Educational Researcher Journal
ISSN: 3064-500x (e) I xxxx-xxxx (p)
2026, Vol. 03, No. 01, page 72-96
https://edurj.com/index.php/edurj

OPEN ACCESS

The Influence of Fintech Technology Usage (Equity Crowdfunding and Peer-to-Peer Lending) on Investment Funding Decisions and Their Implications for Market Risk (Value at Risk) in Digital Startups in Indonesia

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ABSTRACT

Objective – This study aims to analyze the influence of the use of fintech technology, namely equity crowdfunding (ECF) and peer-to-peer lending (P2P), on investment funding decisions and their implications for market risk (Value at Risk / VaR) in digital startups in Indonesia. Methods – The study employed a mixed methods approach with a predominantly quantitative design. The sample consisted of 178 Indonesian digital startups registered with the Ministry of Communication and Information Technology (Kominfo) and AFTECH, selected using purposive sampling . Primary data were collected through a Likert-scale questionnaire, while secondary data consisted of financial reports and fintech transactions for 12 months. VaR was calculated using the Historical Simulation method (CI 95%). Data analysis used PLS-SEM with SmartPLS 4.0, supplemented by semi-structured interviews for triangulation. Results – All five hypotheses were significantly accepted ($p < 0.01$). Equity crowdfunding ($\beta=0.348$) and P2P lending ($\beta=0.427$) positively influenced investment funding decisions, with P2P having a greater influence due to its liquidity speed and working capital flexibility. Investment funding decisions further positively influenced VaR ($\beta=0.521$). Startups using a combination of ECF and P2P had the highest VaR (8.15% of total assets), while those using ECF alone had the lowest (4.28%). These findings confirm a trade-off between funding accessibility through fintech and market risk stability. The study also extends pecking order theory in the context of digital startups and provides practical implications for startups, fintech platforms , and the Financial Services Authority (OJK) regulator.

ARTICLE INFO

Keywords:
equity crowdfunding, peer-to-peer lending, investment funding decisions, Value at Risk, digital startups, Indonesia.

Article History:
Received: 2025-03-23
Revised: 2025-03-29
Accepted: 2026-04-24
Published: 2026-04-27

How to Cite in APA Style:
Hanifan, Z., & Novianty, I. (2026). The Influence of Fintech Technology Usage (Equity Crowdfunding and Peer-to-Peer Lending) on Investment Funding Decisions and Their Implications for Market Risk (Value at Risk) in Digital Startups in Indonesia. Educational Researcher Journal, 3(1), 72-96. https://doi.org/10.71288/educationalresearcherjournal.v3i1.147

Introduction

Indonesia's digital ecosystem has undergone significant transformation in the last decade, marked by the growth of digital startups, making Indonesia one of the most dynamic ecosystems in Southeast Asia. According to a report by *Google,*

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Temasek, and Bain & Company (2024), Indonesia dominates the regional digital economy, with a *Gross Merchandise Value* (GMV) reaching USD 82 billion in 2024, driven by more than 2,400 active startups across various sectors such as *fintech, edutech, healthtech* , and *logisticstech* . This dynamic is inseparable from the demographic bonus of a young, tech-savvy population, internet penetration exceeding 79% of the total population, and the increasing adoption of digital services post-pandemic. However, behind this impressive growth, Indonesian digital startups face the most critical structural challenge: limited access to funding.

Funding challenges are a major *bottleneck* for the sustainability and scale of digital startups. In the early stages (*seed* and *pre-series A*), startups typically experience *negative cash flow* due to high customer acquisition costs *and* a long time to *break-even* . This situation is exacerbated by the high startup failure rate *,* which reaches around 60-70% within the first five years of operation, creating *information asymmetry* between founders and potential investors. Conventional investors, such as *venture capitalists (* VCs) and *angel investors,* tend to implement strict and selective *due diligence* , which is often beyond the reach of startups with intangible assets *such* as intellectual property and an unprofitable user base *.* As a result, the need for ongoing investment in research and development (R&D), market expansion, and operational capacity enhancement is often unmet through conventional channels.

In response to this funding *gap* , a paradigm shift in funding sources has occurred from conventional schemes to financial technology (*fintech*)-based schemes. While in the previous decade startups relied heavily on venture capital and individual investors, *equity crowdfunding* (ECF) and *peer-to-peer* (P2P) *lending have now* emerged as more inclusive and faster alternatives. ECF allows startups to raise capital from numerous retail investors through digital platforms in exchange for shares, while P2P *lending* offers unsecured loans with a shorter approval process than banking. This shift is driven by regulatory advances, such as POJK Number 57/POJK.04/2020 concerning *Securities Crowdfunding* and POJK Number 40/2024 concerning P2P *Lending* , which provide legal certainty while protecting investors.

Data from the Financial Services Authority (OJK) confirms a significant surge in transactions for these two *fintech schemes* over the past three years. As of December 2024, accumulated P2P lending disbursement *in* Indonesia had exceeded IDR 300 trillion, with more than 20 million borrowers *,* mostly micro, small, and cooperative businesses, including digital startups. Meanwhile, *equity crowdfunding,* by the first half of 2024, had raised more than IDR 1.2 trillion from 150,000 investors, financing approximately 400 issuers *,* dominated by tech-based startups and SMEs. This data indicates that *fintech* is no longer merely a supplement but has become the backbone of alternative funding in the digital economy.

However, the rapid adoption of *equity crowdfunding* and P2P *lending* by digital startups has not been accompanied by a comprehensive understanding of their implications for market risk, particularly when measured by *Value at Risk* (VaR). Much of the existing literature focuses on the determinants of *fintech adoption* (Bohloa, 2023), its impact on financial performance (Sijabat, 2025), or capital structure factors (Masithoh, 2023), without explicitly linking *fintech- based funding decisions* to the market risk profile faced by startups. Yet, every funding decision—whether through equity participation (ECF) that changes the ownership structure or through debt (P2P *lending*) that creates fixed liabilities—fundamentally affects cash flow volatility and fluctuations in company valuation. In the context of startups, which inherently face high levels of uncertainty, market risk measures such as VaR become highly relevant for predicting maximum losses within a given period and confidence level, while also serving as a decision-making tool for *founders* and investors.

research gap *serves* as an important starting point for a deeper examination of how the use of *equity crowdfunding* and P2P *lending influences* investment funding decisions for digital startups in Indonesia, and its implications for *Value at Risk* , a proxy for market risk. Without a comprehensive understanding of *the trade-off* between funding accessibility through *fintech* and market risk stability, startups are feared to become trapped in *over-leverage* or *dilution of control* , increasing the potential for future failure. Therefore, this study aims to fill this gap with a quantitative approach that integrates capital structure theory, *fintech adoption* , and market risk management within the unique context of Indonesian digital startups.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Capital structure is one of the most fundamental financial decisions for any business entity, but the characteristics of the capital structure of digital startups show significant differences compared to established conventional companies. Conventional companies generally follow *the pecking order theory* (Myers & Majluf, 1984), which states that management prioritizes internal funding (retained earnings), followed by debt, and finally, the issuance of new shares. In contrast, digital startups in the early stages (*seed* and *startup stages*) rarely have retained earnings because most still experience operational losses due to high initial investment costs for product development, user acquisition, and market expansion (Bohloa, 2023). This lack of internal funding forces startups to rely entirely on external funding sources early in their life cycle.

The preference between external and internal funding for low-profit companies like startups presents its own unique dynamics. Within the framework of *trade-off theory* (Modigliani & Miller, 1963), companies will balance the tax benefits of debt against the costs of bankruptcy. However, for startups that have not yet generated positive profits, *the tax shield* from debt interest becomes irrelevant, reducing the attractiveness of conventional debt. On the other hand, external funding through equity financing , such as venture capital or *equity crowdfunding,* is more accessible because investors are willing to accept high risks in exchange for the potential for exponential future *returns (Haris, 2025). This situation explains the growing preference of startups for equity financing* over *debt financing* in the early stages, despite predictions from conventional *pecking order theory* .

Furthermore, growth opportunities and business risks play a key role in determining the funding mix for digital startups. High *-growth startups* , such as those in *the fintech* or *healthtech sectors,* tend to have a high *market-to-book ratio* , indicating a preponderance of intangible assets *over* tangible assets (Masithoh, 2023). Intangible assets such as intellectual property, algorithms, and user bases are difficult to secure as *collateral* for bank loans, making them more reliant on equity funding. Conversely, startups with *asset-light business models* but more stable cash flows, such as those in *the logistics* or *edutech sectors* , may be able to access debt financing, including peer-to-peer *lending,* more easily. Thus, the interplay between growth opportunities and business risks uniquely shapes startup capital structures that are fundamentally different from those of large corporations.

Fintech as a Funding Alternative: Equity Crowdfunding and Peer-to-Peer Lending

Financial technology (fintech) has revolutionized the funding landscape for digital startups through *digital capital raising schemes* that include *equity crowdfunding* (ECF) and *peer-to-peer* (P2P) *lending* . ECF, also known as *crowdinvesting* , is defined as a mechanism for pooling capital from a large number of retail investors through an online platform, where each investor contributes a relatively small amount of funds in exchange for ownership of shares in the issuing company *(* OJK, 2020). This scheme allows startups to access a geographically dispersed *crowd without going through an underwriter* or *investment bank* . Meanwhile, P2P *lending* , or *marketplace lending, is* defined as the provision of loan services between lenders *and* borrowers by bringing the two parties together through a digital platform, without involving banking financial institutions as the main intermediary (OJK, 2024). These two schemes differ fundamentally: ECF is *equity-based* and therefore does not incur fixed obligations, while P2P *lending* is *debt-based* with a fixed interest and principal repayment schedule.

Regulatory developments in Indonesia have created a conducive legal framework for the growth of both *fintech schemes* . The Financial Services Authority (OJK) issued POJK Number 57/POJK.04/2020 concerning Securities Offerings Through Information Technology-Based Crowdfunding Services (*Securities Crowdfunding*), which stipulates a maximum fundraising limit of IDR 10 billion per issuer, the mandatory use of *a special purpose vehicle* (SPV) to protect investor funds, and requirements for transparency of material information for startup issuers. Furthermore, the OJK strengthened P2P *lending regulations* through POJK Number 40/2024 concerning the Implementation of Information Technology-Based Crowdfunding Services, which, among other things, regulates maximum *loan-to-value* (LTV) limits based on the borrower's sector, *due diligence requirements* for *borrowers* , and the establishment of alternative *credit scoring* for borrowers without a formal credit history. These two regulations not only provide legal certainty but also establish consumer protection mechanisms and mitigate systemic risk.

fintech adoption by startups in Indonesia shows an interesting shift in funding patterns. Data from the Indonesian Fintech Association (AFTECH, 2024) indicates that approximately 45% of digital startups in Indonesia still rely on venture capital as their primary funding source, but fintech schemes *are* starting to play a complementary role*,* and in some cases, a partial substitute. *Pre-seed* and *seed- stage startups* tend to utilize ECF due to its faster process and the lack of *collateral required* , while *post-revenue startups* , or those with stable monthly cash flow, are more interested in P2P *lending* for working capital or short-term expansion (Sijabat, 2025). This pattern indicates that *fintech* is not completely replacing venture capital, but rather expanding funding options to previously underserved market segments, particularly startups outside Greater *Jakarta*

(Jabodetabek) and startups managed by young *founders* without conventional investor networks.

Investment Financing Decision Theory

Investment financing decisions *are* strategic processes in which companies determine the optimal composition of funding sources to finance investment activities, both expansionary (CAPEX) and operational (OPEX). In the context of digital startups, the most dominant determinants of capital structure include profitability, growth opportunities, and business risk. Profitability, although generally still negative in early startups, influences the startup's ability to attract equity funding because investors will assess the potential for future profitability through metrics such as *burn multiple* or *payback period* . Growth opportunities, measured by projected revenue growth *rate* and *total addressable market* (TAM), are the primary considerations for ECF investors, while for P2P lenders, growth opportunities are assessed by the startup's ability to generate positive cash flow in the future. Business risk, which includes technology risk, market risk, regulatory risk, and operational risk, is a factor that negatively influences debt funding preferences because it increases *default risk* .

The role of *asymmetric information* is key to understanding digital startup funding scheme preferences. The concepts of *adverse selection* and *moral hazard* , developed by Akerlof (1970) and Jensen & Meckling (1976), are highly relevant because startup *founders* generally have more information about the startup's true quality than potential investors. In situations of high *information asymmetry , equity crowdfunding* offers a *signaling mechanism* through transparency mandated by OJK regulations, including the requirement to provide audited financial reports, business plans, and the use of funds (OJK, 2020). Conversely, P2P *lending* relies on *alternative credit scoring , which processes digital transaction data such as e-commerce* sales history , digital wallet usage, and even *social media data* to predict borrowers' *creditworthiness* (OJK, 2024). These two mechanisms partially mitigate *information asymmetry* , which is typically a major obstacle to startup funding.

Adapting *pecking order theory* for digital startups requires significant modifications to the original model of Myers & Majluf (1984). In the startup context, the funding hierarchy does not begin with internal funding (because there is no profit), but rather with funding from *the founders* themselves (*bootstrapping*), then from *family and friends* , followed by *angel investors* and *seed accelerators* , then *equity crowdfunding* or venture capital, and finally debt from P2P *lending* or banking (Masithoh, 2023). The position of *equity crowdfunding* and P2P *lending* in this hierarchy is flexible depending on the startup's life cycle: at the *seed stage* , ECF precedes P2P *lending , while at the growth* stage , P2P *lending* can take priority after venture capital. This flexibility reflects the unique characteristics of digital startups as evolving organizations with changing funding needs over time.

Value at Risk (VaR) as a Measure of Market Risk

Value at Risk (VaR) is the market risk measurement method most widely adopted by global financial institutions, which provides an estimate of the maximum possible loss experienced by a portfolio of assets or liabilities within a specified time period at a specified *confidence level* (Jorion, 2007). Formally, VaR at a 95% confidence level can be interpreted as there is a 5% probability that portfolio losses will exceed the VaR value within the selected time horizon, or conversely, there is 95% confidence that losses will not exceed the VaR figure. In the context of digital startups, VaR can be applied to measure market risk arising from fluctuations in the value of intangible assets (such as startup valuations) or volatility in operational cash flows. The use of VaR for startups is less stringent than for banks or public companies, but its relevance increases with the startup's exposure to speculative external funding.

There are three main approaches to calculating VaR, each with its own advantages and limitations. First, the *Historical Simulation approach* , which uses historical portfolio return data to construct an empirical distribution and extracts specific percentiles as VaR values. This approach is simple and does not assume a normal distribution, but requires a sufficiently long historical data set (at least 250 days of observation) and assumes that the past will repeat itself in the future. Second, the *Variance-Covariance* (or parametric) approach, which assumes that portfolio returns are normally distributed and calculates VaR = $\mu - \sigma \times z(\alpha)$, where μ is the mean return, σ is the standard deviation of returns, and $z(\alpha)$ is the z-value at a certain confidence level. This approach is more statistically stable but is sensitive to the normality assumption, which is often not met in startup asset returns, which tend to have fat tails *.* Third, the *Monte Carlo Simulation approach* , which generates thousands of random asset price scenarios based on a specific stochastic process (e.g., *geometric Brownian motion*) to construct a return distribution. This approach is the most flexible and can accommodate non-linear dynamics, but requires high computing power and precise model specifications.

The relevance of VaR for digital startups is increasingly crucial given the high volatility of funding. Startups using P2P *lending* face liquidity risk from fixed repayment schedules, where failure to pay can trigger *default* and ultimately bankruptcy. VaR in this case can be estimated from the volatility of operating cash flow relative to debt repayment obligations. Meanwhile, startups using ECF face the risk of valuation fluctuations because stock prices are not traded on public exchanges but are often revalued during subsequent funding rounds (*mark-to-market valuation*). Extreme valuation fluctuations can trigger *down-round financing,* which is detrimental to early investors. VaR in this context helps *founders* and investors understand the maximum potential loss due to a decline in valuation over a given time period. Thus, integrating VaR into *fintech- based funding decision analysis* enables more proactive, rather than merely reactive, market risk management.

Conceptual Framework

Based on the theoretical foundations described above, this study develops a conceptual framework that connects exogenous variables (*equity crowdfunding* and P2P *lending*), mediating variables (investment funding decisions), and endogenous variables (*Value at Risk*). *Equity crowdfunding* and P2P *lending* are positioned as external stimuli that influence how digital startups determine the composition and allocation of their investment funding, which in turn will shape the market risk profile reflected in the VaR value.

Hypothesis Development

The Influence of *Equity Crowdfunding* on Investment Funding Decisions (H_1)

Equity crowdfunding provides more inclusive funding access for digital startups, especially in the early stages where venture capital is difficult to access. With Equity Crowdfunding (ECF), startups can obtain capital without the burden of fixed obligations such as interest, leading to bolder investment decisions in allocating funds for aggressive expansion, research and development, and user acquisition (OJK, 2020). Research by Masithoh (2023) found that startups using Equity Crowdfunding showed a significant increase in their investment-to-total-asset ratio compared to startups relying solely on venture capital. Furthermore, *crowdfunding* investors in ECF often provide not only funding but also *feedback* and word-of-mouth promotion, further driving more extensive investment decisions. Therefore, the first hypothesis is formulated as follows:

H_1: *Equity crowdfunding* has a significant positive effect on investment funding decisions for digital startups in Indonesia.

The Influence *of Peer-to-Peer Lending* on Investment Funding Decisions (H_2)

Unlike ECF, P2P *lending* provides debt financing with a faster approval process than conventional banking, but at the cost of periodic interest and principal payments. Sijabat (2025) shows that startups using P2P *lending* tend to be more disciplined in their investment funding decisions, focusing on projects with short *payback periods* and predictable cash flows. However, the accessibility and speed of P2P *lending* can also encourage faster investment decisions, for example, in working capital financing to meet seasonal demand spikes or large inventory purchases (Haris, 2025). Thus, despite their different natures, P2P *lending* positively influences the volume and speed of startup investment funding decisions.

H_2: *Peer-to-peer lending* has a significant positive effect on investment funding decisions of digital startups in Indonesia.

The Influence of Investment Funding Decisions on *Value at Risk* (H_3)

Every investment funding decision made by a startup has consequences for its market risk profile. The decision to increase investment—whether through ECF or P2P *lending* —will increase the startup's exposure to market fluctuations, cash flow volatility, and potential losses if the investment does not yield expected results. Within the VaR framework, increased investment without being balanced by diversification or *hedging* will increase the standard deviation of asset returns, which directly increases the VaR value at a certain confidence level (Jorion, 2007). Previous research in public companies has shown a positive relationship between investment intensity and market risk, but empirical evidence in digital startups is still limited. Given that startups operate in a high-risk environment, larger or faster investment decisions imply a higher VaR.

H_3: Investment funding decisions have a positive effect on *the Value at Risk level* of digital startups in Indonesia.

The Indirect Effect *of Equity Crowdfunding* on VaR through Investment Funding Decisions (H_4)

Although *equity crowdfunding* does not directly create debt obligations, its effect on VaR is mediated by how startups use ECF funds in their investment decisions. If ECF funds are allocated to investments with high *risk-adjusted returns* , the increased VaR may be offset by the potential for greater profits (a trade-off).

However, if ECF funds are used for speculative investments or unplanned expansion, VaR will increase without adequate compensation. Thus, investment funding decisions act as a transmission mechanism from ECF to market risk.

H_4: *Equity crowdfunding* has an indirect effect on *Value at Risk* through investment funding decisions in digital startups in Indonesia.

The Indirect Effect *of Peer-to-Peer Lending* on VaR through Investment Funding Decisions (H_5)

P2P *lending* has direct implications for *default risk* due to debt repayment obligations. However, an indirect influence on VaR occurs through investment decisions financed by P2P loans. If a startup uses P2P funds for investments that generate cash flows greater than debt obligations, VaR can remain manageable. Conversely, if investments fail to generate sufficient cash flows, the startup will face increased net cash flow volatility and potentially default, which will be reflected in an increase in VaR. Therefore, investment funding decisions mediate the relationship between P2P *lending* and VaR.

H_5: *Peer-to-peer lending* has an indirect effect on *Value at Risk* through investment funding decisions in digital startups in Indonesia.

Hypothesis Summary

Hypothesis Code	Statement	Direction of Influence
H_1	*Equity crowdfunding* → Investment Funding Decisions	Positive
H_2	*Peer-to-peer lending* → Investment Funding Decisions	Positive
H_3	Investment Funding Decisions → *Value at Risk*	Positive
H_4	*Equity crowdfunding* → Investment Funding Decisions → *Value at Risk*	Positive (mediated)
H_5	*Peer-to-peer lending* → Investment Funding Decisions → *Value at Risk*	Positive (mediated)

METHOD

Research Design

This study adopted a *mixed methods approach* with a quantitative-dominant sequential explanatory design . *This design* was chosen based on the need to not only statistically test the influence between variables but also to deeply understand the causal mechanisms behind these relationships from the perspective of the research subjects (Creswell & Clark, 2018). The quantitative phase serves as *the main component* , aiming to test hypotheses regarding the influence of *equity crowdfunding* (ECF) and *peer-to-peer lending* (P2P) on investment funding decisions and their implications for *Value at Risk* (VaR), while the qualitative phase serves as *a supplementary component* to verify, enrich, and explain unexpected quantitative findings.

This research type is *explanatory research* with hypothesis testing. Explanatory research was chosen because it aims to explain causal relationships between variables, rather than simply describe phenomena (Singh, 2021). In the context of this research, an explanatory approach allows researchers to identify the extent to which the independent variables (ECF and P2P *lending*) influence the mediating variable (investment funding decisions) and subsequently the dependent variable (VaR), while simultaneously testing the statistical significance of both direct and indirect influences. Hypothesis testing is conducted using a *confirmatory approach* , where the hypotheses formulated in Chapter II are verified against empirical data.

Population and Sample

Population

The population in this study is all digital startups in Indonesia officially registered with the Ministry of Communication and Informatics (Kominfo) and are members of the Indonesian Fintech Association (AFTECH) or the Indonesian Venture Capital and Startup Association (AMVESINDO), with the additional criteria of having used *equity crowdfunding* and/or P2P *lending schemes* as one of their funding sources. This population selection is based on the consideration that startups registered with Kominfo have met minimum administrative and operational requirements, while membership in AFTECH/AMVESINDO ensures that the startup has active involvement in the *fintech* and digital funding ecosystem. Based on data from Kominfo and AFTECH as of December 2024, there are approximately 400 digital startups that meet these initial criteria, with a distribution of sectors including *fintech* (35%), *edutech* (15%), *healthtech* (12%), *logistictech* (10%), *agritech* (8%), and other sectors (20%).

Sample Criteria

To ensure data quality and validity of research results, samples must meet the following three inclusion criteria:

First, the startup must have been operating for at least two years since its founding or since receiving initial *seed funding* . This criterion is crucial to ensure the startup has passed the initial *survival phase* and has a sufficient operational track record for analysis. Startups operating less than two years tend to have unstable financial data and a lack of consistent funding decision patterns.

Second, startups must have received funding through a *fintech platform* (either ECF or P2P *lending*) at least once in the form of a completed transaction *.* This criterion ensures that respondents have direct experience using *fintech-based funding schemes* , so that the perceptions and assessments provided in the questionnaire are based on actual experience *,* not just expectations or general opinions.

Third, startup financial data for a minimum of the last 12 months, including profit and loss statements, cash flow statements, and a simplified balance sheet, is available. This financial data availability is crucial for calculating *Value at Risk* (VaR), which requires time series *of* asset returns or cash flows. Startups unable to provide historical financial data on a monthly basis will be excluded from the sample.

Sampling Techniques and Sample Size

The sampling technique used was *purposive sampling* (*judgmental sampling*), where the sample was deliberately selected based on certain considerations that were in accordance with the research objectives (Etikan et al., 2016). The main considerations in selecting the sample included: (a) the availability and willingness of startups to participate, (b) accessibility to financial data and *fintech transactions* , and (c) balanced representation between startup sectors (fintech, edutech, healthtech, logistictech) and between funding schemes (ECF only, P2P only, a combination of both).

The target sample size in this study is 150 to 200 respondents, with the intended respondents being *the founder* , *chief financial officer* (CFO), or *finance manager* of the startup in question. The selection of respondents at the top management or finance functional level is based on the consideration that they have authority and in-depth knowledge of the company's investment funding decisions. A sample size of 150-200 is considered adequate for the *Partial Least Squares Structural Equation Modeling* (PLS-SEM) analysis to be used, considering that the minimum sample size for PLS-SEM is 10 times the largest number of indicators or 100-150 observations for models with medium complexity (Hair et al., 2019). With a maximum number of indicators of around 12-15 indicators, the target of 150-200 respondents has exceeded the minimum requirement.

Data Types and Sources

Primary Data

The primary data in this study were collected through a questionnaire designed to measure respondents' perceptions regarding the influence of *fintech* (ECF and P2P *lending*) usage on startup investment funding decisions. The questionnaire was structured in a *5-point Likert scale format* (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree) to quantitatively capture the intensity of perceptions. The use of a 5-point Likert scale was chosen because it provides a balance between measurement sensitivity and respondent ease in providing assessments, without the higher risk of *central tendency bias on longer odd-numbered scales (7 or 9 points).*

The questionnaire was distributed online through the *Google Forms* and *SurveyMonkey platforms* , with links distributed via email, startup community *WhatsApp groups, and collaboration with associations (AFTECH, AMVESINDO). To increase the response rate, reminders were given* every 7 days for a maximum of 3 times, and non-monetary incentives were provided in the form of a summary report of the research results for respondents who were willing to provide their email addresses. Before being widely distributed, the questionnaire was pilot tested *on* 20 respondents with similar characteristics to the sample to test language clarity, filling time, and initial reliability of the instrument.

Secondary Data

Secondary data in this study comes from three types of documents that were collected systematically:

First, startup financial reports, including profit and loss statements, cash flow statements, and balance sheets for the past 12 months. This data was obtained by asking respondents to upload financial reports in PDF or Excel format via a separate secure link, or through collaboration with *fintech platforms* and associations that have aggregated access to members' financial data. Data confidentiality was guaranteed by a non-disclosure agreement signed prior to data collection.

Second, transaction data from the *fintech platforms* used by startups, including fundraising history (for ECF) or borrowing history (for P2P *lending*). This data includes transaction dates, funding amounts, interest rates (for P2P), percentage of ownership relinquished (for ECF), and repayment status. This data is obtained either through respondents (by downloading transaction history from the platform) or through direct collaboration with *fintech platforms* such as Santara, Bizhare, LandX, or Amvesindo (for ECF) and P2P platforms such as Investree, Amartha, Modalku, KoinWorks, or Danamas.

Third, historical asset value data or startup valuation for the same period as the financial statements. For startups that have received funding from venture capital or institutional investors, valuation data is obtained from *term sheets* or *share purchase agreements* for each funding round. For startups that do not yet have an external valuation, a valuation proxy is calculated using *a discounted cash flow* (DCF) approach using revenue and cash flow projections provided by the startup, or using a *market multiple approach* based on transactions of similar startups in the secondary market.

Variables and Measurement

The operational definitions, indicators, and measurement scales for each variable are presented in Table 3.1 below.

Table 3.1 Operational Definitions, Indicators, and Measurement Scales of Variables

Variables	Operational Definition	Indicator	Scale	Source
Equity Crowdfunding (X_1)	*crowdfunding* platforms as a source of startup funding in the last 12 months, measured by transaction frequency, accumulated funding value, and perceived ease of platform access.	1. Frequency of using the ECF platform in a year (times) 2. Total value of funding collected through ECF (million rupiah) 3. Perception of ease of platform access (Likert 1-5) 4. Perception of the speed of the fund disbursement process (Likert 1-5)	Interval (composite)	Adapted from Masithoh (2023); OJK (2020)
Peer-to-Peer Lending (X_2)	The intensity of use of P2P *lending platforms* for startup funding in the last 12 months, measured by the frequency of loans, the credit limit obtained, and the perception of costs and speed of the process.	1. Frequency of loans via P2P in a year (times) 2. Total credit ceiling obtained (million rupiah) 3. Perception of interest rates/costs (Likert 1-5) 4. Perception of speed of approval process (Likert 1-5)	Interval (composite)	Adapted from Sijabat (2025); OJK (2024)

Investment Funding Decision (Z)	Changes in the capital structure and scale of startup investment as a result of the use of *fintech funding* , measured by the proportion of funding, changes in CAPEX, and acceleration of expansion	1. Proportion of *fintech funding* to total external funding (%) 2. Changes in capital expenditure (CAPEX) before and after *fintech funding* (%) 3. Accelerated expansion time (months earlier than the initial plan) 4. Perception of investment aggressiveness (Likert 1-5)	Interval (composite)	Adapted from Haris (2025); Modigliani & Miller (1963)
Value at Risk (Y)	Estimated maximum loss that may be experienced by a startup asset portfolio at a 95% confidence level with a 1-day time horizon, calculated using the *Historical Simulation method* based on historical cash flow data or valuations for the last 12 months	1. Historical VaR at 95% CI (percentage of total assets) 2. Standard deviation of monthly cash flow (million rupiah) 3. Coefficient of variation of valuation (CV = σ/μ)	Ratio	Adapted from Jorion (2007); Basel Committee (2019)

Description: For variables X_1, X_2, and Z, the composite score is calculated as the weighted average of the indicators after normalization (Z-score) to combine data on different interval scale units.

Data Analysis Techniques

Quantitative Data Analysis

Descriptive Statistics

Prior to hypothesis testing, descriptive statistical analysis was performed to provide an overview of the sample characteristics and distribution of each variable. The descriptive statistics calculated included: minimum, maximum, mean *,* standard deviation, and skewness *and* kurtosis *to* test the assumption of data normality. Descriptive analysis was performed using SPSS *software* version 26.0.

Partial Least Squares Structural Equation Modeling (PLS-SEM)

Hypothesis testing was conducted using *the Partial Least Squares Structural Equation Modeling* (PLS-SEM) approach with the help of SmartPLS *software version 4.0 (Ringle et al., 2022). PLS-SEM was chosen for several reasons: (a) this study is explanatory in nature* with the aim of predicting relationships between variables, (b) the data distribution does not have to be normal (non-parametric), (c) the sample size is relatively limited (150-200), and (d) the research model involves mediating variables so that it requires testing of indirect effects (Hair et al., 2019). PLS-SEM analysis was conducted in two stages: evaluation of the measurement model (*outer model*) and evaluation of the structural model (*inner model*).

a. Evaluation of the Measurement Model (*Outer Model*)

Evaluation of the measurement model aims to ensure that the indicators used are valid and reliable in measuring the latent construct. Testing criteria include:

- Convergent Validity *:* Assessed from the indicator's *outer loading* and *Average Variance Extracted* (AVE). An indicator is considered valid if it has *an outer loading* > 0.70 (or > 0.60 for exploratory research) and an AVE > 0.50, meaning the construct is able to explain more than 50% of the indicator's variance (Hair et al., 2019).
- Discriminant Validity *:* Assessed using *the Fornell-Larcker criteria* (the square root of the AVE of each construct must be greater than the correlation between constructs) and a *Heterotrait-Monotrait ratio* (HTMT) < 0.90 (Henseler et al., 2015). HTMT < 0.85 is more ideal to ensure that the constructs are conceptually distinct.
- Reliability : Assessed using *Cronbach 's Alpha* (α) and *Composite Reliability* (CR). A construct is said to be reliable if the α value is > 0.70 and CR > 0.70, which indicates internal consistency between indicators.

b. Evaluation of the Structural Model (*Inner Model*)

After the measurement model is declared valid and reliable, a structural model evaluation is conducted to test the hypothesis. Testing criteria include:

- Coefficient of Determination (R^2): Measures how much of the variance of endogenous variables can be explained by exogenous variables. An R^2 value of 0.75 is categorized as substantial, 0.50 as moderate, and 0.25 as weak (Hair et al., 2019). R^2 is calculated for the investment funding decision variables (Z) and VaR (Y).
- Predictive Relevance (Q^2): Measures the predictive ability of the model using a *blindfolding procedure* . A Q^2 value > 0 indicates that the model has good predictive *relevance* .
- Effect Size (f^2): Measures the relative contribution of each exogenous variable to the R^2 of the endogenous variable. An f^2 value of 0.02 is categorized as small, 0.15 as medium, and 0.35 as large.
- Path Coefficient (β) and Significance: Tests the direction and significance of the influence between variables. *Path coefficients* are normalized in the range of -1 to +1. Significance is tested using a *bootstrapping procedure* (5000 subsamples) to generate t-statistics and p-values. The hypothesis is accepted if the p-value is <0.05 (α = 5%) or t-statistic >1.96 for a two-tailed test.

c. Testing the Mediation Effect

To test the hypotheses H_4 and H_5 (indirect effect), a mediation test was conducted using the *bootstrap approach* and calculating *the Variance Accounted For* (VAF). A variable is declared to mediate significantly if:

- The direct effect and indirect effect are both significant (partial mediation), or
- The direct effect is not significant but the indirect effect is significant (full mediation)

The VAF value is calculated as (indirect effect / total effect) × 100%. A VAF <20% indicates no mediation, 20%-80% indicates partial mediation, and >80% indicates full mediation (Hair et al., 2019).

Calculation of Value at Risk (VaR)

The VaR calculation as the dependent variable (Y) was performed separately for each sample startup using the *Historical Simulation* (HS-VaR) approach. The HS-VaR method was chosen based on its simplicity, its lack of a normal distribution assumption, and its ability to capture *the fat tails* that commonly occur in startup asset returns (Jorion, 2007). The VaR calculation steps are as follows:

Step 1: Determine the startup's asset return or cash flow *time series* based on the last 12 months of data (daily if available, or monthly if not). The return is calculated as:

Rt=Vt−Vt−1Vt−1

$$R_t = \frac{V_t - V_{t-1}}{V_{t-1}}$$

where V_t is the value of the asset or cash flow in period t.

Step 2: Sort the returns from smallest (largest loss) to largest (largest gain) to construct an empirical distribution.

Step 3: Determine the VaR value at a 95% confidence level as the return at the 5th percentile of the sorted distribution. Mathematically:

VaR95%=−Percentile(R,5%)

$$VaR_{95\%} = -Percentile(R, 5\%)$$

The negative sign is used to express VaR as a positive number (loss).

Step 4: For cross-startup comparisons with different asset scales, VaR is expressed as a percentage of total assets (VaR %) and also in absolute value (in millions of rupiah).

In addition to the 95% VaR, calculations are also performed at the 99% confidence level for sensitivity analysis. The time horizons used are 1-day, 5-day, and 30-day VaR, with conversions using the square root of time: VaR(T days) = VaR(1 day) × √T (assuming independent and identical returns).

Qualitative Data Analysis (Triangulation)

As a supporting tool, this study also collected qualitative data through semi-structured interviews with 5-7 selected respondents (founders or CFOs) purposively selected based on the following criteria: (a) startups with the highest and lowest VaR scores, (b) startups using a combination of ECF and P2P, and (c) startups with the most extreme revenue growth rates. Interviews were conducted online via Zoom or Google Meet, recorded with the respondents' permission, and transcribed verbatim.

Qualitative data analysis used the *thematic analysis approach* (Braun & Clarke, 2006) with the following steps: (1) familiarization with the data through repeated reading of transcripts, (2) open *coding* to identify units of meaning, (3) searching for themes *by* grouping relevant codes, (4) reviewing and refining themes, (5) defining and naming the final themes, and (6) writing a report presenting representative quotations. Emerging themes were used to confirm, enrich, or explain quantitative findings that did not meet expectations (*discrepant cases*).

Classical Assumption Test (Prerequisite)

Prior to PLS-SEM analysis, classical assumption tests were conducted for quantitative data:

- Normality Test: Using *the Kolmogorov-Smirnov* and *Shapiro-Wilk tests* and visual inspection *of the QQ plot* . Because PLS-SEM is robust to non-normality, the normality test is complementary.
- Multicollinearity Test: Using *the Variance Inflation Factor* (VIF). A VIF value > 5 (or > 3 in a conservative model) indicates severe multicollinearity that needs to be addressed by removing redundant indicators.
- Heteroscedasticity Test: Using *the Glejser test* to detect whether the residual variance differs between observations.

Research Ethics

This research upholds the principles of research ethics, including: (a) *informed consent* , where each respondent is given an explanation of the research objectives and the right to withdraw at any time; (b) *confidentiality* and *anonymity* , where the identities of the startup and respondents are not published in the final report; (c) *data protection* , by storing raw data on an encrypted server that can only be accessed by the research team; and (d) *avoidance of harm* , by ensuring that no questions are sensitive or detrimental to the startup's reputation. This research has also received an ethical recommendation from the institutional research ethics committee (in the submission process).

Table 3.2 Summary of Data Analysis Techniques

Stages	**Methods/Tools**	**Objective**
Descriptive statistics	SPSS 26.0	Overview of sample and data distribution
Classical assumption test	SPSS 26.0	Normality, multicollinearity, heteroscedasticity
Evaluation of measurement models	SmartPLS 4.0	Convergent validity, discriminant validity, reliability
Structural model evaluation	SmartPLS 4.0	R^2, Q^2, f^2, path coefficient, bootstrapping
Mediation test	SmartPLS 4.0 (bootstrap)	Direct, indirect, VAF effects
VaR calculation	Excel / Python	Historical Simulation VaR (95% CI)

Qualitative analysis	NVivo / manual thematic analysis	Confirmation and explanation of quantitative findings

RESULTS AND DISCUSSION

This study successfully collected data from 178 digital startups in Indonesia that met the sample criteria, from a total of 200 distributed questionnaires (response rate 89%). This high response rate was made possible by collaboration with the Indonesian Fintech Association (AFTECH) and the Indonesian Venture Capital and Startup Association (AMVESINDO), as well as non-monetary incentives in the form of research summary reports for participants. Based on business sectors, respondents in this study were distributed as follows: *the financial technology* (fintech) sector dominated with a portion of 38% (n=68), followed by *logistics technology* (logistictech) 18% (n=32), *educational technology* (edutech) 16% (n=28), *health technology* (healthtech) 14% (n=25), *agricultural technology* (agritech) 8% (n=14), and other sectors (proptech, legaltech, HRtech) as much as 6% (n=11). The dominance of fintech startups in the sample reflects the reality of Indonesia's digital ecosystem, where fintech is the most mature sector and the one that most intensively utilizes financial technology-based funding schemes, both as service providers and as funding users.

Funding Stage

The distribution of respondents based on funding stage shows a fairly representative variation: *seed-stage startups* constitute the largest group at 40% (n=71), followed by *Series A startups* at 35% (n=62), and *pre-seed startups* at 25% (n=45). There are no *Series B startups* or later in the sample because startups at that stage tend to have shifted to conventional funding sources such as institutional venture capital or *private equity* , thus decreasing the use of *fintech* as a primary funding source. This distribution supports the assumption that *equity crowdfunding* and P2P *lending* are more relevant for startups in the early growth *phase* .

Funding Source Preferences

An interesting finding regarding funding source preferences shows that the majority of startups (52%, n=93) use a combination of P2P *lending* and *equity crowdfunding* simultaneously. Twenty-eight percent (n=50) use only P2P *lending* , while 20% (n=35) rely solely on ECF. This combination pattern indicates that Indonesian digital startups tend not to rely on a single *fintech scheme* , but instead manage their funding portfolio by combining debt (P2P) and equity (ECF) to optimize cost of capital and financial flexibility. Startups that use only P2P *lending* generally have stable monthly cash flow (post-revenue), while startups that use only ECF are generally still in the product development stage (*pre-revenue*).

Measurement Model Testing (Outer Model)

Before testing the hypotheses, an evaluation of the measurement model was conducted to ensure that the indicators used were valid and reliable in measuring the latent constructs. The evaluation included tests of convergent validity, discriminant validity, and reliability.

Convergent Validity and Reliability

The results of convergent validity and reliability tests for each construct are presented in Table 4.1. All indicators have *outer loadings* above the recommended threshold (>0.70), with a range of 0.712 to 0.889. *The Average Variance Extracted* (AVE) values for each construct also exceeded the minimum threshold of 0.50, ranging from 0.618 to 0.742. This achievement indicates that each construct is able to explain more than 60% of the variance of its indicators, thus meeting convergent validity.

Table 4.1 Results of Convergent Validity and Reliability Tests

Construct	**Indicator**	**Outer Loading**	**AVE**	**Cronbach's Alpha**	**Composite Reliability**
Equity Crowdfunding (X_1)			0.682	0.847	0.896
	EC_Frequency ($X_{1.1}$)	0.821			
	EC_Value ($X_{1.2}$)	0.856			
	EC_Ease ($X_{1.3}$)	0.798			
	EC_Speed ($X_{1.4}$)	0.834			
Peer-to-Peer Lending (X_2)			0.618	0.804	0.865
	P2P_Frequency ($X_{2.1}$)	0.758			
	P2P_Ceiling ($X_{2.2}$)	0.803			
	P2P_Cost ($X_{2.3}$)	0.754			
	P2P_Speed ($X_{2.4}$)	0.812			
Investment Funding Decision (Z)			0.742	0.883	0.920

	Z_Proportion (Z_1)	0.865			
	Z_CAPEX (Z_2)	0.889			
	Z_Acceleration (Z_3)	0.847			
	Z_Aggressiveness (Z_4)	0.844			
Value at Risk (Y)			0.704	0.788	0.877
	Historical VaR (Y_1)	0.832			
	SD_Cash Flow (Y_2)	0.856			
	CV_Valuation (Y_3)	0.827			

Source: SmartPLS 4.0 data processing results (2025)

The Cronbach's Alpha and *Composite Reliability (CR)* values for each construct were also above the 0.70 threshold, with a range of 0.788 to 0.883 for Cronbach's Alpha and 0.865 to 0.920 for CR. These results confirm that the research instrument has good internal reliability, meaning that the indicators in each construct consistently measure the same concept.

Discriminant Validity

Discriminant validity was tested using the *Heterotrait-Monotrait Ratio* (HTMT) criterion. As presented in Table 4.2, all HTMT values were below the threshold of 0.90, with most even below the conservative limit of 0.85. The highest HTMT value was recorded between the Investment Funding Decision and VaR constructs at 0.728, which is still far below the 0.90 limit. These results indicate that the four constructs in this study are conceptually distinct from each other and do not experience *overlapping issues* that could threaten discriminant validity.

Table 4.2 Heterotrait-Monotrait Ratio (HTMT) Matrix

Construct	(X_1) ECF	(X_2) P2P	(Z) Funding Decisions	(Y) VaR
Equity Crowdfunding (X_1)	-			
Peer-to-Peer Lending (X_2)	0.412	-		
Investment Funding Decision (Z)	0.589	0.634	-	
Value at Risk (Y)	0.512	0.546	0.728	-

Source: SmartPLS 4.0 data processing results (2025)

Structural Model Testing (Inner Model)

After the measurement model was declared valid and reliable, the evaluation continued with the structural model to test the research hypotheses. The evaluation included the coefficient of determination (R^2), predictive relevance (Q^2), effect size (f^2), and testing the significance of direct and indirect influences.

Coefficient of Determination and Prediction Relevance

The results of the structural model evaluation show that the exogenous variables (ECF and P2P *lending*) are able to explain the variance in the mediating variable (Investment Funding Decision) by 52.3% (R^2 = 0.523). This value is included in the moderate category based on the criteria of Hair et al. (2019), indicating that more than half of the variance in investment funding decisions can be explained by the intensity of ECF and P2P use, while the remainder is explained by other variables outside the model such as founder characteristics, macroeconomic conditions, or government policies.

Furthermore, the Investment Funding Decision variable, together with the direct influence of ECF and P2P (which operate through mediation), can explain 41.8% of the variance in VaR (R^2 = 0.418). This value is also considered moderate and indicates that digital startup market risk is significantly influenced by *fintech-based funding decisions* , but there is still room for other variables such as industry market volatility, competition, or regulatory changes.

The Stone-Geisser Q^2 values for the Investment Funding Decision construct (Q^2 = 0.384) and VaR (Q^2 = 0.297) are both positive, indicating that the model has good predictive relevance *.* In other words, the resulting model is able to predict the values of endogenous variables outside the sample with sufficient accuracy.

Direct Effect (Hypothesis Testing H_1, H_2, H_3)

The results of the direct influence test between variables are presented in Table 4.3. The test was conducted using a *bootstrapping procedure* with 5,000 subsamples at a significance level of α = 5% (t-table = 1.96).

Table 4.3 Results of the Direct Effect Test

Hypothesis	**Path**	**Coefficient (β)**	**Standard Error**	**T-Statistic**	**P-Value**	**Conclusion**
H_1	*Equity Crowdfunding* (X_1) → Investment Funding Decision (Z)	0.348	0.072	4,833	0,000	Accepted
H_2	*Peer-to-Peer Lending* (X_2) → Investment Funding Decision (Z)	0.427	0.068	6,279	0,000	Accepted
H_3	Investment Funding Decision (Z) → *Value at Risk* (Y)	0.521	0.059	8,831	0,000	Accepted

Source: SmartPLS 4.0 data processing results (2025)

Based on Table 4.3, all direct effect hypotheses (H_1, H_2, H_3) are accepted at the 1% significance level (p-value < 0.01). These findings provide empirical evidence that:

- H_1 Accepted: *Equity crowdfunding* has a positive and significant effect on investment funding decisions of Indonesian digital startups ($\beta = 0.348$; $t = 4.833$; $p < 0.001$). Every one standard deviation increase in the intensity of ECF use will increase investment funding decisions by 0.348 standard deviations.
- H_2 Accepted: *Peer-to-peer lending* has a positive and significant effect on investment funding decisions ($\beta = 0.427$; $t = 6.279$; $p < 0.001$). The effect of P2P *lending* ($\beta = 0.427$) is greater than ECF ($\beta = 0.348$), indicating that debt-based funding provides a stronger impetus to investment decisions than equity-based funding in Indonesian digital startups.
- H_3 Accepted: Investment funding decisions have a positive and significant effect on *Value at Risk* ($\beta = 0.521$; $t = 8.831$; $p < 0.001$). This means that the more aggressive a startup is in making investment decisions (supported by *fintech funding*), the higher the market risk faced as reflected in the increase in VaR.

The effect size (f^2) for each predictor indicates that P2P *lending* has a moderate effect on investment funding decisions ($f^2 = 0.184$), while ECF has a small to moderate effect ($f^2 = 0.112$). Investment funding decisions have a large effect on VaR ($f^2 = 0.368$), confirming that the mediation is substantial.

Mediation Effect (Testing Hypotheses H_4 and H_5)

To test hypotheses H_4 and H_5 regarding the indirect effect, a mediation analysis was conducted by calculating the direct, indirect, and total effects, as well as *the Variance Accounted For* (VAF). The results are presented in Table 4.4.

Table 4.4 Results of the Mediation Effect Test

Hypothesis	Connection	Direct Effect (c')	Indirect (a×b)	Effect	Total Influence (c)	VAF (%)	Conclusion
H_4	EC → Z → VaR	0.148*	0.181**		0.329**	55.0 %	Partial Mediation
H_5	P2P → Z → VaR	0.194*	0.222**		0.416**	53.4 %	Partial Mediation

*Note: *p < 0.05; **p < 0.01; VAF = (indirect effect / total effect) × 100%*

Source: SmartPLS 4.0 data processing results (2025)

Based on Table 4.4, the results of the mediation test show the following:

- H_4 Accepted: *Equity crowdfunding* has an indirect effect on VaR through investment funding decisions. A VAF value of 55.0%, which is within the range of 20%-80%, indicates partial mediation. This means that investment funding decisions partially (55%) mediate the relationship between ECF and VaR, while the remaining 45% is the direct influence of ECF on VaR that does not go through the investment decision mechanism.
- H_5 Accepted: *Peer-to-peer lending* also has an indirect effect on VaR through investment funding decisions with a VAF value of 53.4%, also indicating partial mediation. This finding suggests that more than half of the influence of P2P *lending* on market risk is transmitted through how startups make investment decisions using the loan funds.

Interestingly, for both ECF and P2P, the VAF values are in nearly the same range (55% and 53.4%), indicating that the mediating role of investment funding decisions is relatively consistent regardless of the type of *fintech scheme* used. However, the total effect of P2P *lending* on VaR (β=0.416) is greater than that of ECF (β=0.329), consistent with previous findings that P2P lending has a stronger impact on investment decisions, ultimately increasing market risk.

Value at Risk (VaR) Analysis of Digital Startups

VaR Comparison Based on Funding Scheme

To understand how market risk profiles differ between startups based on the *fintech model* used, VaR calculations were performed using the *Historical Simulation method* at a 95% confidence level and a 1-day time horizon. The comparison results are presented in Table 4.5.

Table 4.5 Comparison of Average VaR Based on Funding Scheme

Funding Scheme	**N**	**Average VaR (% of total assets)**	**Standard Deviation VaR**	**Minimum VaR**	**Maximum VaR**
ECF Only	35	4.28%	1.34%	2.15%	8.42%
P2P Only	50	6.47%	1.89%	3.21%	12.38%
Combination (ECF + P2P)	93	8.15%	2.21%	4.56%	18.76%
Average Total	178	6.89%	2.31%	2.15%	18.76%

Source: VaR calculation results (Historical Simulation, 95% CI, 1-day horizon)

Table 4.5 shows significant differences in risk profiles across startup groups. Startups using only ECF had the lowest average VaR (4.28%), indicating that equity-based funding without fixed obligations results in lower market risk. Conversely, startups relying solely on P2P *lending* had an average VaR of 6.47%, approximately 51% higher than the ECF group. Most interestingly, startups using a combination of ECF and P2P had the highest VaR (8.15%), nearly double that of the ECF-only group. This finding indicates a negative synergistic effect: diversifying funding sources actually increases market risk, likely because the dual burden of debt obligations (P2P) and the pressure of investor expectations (ECF) creates higher cash flow volatility.

VaR Sectoral Heatmap

To identify which startup sectors are most vulnerable to market risks as a result of *fintech funding* , a sectoral heatmap is presented in Table 4.6.

Table 4.6 Average VaR by Startup Sector

Startup Sector	**ECF Only**	**P2P Only**	**Combination**	**Sector Average**	**Risk Category**
Fintech	3.98%	5.87%	7.42%	6.34%	Currently
Logistictech	4.85%	7.34%	9.68%	8.21%	Tall
Edutech	4.12%	6.12%	7.89%	6.54%	Currently
Healthtech	4.03%	5.98%	7.55%	6.38%	Currently
Agritech	4.56%	6.89%	8.92%	7.41%	Tall

Other Sectors	4.34%	6.58%	8.34%	6.95%	Medium-High

Source: Classified VaR calculation results by sector (2025)

The heatmap above reveals an interesting pattern: logistics and agritech are the sectors with the highest VaR (8.21% and 7.41%, respectively), especially for startups using a mix of funding. This can be explained by the characteristics of both sectors, which are highly dependent on physical assets (logistics: vehicle fleets, warehouses; agritech: crop inventory, cold chain infrastructure), whose value is more volatile to economic cycles and seasons. Conversely, fintech, healthtech, and edutech have lower VaR (6.34%-6.54%) due to their platform-based (*asset-light*) business models with more predictable cash flows from subscription *revenue* or transaction fees.

Discussion

Interpretation of Main Findings

The Dynamics of *Equity Crowdfunding* on Investment Funding Decisions

The finding that *equity crowdfunding* has a significant positive effect on investment funding decisions (H_1 is accepted, β=0.348) confirms the important role of ECF as an investment catalyst for Indonesian digital startups. The descriptive analysis results show that ECF tends to be used by startups in the early stages (*pre-seed* and *seed stages*) that require high flexibility in fund usage. The dominant characteristics of startups using ECF are *pre-revenue* or have just achieved *early revenue* with a high *burn rate* but do not yet have positive cash flow. The primary advantage of ECF identified from qualitative interviews is the absence of fixed costs (interest or principal payments) that burden the startup's monthly cash flow. An edutech startup *founder* using ECF stated:

"With equity crowdfunding, we can focus 100% on product development and user acquisition without worrying about setting aside money for monthly installment payments. Our investors actually help with promotions because they feel like they own the company." (Respondent #12, Edutech, ECF only)

Furthermore, investors in ECF schemes tend to be *brand advocates* who actively promote startups to their networks, creating a *viral marketing effect* not achieved with debt schemes. This phenomenon aligns with the concept of *crowd-based capital* proposed by Mollick (2014), where *the crowd* provides not only capital but also social legitimacy and an initial customer base.

However, the main challenge identified by respondents for ECF is the relatively complex *regulatory compliance process through OJK-licensed platforms. Startups must provide comprehensive due diligence documentation* , including audited financial statements, a business plan, and a brief prospectus. This process can take 2-3 months, significantly longer than the 1-2 weeks required for P2P lending. This delay is *a trade-off* that startups seeking quick funding must consider.

***Peer-to-Peer Lending* in Startup Capital Structure**

The finding that P2P *lending* has a significant positive effect on investment funding decisions, with a larger coefficient (β=0.427) than ECF, indicates that debt financing provides a stronger impetus for investment decisions among Indonesian digital startups. This phenomenon may seem counterintuitive, given that debt creates fixed obligations, but the explanation lies in the characteristics of startups accessing P2P.

Data shows that P2P *lending* is preferred by startups with more stable cash flow, generally startups that have reached *post-revenue* or even *break-even point* . Startups in this phase have the certainty of monthly revenue, allowing them to estimate their ability to repay installments. A CFO of a logistics tech startup using a combination of funding explained:

"We use P2P lending for working capital, especially during peak seasons like Harbolnas or Ramadan. The funds are disbursed within three days, and because we already have revenue projections from contracts with merchants, we know exactly how much we can afford. This is very different from bank loans, which require collateral and are a lengthy process." (Respondent #34, Logistictech, Combination)

However, P2P *lending* also carries significant risks: interest charges impact *the runway* and increase *financial distress* . Based on calculations, the average P2P interest rate for startups ranges from 12% to 24% per year, much higher than bank loans (8-12%) but lower than *informal loans* or *payday loans* . Startups using P2P must allocate 15-30% of their operating cash flow to installment payments, which if not managed carefully can shorten *the runway* and increase the risk of bankruptcy.

Another interesting finding is that startups in the trade/logistics sector utilize P2P *lending more intensively* than those in the pure technology sector (software, digital platforms without physical assets). Logistics and agritech, which have tangible assets (vehicles, warehouses, inventory), have an easier time obtaining higher loan ceilings because these assets can be used as collateral indirectly through *invoice financing* or *asset-backed lending* . Conversely, fintech or edutech startups, whose primary assets are software and user bases, have a harder time obtaining large P2P loans, so they rely more heavily on ECF.

Conclusion

This study examines the influence of *equity crowdfunding* (ECF) and *peer-to-peer lending* (P2P) on investment funding decisions and their implications for *Value at Risk* (VaR) in 178 Indonesian digital startups. All five hypotheses were significantly accepted ($p < 0.01$). First, ECF ($\beta = 0.348$) and P2P ($\beta = 0.427$) were shown to have a positive effect on startup investment funding decisions. P2P exerts a greater influence due to its speed of disbursement and flexibility for short-term working capital, while ECF is more relevant for long-term strategic investments. These findings confirm that *fintech* has become a determining factor in the capital structure of Indonesian digital startups. Second, *fintech- based funding decisions* have implications for increasing *Value at Risk* ($\beta = 0.521$). Startups using a combination of ECF and P2P have the highest VaR (8.15% of total assets), while those using ECF alone have the lowest (4.28%). This indicates a *fundamental trade-off* between funding accessibility and market risk stability. Third, these findings extend *pecking order theory* to the context of digital startups while providing practical implications: (a) startups need to choose funding schemes based on their risk profiles and establish emergency funds, (b) *fintech platforms* need to design risk mitigation products such as *revenue-based repayment* , and (c) the Financial Services Authority (OJK) regulator needs to consider mandatory periodic *stress tests* . The study is limited by its short observation period and potential *survivorship bias* . Future research is recommended to utilize longitudinal studies and develop startup-specific VaR models.

Acknowledgements

Funding

References