

The Eight Verbs of Investing

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Master chefs, we're told, can conjure mouth-watering dishes from a handful of basic ingredients. Now, put those same ingredients in the wrong hands (er... mine), and you'll gain a newfound appreciation for reheated takeout. And while a stop at the artisanal grocer won't elevate my culinary output, those foraged matsutake and Almas caviar can become Michelin-starred dishes in skilled hands.

Markets, companies, trends, and forecasts provide the raw ingredients for the investment meals we call portfolios. Just as innovations in agriculture and logistics have given us access to more, higher-quality ingredients, technology has transformed our investment inputs. From the spreadsheet to the database to the LLM... we have access to far more investment ingredients. But what are we cooking?

Quants rarely opine on specific investments or forecasts (and are thus rarely sighted in the wild, opining on Bloomberg about the next Fed meeting), precisely because systematic investing concerns itself with the *process*. Our industry's obsession with inputs can distract us from the equally important (if less celebrated) topic of portfolio construction itself.

Enter AI, a catch-all term amalgamating machine learning (which includes LLMs), data science (which includes procurement and ingestion), and process automation (which includes agentification). Former IT managers (freshly rebadged as AI experts) consume escalating budgets, even as management fees compress and traditional research budgets shrink. The industry hopes, tacitly or

explicitly, that AI will eventually bend the curve of labour unit costs downward, sparing active management's margins from a slow death at the hands of a cost structure designed for fees that have since fallen by over 40%.

My claim: every investment process, discretionary or systematic, reduces to eight verbs: Observe, Believe, Categorize, Qualify, Analyse, Rank, Weight, Commit. AI belongs to the verbs, not to the job titles currently charged with their execution. If I'm right, any project, hour, or dollar that fails to accelerate or sharpen at least one of them does not improve our investment process, and thus does not improve the quality of our portfolios. Improve the actions themselves, and the output benefits.

Automate the process, not the job

On 1990s Wall Street, we wrote documents on computers, printed them, scanned them into fax machines, transmitted them to other fax machines, and scanned the results back onto computers. This represented a notable productivity improvement over bike messengers. But automating couriers didn't stick. There were still too many unnecessary steps. Email automated "deliver."

As of this writing, most AI initiatives in asset management focus on automating couriers. Take an extreme case: a CEO reads an LLM-generated commentary on an earnings call, the transcript of which gets consumed and summarized by an LLM for an analyst, whose LLM-driven findings are written up by an LLM and fed to a PM who uses LLMs to summarize and compare all his inputs to reach an investment decision. That's a lot of faxing and scanning.

To understand the process as opposed to the couriers, we must first abstract portfolio construction into concrete, evergreen actions. Verbs. AI shouldn't settle for automating existing jobs, constrained as those jobs remain by the physical world, human analytical capacity, and how firms chose to organize themselves decades ago. AI does its best work when we rebuild the process in digital space around the actions we take, rather than around the org chart.

This paper proposes a framework for subjugating AI to the investment process that won't go obsolete with the next model release. I'll first explain what the verbs entail, carry them through an example (a thematic portfolio built around Gulf wealth), and then consider how organizing our resources (be they human or AI) around verbs can focus our investment efforts on improving our clients' outcomes.

⁰¹ Observe

We begin with *observe*. The composition and volume of observable data have changed profoundly. What began as structured tables (income statements, balance sheets) and physical interactions (company meetings, committee discussions) has exploded into video scraping, topical inference, satellite image parsing, social-media reaction analysis, and countless other measurable tidbits. To observe, in this sense, gathers; it does not process. If our ability to interpret complex data grows over time, we should gather broadly today, even if some data remain unused at present; today's digital exhaust might help solve tomorrow's intractable problem. Every interoffice chat, hallway conversation, half-read article, elevator wait time, and eye roll can be thought of as an observation. Not all of it fits neatly into rows and columns.

Counting cars in parking lots. Noticing a bead of sweat dripping down a nervous CFO's brow. Tallying patents. Aggregating a country's economic output. Plotting a sector's rising market sensitivity.

Planet-scale infrastructure already exists. GDELT scans print, web, and broadcast media in 100+ languages on a 15-minute cadence, turning global news into structured signals. The 2024 Lowenstein Sandler alternative data survey found that 67% of investment managers surveyed (hedge funds, private equity, and venture capital) were using alternative data, and 61% were already using AI to assist with investing and trading. The instinct to hoard indiscriminately, though, runs into real costs: storage, governance, regulatory exposure, downstream liability.

Observations can cluster, and both humans and AI can connect these clusters. Take our example: we observe that wealth across the Gulf Cooperation Council (GCC) countries has grown and spread significantly in recent years. More high-net-worth individuals (HNWIs). More expensive cars. Increased spending on luxury travel.

⁰²
Believe Observations interact (in our minds, in our algos) to form predictions, or hypotheses. In other words, we must *believe* something based on our observations. When investing, to believe is to predict. A pattern we recognize or a trend we detect becomes a societal shift we anticipate or a line we extrapolate.

A company's sales will increase more than expected. A country's debt will become unserviceable. One sector will disrupt another. A natural resource will become scarce.

BloombergGPT, a 50-billion-parameter model trained on roughly 700 billion tokens, outperformed comparably sized general-purpose models on financial NLP tasks at its 2023 release without losing general capability, which makes automated thesis generation across filings, transcripts, and Q&A more credible. S&P Global Market Intelligence found that a fine-tuned LLM sentiment model applied to earnings calls would have delivered an 8.4% annualized long-short return, double the 4.2% generated by traditional lexicon-based approaches.

Consider a working hypothesis: sustained HNWI inflows, liberalized markets, and favourable tax zones will drive 2–3× growth in Gulf wealth management AuM by 2035, with UAE and Saudi Arabia as dual hubs. The hypothesis carries explicit KPIs (AuM, inbound UHNW flows, alt/credit penetration), decision gates (12/36/60-month AuM targets), and kill conditions (UAE HNWI inflows turn negative for two years; loss of free-zone tax benefits; geopolitical shocks cut flows by more than half). That structure separates a feeling from a belief.

⁰³
Categorize A broad belief often requires that we *categorize* it into tangible subsets. If we observe rising productivity in an economy and attribute it to automation, we break it down into components: physical automation, digital automation, process improvement, and so on. An entire industry exists to classify broad markets into subsets (asset classes, sectors, industries, countries, themes), but when our belief inconveniently falls outside our pre-defined buckets, we must allow specialists, human or machine, to decompose the broader problem and apply domain-specific expertise. Successful agent deployments already depend on knowing which specialist handles which problem; the more flexibly we can redraw those boundaries, the better we allocate resources.

Hoberg and Phillips's TNIC framework, built from 10-K product-description text and maintained in a data library at Dartmouth's Tuck School (now covering 1989–2023), already demonstrates that text-based peer networks capture competition and the rivals managers themselves name as peers better than SIC/NAICS codes do.

The GCC wealth thesis, for example, does not map cleanly onto GICS. Working from text embeddings rather than sector codes, we split it instead into seven driver-based categories: Prestige Wealth & Financial Services; Haute Lifestyle & Luxury Consumption; Elite Travel & Bespoke Mobility; Iconic Real Estate & Residences; Wellness, Aesthetics & Longevity; Elite Education & Cultural Experiences; Private Security & Lifestyle Management. These categories are necessarily dynamic: they can change, merge, split, or give way to new ones.

04 Qualify

A portfolio does not consist simply of hypotheses; we must know which, among millions of tangible investments, our mandate permits. A *qualified* investment must align with our categorized beliefs and also clear scrutiny from regulators, benchmarks, risk managers, morals, operational capabilities, and client guidelines. Humans notoriously fall prey to cognitive traps here (the streetlight effect, the familiarity principle). Correcting those biases and building impartial eligible universes represents the most straightforward, immediate, and high-ROI application of data science to a fundamental investment process.

A RUSBoost ensemble trained on raw accounting items (*Journal of Accounting Research*, March 2020) outperformed the Dechow logistic and Cecchini SVM benchmarks by a wide margin in detecting accounting fraud, which makes it practical for filtering higher-probability accounting risks before an analyst spends time on them.

In the GCC case, the qualification funnel ran from roughly 1,278 candidate companies to 548 at least moderately aligned with the theme, narrowing further to 129 tightly aligned.

05 Analyse

Portfolio management must *analyse* qualified investments and discriminate between them. Each mode of research (factors to quants, styles to discretionary investors) applies domain-specific expertise to each qualified option, yielding some scalar measure of desirability: an alpha score, a price target, a buy/sell recommendation. Passive investment typically deploys a single mode (market

capitalization); active managers deploy several: quality of management, valuation versus peers, underpriced growth, balance-sheet strength. Each offers a different angle on the same asset.

A 2019 MIT study (Fleder and Shah, ACM SIGMETRICS) showed that a model fusing anonymized weekly credit-card transactions with quarterly reports beat the Wall Street consensus on 57% of quarterly sales forecasts across 34 retailers. Consumer-spend exhaust, in other words, can give a forecaster an edge when combined with traditional inputs.

In our GCC example, we must choose which modes of research to apply to the 129 qualified names. We could meet the management of each company, create alpha factors based on historical data, or look at government support or the sources of client income. The resulting shortlist ran to 93 names, scored on market cap and revenue purity to the theme.

⁰⁶ Rank

Modes disagree. A cheap-looking company may carry untrustworthy management; a fundamentally sound business may sit in a geopolitically unstable country. Reconciling these contradictions requires that, after we have analysed each option across every pertinent mode, we *rank* all choices in the eligible universe from most to least desirable. Tradeoffs between modes (what quants call *signal weighting*) can be static (“valuation always drives 90% of the decision”), dynamic (“avoid politically unstable countries”), or domain-specific (“consult social media for consumer stocks”), and can scale in complexity up through subjective measures (a PM's familiarity with an analyst's biases) and full quantitative ensembles that rotate modes to fit recent conditions. At the end of ranking, we have sorted the universe by desirability, which for most managers means expected return.

Gu, Kelly, and Xiu's horse race of ML models against classical regressions (*Review of Financial Studies*, 2020) showed that a value-weighted long-short decile strategy built on stock-level neural-network forecasts delivered an annualized out-of-sample Sharpe ratio of roughly 1.35, more than double a leading regression-based benchmark (0.61). The gains came specifically from allowing nonlinear interactions that linear models miss.

In the GCC portfolio, alignment with the theme stood in for expected return: we ranked names by a market-cap-weighted alignment score.

⁰⁷ Weight

Since portfolios contain multiple positions, the next phase, *weight*, considers interactions between highly ranked choices and sizes each against the risk we want to take. Rank preference alone can output a set too concentrated (or too diversified) to suit a portfolio. At this stage we need two things. The first is a risk model: boundaries at aggregate and sub-aggregate levels (country, currency, position size, correlation), plus contingencies triggered by proximity or breach. The second is an objective function: maximize return, maximize reward-to-risk versus a benchmark, or target a specified volatility level.

Fundamental PMs may never explicitly define either, relying instead on intuition to size positions, weigh correlations, and trade off risk against reward. But whether intuitive or specified, the result emerges as a set of weights that incorporate, and ultimately define, the level of risk and return achievable by the portfolio as a whole.

Recent work on hybrid LSTM-GARCH architectures (Roszyk and Ślepaczuk, 2024) demonstrates meaningful improvement over vanilla GARCH for S&P 500 volatility forecasting, which should translate into sharper risk-scaling and tighter turnover control.

In the GCC portfolio, the final weighting step allocates equal risk to each of the seven categories, a deliberately simple choice that still demands a correlation estimate to execute.

⁰⁸ Commit

Once the portfolio holds investments and weights, the final stage *commits* those decisions to the market. Of all eight verbs, commit has seen the most technological advancement in public markets. The seniormost cohort of today's investment community recalls trading with paper tickets and animated phone conversations over dedicated landlines. Public-market execution has since shifted to algorithmic routing (VWAP, POV, implementation shortfall), monitored by real-time TCA and increasingly handled by machine-learning execution engines such as J.P. Morgan's LOXM that adapt mid-order and learn from realized outcomes. The GCC portfolio used adaptive execution.

Private markets, though, remain largely untouched at the commit phase. The absence of observable, objective, actionable price discovery, along with the non-conforming nature of bespoke financing, has served both as a critical drawback and as a prized feature of private markets. AI's ability to apply analytic frameworks to unstructured data holds promise for the asset class, though buyer

and seller may privately agree that less transparency suits them both. Expect AI to compress diligence, comps, and structuring; do not expect it to erase opacity. Opacity, in this asset class, forms part of the product.

The GCC thesis, end to end

Put together, the eight verbs trace a single investment process from end to end:

Observe	Wealth distribution broadens sharply across the GCC.
Believe	WM services and ecosystem will grow 2–3× by 2035; UAE and Saudi Arabia as dual hubs, with defined KPIs and kill conditions.
Categorize	Seven driver-based categories, constructed from embeddings rather than GICS.
Qualify	1,278 candidates, then 548 moderately aligned, then 129 tightly aligned.
Analyse	93-name shortlist, scored on market cap and revenue purity to the theme.
Rank	By market-cap-weighted alignment score.
Weight	Equal risk across the seven categories.
Commit	Implemented via adaptive execution.

None of this requires AI. All of it can benefit from AI—provided both humans and machines focus on the verb.

So what

Any AI project that doesn't measurably improve the efficiency or accuracy of at least one verb automates a courier or polishes a PowerPoint.

Each verb of portfolio construction presents an opportunity for AI to knit together the techniques, practical learning, and domain expertise of discretionary investors with the breadth, scale, and risk precision of

quantitative ones. Without the common language of these verbs, though, we risk deploying AI to automate tasks that would no longer need doing after a full process review.

Modularity within and between verbs allows for entirely different portfolios to benefit from common techniques, experts, datasets, and research. It also makes portfolio customization far more efficient and scalable, a topic for another paper.

Three implications follow. First, accountability does not migrate with the work. Source-grounded outputs, audit logs, sandbox validation, and MNPI controls earn AI outputs the right to enter a fiduciary process at all. Treat every AI claim that could shape a decision as non-actionable until it cites its source.

Second, any edge from AI inside a single verb will likely commoditize. Taste still matters in framing questions and constructing portfolios; durable advantage comes from proprietary data, tailored workflows, and design sensibility.

Third, and most important: portfolio management verbs will survive, but more of the craft will be written down as code. The firms that do well will build accountable, modular systems around the eight verbs. Others will automate their couriers, call the result transformation, and keep serving reheated takeout at Michelin prices.

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