From Instinct to Insight: A Multi-Criteria Decision-Making Framework for AI-Assisted Startup Investment Curation

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Wawan Dhewanto, Taufik Faturohman, Siti Insani, Arianne Muthia Zahra

School of Business and Management, Institut Teknologi Bandung

Abstract

Generative artificial intelligence (AI) has become an everyday tool for startup investors, yet research on AI in entrepreneurial finance remains model-centred: it reports what algorithms can predict, not how investors divide evaluative judgement with them. This study examines which tasks early-stage investors delegate to generative AI, which judgements they withhold and why, and which organisational conditions shape that boundary.

Drawing on semi-structured interviews with six decision-makers in six investor organisations active in Indonesia (angel networks, venture capital and bank-owned corporate venture capital), analysed with the Gioia methodology, we find that AI functions as a 'junior analyst' that automates evidence work while the investment verdict remains human. AI use is individual-led and informally governed in independent funds, but formally governed where a regulated parent institution exists. Contrary to prior expectations, AI adds most value at due diligence and portfolio monitoring rather than screening: its value depends less on the decision stage than on the architecture of deal flow.

Keywords: artificial intelligence; investor decision-making; venture capital; angel investors; entrepreneurial finance; startups

Introduction

Business angels and venture capitalists commit capital to ventures with little operating history, combining formal criteria, heuristics and intuition, and weighting founders and teams heavily (Huang and Pearce, 2015; Gompers et al., 2020). AI is now entering this judgement-intensive domain: machine-learning models predict exits and valuations, and large language model (LLM) evaluations of business plans correlate with those of experienced investors (Csaszar et al., 2024), although such predictions deteriorate for genuinely novel ventures (Kleinert and Urbig, 2026).

Three gaps follow. Evidence is model-centred rather than actor-centred; AI's value is assumed to be a property of the decision stage, peaking at sourcing and screening; and empirical work relies on North American and European data, leaving emerging ecosystems such as Indonesia underexplored.

RQ1: How do early-stage investors incorporate AI into their decision practices, and how do they justify its boundaries?
RQ2: Which investment criteria do they apply across startup life-cycle stages?
RQ3: Under what conditions does AI add marginal value at different stages of the investment process?

Research Method

An interpretivist, abductive and exploratory qualitative design (theory elaboration; Gioia et al., 2013), guided by a sensitising framework from a systematic review of 67 studies on AI in startup investment (Dhewanto et al., 2026).

Sample. Purposive sampling of six decision-makers from six organisations (INV-A to INV-F): two angel investors, three venture capital firms headquartered in Indonesia, Singapore and Japan, and one bank-owned corporate venture capital firm.

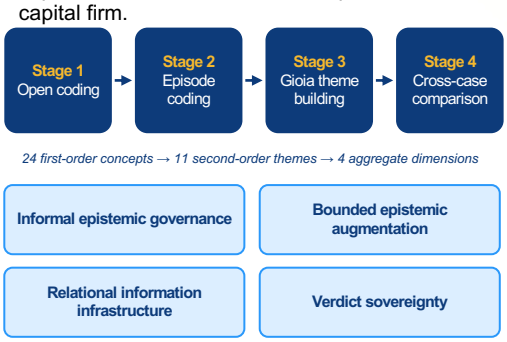


Figure 1. Analysis process and data structure

Data collection. Semi-structured interviews (July–November 2026; 45–60 minutes; Bahasa Indonesia with English code-switching), transcribed verbatim and verified against the audio (29,560 words). Deal-anchored reconstructions and boundary probes kept accounts close to enacted rather than espoused practice; public documents were used for triangulation.

Analysis. Coding in ATLAS.ti 26.1.1 proceeded iteratively: open coding by two authors into a shared codebook; episode coding of each AI-use episode by investment stage, AI role (from absent to delegated decision; Shrestha et al., 2019) and evidence relied on; Gioia theme building; and cross-case comparison against the sensitising constructs. Inter-coder consistency was reached by consensus, and sample adequacy was judged by information power (Malterud et al., 2016).

	Sourcing	Screening	Due diligence	Valuation/ structuring	Final decision	Monitoring
INV-A Angel	Low	Low*	High	Moderate	Human	–
INV-B VC	High	High	High	Moderate	Human	High
INV-C VC	Moderate	Low–mod.	High	High*	Human	High
INV-D VC	Low	Low	High*	–	–	Moderate
INV-E Angel	–	High	Moderate	–	Human	–
INV-F CVC	Low	Moderate	High	High	–	Moderate

* prospective; Human = verdict reserved to humans; – = not reported

Figure 2. Reported value of AI by decision stage and investor

Discussion & Result

Configuring AI work. In the four independent funds, AI use is individual-led, often personally paid and without written policy, a governance–practice gap. Only the bank-owned INV-F inherits formal governance from its regulated parent: corporate accounts, data-loss prevention, role-based access and masking of company names. Agentic practices are emerging (one VC runs fourteen orchestrated agents), yet AI is framed as a 'junior analyst'.

The verdict stays human. Informants place the final decision beyond AI on statistical (LLMs converge on the average, while venture returns depend on outliers), epistemic (imagining markets that do not yet exist) and relational grounds (founder 'chemistry has no code yet').

Criteria. Team and human capital dominates early stages; deal terms act as a gate for minority-stake investors; syndicate signals are valued under a venture logic but discounted under a private-equity logic.

Deal-flow architecture. Four of six investors locate AI's greatest value at due diligence, not screening (Figure 2); screening value arises only where funnels are open and voluminous.

Conclusion

AI augments investor judgement in a bounded, architecture-contingent way: it automates evidence work while the verdict remains human, and where it adds value depends on deal-flow structure, documentary load and institutional embedding. Five testable propositions formalise these relationships.

Theoretical contributions. The study (1) extends intuition-as-resource accounts to human–AI decision-making; (2) refines the automation–augmentation paradox at task level, as analytic labour is automated so that partner judgement can be augmented; (3) shows that preference encoding externalises tacit decision policies, enabling explicit criteria but risking automated similarity bias; and (4) identifies institutional embedding as an AI governance mechanism.

Practical implications. Investors should formalise AI governance (data privacy, access, masking), deploy AI first in due diligence and monitoring, and request comparables and disconfirming evidence rather than verdicts. Locally grounded data and explicit, contestable inclusion criteria are needed to keep AI-mediated startup finance inclusive.

Limitations. Six self-reported cases limit transferability; the propositions warrant testing across ecosystems and quantification of criteria weights, e.g. through AHP.