpose	Credit_Worthiness	ope
0	24890	2019	0	3	0	0	0	0	0
1	24891	2019	0	2	0	1	0	0	0
2	24892	2019	0	2	1	0	0	0	0
3	24893	2019	0	2	0	0	3	0	0
4	24894	2019	0	1	1	0	0	0	0
5	24895	2019	0	1	1	0	0	0	0

Figure 3 showed remove the unnecessary or irrelevant variables to simplify the dataset and enhance model performance. The year variable was dropped because it is unlikely to directly affect loan default and may introduce noise. Additionally,

columns such as construction type, secured by and security type were removed because they contained the same value for all records, providing no useful information to the model.

Figure 3

Drop Unnecessary Column

```

In [13]: LoanDefault = LoanDefault.drop(columns=["year", "construction_type", "Secured_by", "Security_Type"])

```

Figure 4 illustrates the process of detecting outliers using the Interquartile Range (IQR) method. This technique was applied to four key numerical columns, including property_value, income, LTV,

and dtir1. For each column, a table was generated to list the identified outlier values for further review.

Figure 4

Detect Outlier

```

# Function to detect outliers using IQR
def detect_outliers_iqr(data, column):
    Q1 = data[column].quantile(0.25)
    Q3 = data[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return data[(data[column] < lower_bound) | (data[column] > upper_bound)]

# Function to remove outliers using IQR
def remove_outliers_iqr(data, column):
    Q1 = data[column].quantile(0.25)
    Q3 = data[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return data[(data[column] >= lower_bound) & (data[column] <= upper_bound)]

# Same setup as before
outlier_columns = ["property_value", "income", "LTV", "dtir1"]
outlier_tables = []

for col in outlier_columns:
    df = detect_outliers_iqr(LoanDefault, col)[["ID", col]].copy()
    df.insert(0, "Column", col)
    df.rename(columns={col: "Outlier Amount"}, inplace=True)
    outlier_tables.append(df)

# Combine all vertically (row-wise) in the order specified
stacked_table = pd.concat(outlier_tables, ignore_index=True)

# Display result
print("Detected Outliers (Stacked by Column Order):")
stacked_table

```

Figure 5 shows the removal of these outliers from the dataset. Outliers are unusual values that can negatively impact model performance by introducing

noise or skewed results. Removing them helps improve the model's accuracy and reliability.

Figure 5

Remove Outlier

```

# Remove outliers from each column
LoanDefault = LoanDefault.copy()
for col in outlier_columns:
    LoanDefault = remove_outliers_iqr(LoanDefault, col)

print("Data after removing outliers:")
LoanDefault

```

Model

In this study, the LR, DT, RD, XGBoost, and KNN algorithms used to analyze borrower data from Kaggle and predict the likelihood of default (Table 1). These algorithms are widely used for classification problems in financial risk analysis.

Table 1

Libraries Used for Models

Model	Library	Class
Random Forest	scikit-learn	RandomForestClassifier
XGBoost	XGBoost	XGBClassifier
Decision Trees	scikit-learn	DecisionTreeClassifier
KNN	scikit-learn	KNeighborsClassifier
Logistic Regression	scikit-learn	LogisticRegression

First, the RF model was selected to predict loan default due to its ability to handle large datasets and complex data structures effectively. It can minimize the impact of noise and outliers, which is beneficial given the diverse nature of the dataset. The model was implemented using the RandomForestClassifier from the scikit-learn library with 100 decision trees (`n_estimators=100`) to enhance prediction accuracy. Using 100 decision trees because it provides a balance between reliable predictions and manageable processing time, especially for large datasets with diverse patterns. Second, the XGBoost was chosen for its efficiency in handling large datasets and its strength in managing imbalanced data through gradient boosting. The model was built using the XGBClassifier from the XGBoost library with 100 estimators (`n_estimators=100`), which is similar to the Random Forest.

Third, the DT model was applied for its simplicity and ease of interpretation. It effectively handles both numerical and categorical data, making it flexible for diverse datasets. The model was implemented using the DecisionTreeClassifier from the scikit-learn library, with a set random state (`random_state=42`) for consistent results. The value 42 was chosen because it is widely used as a standard seed to ensure reproducibility when splitting the dataset results. In addition, the hyperparameter tuning was conducted using GridSearchCV from the scikit-learn library to optimize the model. The `param_grid` explored different values for `max_depth`, `min_samples_split`, and `min_samples_leaf`. Setting `max_depth` limits the tree's depth, preventing overfitting; `min_samples_split` controls the minimum samples required to split a node, helping the model generalize better; and `min_samples_leaf` ensures a minimum number of samples at a leaf node, reducing overfitting. GridSearchCV used 5-fold cross-validation (`cv=5`), `scoring='accuracy'` to focus on prediction precision, and `n_jobs=-1` to speed up processing. This approach aimed to find the best combination of hyperparameters, enhancing model performance and reducing overfitting.

Fourth, the KNN was chosen for its simplicity and effectiveness in handling classification tasks such as predicting loan defaults. The model was implemented using the KNeighborsClassifier from the scikit-learn library. Before training the model, the StandardScaler was used to normalize the dataset (`X_balanced_scaled` and `X_test_scaled`). This scaling process was necessary because KNN relies on distance calculations, and having features on a similar scale ensures fair comparisons. The number of neighbors (`n_neighbors=5`) was set to balance bias and variance. Using 5 neighbors helps the model generalize better, avoiding overly complex decision boundaries while maintaining accuracy. Fifth, the LR was chosen because of its simplicity and efficiency in binary classification tasks such as predicting loan defaults. It is effective in situations where the relationship between variables is mostly linear. The model was implemented using the LogisticRegression from the scikit-learn library. Before fitting the model, the StandardScaler was applied to normalize the dataset (`X_train_scaled` and `X_test_scaled`), stabilizing the model's performance and speeding up convergence. Hyperparameter tuning was conducted using GridSearchCV with a parameter grid (`param_grid = {'C': [0.01, 0.1, 1, 10, 100]}`) to optimize the regularization strength.

Results and Discussion

Descriptive Analysis

The heatmap visualizes the correlation coefficients between variables, providing an intuitive way to examine relationships and dependencies within the dataset. Colors represent both the strength and direction of correlations, making it easier to detect patterns (Jain, 2024). In Figure 6, the correlation values range from -0.4 to 0.8, indicating weak to strong linear relationships. A strong positive correlation is observed between *property value* and *loan amount* (0.82), indicating that applicants requesting larger loans are generally purchasing higher-value properties. Likewise, *income* is

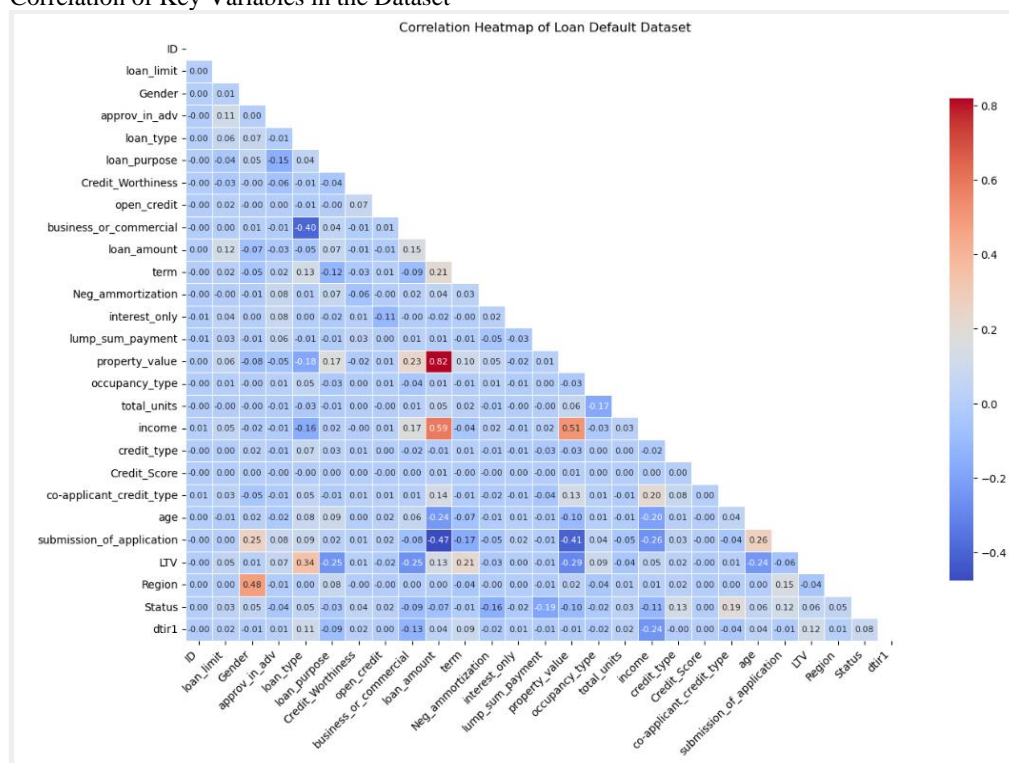
positively correlated with both *loan amount* (0.59) and *property value* (0.51), suggesting that higher-income individuals are more likely to purchase expensive properties and apply for larger loans. A moderate positive relationship is also identified between *gender* and *region* (0.48), which may reflect demographic trends across different geographical areas.

On the negative side, the *submission of application* variable shows a moderate negative correlation with both *loan amount* (−0.47) and *property value* (−0.41). This indicates that applications not submitted through institutional channels are generally associated with smaller loan

sizes and lower-value properties. Similarly, *business or commercial* shows a negative correlation with *loan type* (−0.40). These correlation patterns provide meaningful insights into applicant behavior and loan characteristics. However, it is important to note that no variable exhibits a strong correlation with the dependent variable, Status (loan default outcome). This finding implies that default behavior is unlikely to be explained by a single predictor but rather by a combination of multiple factors or complex non-linear interactions. Consequently, advanced predictive modeling techniques are essential to uncover the underlying drivers of loan default more accurately.

Figure 6

Correlation of Key Variables in the Dataset



Source: Anaconda Jupyter Notebook

Data Splitting

The dataset was partitioned into training and testing subsets using an 80:20 split ratio implemented via the *train_test_split* function in *scikit-learn* (Figure 7). In this approach, 80% of the data (96,962

records) was used to train the models, enabling them to learn underlying patterns, while the remaining 20% (24,241 records) served as the test set to evaluate performance on unseen data. To ensure reproducibility, the split was performed with a fixed

random state (=42), guaranteeing that repeated runs would yield consistent partitions.

An examination of the target variable (*Status*) revealed a class imbalance: the majority of cases were non-defaults (0), while defaults (1) constituted a smaller proportion. Specifically, the training set contained 72,924 non-defaults and 24,038 defaults, whereas the test set comprised 18,192 non-defaults and 6,049 defaults. This imbalance reflects the real-world lending environment, where defaults occur less frequently than successful repayments.

Rather than artificially altering the dataset distribution through resampling, the study focused on selecting models that are naturally more robust to imbalance. Ensemble methods such as Random Forest and XGBoost are particularly well-suited in this context, as they can better handle skewed datasets by capturing complex patterns and weighting misclassifications more effectively. This approach ensures that predictive modeling remains aligned with practical applications, where imbalanced credit datasets are the norm.

Figure 7

Training and Testing Datasets After Splitting

```
X_train shape: (96962, 26)
X_test shape: (24241, 26)
y_train shape: (96962,)
y_test shape: (24241,)

Class distribution in y_train:
Status
0    72924
1    24038
Name: count, dtype: int64

Class distribution in y_test:
Status
0    18192
1     6049
Name: count, dtype: int64
```

Test Results

Table 2 presents the evaluation outcomes for the five machine learning models using accuracy, precision, recall, and F1-score. Among them, XGBoost demonstrates the strongest overall performance, achieving the highest accuracy of 89.70% with a strong balance across precision, recall, and F1-score. This indicates its effectiveness in handling the imbalanced dataset and capturing complex feature interactions. Random Forest closely follows with an accuracy of 89.07% and a Class 1 F1-score of 0.73; however, its recall of 0.60 is slightly lower than that of the Decision Tree model. Decision Tree (DT) achieves a competitive accuracy of 88.47%, though its recall of 0.64 highlights some difficulty in consistently identifying all default cases, reflecting its vulnerability to overfitting despite being highly interpretable. By contrast, K-Nearest Neighbors (KNN) performs less effectively, with an accuracy of 84.78% and a Class 1 F1-score of 0.64, suggesting difficulty in distinguishing between defaults and non-defaults due to its sensitivity to class imbalance and distance metrics. Logistic Regression (LR) shows the weakest performance, achieving only 77.32% accuracy, with a recall of 0.22 and a Class 1 F1-score of 0.32, indicating significant misclassification of default cases. Overall, the results highlight the superiority of ensemble methods such as XGBoost and Random Forest, which not only deliver the highest accuracies but also provide the best trade-off between precision and recall. For financial institutions, this translates into models that more effectively capture true defaults, thereby reducing potential credit losses, while minimizing false positives and avoiding unnecessary loan rejections. In contrast, the weaker performance of simpler models such as KNN and LR underscores the challenges of applying traditional approaches to complex and imbalanced credit datasets.

Table 2

Performance Evaluation of Machine Learning Models for Loan Default Prediction

Model	Class	Precision	Recall	F1-score	Accuracy
Random Forest	0	0.88	0.99	0.93	89.07%
	1	0.94	0.60	0.73	
XGBoost	0	0.89	0.98	0.93	89.70%
	1	0.92	0.64	0.76	
Decision Trees	0	0.88	0.98	0.93	88.47%
	1	0.92	0.59	0.72	
KNN	0	0.86	0.95	0.90	84.78%
	1	0.77	0.55	0.64	
Logistic Regression	0	0.79	0.96	0.86	77.32%
	1	0.63	0.22	0.32	

Receiver Operating Characteristic (ROC) Curve Analysis

The Receiver Operating Characteristic (ROC) curve was used to evaluate the trade-off between sensitivity (true positive rate) and specificity (true negative rate), with the Area Under the Curve (AUC) serving as a summary measure of each model's discriminatory power. The Random Forest (RF) model achieved an AUC of 0.89, indicating strong ability to distinguish between defaulters and non-defaulters while maintaining a good balance between identifying true positives and minimizing false positives. Similarly, the XGBoost model also recorded an AUC of 0.89, reflecting excellent discriminatory capability, largely due to its advanced boosting technique that optimizes learning from misclassified cases. The Decision Tree (DT) model performed slightly lower with an AUC of 0.86, suggesting decent performance but with potential risks of overfitting that may reduce generalization. The K-Nearest Neighbors (KNN) model achieved a moderate AUC of 0.81, showing reasonable but less effective differentiation, likely due to its sensitivity to class imbalance and distance metrics. Logistic

Regression (LR) recorded the lowest AUC of 0.74, indicating limited ability to separate the two classes, though it remains valuable as a simple, fast, and interpretable baseline. Taken together, the ROC analysis reinforces that ensemble models, particularly RF and XGBoost, provide the most reliable performance for loan default prediction, whereas simpler models demonstrate weaker classification ability under imbalanced conditions.

Importance Feature in Loan Default Prediction

Figure 8 shows that the most crucial feature for Random Forest (RF) in predicting loan defaults is the loan-to-value (LTV) ratio. Gonzalez et al. (2016) found that higher initial LTV ratios are associated with greater default risk. Other significant features include property value, credit type, and the debt-to-income (DTI) ratio, which emphasize the borrower's financial standing and ability to manage debt. In addition, features such as income and credit score also play important roles, reinforcing the borrower's earning capacity and creditworthiness. Zhou et al. (2018) reported that the total assets of the borrower have no significant impact on loss given default (LGD). However, a better credit score and lower DTI ratio help reduce loan default risk, while longer loan tenures and larger loan amounts increase it. Therefore, when evaluating a borrower's repayment ability, greater attention should be given to the structure of assets rather than the overall size of total assets (Zhou et al., 2018). Overall, the RF model appears to prioritize financial stability and traditional risk factors when assessing loan default risk.

Figure 8

Importance Feature in Loan Default Prediction for RF

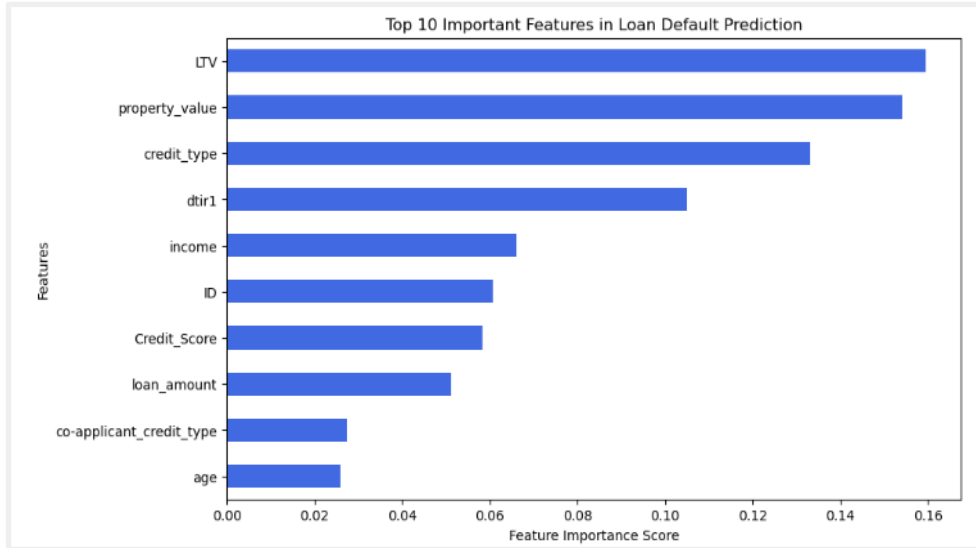
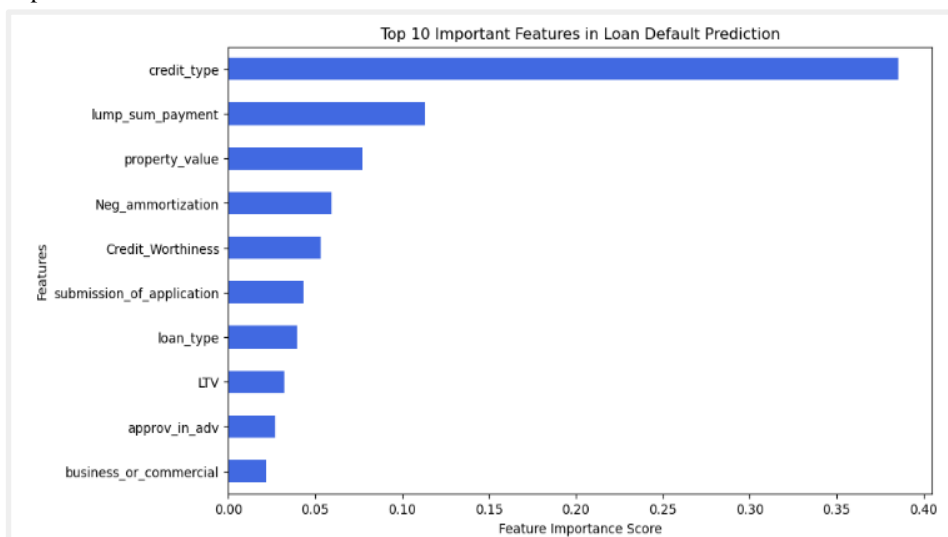


Figure 9 shows that the most crucial feature for XGBoost in predicting loan defaults is the credit type, indicating that the kind of credit a borrower holds plays a central role in assessing default risk. In addition, lump sum payment emerges as an important factor, suggesting that a borrower's ability to make substantial payments may reduce the likelihood of default. The inclusion of property value further highlights the relevance of the asset's worth in prediction. The study also shows that loan type and negative amortization are important features in the

XGBoost model, demonstrating its ability to capture detailed loan and borrower behaviors. Negative amortization occurs when a borrower's monthly loan payment is insufficient to cover the interest on the loan. In contrast, the Random Forest model ranks LTV as one of the top features, whereas LTV is less important in XGBoost. This suggests that XGBoost emphasizes loan-specific details and borrower behavior rather than relying primarily on traditional financial ratios.

Figure 9

Importance Feature in Loan Default Prediction for XGBoost



Conclusion

Loan default significantly impacts banks' profitability, credit circulation, and market confidence. High default rates not only lead to an increase in non-performing loans but also prompt banks to adopt more stringent lending practices, thereby limiting credit access for both households and businesses. Therefore, enhancing credit risk evaluation is essential for supporting healthy lending activities and maintaining the stability of the financial system.

This study aimed to develop an effective predictive model for loan default using a publicly available dataset from Kaggle, which originally contained 34 features. A series of comprehensive data preprocessing steps were conducted to ensure data quality and model readiness. First, missing values were addressed to ensure the dataset was clean and suitable for analysis. Second, categorical variables were transformed using label encoding, converting them into numerical values that ML algorithms can process effectively. This method assigns a unique integer to each category, ensuring proper interpretation by the models. In addition, the "year" column was dropped, as it was unlikely to contribute meaningfully to loan default prediction and could introduce unnecessary noise. Outlier detection was then performed using the Interquartile Range (IQR) method on four key numerical columns—property value, income, LTV, and DTI ratio. For each of these columns, outliers were identified and removed to enhance model performance. Eliminating outliers helped reduce noise and potential distortions in model training, thereby improving accuracy and reliability.

The original dataset consisted of 148,670 records with 34 features. After preprocessing, the dataset was refined to 121,203 records with 27 features. To predict loan default, five ML algorithms were applied: LR, DT, RF, XGBoost, and KNN. The dataset was split into training and testing sets using

an 80:20 ratio before model training began. Among the five ML models, XGBoost and RF delivered the best performance, both achieving high accuracy (89%), strong F1-scores, and AUC scores of 0.89. The DT model also showed good performance (88.47% accuracy, 0.86 AUC score), while KNN (84.78% accuracy) struggled with false positives, lowering its precision. LR performed the weakest, particularly in recall and AUC score (0.74). Overall, XGBoost and RF emerged as the most effective models for credit risk assessment. In summary, this study demonstrates the value of ML models—particularly ensemble methods such as XGBoost and RF—in improving the accuracy and reliability of loan default prediction. These models enable more effective identification of high-risk borrowers, leading to better lending decisions, reduced bad debt, and stronger credit risk management. As the financial industry continues to move toward data-driven decision-making, the application of these models in loan assessments can enhance the stability and resilience of lending systems.

From a theoretical perspective, previous research on loan default prediction has primarily relied on traditional methods such as rule-based credit scoring, expert judgment, and basic statistical models. These approaches often fail to capture the complex patterns in borrower behavior. This study addresses these limitations by applying advanced ML algorithms to improve prediction accuracy. By comparing model performance using metrics such as accuracy, recall, and F1-score, the study demonstrates the value of data-driven approaches in enhancing credit risk assessment and contributes to the advancement of financial risk management techniques.

From a practical perspective, this study recommends implementing the RF model into financial institutions' automated credit scoring systems. This integration would allow institutions to identify high-risk applicants early in the process, thereby increasing efficiency and reducing subjectivity in loan decisions. The model offers a

scalable and dependable solution that supports loan officers in making faster, more informed decisions while minimizing manual workload and potential bias.

At the policy level, this study calls for government support through targeted research and development (R&D) subsidies and innovation funding. By establishing dedicated funds and offering grants or low-interest loans, policymakers can incentivize collaboration between financial institutions and technology firms to develop ML tools tailored for credit risk evaluation. Such initiatives foster innovation, strengthen the industry's risk control capabilities, and encourage the responsible and inclusive adoption of data-driven lending practices.

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Financial Literacy, Planning Behavior, and Bank Choice: A Comparative Review of Islamic and Conventional Depositors

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Received: 20.03.2025, Revised: 30.05.2025, Accepted: 12.08.2025

Abstract

This review critically examines how financial literacy and financial planning behavior shape depositor preferences in dual banking systems, with a comparative focus on Islamic and conventional banks. Synthesizing 42 peer-reviewed studies from Southeast Asia, South Asia, and the Middle East, the findings reveal that Islamic financial literacy enhances ethical banking intentions, while planning behavior serves as a behavioral bridge between knowledge and action. Trust in financial institutions mediates the relationship between literacy and bank choice, and religious motivation moderates the alignment between depositor values and actual behavior. Despite increasing interest in Islamic finance, gaps persist in functional literacy, digital financial planning tools, and the integration of Islamic ethics into mainstream financial education. This study proposes a conceptual framework linking cognitive, behavioral, and institutional factors, and offers policy recommendations to strengthen Shariah governance, improve financial inclusion, and embed Islamic principles in national literacy programs. Future research should explore longitudinal impacts, develop multidimensional literacy scales, and investigate digital trust and social norms in depositor decision-making.

Keywords: Islamic financial literacy, financial planning behavior, depositor behavior

Introduction

The emergence of dual banking systems, where Islamic and conventional banks coexist, has significantly transformed the financial landscape in many Muslim-majority countries, including Indonesia. This structure offers consumers a broader spectrum of financial products, allowing them to align their banking choices with both economic and ethical considerations (Quang Trinh, 2022). In particular, the decision to deposit funds in either Islamic or conventional banks reflects not only financial motives but also religious values, trust in institutions, and long-term financial planning goals.

Despite the growing market share of Islamic banking, its penetration remains modest compared to conventional banking. For instance, Indonesia's Islamic banking sector accounts for less than 10% of total banking assets, a figure often attributed to low levels of Islamic financial literacy and limited public

understanding of Shariah-compliant financial instruments (Masrizal et al., 2025). This suggests that depositor behavior is influenced not only by product availability but also by the depth of financial knowledge and planning capacity among consumers.

Financial literacy, defined as the ability to understand and apply financial concepts, has been widely recognized as a key determinant of sound financial behavior (Robb & Woodyard, 2011). In the context of Islamic finance, this extends to understanding the principles of *riba* (interest), *gharar* (uncertainty), and *maysir* (speculation), which are prohibited under Shariah law (Khan & Arif, 2022). Research has shown that Islamic financial literacy positively influences attitudes toward Islamic banking and enhances the intention to use Shariah-compliant products (Anindita et al., 2024; Firdausi & Kasri, 2022). However, the extent to which financial

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literacy shapes actual deposit behavior, particularly in comparison to conventional banking, remains underexplored.

Equally important is financial planning behavior, which encompasses budgeting, saving, goal-setting, and risk management. These behaviors are foundational to household financial resilience and are closely linked to deposit decisions (Yeo et al., 2024). Individuals who engage in structured financial planning are more likely to evaluate banking options based on long-term goals rather than short-term incentives. Yet, in dual banking environments, planning behavior may be moderated by religious beliefs, perceived institutional trust, and digital access—factors that vary significantly between Islamic and conventional banks.

Despite the relevance of these behavioral dimensions, the literature remains fragmented. Most studies focus either on financial literacy or on religious motivations, without integrating these factors into a comprehensive framework of financial planning and bank choice. Moreover, few comparative studies have examined how these variables interact to influence deposit behavior across banking types. This gap is particularly pronounced in emerging economies, where financial inclusion and literacy remain unevenly distributed.

This review article aims to synthesize and critically evaluate the existing literature on financial literacy, planning behavior, and deposit preferences in dual banking systems. Specifically, it seeks to (i) identify the behavioral and cognitive determinants of bank choice, (ii) assess how financial literacy and planning behavior mediate depositor decisions, and (iii) highlight gaps in the literature that warrant further empirical investigation. By integrating insights from behavioral finance, Islamic economics, and consumer decision theory, this study contributes to a more holistic understanding of depositor behavior and offers a conceptual foundation for future research.

Literature Review

Financial Literacy and Bank Choice Behavior

Financial literacy is widely recognized as a foundational determinant of financial decision-making. Robb and Woodyard (2011) define it as the ability to understand and apply financial concepts, which directly influences budgeting, saving, and investment behavior. In conventional banking contexts, higher financial literacy correlates with increased use of formal financial services and more rational deposit decisions (Yeo et al., 2024).

In Islamic banking, financial literacy encompasses not only conventional financial knowledge but also an understanding of Shariah principles such as the prohibition of *riba* (interest), *gharar* (uncertainty), and *maysir* (speculation). Khan and Arif (2022) found that Islamic financial literacy significantly predicts the intention to use Islamic banking services, especially when financial considerations are aligned with religious values. Similarly, Firdausi & Kasri (2022) observed that Muslim students with higher Islamic financial literacy were more likely to choose Islamic banks, suggesting that literacy acts as both a cognitive and ideological filter in bank selection.

However, the literature also reveals a persistent gap between intention and behavior. While many consumers express a preference for Islamic banking, actual usage remains low due to limited product awareness, perceived complexity, and lack of trust in Islamic financial institutions (ShabbirHusain et al., 2024). This indicates that financial literacy alone may be insufficient to drive behavioral change without complementary factors such as institutional credibility and service accessibility.

Financial Planning Behavior and Depositor Preferences

Financial planning behavior, encompassing goal-setting, budgeting, and long-term saving, is another

critical factor influencing deposit decisions. Yeo et al. (2024) argue that individuals who engage in structured financial planning are more likely to evaluate banking options based on long-term financial goals rather than short-term incentives. This behavior is particularly relevant in deposit decisions, where risk tolerance, liquidity needs, and interest expectations play a role.

In Islamic banking, planning behavior is often moderated by religious beliefs and ethical considerations. Anindita et al. (2024) found that Islamic financial literacy, money attitudes, and the social environment significantly influence financial planning among young Muslim couples. Their study suggests that planning behavior in Islamic contexts is not merely utilitarian but also shaped by communal norms and spiritual values.

Despite these insights, few studies have examined how financial planning behavior interacts with bank choice in dual banking systems. Most research treats planning as a standalone variable, without exploring its mediating role between literacy and deposit behavior. This limits our understanding of how consumers integrate financial knowledge with behavioral strategies when choosing between Islamic and conventional banks.

Trust, Institutional Perception, and Religious Motivation

Trust in financial institutions is a recurring theme in deposit behavior literature. In conventional banking, trust is often built through transparency, regulatory compliance, and service quality. In Islamic banking, trust also hinges on perceived Shariah compliance and the credibility of religious oversight bodies (AlQassar & Ahmed, 2022; Ayub et al., 2024).

Religious motivation plays a nuanced role in bank choice. While some consumers prioritize Shariah

compliance, others weigh it against financial returns and convenience. Zulfaka and Kassim (2023) noted that low Islamic financial literacy contributes to skepticism about the authenticity of Islamic banking products, leading many consumers to default to conventional banks despite religious preferences.

This tension between religious ideals and practical considerations underscores the need for more integrative models of depositor behavior. Existing studies often isolate religious motivation from financial planning and literacy, resulting in fragmented insights that fail to capture the complexity of decision-making in dual banking environments.

Literature Gap and Theoretical Implications

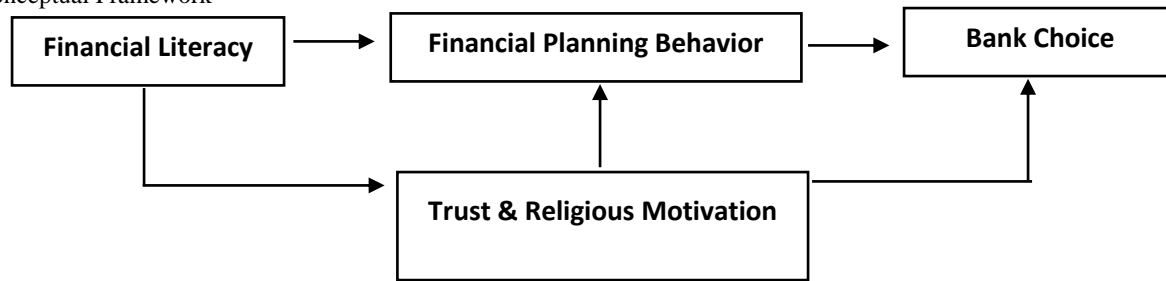
The reviewed literature highlights several gaps:

- **Limited integration of behavioral and cognitive factors** – Most studies examine financial literacy or planning behavior in isolation, without exploring their interaction or combined effect on bank choice.
- **Scarcity of comparative studies** – Few empirical works directly compare Islamic and conventional depositors, especially in emerging economies with dual banking systems.
- **Underexplored mediating variables** – Trust, digital access, and social norms are often mentioned but rarely modeled as mediators or moderators in depositor behavior frameworks.

These gaps suggest a need for a more holistic approach that synthesizes behavioral finance, Islamic ethics, and consumer psychology. Such a framework (see Figure 1) would enable researchers to better understand the nuanced trade-offs consumers make when choosing between Islamic and conventional banks.

Figure 1

Conceptual Framework



Methodology

This study adopts a systematic literature review approach to synthesize existing research on financial literacy, financial planning behavior, and bank choice within dual banking systems. The review aims to identify behavioral and cognitive determinants that influence depositor preferences between Islamic and conventional banks, particularly in emerging economies. To ensure methodological rigor, the review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.

A comprehensive search was conducted across multiple academic databases, including Scopus, Web of Science, ScienceDirect, Google Scholar, and the Directory of Open Access Journals (DOAJ). The search strategy employed a combination of keywords such as “Islamic financial literacy,” “financial planning behavior,” “bank choice,” “Islamic banking,” “conventional banking,” “dual banking system,” and “deposit behavior.” Boolean operators (AND, OR, NOT) were used to refine the search and capture relevant studies across disciplines.

The inclusion criteria were defined to ensure relevance and quality. Only peer-reviewed journal articles published between 2010 and 2024 were considered. Eligible studies had to focus on depositor behavior in Islamic and/or conventional banking contexts, be written in English or Bahasa Indonesia,

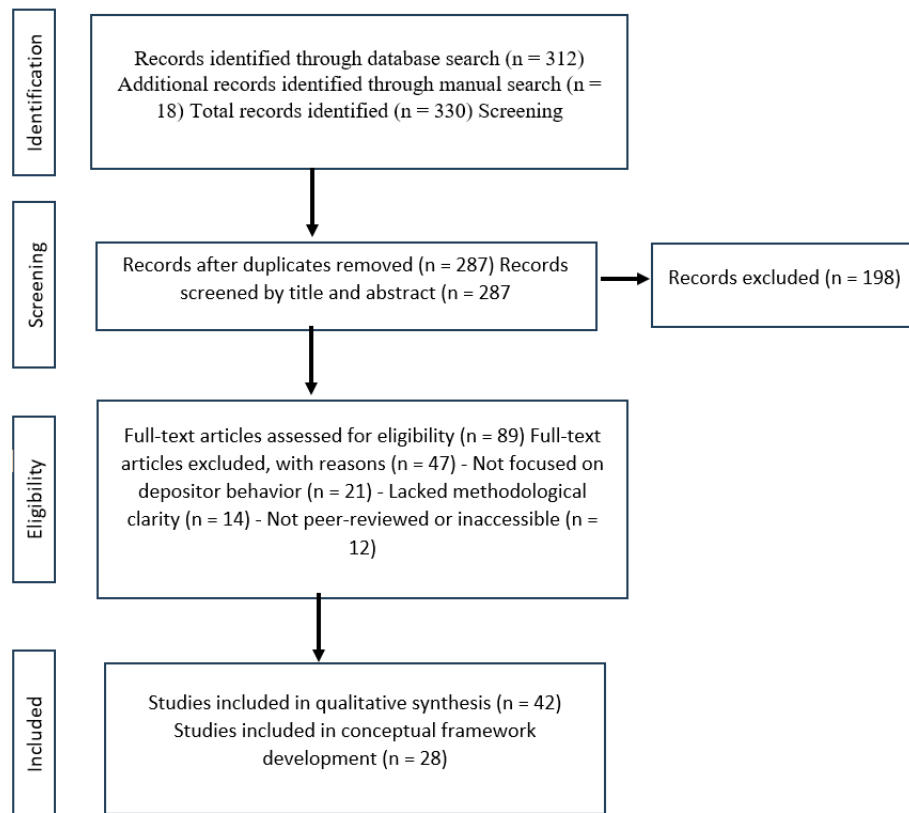
and present empirical or conceptual findings with clear methodological frameworks. Studies were excluded if they were non-peer-reviewed (e.g., blogs, news articles), lacked full-text access, or did not directly address financial literacy, planning behavior, or bank choice.

The screening process was conducted in three stages. First, titles and abstracts were reviewed to eliminate clearly irrelevant studies. Second, full-text articles were assessed for thematic relevance and methodological soundness. Third, a standardized coding sheet was used to extract key data, including author, year, country, variables studied, and main findings. To ensure consistency and reliability, each study was evaluated using the Mixed Methods Appraisal Tool (MMAT), which assesses the quality of qualitative, quantitative, and mixed-methods research.

Data synthesis was performed using a narrative approach, allowing for thematic integration of findings across diverse contexts. Patterns, contradictions, and gaps in the literature were identified and discussed in relation to the conceptual framework. The PRISMA flow diagram as shown in Figure 2 illustrates the systematic review process, including the number of records identified, screened, assessed for eligibility, and included in the final synthesis.

Figure 2

PRISMA Flow Diagram



Results and Discussion

This systematic review synthesized 42 peer-reviewed studies spanning Southeast Asia, South Asia, and the Middle East, offering a multidimensional understanding of depositor behavior in dual banking systems. The findings reveal a complex interaction between financial literacy, planning behavior, trust, and religious motivation, each shaping the decision to deposit in Islamic or conventional banks.

Financial Literacy: Beyond Awareness Toward Functional Understanding

Financial literacy emerged as a foundational cognitive determinant of bank choice. In conventional banking, it enables consumers to assess interest rates, compare products, and manage risk (Robb & Woodyard, 2011). In Islamic banking, however, literacy must encompass Shariah principles such as *riba* prohibition, risk-sharing, and ethical investment.

Studies by Khan and Arif (2022) and Firdausi & Kasri (2022) confirm that Islamic financial literacy (IFL) positively influences the intention to use Islamic banking services.

Yet, the review reveals a critical distinction between awareness-based literacy and functional literacy. Many consumers possess superficial knowledge of Islamic finance, recognizing terms like *riba* or “halal investment,” but lack the ability to evaluate product structures or compliance mechanisms (Dinc et al., 2021). This gap undermines informed decision-making and contributes to the low conversion of intention into actual usage. Bank Indonesia (2017) highlights that its financial education programs often subordinate Islamic financial values to conventional norms, resulting in fragmented understanding among consumers.

Moreover, the development of robust IFL measurement tools remains limited. While Dinc et al.

(2021) proposed a multidimensional IFL scale covering banking, takaful, and fund management, its application across diverse jurisdictions is still evolving. Without standardized metrics, assessing the true impact of literacy on depositor behavior remains challenging.

Financial Planning Behavior: A Behavioral Bridge Between Knowledge and Action

Financial planning behavior, defined by budgeting, saving, and goal-setting, acts as a behavioral bridge that translates financial literacy into tangible decisions. Yeo et al. (2024) argue that individuals with strong planning habits are more likely to engage in strategic deposit behavior, evaluating banks based on long-term goals rather than short-term incentives.

In Islamic contexts, planning behavior is deeply embedded in religious and social norms. Anindita et al. (2024) found that young Muslim couples who engage in financial planning are more inclined to choose Islamic banks, driven by both ethical alignment and perceived financial stability. However, planning behavior is not uniformly distributed. Rural populations and lower-income groups often rely on informal financial practices, lacking access to structured planning tools or advisory services.

This disparity suggests that financial planning behavior is not merely a personal trait but a socially conditioned practice. Educational interventions must therefore go beyond individual skill-building to address systemic barriers such as digital exclusion, limited outreach, and cultural perceptions of banking.

Trust and Religious Motivation: Mediating and Moderating Influences

Trust in financial institutions plays a pivotal mediating role in deposit decisions. In Islamic banking, trust is closely tied to perceptions of Shariah compliance, transparency, and institutional integrity. Rashid & Hassan (2009) found that trust significantly

mediates the relationship between Islamic financial literacy and the decision to use Islamic banks. Consumers who perceive Islamic banks as authentically Shariah-compliant are more likely to act on their intentions.

Religious motivation, while often cited as a driver of Islamic banking adoption, operates more as a moderating variable. Nazir & Saqib (2024) observed that while many consumers express a desire to align their financial behavior with Islamic values, practical considerations—such as product availability, digital access, and service quality—frequently override religious preferences. This tension reflects a broader challenge: Islamic banking must compete not only on ethical grounds but also on operational excellence.

Furthermore, Zulfaka & Kassim's (2023) discourse analysis reveals that national financial education programs often fail to integrate Islamic ethical frameworks, resulting in cognitive dissonance among Muslim consumers. This underscores the need for a paradigmatic shift in financial education, one that embeds Islamic values into mainstream financial literacy curricula.

Conclusion

This review has synthesized and critically examined the literature on financial literacy, financial planning behavior, and depositor preferences within dual banking systems, particularly in the context of Islamic and conventional bank choice. Drawing from 42 peer-reviewed studies across Southeast Asia, South Asia, and the Middle East, the findings reveal that depositor behavior is shaped by a complex interplay of cognitive understanding, behavioral habits, institutional trust, and religious motivation.

Financial literacy, especially Islamic financial literacy, serves as a cognitive filter that informs depositor attitudes and intentions. However, the gap between awareness and functional understanding remains a persistent barrier to Islamic banking

adoption. Financial planning behavior acts as a behavioral catalyst, translating knowledge into action, yet its distribution is uneven across demographic and socioeconomic groups. Trust in financial institutions mediates the relationship between literacy and bank choice, while religious motivation moderates the extent to which ethical values influence actual behavior.

These insights confirm the conceptual framework proposed in this study and underscore the need for a more integrated approach to understanding depositor behavior in dual banking systems. The review also highlights significant gaps in the literature, including the lack of comparative models, limited exploration of digital financial planning tools, and insufficient integration of Islamic ethical frameworks in mainstream financial education.

From a policy perspective, the findings suggest that national financial literacy initiatives should be restructured to incorporate Islamic financial principles, ensuring cultural and ethical relevance for Muslim-majority populations. Financial planning programs must be designed with greater sensitivity to demographic disparities, particularly targeting rural communities and low-income households that often lack access to formal financial education. Moreover, regulators and Islamic banking institutions should prioritize transparency, strengthen Shariah governance frameworks, and improve consumer engagement to build institutional trust. The development of Shariah-compliant digital banking platforms and financial planning tools also presents a strategic opportunity to enhance financial inclusion, especially among younger and digitally literate consumers.

Looking ahead, future research should focus on developing and validating multidimensional Islamic financial literacy scales that are adaptable across diverse cultural and economic contexts. Longitudinal and experimental studies are needed to establish causal relationships between financial literacy,

planning behavior, and bank choice, moving beyond the correlational insights that dominate current literature. The role of digital financial planning tools in shaping depositor behavior warrants deeper investigation, particularly in Islamic banking environments where ethical compliance intersects with technological innovation. Additionally, scholars should explore the influence of social norms, peer networks, and community-level dynamics using network-based or agent-based modeling approaches. Comparative studies across jurisdictions with varying levels of Islamic banking penetration could also yield valuable insights into structural and cultural determinants of depositor behavior.

Despite its contributions, this review is not without limitations. The scope was confined to peer-reviewed articles published in English and Bahasa Indonesia, potentially excluding relevant studies in other languages. The reliance on narrative synthesis may introduce interpretive bias, although thematic consistency was maintained through rigorous coding and cross-validation. Furthermore, the conceptual framework proposed remains theoretical and requires empirical validation through future research. Nonetheless, the review provides a robust foundation for understanding depositor behavior in dual banking systems and offers actionable insights for scholars, practitioners, and policymakers seeking to enhance financial inclusion and ethical banking engagement.

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Old Bands, New Signals: ESG-Driven Donchian Strategy in the Malaysian Stock Market

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Received: 04.03.2025, Revised: 20.05.2025, Accepted: 28.07.2025

Abstract

This paper investigates the performance of the rule-based Dual Donchian Bands (DC) technical strategy within the context of ESG-aligned equity portfolios in the Malaysian stock market. While the Efficient Market Hypothesis (EMH) asserts that asset prices fully reflect all available information, the consistent excess returns observed from technical trading strategies challenge the completeness of this framework, especially in markets influenced by non-financial factors such as ESG screening. To conduct the empirical study, we utilized more than 10 years of daily data from the FTSE4Good Bursa Malaysia Index (F4GBM) between 01/01/2015 and 31/05/2025. We implement a dual breakout system that synthesizes short- and long-term price channels to generate systematic entry and exit signals. Our results reveal that the DC delivers returns that outperform the passive buy-and-hold benchmark, with superior performance across key metrics such as the Sharpe ratio, Sortino ratio, and maximum drawdown. These findings suggest the presence of exploitable inefficiencies in the ESG-tilted market, which is often presumed to be less driven by speculative forces. Our results challenge the weak-form efficiency of Malaysian ESG stocks and contribute to the growing body of behavioural finance literature that highlights the potential for systematic predictability in asset prices.

Keywords: ESG, Bursa Malaysia, Donchian strategy, EMH, technical analysis

Introduction

The increasing complexity of global capital markets has led scholars and practitioners to reassess traditional views on asset pricing, portfolio construction, and investment strategy. Central to this issue, the EMH posits that all available information is rapidly reflected in asset prices, rendering systematic outperformance unfeasible through either fundamental or technical means (Fama, 1970). However, numerous empirical studies have reported inconsistent findings with this idea, particularly due

to market inefficiency, information asymmetries, and investor behavioural biases (Lo, 2004; Lim & Brooks, 2011). The controversy surrounding EMH has triggered the use of different approaches that include technical analysis (TA). This method employs historical price and volume data to identify trends, reversals, and support and resistance levels. It offers rule-based guidance for market entry and exit decisions (Murphy, 1999). A stream of studies documents the profitability of technical rules, especially in emerging markets or under weak-form efficiency environments (Nor & Wickremasinghe,

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2017; Park & Irwin, 2007). The use of advanced statistical tests and data-snooping adjustments, along with the advancement in computing ability, has further strengthened the empirical rigour of TA-based studies (Nor et al., 2023).

In addition, regulatory shifts in sustainability, ethical investing preferences, and long-term risk mitigation objectives have increased demand for environmental, social, and governance (ESG) investing. Several global market indexes, such as FTSE4Good and MSCI ESG Select, classify companies based on specific sustainability and governance criteria and track their performance over time. As ESG investing has conventionally been established by fundamental screening, recent literature has documented the application of TA in exploring the profitability of ESG-aligned stocks (Lee et al., 2024; Dutta et al., 2024). Furthermore, evidence linking green finance and sustainability outcomes in emerging markets (Ghouse et al., 2025) reinforces the relevance of integrating TA with sustainable investments. Notably, Nor et al. (2023) demonstrated that renewable energy stocks, which are aligned with ESG principles, exhibit sufficient technical characteristics for trend-based and hybrid-fractal trading strategies to outperform passive benchmarks.

The convergence of technical analysis and ESG investing holds practical implications not only for active asset management but also for personal financial planning. As more individuals adopt sustainability criteria in their investment objectives, financial planners are increasingly expected to integrate ESG preferences into holistic wealth management strategies. It enables planners to advise clients on the importance of market timing, tactical allocation, and short-term positioning within long-term ESG mandates. By incorporating rule-based trading systems, financial planners can simulate a dynamic portfolio construction approach. This is particularly important when navigating volatile or sentiment-driven ESG sectors. In terms of TA, the

Dual Donchian Bands (DC) presents a compelling case. This approach combines breakout signals from short-term and long-term Donchian Channels to capture sustained momentum while filtering noise from market fluctuations. Moreover, its simplicity and adaptability make it particularly suitable for ESG-focused investment portfolios, where price trends are often shaped by thematic flows and investor sentiment.

Despite its practical utility, the DC method remains underexplored in finance literature, unlike the more popular indicators like moving averages, relative strength index, and Bollinger Bands. Accordingly, this study contributes to the growing discourse at the intersection of sustainable investing and evidence-based market timing by evaluating the performance of the DC strategy applied to ESG index constituents.

Research Design

This study investigates the profitability of technical price patterns within the sustainable equity segment. We analyse daily stock data from the constituents of the FTSE4Good Bursa Malaysia Index (F4GBM) over the period from 1 January 2015 to 31 May 2025. The analysis encompasses 142 companies across a broad range of sectors, such as financial services, healthcare, consumer goods, technology, and plantations. The sample period includes several economic, geopolitical, and health crises such as the US-China trade war, Russia-Ukraine war, COVID-19, and the more recent Trump trade war.

In executing rule-based trading signals, we use DC, which is a trend-following system based on two Donchian channels. In short, the longer (shorter) band is used to gauge trend direction (as buy signals), while a drop below the shorter band low triggers a sell signal. Due to short-selling restrictions in Bursa Malaysia, we explore a long-only policy. For robustness, we run the analysis 18,176 times by

exploring standard and different combinations of short-long bands in the F4GBM portfolio. Further, instead of using simple return on investment, we investigate various metrics to gauge risk, return, and risk-return trade-off. These metrics include the Sharpe ratio, Sortino ratio, maximum drawdown (%), performance ratio, MAR ratio, recovery factor, and ulcer index. Consistent with prior literature in this area, we employ the buy-and-hold policy (BH) as the benchmark. This allows us to gauge the trading performance of active TA against a passive rule and formulate implications for the weak-form Malaysian ESG market efficiency.

Results and Discussion

In Table 1, we summarize the performance of DC against BH. The empirical results provide compelling

evidence of the superior risk-adjusted performance of DC relative to the traditional BH policy when applied to the F4GBM constituents. Notably, the top-performing DC configurations, particularly those with shorter entry channels, achieved markedly higher Sortino and Sharpe ratios compared to the modest ratios gained from the BH approach. These best channels also delivered substantial improvements in downside risk management (lower maximum drawdown) and superior effectiveness in mitigating capital erosion during adverse market conditions (lower ulcer index). Moreover, the MAR ratio and recovery factor for the best DC channels indicate greater efficiency in translating volatility exposure into excess returns, far surpassing the BH rule.

Table 1

Investment performance of Dual Donchian Bands and Buy-and-Hold policy

	Rank	Shorter Channel	Longer Channel	Sortino ratio	Sharpe ratio	Max Drawdown %	Performance Ratio	MAR Ratio	Recovery Factor	Ulcer Index
Panel A: Dual Donchian Bands										
Standard	33	20	120	1.95	0.68	-0.28	0.09	0.53	2.83	9.88
	1	15	150	2.67	0.76	-25.83	0.08	0.66	3.79	7.05
	2	15	270	2.65	0.79	-23.96	0.11	0.73	5.08	7.52
Best Channels	3	15	210	2.52	0.74	-25.29	0.09	0.67	3.86	7.77
	4	15	300	2.51	0.74	-24.20	0.09	0.66	4.07	7.99
	5	10	300	2.47	0.85	-18.09	0.09	0.89	5.43	6.59
	124	60	90	0.58	0.34	-21.10	0.05	0.15	1.19	8.86
	125	65	90	0.55	0.31	-24.76	0.04	0.11	0.78	8.89
Worst Channels	126	35	90	0.54	0.27	-22.88	0.04	0.15	1.05	10.03
	127	40	120	0.47	0.26	-24.74	0.03	0.11	0.82	11.25
	128	80	120	0.18	0.15	-35.24	0.03	0.03	0.30	17.46
Panel B: Buy-and-Hold Strategy										
				0.63	0.47		0.09	0.17	0.91	13.8

For transparency purposes, we also provide the suboptimal Donchian configurations. They exhibit notable underperformance, highlighting the sensitivity of trend-following strategies to parameter selection. Specifically, combinations involving longer short channels and narrower channel ranges (e.g., 80/120) not only yielded depressed Sortino and Sharpe ratios (0.18 and 0.15, respectively), but also suffered from severe drawdowns and elevated ulcer index scores (up to 17.46), effectively eroding investor confidence and long-term capital. For

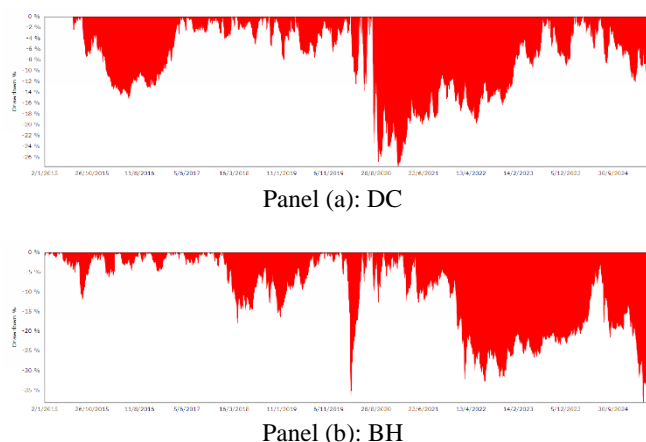
illustration purposes, Figure 1 shows the drawdowns of both DC and BH during the sample period.

It can be seen from the figure that DC experienced shallower drawdowns than the BH policy during the COVID-19 period, but its drawdown duration was longer. In contrast, BH endured a deeper drawdown exceeding 35% but began recovering more swiftly following initial stimulus-led rebounds. In more recent periods, DC continues to offer better downside protection. In summary, the findings highlight the

significant trade-off between trend responsiveness and noise filtration inherent in Donchian-based systems. The results reinforce the potential of technically informed ESG investing through DC, particularly with optimal parameters to balance trend duration and signal validity. Collectively, DC provides better return, lower risk, and greater risk-return trade-off against the BH policy.

Figure 1

Drawdowns for Dual Donchian Bands and Buy-and-Hold policy



Building upon the points established earlier, our results align closely with behavioural finance perspective. In short, investors exhibit systematic underreaction to ESG disclosures, delaying the full assimilation of sustainability-related information into stock prices. This inertia is periodically compounded by episodic surges of capital into green funds, which generate transient distortions in asset valuations and amplify short-term mispricing. Hence, this creates an exploitable setting for technical trading strategies to systematically profit from inefficiencies, allowing rules such as DC to capture persistent returns within ESG-oriented portfolios.

Conclusion and Implications

In this study, we employ daily price data from F4GBM constituents to evaluate the performance of DC relative to the BH policy. Using a systematic technical analysis approach, the strategy was tested

across various parameter combinations, with risk-adjusted performance assessed via several trading metrics. Our results reveal that wider channel DC configurations outperform BH in terms of both return-to-risk measures and capital preservation. However, the strategy also exhibited delayed recoveries due to its trend confirmation mechanics. Overall, our findings suggest the presence of exploitable price patterns and time-series dependencies in the ESG segment of an emerging market, thereby challenging the validity of weak-form efficiency. The evidence supports the incorporation of rule-based technical strategies in sustainable investment portfolios to enhance return and downside protection.

Note that while the results demonstrate superior performance of the DC over the BH rule, they should be interpreted with caution. In particular, the findings might reflect sample-specific dynamics, unaccounted trading frictions, or temporal anomalies that limit their generalisability across different markets and periods.

Future studies can further enhance this research by considering other factors or framework. For example, a deeper investigation can be made using fractals to identify different market phases for utilizing appropriate trending or contrarian indicators, as recently introduced by Nor et al. (2023) in their novel hybrid trading system approach. Moreover, formal statistical tests can be used to support our findings academically, by comparing the returns of the trading rules against the buy-and-hold policy. Future studies can also explore different equity markets, sectors, time periods (e.g. geopolitical conflicts, wars and health pandemic) and frictions, such as different types of trading costs and constraints, including round-lot and limited short-selling allowance. Finally, further research into different technical-based configurations, factors and optimization using machine learning techniques can be investigated, such as artificial neural networks and particle swarm optimization.

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Empowering Tomorrow's Seniors: Fostering Dignity Through Financial Literacy and Innovative Care Solutions

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A Real Story of Care: Family and Future Challenges

Amirul and Zulkarnain, two long-time friends, recently reunited at a local mamak restaurant after being apart since their graduation five years ago. Their conversation revealed the challenges they both face in caring for their ageing parents.

Amirul has been working in a big city but returned home to support his family during a difficult time. His mother was diagnosed with stage 4 liver cancer, which necessitates significant care and attention. He is concerned about her deteriorating health and shared that she requires expensive medication costing RM5,000, placing a financial strain on the family. Fortunately, Amirul's siblings were able to contribute to a pooled fund to cover the medication costs, easing some of the immediate financial pressure.

Similarly, Zulkarnain is also facing challenges related to his father's health. His father suffers from kidney problems that require regular dialysis treatment, which incurs substantial costs. Unlike Amirul, Zulkarnain works at a small company in their hometown, allowing him the flexibility to care for his father. This arrangement has given him the time necessary to manage his father's treatment and support.

As they discussed their situations, Amirul and Zulkarnain began to contemplate their futures. They expressed concerns about the potential health issues they might face in the future and how much they would need to save to ensure adequate healthcare coverage in their later years. They recognised the

importance of financial preparedness for future medical needs.

Key questions that emerged from their discussion include:

- How much do they need to save to fund their medical care in the future?
- What strategies can they implement to ensure financial stability as they age?
- How can they balance caregiving responsibilities with their own health and financial needs?
- What role can healthcare providers play in offering affordable treatment options and financial guidance?

How can local government initiatives or programs help alleviate the financial burden of medical expenses for families like theirs?

These questions highlight the essential issues that Amirul and Zulkarnain must confront as they progress in their lives as future seniors. They underscore the necessity of a supportive ecosystem to assist them in managing the challenges of caregiving and financial preparedness.

Malaysia's Ageing Population: Facing the Challenges Ahead

Malaysia is undergoing a significant demographic transition towards an ageing society, with the proportion of individuals aged 60 and above rising from 10.3% in 2020 to 11.6% in 2024. Similarly, those aged 65 and above increased from 6.8% to

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7.7% during the same period. This trend highlights the need for awareness and preparation for the financial and caregiving responsibilities associated with an ageing population, as exemplified by Amirul and Zulkarnain, who returned to care for their elderly parents.

Over the next 35 years, the elderly demographic is projected to grow significantly, with the population aged 60 and above expected to rise from 11.6% (approximately 3.9 million) in 2024 to 17.3% (around 6.4 million) by 2040. This shift will elevate Malaysia from an ageing to an aged nation, as defined by the United Nations. By 2057, over 20.5% of the population is expected to be aged 60 and above, reflecting declining birth rates and increasing life expectancy.

Elderly Malaysians face various health issues, including non-communicable diseases (NCDs) such as hypertension (51.1%), diabetes (27.7%), and hypercholesterolemia (41.8%). These conditions, along with dementia risks and mobility challenges, are increasing the demand for healthcare services, putting pressure on a system already facing shortages of geriatric specialists and inadequate infrastructure, especially in rural areas.

Financial Challenges Facing Malaysia's Seniors

Amirul and Zulkarnain's experiences exemplify the financial challenges many families face while caring for ageing parents. As they navigate the emotional and physical demands of caregiving, they also face significant financial burdens. Amirul worries about his mother's medical expenses, while Zulkarnain struggles with the costs of his father's dialysis. Their stories reflect the broader issue of financial vulnerability among older Malaysians and the complexities of caregiving.

Malaysia's ageing population presents substantial challenges, particularly regarding financial security. Understanding the specific difficulties faced by the elderly, including financial abuse and overall financial

well-being, is crucial. The key financial challenges are as follows:

1. Financial Stress and Insecurity

Many elderly individuals in Malaysia rely on fixed incomes, such as pensions or savings, which often fall short of covering living expenses. A study by the Malaysian Institute of Health Management (MIHM, 2022) found that about 60% of elderly respondents reported financial stress, primarily due to rising healthcare costs and inadequate retirement savings. Additionally, a survey by the Malaysian Financial Planning Council (MFPC, 2020) revealed that nearly 70% of elderly individuals are concerned about their financial security, particularly regarding healthcare and daily expenses. This burden often extends to younger family members, creating intergenerational financial strain (Ng, 2023).

2. Rising Healthcare Costs and Lack of Coverage

As people age, they often face chronic health conditions requiring ongoing care. Unfortunately, healthcare expenditure in Malaysia has been rising, particularly for services catering to the elderly. According to the Ministry of Health Malaysia (2020), healthcare spending has surged due to inflation and an increasing incidence of chronic diseases. Despite these rising costs, insurance uptake among the elderly remains low, often due to affordability and awareness issues (Koh, 2022). The AKPK (2023a) notes that many elderly Malaysians struggle to afford healthcare, leading to difficult choices between necessary medical care and financial stability.

3. Financial Abuse

Research by AKPK (2023b) indicates that over 10% of older adults experience financial exploitation, often by family members or

caregivers. This abuse can include unauthorised use of funds or coercion to change wills, resulting in a loss of financial independence and increased stress. Many cases go unreported due to stigma and fear, highlighting the need for greater awareness and education on financial abuse to empower the elderly and encourage reporting.

Strategies for Future Seniors in Malaysia's Long-Term Care Ecosystem

The experiences of Amirul and Zulkarnain highlight the pressing need for a comprehensive approach to long-term care in Malaysia, especially as they navigate the challenges of caring for their ageing parents while contemplating their own futures. Preparing for an ageing population requires a multifaceted strategy that addresses the financial aspects of long-term care. By enhancing financial literacy among individuals like Amirul and Zulkarnain, raising awareness of care expenses, and developing innovative insurance products, Malaysia can better equip families to manage the costs associated with caregiving.

Additionally, addressing affordability, strengthening pension systems, and prioritising research will contribute to a robust long-term care ecosystem. The concerted efforts of both public and private sectors are essential to ensure that future seniors—today's youth of Malaysia—are equipped with the tools and resources to navigate their caregiving journeys, just as Amirul and Zulkarnain are doing today. The following recommendations are proposed:

1. Financial Literacy and Awareness

Research indicates that individuals with higher financial literacy are better prepared for retirement and associated healthcare costs (Lusardi & Mitchell, 2014). In Malaysia, initiatives should be implemented to educate young people about the financial implications

of ageing, including the costs associated with long-term care services. This could involve integrating financial education into school curricula, focusing on topics such as savings, investments, and the importance of early planning for retirement (OECD, 2020).

2. Preparation for Elderly Care Services Expenses

Awareness of the potential expenses related to elderly care is crucial. In Japan, the LCTI system has successfully raised awareness about the costs of long-term care, encouraging individuals to plan ahead (Ikegami & Anderson, 2004). Malaysia could adopt similar strategies by launching public awareness campaigns that highlight the importance of preparing for elderly care expenses. These campaigns should provide information on the average costs of care services, the potential need for assisted living, and the financial implications of chronic health conditions.

3. Insurance Coverage and Innovative Products

Insurance coverage plays a pivotal role in mitigating the financial burden of long-term care. In Japan, the LCTI system provides a framework for comprehensive insurance coverage for elderly care, which could serve as a model for Malaysia (Kakuma et al., 2016). Both public and private sectors could consider developing innovative insurance products tailored to the needs of the ageing population. This could include hybrid insurance plans that combine life insurance with long-term care benefits, thereby addressing both mortality and morbidity risks.

4. Addressing Affordability

Affordability continues to be a significant barrier to accessing long-term care services. In developed countries, various strategies have been employed to enhance affordability, such as subsidies for low-income seniors and tax incentives for families providing care (Wiener

et al., 2018). Malaysia could explore similar approaches, ensuring that financial assistance is available for those who require long-term care but lack the means to afford it. Additionally, partnerships with private sector entities could facilitate the development of affordable care options.

5. Pension Funds and Retirement Planning

A robust pension system is essential to ensure that seniors have adequate financial resources in their later years. Malaysia's Employees Provident Fund (EPF) serves as a primary retirement savings scheme; however, it may not be sufficient to cover long-term care costs (Mokhtar et al., 2020). An additional pension scheme dedicated to long-term care expenses could provide greater financial security for future seniors.

6. Research Priorities

To inform policy and practice, it is crucial to establish research priorities focusing on the financial aspects of long-term care. This includes studying the effectiveness of various funding models, the impact of financial literacy initiatives, and the long-term sustainability of insurance products. Collaborative research between academic institutions, government agencies, and private sector stakeholders can yield valuable insights that drive policy development (Chai et al., 2021).

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The Hidden Threat: Elder Financial Abuse in Malaysia

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Introduction

As Malaysia's population ages, financial advisors must be aware of a serious yet often hidden threat to older adults: elder financial abuse (EFA). The World Health Organization (WHO) defines elder abuse as any action or failure to act that harms or distresses an older person, usually done by someone they trust. One of the most common but underreported types of elder abuse is financial exploitation. This occurs when someone illegally or improperly uses an elder's money, property, or assets. It can occur in various ways, such as family members or caregivers pressuring older adults to give them access to their finances or taking money without permission. This exploitation can severely damage the financial well-being and independence of elderly individuals. The abusers are typically trusted people, such as family members, caregivers, or friends, and their actions may not be easy to spot.

Elders at Risk

Older adults are more likely to face financial abuse due to several risk factors. These risks are linked to health, family relationships, and life circumstances. Below are key risk factors supported by research studies of elders at risk for financial abuse.

Cognitive Impairment. Older adults with memory loss, dementia, or Alzheimer's may not fully understand what they are signing or giving away. The National Health and Morbidity Survey 2018 found that over 8.5% of Malaysians aged 60 and above show signs of dementia (Living with dementia, n.d.). These individuals are less able to manage their finances and more likely to become victims of abuse.

Physical Disabilities and Dependence on Others.

When older people cannot care for themselves, they must depend on others, sometimes to an excessive degree. Without checks, this trust can be misused. Pillemer et al. (2016) in *The Lancet Global Health* found that older adults with physical limitations are at greater risk of being exploited, especially if no one else is monitoring their care.

Female Elders. Many older women live alone and are not used to handling finances. This makes them more likely to trust someone who offers help, even if it is for the wrong reasons. Dey & Tripathi (2022) show that older women face higher risks of abuse, especially in cultures that expect them to rely on family. They often feel obligated to give money, land, or other valuables to younger relatives.

Home Ownership. A house is a valuable asset, family members under financial pressure may see it as an easy source of money, even if the elder does not want to sell. Wu et al. (2012) found that older people who own property are more likely to be pressured by others, especially by family who see the house as a financial "resource."

Living with Family Facing Financial Stress or Addiction. When older adults live with family members who are in financial or emotional trouble, they are more likely to be taken advantage of. Che Amani et al. (2021) found that elders living with unemployed or financially stressed children face a higher risk of financial abuse, mainly when they depend on them for daily needs.

Low Financial Literacy and Digital Skills. Scammers often target seniors unfamiliar with digital banking, apps, and online fraud. AKPK's 2022 Financial Behaviour Report shows that older Malaysians have lower financial and digital literacy.

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This makes them easy targets for phone scams, fake messages, and online fraud.

Social Isolation and Emotional Vulnerability.

When older adults feel lonely or look for companionship, they may be vulnerable to individuals who only seek their financial gain. Zannettino et al. (2014) and Redmond (2016) highlight that emotional needs can cloud judgment. According to the *New Straits Times*, many elderly women in Malaysia fall victim to “love scams,” losing large sums of money (Al-As, 2025).

Legal Vulnerabilities. Giving someone Power of Attorney (POA) protects older people. However, if the wrong person is given that power, it can lead to severe abuse. Rabiner et al. (2006) found that misusing POA is common in financial abuse cases. Trusted individuals sometimes use this power to take money or property for themselves.

The Signs of Financial Abuse

Unlike physical abuse, financial abuse does not leave bruises or scars. Instead, it often hides behind behaviour, spending, or lifestyle changes. Recognising the signs can help protect older adults from harm. Below are real-life examples of what financial abuse may look like in different settings.

At Home or in Personal Life

- Confused about money matters. An elderly woman is sure she paid her electricity bill, but her power is cut off. Later, her grandson admits to using her ATM card without permission.
- Afraid to talk about money. A retiree becomes nervous and avoids questions when asked how he manages his EPF or monthly expenses.
- Missing basic needs despite having money. An older woman receives a pension but has little food in the house, wears old clothes and looks neglected. However, she lives in a well-furnished home.

- Unpaid bills and money troubles with no explanation. An elderly man has savings but is almost evicted for unpaid rent. A family member handling his money had been using it for personal expenses.
- Isolation from loved ones. A once-social older woman suddenly stops going to prayers or community events. A new “friend” now manages her money and limits her outside contact.

At the Bank

- Unusual or large withdrawals. A retiree who usually spends RM1,000 a month suddenly makes multiple RM5,000 withdrawals in one week.
- ATM activity that appears suspicious or inconsistent. A housebound senior has daily ATM withdrawals, even though he has not left home in weeks.
- Suspicious signatures or account changes. A bank staff member notices a cheque signature that looks off and sees a new name added to the elder’s account.
- Bank letters are sent somewhere else. An elder’s bank statements are now mailed to a nephew’s apartment. When asked, the elder does not seem to know this has happened.

In Legal Matters

- Sudden changes to wills or property. A woman who had always planned to divide her assets among all her children suddenly gave everything to one daughter, who now takes care of her.
- Legal papers are signed in unclear situations. A son says he has power of attorney, but his mother, who has early dementia, does not remember signing anything.
- New people are claiming control over money. A neighbour demands access to an older woman’s

pension, saying he buys her groceries. However, no one asked the elder what she wanted.

In Healthcare Settings

- Missing doctor visits without a reason. A senior stops going to regular diabetes check-ups. She has enough money, but her caregiver would not take or give her the transport fare.
- Health is getting worse due to unpaid medical needs. An elderly man's medicine is not refilled, and his condition worsens, despite his steady retirement income.
- The caregiver controls all conversations with doctors. During medical visits, a caregiver insists on staying in the room and answers all monetary questions, even when doctors ask to speak to the elder alone.

Characteristics of Perpetrators and Their Tactics

Characteristics of Perpetrators

- Caregivers or Family Members. Many cases of elder abuse involve family members, especially adult children and spouses. About 60% of elder abuse cases are committed by family members (Jones, 2024). These abusers often depend on older adults for money or care. This reliance creates a power imbalance that can lead to abuse. The abusers take advantage of their close knowledge of the victim's weaknesses and resources.
- Caregivers or Family Members with Psychological or Substance Abuse Issues. Psychological factors play an important role in who becomes an abuser. Many abusers show signs of mental health problems like depression, anxiety, or issues with substance abuse. People who struggle with addiction may take advantage of their elderly relatives to pay for their habit.
- Predatory Strangers or New "Friends". These perpetrators build trust with the elder, often

through online platforms, before manipulating them into giving away money or assets.

Tactics Used by Perpetrators

- Grooming. Some abusers slowly gain the elder's trust by pretending to care deeply about them. They may initially show kindness and concern, but their underlying goal is to control the elder's money. Over time, they take advantage of the elder's emotional needs, making the elder feel like they owe the abuser help or money, often under the excuse of "support" or "care".
- Isolation. Abusers may try to keep the elder away from other people, like friends, neighbours, or even other family members. This makes the elder more dependent on the abuser. Without outside contact, the elder may not realise they are being abused and may begin to believe they have no other choice or support.
- Coercion. Some abusers use pressure or threats to get what they want. They might say things like, "If you do not help me, I will not take care of you," or claim the elder agreed to something they did not. Sometimes, they trick the elderly into signing documents to give away money or property. They may even misuse the Power of Attorney to move money or make legal decisions that benefit them.

Implications of Elder Financial Abuse

Elder financial abuse causes serious harm. It affects the older person, their family, caregivers, and the community. These effects can be financial, emotional, physical, and social.

Financial Impact. Older adults who experience financial abuse may lose their savings, pension funds, or property. This loss can make paying for daily needs such as food, housing, or medical care difficult. Some may become dependent on others or government support. This adds stress to family members who are already managing their finances.

Emotional and Mental Health. Victims often feel ashamed, embarrassed, or guilty. They may become depressed or anxious, especially if they do not know how to recover their money. These feelings can last a long time. Some may avoid talking about the abuse, which allows the problem to continue.

Physical Health. Financial loss can lead to poor health. Older adults may stop buying medicine or seeing doctors to save money. They might also cut back on food or home care. This can make health conditions worse. Stress from the abuse can lead to high blood pressure or heart problems.

Social Isolation. Victims may pull away from family or friends. They may feel embarrassed or afraid to talk about what happened. Being alone makes them more vulnerable to further abuse. They often do not know who to trust or ask for help without support.

Impact on Family Relationships. If a family member is the abuser, it can damage trust and cause deep emotional pain. The victim may feel betrayed. Other family members may fight over money or caregiving responsibilities, breaking families apart.

Legal and Community Impact. More cases of elder financial abuse mean more pressure on social workers, lawyers and the courts. Professionals like financial planners, doctors, and lawyers need training to spot and report abuse. Governments must improve laws and support systems to protect older people and punish wrongdoers.

Preventive Strategies: Financial Planners Are the First Line of Defense

Financial planners do more than manage money; they protect their clients' dignity, independence, and life savings. Regularly reviewing clients' finances can identify unusual activities, prevent problems, and support long-term financial health. This role is important for two reasons. First, older clients deserve protection from harm. Second, failing to address

financial abuse can harm their finances, family relationships, and the advisor's reputation. Therefore, financial planners need to engage in prevention and incorporate protective measures into their daily work.

Encourage Transparency and Oversight. Create a culture of transparency through scheduled account reviews, clear documentation of large transactions, and the use of checklists for estate and investment decisions. Regular reviews help detect sudden changes, new beneficiaries, or withdrawals that deviate from known patterns.

Example: A sudden RM50,000 transfer to a previously unknown person could be flagged in a quarterly review and halted in time.

Promote Tailored Legal Safeguards. Work with legal professionals to ensure that documents like Powers of Attorney (POA) are precise, conditional, and time-bound. Ensure wills and trusts are reviewed annually or after significant life events. Family members frequently misuse vague or open-ended POAs. Specific, conditional instruments limit abuse.

Example: A POA that activates only after two medical professionals certify cognitive decline prevents premature misuse.

Support Digital and Financial Literacy. Organise or refer clients to workshops on online banking, fraud detection, and secure financial practices. Provide curated materials explaining current scam tactics. Seniors unfamiliar with technology are prime targets for phishing, impersonation and malware scams.

Example: Teaching clients to verify a bank email URL could prevent a phishing attack that wipes out their savings.

Screen Third-Party Access Requests. Implement standardised vetting processes for any individual requesting financial access or acting on behalf of a client. Require signed declarations or third-party

verification. Many financial abuses begin with an unexamined request from a seemingly well-meaning relative.

Example: Requiring a notarised consent form before sharing information could expose fraudulent intentions early.

Empower Client Autonomy and Privacy. Offer private, one-on-one consultations with older clients. Ask open-ended questions about how they feel about recent financial decisions or interactions. Many elders do not disclose abuse out of shame or fear, especially if the abuser is a loved one.

Example: A client might only admit coercion if asked in a private, safe setting without the presence of a caregiver or family member.

Know the Referral Pathways. Maintain an updated list of relevant authorities, such as the Legal Aid Department, the Social Welfare Department and Bank Negara Malaysia's financial ombudspersons. When abuse is suspected, timely referral can mean the difference between recovery and prolonged harm.

Example: Referring a client to the Department of Social Welfare can trigger a formal investigation while protecting client confidentiality

Conclusion: From Stewardship to Safeguarding

Elder financial abuse is not just about money; it is about trust, respect, and human dignity. The damage can be profound and lasting when older adults are taken advantage of. It is excruciating because it often happens at a time when they should feel safe, supported, and valued. Financial planners are often the first to notice when something seems wrong. That makes their role very important. They are not just managing savings or investments; they are in a strong position to protect their elderly clients from being misled, pressured, or exploited. This responsibility goes beyond numbers; it is about standing up for what

is right. Older clients are more than just clients; they are parents, grandparents and elders who have worked hard and saved for their future. They deserve to be treated with care and protected from harm. Financial planners can help ensure that older adults live their later years with confidence and peace of mind. Every year on June 15, World Elder Abuse Awareness Day reminds people around the world to protect older adults from harm. Financial professionals play a key part in that protection. They help prevent abuse, speak up when something is wrong and show what it means to be trustworthy and ethical in their work. Protecting the elderly is not just good; it is the right thing to do.

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Fintech Future: The Digital DNA of Finance

Janani, M.

Author : Sanjay Phadke
Publisher : SAGE Publications Pvt Ltd
No. Pages : 192
Price : Open Access (eBook)
eISBN : 978-93-5388-249-5

Fintech Future: The Digital DNA of Finance by Sanjay Phadke is crafted to address a broad and diverse audience, aiming to demystify the complex interplay between finance and technology, and was published on January 29, 2021. With the author's extensive 20 years of experience in both financial services and technology, including roles with global leaders like JPMorgan and HSBC, the book serves as a connecting bridge between these two rapidly evolving domains. The author has recognized a widening gap between business and technology, especially as technology accelerated, and thus, felt a strong need to help professionals from both sides understand each other better, communicate and collaborate.

The book's appeal extends from finance and technology enthusiasts to lay readers, largely due to its commitment to avoiding excessive jargon and lucidly explaining complex concepts, starting with the fundamental idea of money itself. It provides a bird's eye view of the profound changes occurring in the financial world and their implications for banks, fintech, Tech Fin companies and the average customer, making it a must-read for those keen on understanding the fintech space, particularly in the context of India's digital future.

Fintech Future offers a sweeping yet detail-rich analysis of the converging paths of technology and finance. It chronicles the enthralling journey of finance from its historical roots to a future where it is deeply intertwined with technology, speaking new languages such as artificial intelligence (AI), blockchain, and crypto.

Fintech Future Book is structured into four parts, reflecting the evolutionary stages of financial

technology as Fintech 1.0, 2.0, 3.0 and 4.0. This allows the readers to understand the past, present and the future of the finance in a cohesive narrative.

Part 1: The Evolution of Money and the Digital Shift

The book begins with an exploration of money as a foundational concept, as ancient as humanity itself, initially as a means of exchange to enable collaboration among people, replacing the tedious barter system. It traces money's historical forms, from cowrie shells 10,000 years ago, to metallic coins (2,000 years ago), and paper money (7th century China). The advent of central banks around 100 years ago solidified their role as sole currency issuers and gatekeepers of finance. A pivotal shift occurred when banknotes ceased to be backed by physical assets like gold, becoming mere promises or claims on value, marking their transition to a phygital (physical and digital hybrid) state. Today, physical money constitutes less than 5% of global monies, with the rest being digital data stored in computers. This inherent digital nature of money made it ripe for technological disruption.

The book highlights how technology fundamentally changed the interaction with money. Digital money, being a piece of software code or bits and bytes, resembling digital music or images, which can travel freely around the world at the stroke of a button or a verbal command. This transformation introduced notions of cybersecurity and the critical importance of digital trust. The book moves into the core problem that despite the world being awash with money (total supply doubling to \$75 trillion in 10 years), access to loans for small businesses or marginal workers remains difficult, leading to

increasing inequality. The traditional financial system, based on mistrust and requiring physical identity proofs and collateral, inadvertently discriminates against those without data or identity, essentially robbing the poor and paying the rich. The book argues that technology, particularly Fintech, holds the potential to unshackle money stored in banks or vaults and channel it into fountains of society, fostering a more equitable distribution of capital and democratizing access to capital.

Part 2: Fintech 1.0: Technology Enters Financial Services

The book details how technology first entered financial services, shifting activities from physical bank branches from bricks and mortar to digital platforms of click and order. This digitalization expanded market reach, enabling even migrant workers to access micro insurance and transfer money via mobile apps, and small businesses to secure loans from peer-to-peer lending schemes. This era saw the rise of digital-only banks like Monzo, N26, and MyBank, as well as neobanks such as Open and NiYo. The author emphasizes that consumers, accustomed to intuitive technology from Apple, Amazon, and Uber, now expect real-time financial services, a demand that traditional banks, burdened by legacy IT systems, struggle to meet. This created a "huge vacuum in finance" for innovative fintech solutions.

Mega technology companies like MASAA (Microsoft, Apple, SoftBank, Amazon, and Alibaba) are increasingly entering the financial sector. These companies set higher consumer expectations, leveraging their extensive user data and technological prowess. Amazon and Alibaba, through their marketplace models, see both merchant and consumer sides of transactions, giving them rich data for lending and payments. Alibaba's Ant Financial, operating Alipay and Yu'e Bao, is one among the world's largest valued fintech, worth over \$150 billion, demonstrating how tech giants are redefining financial services. Microsoft, with its Azure cloud, focuses on empowering banks and fintechs as a collaborator.

Apple's Apple Pay and Apple Card aim to tie users more strongly to its ecosystem. SoftBank's Vision Fund actively invests in disruptive technologies and fintech startups globally. Even Facebook has entered the arena with its Libra digital currency initiative.

Part 3: Fintech 2.0: Indian Digital Renaissance

The narrative then shifts to Fintech 2.0, focusing on India's digital renaissance. India is presented as a country undergoing a huge transformation to digitize cash, banks, financial infrastructure, and government, with the potential to leapfrog a few generations in technology. This is particularly relevant given India's large unbanked population as two out of three of whom have mobiles and its young, tech-savvy population. Central to India's transformation is the JAM trinity (Jan Dhan account + Aadhaar + Mobile), which has sparked a revolution.

Aadhaar (UID) is highlighted as the largest digital biometric identity programme in the world, aiming to replace numerous disparate government IDs. Its implementation has significantly reduced leakages in government schemes and enabled billions of Aadhaar-enabled payment services (AEPS) transactions.

Unified Payment Interface is described as a post-Internet product. UPI has revolutionized payments in India, allowing multiple bank accounts to be managed via a single mobile application, enabling seamless fund transfers and merchant payments. Its growth has been mind-boggling, with a vast majority of transactions contributed by non-banks like Google Pay, PhonePe, and Paytm.

Goods and Services Tax is presented as the backbone for the explosive transformation in the B2B world of financial services. It mandates digitization of business sales and purchases, using an API-based ecosystem and invoice matching to promote transparency and formalize the economy. This accurate, authenticated data can fundamentally reform corporate credit systems, leading to more automated

lending decisions and cheaper credit, crucial for India's goal of becoming a \$10 trillion by 2030. The book also introduces the Data Empowerment and Protection Architecture (DEPA), an innovation coordinated by the RBI, which empowers individuals and small businesses to control and share their data for better services, potentially solving the data wars and enabling true equality of opportunity. India's approach of government-led public digital infrastructure, unlike the private ecosystem models of the USA and China, is portrayed as a marvel of technology.

Part 4: Fintech 3.0 – The New ABC of Fintech

This section dives into the cutting-edge technologies shaping the future of finance:

Artificial Intelligence (AI), Algorithms, Anomaly, and Autonomous: AI, described as the new electricity, is no longer mere hype but a robust technology poised to bring efficiency improvements in a large range of tasks by enabling machines to learn from itself. The book differentiates between narrow AI and Artificial General Intelligence (AGI), which aims to mimic the human brain's capabilities. It explains Machine Learning (ML) types like supervised, unsupervised, and reinforcement learning, and Deep Learning (DL), which mimics neural networks for unstructured data. A key financial application discussed is anomaly detection, crucial for fraud monitoring and large-scale automated processing in high-throughput systems, as demonstrated by Danske Bank's success in reducing false positives in fraud detection using AI. The book also touches upon the critical issue of bias in AI, stemming from training data or statistical skews by the 2008 GFC, and stresses the need for human judgment and ethical standards in AI deployment.

Big Data, Blockchain, and Bitcoin: Big Data signifies an exponential explosion in data from digital devices, requiring new approaches to manage unstructured information images, voice, videos and serving as the raw material for AI. Its use in fraud monitoring and security is principal. Then introduces

Bitcoin, aftermath of the 2008 financial crisis as a decentralized, peer-to-peer digital currency. Its underlying technology, blockchain, creates a distributed ledger and establishes digital trust without central authority. Bitcoin's volatile journey, from near-zero to \$20,000 and back, is detailed, highlighting its re-emergence as digital gold. The book contrasts regulatory stances in the USA, China and India regarding cryptocurrencies, noting India's restrictive approach. While Bitcoin's bubble burst, blockchain's underlying promise gained prominence, seen as a mechanism to establish trust in global supply chains and potentially revolutionize various industries. Facebook's Libra project is presented as a middle-of-road hybrid solution, seeking stability by backing its digital currency with existing financial assets.

Cloud, Crypto (Ethereum, Smart Contracts) and Cybersecurity: Cloud computing is presented as a re-organization of old technology for new times, moving IT infrastructure off-premise. Its benefits include economies of scale, innovation for providers, and reduced capital expenditure for users, shifting to operational expenditure (opex). This pay-per-use model, mirroring the sharing economy from Uber and Airbnb, enables nimble new-age companies to scale rapidly. The book notes Amazon's dominance with AWS and the ongoing cloud wars with Microsoft and Google. While banks have been laggards in cloud adoption, initiatives like India's GST rollout have pushed Indian companies towards cloud infrastructure. Cybersecurity is identified as the biggest risk in the increasingly digital world, escalating into a tool in geopolitics. Major incidents like the WannaCry ransomware attack, Capital One data breach (on AWS), and Equifax data breach underscore the vulnerability of even secure systems. The book discusses the constant threat from malicious hackers, the role of protocols like OWASP, and the growing internal threats. This highlights the growing importance of data localization laws (e.g., EU GDPR, Russia, China, India), as governments seek to regain control over digital data from tech giants. The rise of Internet of Things (IOT) devices is depicted as

enabling instant data collection and partial processing for personalized services and invisible finance. Finally, Quantum Computing is introduced as a future supercomputer and code-breaker that could process information at unimaginable speeds, but also act as a new-challenges to existing cybersecurity protocols by breaking encryption.

Part 5: Fintech 4.0 – All Finance Becomes Fintech

This concluding section envisions Fintech 4.0 as the complete merging of finance into technology, making it an invisible and ubiquitous presence embedded in daily life stating Finance as a Service - FaaS. This evolution progresses from digital wallets on mobiles to edge devices like IOT sensors. The author illustrates this with futuristic scenarios, such as paying for a ride with a wallet funded by carbon dioxide consumed by a tree or autonomous cars becoming public utilities with usage-based payments linked to digital wallets. These scenarios highlight three key transformations: linking the source of money to its use across the supply chain, shifting from upfront capital expenditures (capex) to pay-as-you-go operational expenditures (opex), and devices becoming economic entities with usage charges.

The book indicates that in this new world, traditional banks dominance is no longer guaranteed. They may evolve into creators of algorithms or service providers for automated products, but they must fundamentally transform into technology companies to be able to beat them at their own game. The financial regulators, while encouraging innovation, face the crucial role of ensuring systemic stability and individual data privacy, acknowledging the new elements in the risk-benefit balance introduced by big techs.

The book draws parallels with the disruption of the retail and telecommunications industries by technology, suggesting banks face a similar, drastic change in DNA, similar to a heart transplant. The potential upside for consumers and small businesses is

tremendous, as fintech and big tech can overcome the inability of the banks to be able to see every person as a valued customer. The future of finance, as depicted, will be pervasive, contracted, tailored, intelligent and embedded, making financial transactions as effortless as interacting with a digital assistant or smart devices.

The book concludes by advocating a new paradigm—Universal Credit Access Limit (UCAL)—in which every newborn receives a basic account with state-accrued income, enabling access to capital for education or business, contrasting it with Universal Basic Income (UBI) which could dull productivity and creativity. This scheme, combined with India's digital infrastructure, holds the potential to democratize access to capital and drive explosive economic growth, making India a true superpower. The author emphasizes that while fintech offers immense power, it must also bear greater responsibility to uphold the traditional values of banking trust, ensuring sustainable contributions to civilization by unblocking the arteries of finance. The ultimate vision is a world where money will be increasingly behind the scene, as contextual infrastructure—almost like magic enabled by advanced technology.

In conclusion, "Fintech Future" is not just a descriptive interpretation but an insightful commentary on the profound shifts in finance, driven by technological advancements, with a keen focus on India's unique position and potential in this global transformation. The author's blend of financial and technological expertise allows for the discussion of both opportunities and challenges, making it a valuable read for anyone interested in the evolving landscape of digital money and its societal implications.

The Total Money Makeover - Dave Ramsey

Siti Yuliandi Ahmad

Author : Dave Ramsey
Publisher : Thomas Nelson
No. Pages : 256
Price : between USD 15 to 25
ISBN : 978-1595555274

Dave Ramsey is a prominent American personal finance educator, who built his reputation not on academic credentials but through lived experience. He holds a degree in Finance and Real Estate and began his professional journey by accumulating substantial wealth through property investments in his twenties. However, his early success was short-lived. Relying heavily on borrowed money and short-term bank financing, Ramsey found himself bankrupt when banks demanded repayment and withdrew credit. This financial collapse became a defining turning point in his life.

Instead of retreating from the financial world, Ramsey chose to rebuild from scratch. He started studying personal finance with a focus on practical solutions rather than theoretical models. Drawing on biblical principles, personal trial and error, and his own failures, he developed a philosophy centered on complete debt elimination, disciplined spending, and long-term financial independence.

Ramsey launched a small financial counselling business that quickly expanded into what is now known as Ramsey Solutions, a multi-platform financial education company. His national radio show, now titled The Ramsey Show, reaches millions of listeners and is renowned for its candid advice, heartfelt testimonials, and strong emphasis on personal accountability. His core audience largely consists of middle-income earners, many of whom feel overwhelmed by debt or financial instability and seek clear guidance.

He presents financial literacy through the lens of moral clarity. Financial problems, in his view, are not merely mathematical but behavioural. His tone is

often forceful and urgent. He does not encourage readers to carry debt, even when it may appear mathematically sound, and he rarely engages with complex investment vehicles or systemic critiques of inequality.

Although Ramsey does not hold formal certifications such as a Certified Financial Planner or a Chartered Financial Analyst designation, he has built a lasting influence by staying consistent in his messaging. He speaks in plain language, avoids technical jargon, and structures his lessons in an emotionally compelling way. Critics often note that his advice may not be optimal in every situation, particularly for those with high financial literacy or access to complex investment opportunities. Yet his strength lies in providing structure, motivation, and hope to those facing financial disorder.

Chapter 1: The Total Money Makeover Challenge

Ramsey opens with a direct challenge to the reader. He frames debt, overspending, and financial chaos not just as personal failings, but as symptoms of a broken cultural narrative. His tone is provocative, asking readers to confront uncomfortable truths regarding their financial habits. The central argument is that real transformation demands total commitment and a rejection of conventional financial thinking. Ramsey's strength in this chapter lies in his ability to create urgency. He does not offer a gentle introduction but instead disrupts complacency. However, his reliance on stark either-or propositions lacks nuance. Financial change does not always require a complete philosophical overhaul. Readers seeking technical tools may be frustrated by the motivational tone, but the emotional hook sets the tone for the book's behavioural foundation.

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Chapter 2: Denial: I'm Not That Out of Shape

This chapter introduces the concept of financial denial, comparing it to the physical delusions people maintain about their health. Ramsey argues that most people do not realise how bad their financial condition is because they normalise debt and living beyond their means. He relies on analogies between physical and financial health to make the problem feel relatable. The chapter's argument rests on the assumption that awareness is the first barrier to change. While this holds true for many, it flattens more complex causes of financial struggle, like systemic inequality, medical debt, or economic insecurity. Still, the chapter is effective in targeting personal accountability. Its rhetorical power lies in its simplicity, even if that comes at the cost of structural depth.

Chapter 3: Debt Myths: Debt is Not a Tool

Ramsey takes direct aim at common financial assumptions by claiming that debt is never beneficial. He critiques the notion that student loans, credit cards, car loans, and mortgages are necessary instruments for building wealth. Instead, he sees debt as a form of financial enslavement. His argument is morally charged and absolute. From a technical standpoint, this is where the book begins to show its rigidity. While Ramsey is right that debt can create long-term vulnerability, especially high-interest consumer debt, he dismisses low-interest or strategic debt as inherently harmful. He overlooks the role of debt in facilitating investments with a positive return on equity, such as education or business expansion. The chapter's strength lies in challenging the reader's complacency, but its weakness lies in overgeneralization. The critique is emotionally compelling but not analytically balanced.

Chapter 4: Money Myths: The (Non)Secrets of the Rich

In this chapter, Ramsey targets financial myths that often circulate in popular culture. He argues that wealth is not the result of luck, family inheritance, or secret investment strategies. Instead, he claims that discipline, patience, and consistency are the real drivers. Ramsey's narrative emphasises behaviour over tactics. This chapter resonates strongly with those disillusioned by get-rich-quick schemes or speculative investment trends. However, the argument suffers from selective framing. While discipline matters, the chapter downplays the role of systemic factors, such as class privilege or access to financial education, in shaping wealth accumulation. His critique of the financial industry also lacks empirical grounding. For readers looking for inspiration, the message is powerful. For those looking for rigorous financial insight, it remains anecdotal.

Chapter 5: Two More Hurdles: Ignorance and Keeping Up with the Joneses

Ramsey concludes the setup phase of the book by identifying two remaining barriers to financial change: ignorance and social pressure. He explains that many people simply do not know how money works, and even when they do, they sabotage themselves trying to meet the expectations of others. His discussion of ignorance is straightforward. He blames a lack of personal finance education and the misleading practices of lenders and marketers. This is one of the more balanced arguments in the early chapters. His critique of social comparison is also timely, particularly in a digital age shaped by curated lifestyles and consumerism. However, the solutions offered are still framed in moral and behavioural terms. Ramsey calls for a psychological shift rather than a structural intervention. The underlying assumption is that change starts within, which is a motivational thesis but not a comprehensive financial one.

Chapter 6

Chapter six marks the transition from philosophy to action. Ramsey begins his tactical program with a push to quickly save \$1,000 as a starter emergency fund. He emphasises speed over size, arguing that liquidity matters more than quantity at this stage. The argument is emotionally resonant and practically sound. For many households living paycheck to paycheck, this first step builds psychological momentum. Technically, however, the one-size-fits-all nature of this advice ignores variables such as household size, income volatility, and regional cost of living.

Chapter 7

This chapter presents the debt snowball method. Ramsey argues that people should pay off their smallest debts first, regardless of interest rate. His logic is behavioural, not mathematical. He believes that small victories provide emotional reinforcement, which in turn builds discipline. While many critics point out the inefficiency of ignoring interest rates, the debt snowball has proven effective for those struggling with motivation. Ramsey is unapologetically focused on behaviour modification, making this chapter a cornerstone of his practical philosophy.

Chapter 8

After eliminating debt, Ramsey advises readers to establish a fully funded emergency fund of three to six months' worth of expenses. He frames this as an essential shield against life's unpredictability, referencing 'Murphy's Law.' The argument is strong in its emphasis on financial resilience. However, the range of three to six months is vague and not tied to specific risk variables such as employment volatility or family structure. Nevertheless, this chapter is grounded in the concept of financial self-discipline and long-term security.

Chapter 9

In Chapter Nine, Ramsey turns toward wealth building. He suggests investing fifteen per cent of household income into retirement accounts. He promotes tax-advantaged vehicles, such as Roth IRAs and employer-matching 401(k) plans. This chapter is less dogmatic and more technically sound. However, Ramsey's recommendation does not account for households with late starts or those carrying high-interest debt from medical or legal expenses. Still, this section introduces the idea of delayed gratification and long-range planning.

Chapter 10

This chapter addresses saving for children's college education. Ramsey prioritises retirement savings over college funding, arguing that while loans can fund education, they cannot fund retirement. He suggests using ESAs or 529 plans. The chapter is pragmatic but may come across as harsh to parents anxious about educational mobility. It reflects a broader Ramsey principle of personal responsibility. He encourages parents to involve children in the process, promoting accountability. The technical guidance is solid, although it might not reflect global differences in higher education financing.

The Total Money Makeover by Dave Ramsey distinguishes itself in a crowded field of personal finance books through its unapologetically rigid structure, its moral framing of financial decisions, and its deep emotional appeal. While many finance books focus on technical optimisation, Ramsey's approach is built around behavioural change, using simple language, real-life testimonials, and repeatable steps to guide readers through a transformative process. What sets this book apart is its clarity and refusal to cater to complexity. Ramsey does not bombard readers with compound interest tables or portfolio diversification strategies. Instead, he offers a straightforward series of seven "baby

steps" that focus on immediate action and long-term discipline. This simplicity may seem reductive to some experts, but it is exactly what makes the book accessible and effective for people who feel overwhelmed by their finances. Rather than merely explaining money, Ramsey constructs a narrative of personal responsibility and redemption, drawing from his own bankruptcy experience. His evangelical tone resonates with a broad audience that seeks not just financial knowledge but hope and reassurance.

Unlike many financial authors who speak in probabilistic terms and encourage personalised flexibility, Ramsey treats financial advice with moral certainty. He presents debt as inherently dangerous and budgeting as a character-building exercise. This rigidity, though sometimes controversial, serves a purpose; it removes decision fatigue and reframes financial recovery as a moral victory. While other books might encourage using credit responsibly, Ramsey insists on cutting up credit cards and building emergency funds as acts of defiance against cultural norms.

Technically, this book may lack nuance, especially for high-income earners, late-career investors, or those with complex financial portfolios. However, its strength lies in its behavioural framing. Ramsey recognises that most financial problems are not caused by a lack of knowledge but by a lack of consistent action. By offering a structured, emotionally engaging path to financial wellness, *The Total Money Makeover* acts as both a guidebook and a motivational blueprint that helps readers rewire their relationship with money.

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Based on the Seventh Ed. of the
*Publication Manual of the American
Psychological Association*



Writing in APA Style 7th Edition Example Paper

Title in bold, Capitalize All
of the Major Words; no
word limit.

Use same font size
for everything in the
entire document

One blank double-spaced
line under title.

**First name Last name1,
First name Last name2 and First name Last name3
1Department name, Institution name
2Department name, Institution name
3Department name, Institution name**

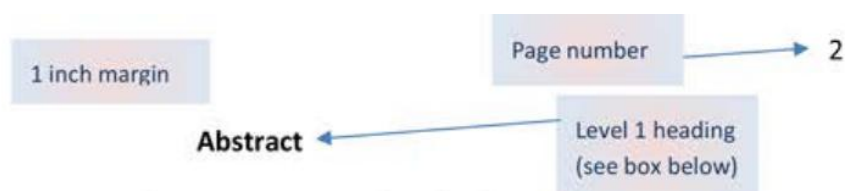
Writer(s) name (s),
Department name(s) and
Institution name(s)

Entire document should be
double-spaced.

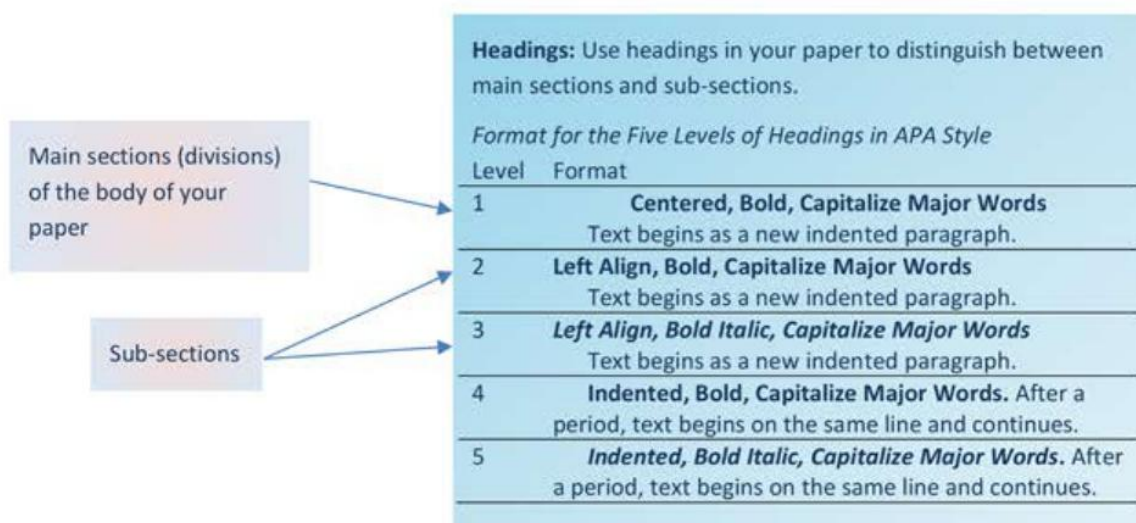
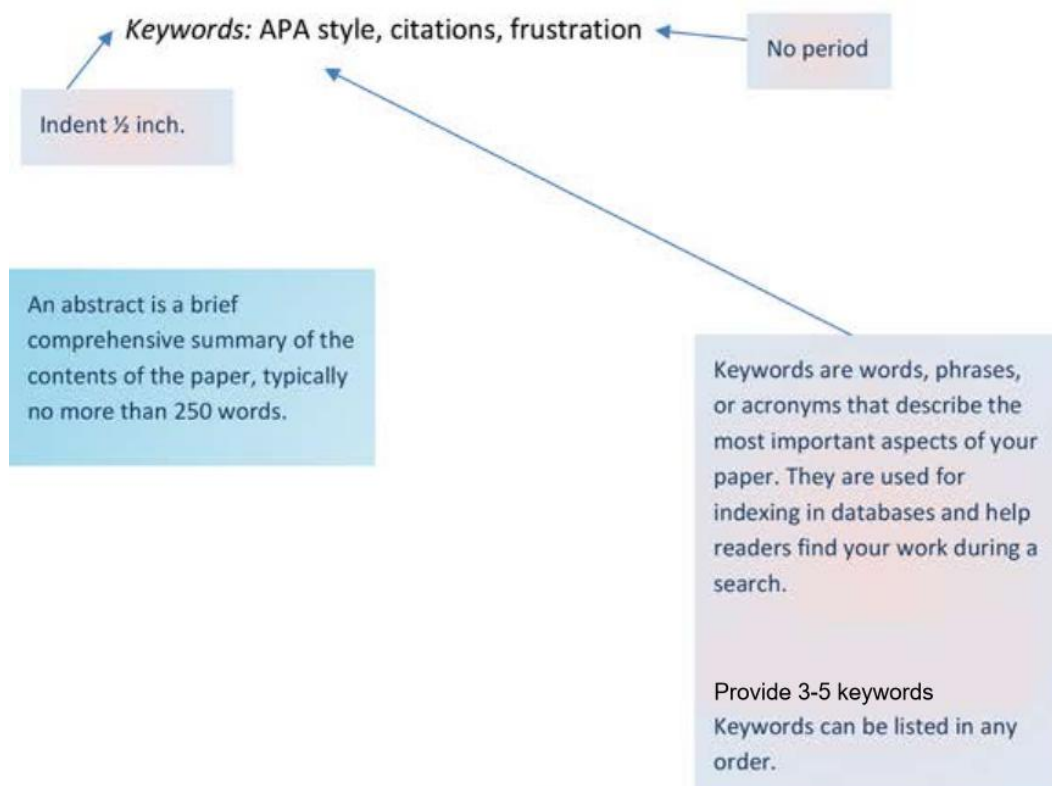
APA 7 no longer requires
12-pt. Times New Roman.

Permitted fonts:

- 12-pt. Times New Roman
- 11-pt. Georgia
- 11-pt. Calibri
- 11-pt. Arial
- 10-pt. Lucida Sans



This paper describes some basic parts of writing in APA style 7th Edition. These components include seven major areas: the title page, abstract, formatting concerns for student writing, use of language, in-text citations, the references page, and titles and figures. This paper also provides examples of specific changes that are required by APA style 7th Edition.



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Title is bolded and centered, Capitalize All of the Major Words → **Writing in APA Style 7th Edition Example Paper** ← Level 1 heading (see p. 2)

Repeat title from Title page

Writing in the style of the American Psychological Association (APA) is a regular practice for students of higher degree programs in psychology and many programs in science. The new edition of the manual has made several changes, such as endorsing the use of the singular *they*, as exemplified in the next sentence. Each student writer who applies the new APA student writing standards may encounter different challenges, however, they may use the resources provided by the AUSB Writing Center for support in learning the relevant new rules.

Use singular "they"

According to the seventh edition of the *Publication Manual of the American Psychological Association* (2019), the style's broad applicability "helps authors present their ideas in a clear, concise, and organized manner" that "uniformity and consistency enables readers to (a) focus on the ideas being presented rather than formatting and (b) scan works quickly for key points" (p. xvii). Since this paper is mostly written in the seventh edition of APA style, attentive readers will note that it has many examples of changes from the sixth edition. Most of the rules demonstrated here are those a student will need to have some acquaintance with in order to write easily according to the student writing guidelines, which are distinct from APA's new journal article reporting standards (Paiz et al., 2013).

1 inch margins on all sides

One space after a period

New in APA 7: Use "et al." for three or more authors

Level 1 heading (a main section) → **The Structure of a Paper in APA Style**

The APA style guidelines are designed for primary research papers that usually contain the following sections: (a) introduction, (b) method, (c) results, (d) discussion, and (e) references. However, the actual headings may vary depending on the type of paper one is writing (American Psychological Association, 2019). For example, papers that do not describe primary research or original experimental data may omit the method, results, and discussion

sections (Xyers, Young, Zucherman, & Anne, 2019, p. 291). Some sections may be broken into subsections, in which case the authors must use the appropriate headings and subheadings (Xyers, Young, Zucherman, & Roberts, 2019, para. 4).

Exception to "et al." rule for 3 or more authors:
Include as many authors as needed to distinguish
between sources with the same first author(s).

Organizing the Main Body

Level 2
heading
(a sub-
section)

Most APA style papers written by students are not experimental; the organization of headings and subheadings within the main body of the paper is therefore particularly important. In certain cases, the author might use additional major sections, such as a literature review, to introduce their own material.

Organizing the Main Body When There are Additional Content Concerns

Level 3 heading (a
sub-section of the
Level 2 sub-section)

Short
papers
usually
only
need
Level 1
and 2
headings

In some common graduate assignments, students are instructed to compare therapeutic models, provide possible interventions given specific presenting problems, or engage in case study analyses. These papers may have particular sections (such as presenting problem, or socio-cultural considerations of a given model).

Level 4
heading
(see
p. 2)

Language Concerns in the Body of the Paper. Sometimes, writers who are just becoming comfortable with APA style, or with academic writing in general, will mimic academic language in ways subtly less clear than writers who use academic register fluently. For example, one might write the following sentence, which sounds academic to the mental ear, but in which almost everything is done poorly:

during the preparatory process of elucidating the critical and fundamental elements of this theory for analysis, it would be observed that certain subjective elements of the theory would be excessively situational to the point of being non-applicable outside of the theorists' particular circumstances. (Goodwin, 2012a)

For block quotes,
period comes
before citation.

If a quotation
is 40 words
or more, use
a block quote
format: new
line, indent ½
inch, double
space, no
quotation
marks.

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We observe that such a sentence serves little use beyond parody. The same sentiment can be expressed in appropriate academic register in the following fashion: this theory is based on subjective components and thus is not widely applicable (Goodwin, 2012b).

Level 4 heading

Language Concerns as Issues of Unstated Academic Expectation. Writers for whom the

distinction between the two earlier examples is unintuitive should not be dismayed. Graham and Harris (1997) have shown that an academic style of writing is slowly learned, and is not

Para-phrase

often intuitive. Often, the rules of academic English, and American academic English in

particular, are presented as assumptions rather than with explicit guidance (Graham & Harris,

No page # (see box below)

1997). A student may look at their peers and see no one else asking questions about unclear elements of an assignment, or unclear expectations, and try to muddle through on their own rather than raising the issue. However, most academic expectations need to be explicitly taught at some point, so students should not feel bad asking for clarification. Often, if one writer has a question about the expectations, many others do also (S. Harter, personal communication, September 30, 2018).

Personal communication formatting example. Cite in text but not on References page. (see p. 7)

Level 1 heading

In-Text Citations and References

The American Psychological Association (APA) encourages authors to cite any works that have impacted their own (APA, 2019). In general, the style guide recommends paraphrasing sources rather than using too many direct quotes, “because paraphrasing allows you to fit material to the context of your paper and writing style” (APA, 2019, p. 270).

Cite the specific page number of direct quotes.

A direct quote is best employed when the original author has stated a point particular memorably, concisely, or effectively, or when the original author is providing a technical

About page numbers:

- Use for direct quotes
- Use for paraphrases of *information on a specific page*
 - Otherwise, optional for paraphrases

definition or explanation of a term. Under other circumstances, a paraphrase is usually more efficient than a direct quotation. Both paraphrased ideas as well as quotations need to be cited, though; only common knowledge does not require a citation. A good general rule of thumb might be: “when in doubt, cite it, and if you don’t have a citation, double-check” (S. Chase, personal communication, August 12, 2017).

Personal communication formatting example. Cite in text but not on References page. (see p. 7)

Writers using APA style should be careful to format their citations appropriately. Most in-text citations follow the format of author and year in parentheses, providing page numbers (or paragraph numbers) for every direct quotation. For paraphrases/summaries in your own words, include a page number when information is from a specific page of a source; otherwise a page number is optional, but may be helpful. The formatting of references in the references list, however, is more complicated, and writers should check their work to ensure that they have used the appropriate format for each citation, depending on the type of source.

Figures and Tables

As shown in Table 1, the seventh edition of APA has made some changes to the formatting of figures and tables. For example, figures now use the same title format as tables (see Figure 1).

Use table and figure numbers to refer the reader to tables and figures. Do not write “see the table above/below”.

Final Recommendations

APA style is an effective way of formatting and presenting complex material. APA can be time-consuming to learn; visit us in the AUSB Writing Center for help with any of your APA questions.

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References should be in alphabetical order and double spaced.

Level 1 heading

References

American Psychological Association. (2019). *Publication manual of the American Psychological Association* (7th ed.).

When publisher & author are the same, omit that info.

Goodwin, J. (2012a). Made up examples of bad academic writing. *Academic Writing*, 343(1), 1006–1010. <http://doi.org/11.1136/acadbad.12345>

Same author, same year: use a & b

Include DOI as hyperlinked URL

Goodwin, J. (2012b). Good reading is hard writing: Another made-up journal article about academic writing. *Reading & Writing*, 25(3), 143–152.

Capitalize only the first word of a journal article and subtitle.

<http://doi.org/10.1234/readwrite.123456789>

Graham, S., & Harris, K. R. (1997). It can be taught, but it does not develop naturally: Myths and realities in writing instruction. *School Psychology Review*, 26(6), 414–424.

Paiz, J. M., Angeli, E., Wagner, J., Lawrick, E., Moore, K., Anderson, G., Franks, M., Paul, R., Keech, E., Ruiz, G., Allison, A., Caterelli, B., Zhou, M., Soong, R., Nguyen, Y., Bedo, O., Sanders, B., Howard, C., Denny, H., ... Keck, R. (2013). Online writing: The challenges of learning APA. *Journal of Psychotherapy*. <http://doi.org/10.4567/apa-style.67810>

Use a hanging indent

Xyers, K., Young, G., Zucherman, F., and Anne, A. (2019). Example with multiple authors. In G. Y. Iwamasa & P. A. Hays (Eds.), *Big Book of Examples* (2nd ed., pp. 287–314). CRC Press.

Xyers, K., Young, G., Zucherman, F., and Roberts, B. (2019, June 1). *Example citation for multiple authors*. BBC News. <http://www.bbcnews.com/example-for-multiple-authors.html>

Include up to 20 authors

The References provides the information necessary for a reader to locate and retrieve any source you cite.

- Every source you cite must appear on your References page.
- References page *only* includes sources cited in the body of your paper.

New in APA 7:

- No place of publication for books
- Do not use “retrieved from” or a retrieval date unless the website content updates often by design (e.g., social media)
- Leave hyperlinks

Exception: Do not include personal communication on your References page, e.g., emails or interviews, since they are not recoverable. Instead, cite them in-text. (See p. 6.)

Table 1

An Example of an APA Style Table

Limited shading and borders now preferred. (Do not use vertical borders to separate data.)

Table or Figure	Change from 6th Edition
Table	Mostly the same for simple tables, but avoid unnecessary borders or shading in a table
Figure	Now uses same title format as tables

Note. A table note may optionally be included under the table to clarify the contents of the table for the readers of the manuscript.

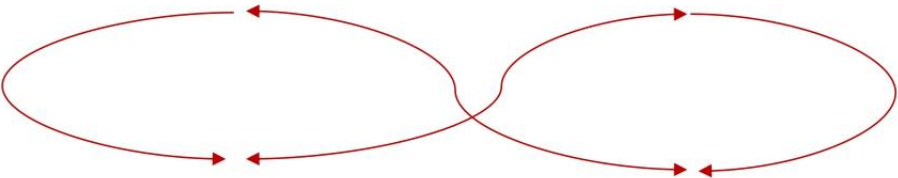
Figures and tables are left-aligned

Place each table on a separate page, followed by each figure on a separate page

Figure 1

Writing in APA Style

Figure titles now parallel to table titles (above the figure)



Note. A figure note may optionally be included under the figure to clarify the contents of the figure for the readers of the manuscript.



APA Style 7th edition

IMPORTANT NOTE: This Library Guide has been produced in single space in order to minimize paper use. **Please remember that when you produce your own APA documents, all text and references must be double-spaced.**

- The American Psychological Association (APA) style, as presented in this handout, is widely accepted in the Social Sciences.
- The APA citation format requires citation within the text rather than endnotes or footnotes.
- In-text citations usually include the name of the author and the date of publication, to lead the reader to the listing found in the "References" section, which is placed at the end of the research paper.
- Complete information about each source cited in the text is supplied in the "References" list.

Based on the *Publication manual of the American Psychological Association* (7th ed.). Washington, DC: American Psychological Association. For more information also go to <https://apastyle.apa.org/>

Citing in Your Paper (In-Text Citation)

In the text of a research paper, if the author's name is part of the narrative, include only the year of publication in the parentheses.

According to Smith (1998), APA style is an easy citation format for first-time learners.

APA style is an easy citation format for first-time learners (Smith, 1998).

If citing a particular page or chapter of a document, include that information in the parentheses.

APA style is an easy citation format for first-time learners (Smith, 1998, p. 203)

At the end of the paper, in a section called "References," full citations are listed in alphabetical order.

Smith, P. (1998). Learning to cite using APA Style. *Journal of College Writing*, 6, 60513.

Author Type	Parenthetical citation	Narrative citation
One author	(Gonzalez, 2019)	Gonzalez (2019)
Two authors	(Gonzalez & Jones, 2019)	Gonzalez and Jones (2019)
Three or more authors	(Gonzalez et al., 2019)	Gonzalez et. al. (2019)
Group author with abbreviation:		
First citation	(American Psychological Association [APA], 2020)	American Psychological Association (APA, 2020)
Subsequent citations	(APA, 2020)	APA (2020)
Group author without abbreviation	(University of California, 2020)	University of California (2020)
No author	("New drug," 1993) <i>Use an abbreviated version of the title.</i>	

Citations in Text with no page numbers:

If citing a particular part of a document which has no page numbers, include the paragraph (para.) or section heading with the number of the paragraph.

Use paragraph number or section heading with the number of the paragraph.

(Myers, 2000, para. 5)
(Beutler, 2000, Conclusion section, para.1)

Citation of a work discussed in another (secondary) source:

In general it is expected that you seek out and use the *original* source of the information. However, this is not always practical. To cite a secondary source, do the following.

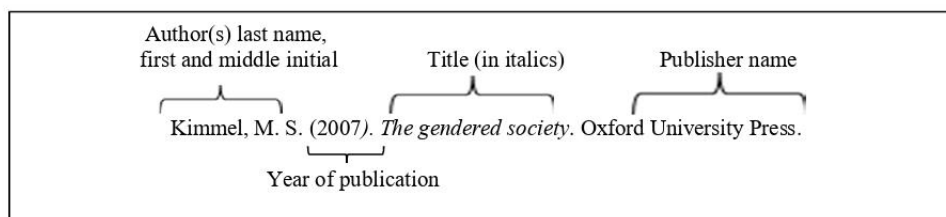
In the Text:

Seidenberg and McClelland's study (as cited in Coltheart, Curtis, Atkins, & Haller, 1993)

Note: You will list the Coltheart reference in the reference list.

Creating a Reference List at the End of Your Paper

Remember: All references in your list must be double-spaced, both between references and within references, with a hanging indent of ½ inch for references with more than one line.

Books and eBooks**Books:**By a Single AuthorBy Two or More Authors

DiFonzo, N., & Bordia, P. (2007). *Rumor psychology: Social and organizational approaches*. American Psychological Association.

By a Corporate (Group) Author

American Sociological Association. (1975). *Approaches to the study of social structure*. Free Press.

Edited Book

Rhodewalt, F. (Ed.). (2008). *Personality and social behavior*. Psychology Press.

No Author

The universal declaration of human rights. (1974). U.S. Catholic Conference, Division of Latin America.

Ebooks:With a doi

Gillam, T. (2018). *Creativity, wellbeing and mental health practice*. Wiley Blackwell.
<https://doi.org/10.1007/978-3-319-74884-9>

Without a doi (Cite the same as a print book)

Lauwers, J., Opsomer, J. & Schwall, H. (Eds.). (2018). *Psychology and the classics: a dialogue of disciplines*. De Gruyter.

From a website:

Sanger, M. (2000). *Woman and the new race*. Bartleby.com. <http://www.bartleby.com/1013/> (Original work published 1920).

Chapters in Books

Levi-Strauss, C. (1971). Totem and caste. In F. E. Katz (Ed.), *Contemporary sociological theory* (pp. 82-89). Random House.

Article, entry, or chapter from an online reference book (encyclopedia, dictionary, handbook):Online with a doi:

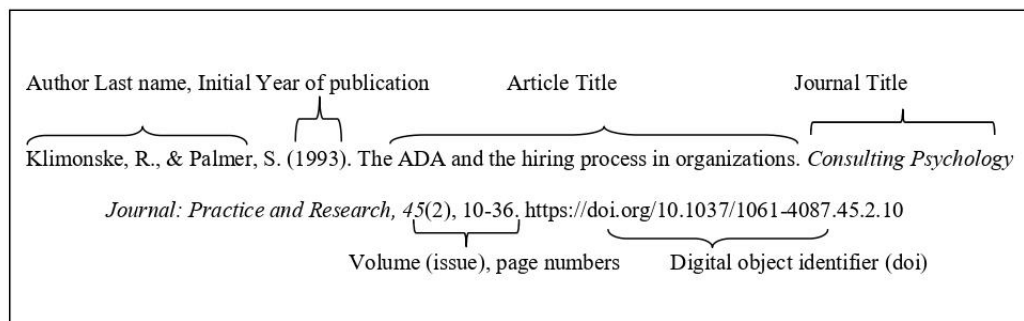
Watkins, M. (2013). Mind-body problem. In H. Pashler (Ed.), *Encyclopedia of the mind*. SAGE.
<http://dx.doi.org/10.4135/9781452257044.n191>

Online with no doi:

Shevell, S. K. (2000). Color vision. In A. E. Kasdin (Ed.), *Encyclopedia of psychology* (Vol.2, pp.182-186). Oxford University Press.

ERIC Documents

Evans, V. (2016). *An Evaluation of CHAMPS for classroom management* (ED581571). ERIC.
<https://eric.ed.gov/contentdelivery/servlet/ERICServlet?accno=ED581571>

Journal ArticlesArticle without DOI or in print:

Scroggins, W. A., Thomas, S. L., & Morris, J. A. (2008). Psychological testing in personnel selection, Part II: The refinement of methods and standards in employee selection. *Public Personnel Management*, 37(2), 185-199.

Two or more authors (up to 20 authors)

Klimonske, R., & Palmer, S. (1993). The ADA and the hiring process in organizations. *Consulting Psychology Journal: Practice and Research*, 45(2), 10-36. doi:10.1037/1061-4087.45.2.10

Note: If an article has 21 authors or more, list the first 19 authors, then insert an ellipsis (...) and then the last name and first initials of the last author.

Wolchik, S. A., West, S. G., Sandler, I. N., Tein, J., Coatsworth, D., Lengua, L., Johnson, A., Ito, H., Ramirez, J., Jones, H., Anderson, P., Winkle, S., Short, A., Bergen, W., Wentworth, J., Ramos, P., Woo, L., Martin, B., Josephs, M., ... Brown, Z. (2005). Study of the brain. *Psychology Journal* 32(1), 1-15. doi:10.1037/1061-4087.45.1.11

Newspaper and Magazine Articles

Newspaper Article

Online:

From a database (note: do not include database URL or name)

Article Author	Publication	Article Title	Newspaper
Last name, first initial	Date		
Cieply, M.	(2013, November 11).	Gun violence in American movies is rising, study finds.	<i>New York Times</i> .

From a website, with no author:

It's subpoena time. (2007, June 8). *New York Times*. <https://www.nytimes.com/2007/06/08/opinion/08fri1.html>

Print:

Jones, S. (1997, October 19). Hit-and-run suspect commits suicide. *New York Times*, p. 17.

Magazine Article:

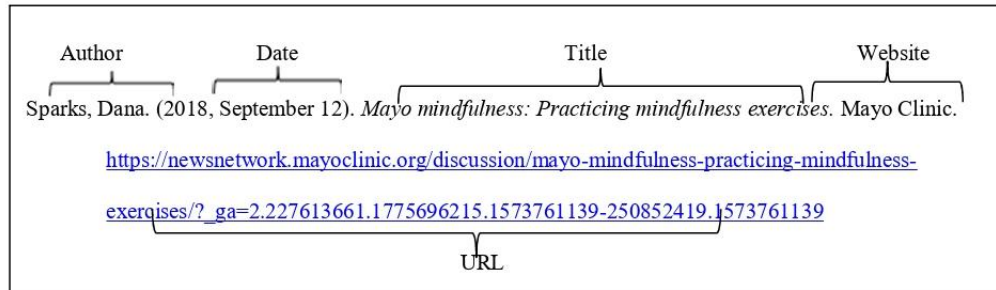
From a database or print:

Kluger, J. (2010, November 1). Keeping young minds healthy. *Time*, 176(18), 40-50.

From a website:

Heid, M. (2015, August 12). You asked: Why do I blush so much? *Time*. <http://time.com/3992760/blush-blushing/>

Web sites



Organization name as author (Group author):

National Institutes of Mental Health. (2015, May). *Anxiety disorders*.
<http://www.nimh.nih.gov/health/topics/anxiety-disorders/index.s>

Note: when the author and the name of the website are the same, you don't need to list it as the name of the website.

No author, no date:

What is psychology? (n.d). BestPsychologyDegrees.com. <https://www.bestpsychologydegrees.com/what-is-psychology/>

Notes:

- Only include a retrieval date if the information on the page is designed to change over time.
- If you cite multiple webpages from a single website, you should create a separate reference for each webpage. If you want to mention a website in its entirety, just mention it in your text with the URL in parentheses; don't include it in your references.

Blog posts:

Selingo, J. (2014, June 22). Reimagining the undergraduate experience: 4 provocative ideas. *Next*.
<http://chronicle.com/blogs/next/2014/06/22/reimagining-the-undergraduate-experience-4-provocative-ideas/>

Other Sources

Test Reviews

Online

Newmann, D. L., & Rust, J. O. (1989). [Review of the test *A.S.S.E.T.S—A survey of students educational talents and skills*]. In J. C. Conoley & J. J. Kramer (Eds.), *The tenth mental measurements yearbook*. Mental Measurements Yearbook with Tests in Print.

Charts, Tables and Graphs

If you are reproducing a graphic, chart, or table, from some other source, you must provide a special note at the bottom of the item that includes copyright information. If you are submitting your work for publication or if your work is a dissertation or master's thesis you should also submit written permission along with your work. If your work is a paper submitted for course work, permission is not necessary. In either case, begin the citation with "Note."

Note. From “Experiences of peer aggression and parental attachment are correlated in adolescence,” by R.M. Earl and N.R. Burns, 2009, *Personality and Individual Differences*, 47, p. 751. Copyright 2009 by the authors. Reprinted with permission.

If permission is not sought, substitute “Permission not sought” in place of “Reprinted with permission.”

Video

DVD or VHS:

Staveley-Taylor, H. (Director). (2006). *Introduction to designing experiments* [Film; DVD]. Uniview Worldwide; Cambridge Educational.

Streaming Online:

From a database:

BBC (Producer). (2014). *Living with autism*. [Film; Streaming Video]. Films on Demand.

From a website:

Lancaster, B. (Presenter). (2018, Jun 22). *Behavioral treatments for ADHD* [Video]. Michigan Medicine. YouTube. https://www.youtube.com/watch?v=iUgs8N_-nlo

Dissertations or Theses

Electronic copy of a thesis or dissertation from a database:

Rockey, R. (2008). *An observational study of pre-service teachers' classroom management strategies* (Publication No. 3303545) [Doctoral dissertation, Indiana University of Pennsylvania]. ProQuest Dissertations and Theses Global.

Electronic copy of a thesis or dissertation from an online archive or repository:

Gerena, C. (2015). *Positive Thinking in Dance: The Benefits of Positive Self-Talk Practice in Conjunction with Somatic Exercises for Collegiate Dancers* [Master's thesis, University of California Irvine]. University of California, eScholarship. <https://escholarship.org/uc/item/1t39b6g3>

Personal Communications:

Personal communications such as Emails, lectures, or conversations should be cited as personal communications in the text only (not in the reference list) in the following format:

R. J. Smith (personal communication, August 15, 2015)



Malaysian Financial Planning Council (Reg. No.: 0402-04-5)

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