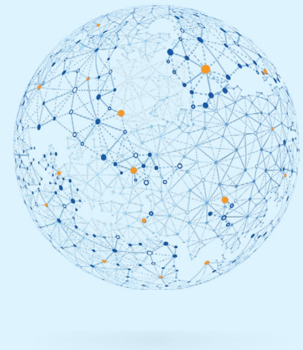
Mackenzie Investments

A holistic approach to quantitative investing



Defining holistic quantitative investing

We often meet asset owners who shun all quantitative strategies and lump them into a single bucket. Others who are former quant advocates may have abandoned their exposures during the "quant winter" – an event that was driven in large part to the space's over-reliance on the value factor. While single or dynamic multi-factor quantitative approaches can lead to unintended risk and underperformance, we believe that holistic quantitative approaches are differentiated in generating uncorrelated alpha within multi-manager equity structures.

For those that would lump all quant approaches into a single bucket, we differentiate holistic quant from many related approaches in **Figure 1** below, including the concept of "smart beta," the challenges of which we will present in detail later in this paper.

We define holistic quant investing as any investment process relying heavily on quantitative methods to generate alpha and manage risk, while simultaneously incorporating some combination of the following:

- active positioning;
- idiosyncratic stock risk;
- fundamental perspectives;
- forward- and rearward-looking investment signals;
- multi-style – including core – positioning; and
- In awareness of the impact of portfolio implementation.

FIGURE 1: SPECTRUM OF QUANTITATIVE INVESTMENT STRATEGIES

SPECTRUM OF QUANTITATIVE STRATEGIES		
Beta		Alpha
Systematic/pre-defined rules/Process driven	Holistic long-only and long/short	Opportunistic/objective decisions/adaptable
Alpha via factor selection	Active long-only and long/short	Alpha via factor selection and stock selection
Low tracking error	Trend following CTAs	Higher tracking error
Accepted academic research/long term	Short enabled style premia	Proprietary factors and investment signals (short and long term)
Rearward focused	Multi-factor active timing	Forward and rearward focused
Rules based rebalancing (monthly/quarterly)	Multi-factor "smart beta" strategies	Daily trading/transaction cost efficacy
Narrow and/or static style exposure	Single-factor "smart beta" strategies	Active style weighting and/or core style
Purely model	Alternative weighted indexes (e.g. equal weighted or fundamental)	Potential for human overlay

Source: Mackenzie Global Quantitative Equity Team.

We believe that both quantitative and qualitative approaches can be equally fundamental and bottom-up. As such, we suggest that "qualitative" (as opposed to "fundamental") is the more accurate opposite of "quantitative."

We readily concede that quant investing has not reached the stage where it can credibly compete with the depth of many qualitative processes, such as meeting face to face with company management, assessing new product innovation, identifying moats and sustainable franchises, evaluating a restructuring, etc.

However, we do not concede that these limitations give qualitative processes an advantage over quant. We believe both quantitative and qualitative methods inherently possess their own advantages and disadvantages and can be used to complement one another in a portfolio.

The most prominent advantage for quants is breadth of coverage. The public equity investment universe is massive, with over 3,000 US and 5,000 international developed stocks, and over 10,000 emerging market and frontier securities. Since data availability differs by region, quants can fully apply their methodologies to the whole universe, whereas qualitative investors can only fully apply their methodologies to a small subset of their chosen investment universe.

We believe breadth is a distinct advantage for quants. This is supported by Grinold & Kahn's Fundamental Law of Active Management, which suggests that a manager's alpha is determined by their stock picking skill, multiplied by the breadth of investment decisions. Quant has long been viewed as a way to get breadth inexpensively. You don't need massive teams of analysts on the ground or a massive budget for plane tickets to cover a broader universe of opportunities.

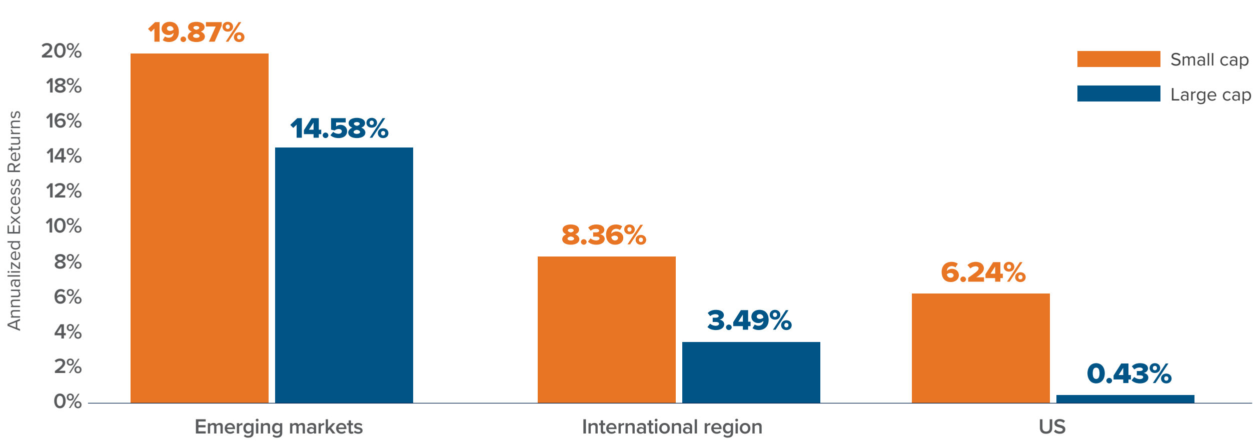
We also argue that quants have an advantage in less-efficient market segments, such as small cap or emerging markets, where the spread of model returns is wider **(see Figure 2).** Our rationale is that a quant's ability to evaluate the entire investment universe also enables them to evaluate a significantly larger range of potential outcomes.

Other commonly accepted attributes of quantitative investing include:

- ✓ More conducive to controlling risk relative to a benchmark.
- ✓ More consistent to the extent that their models systematically apply the same methods.
- ✓ Less susceptible to human bias and errors in judgement.
- ✓ Faster and better at implementation than traditional qualitative analysis.

What is new is the recently increased access to massive computational power combined with the rapidly advancing capabilities of AI and machine learning to evaluate larger and non-traditional data sets. As a result, quantitative managers can now identify new and more forward-looking investment signals that have the potential to generate more consistent and differentiated sources of alpha.

FIGURE 2: QUANTITATIVE ALPHA EFFICACY, SEPTEMBER 2002 - DECEMBER 2023



Source: Bloomberg. Represents inter-quintile return spreads using 50/50 blend of Value and Momentum from September 2002 – December 2023. Source: Mackenzie Global Quantitative Equity boutique proprietary research

The evolution of quantitative investing

The foundational concepts for quantitative investing first appeared in the 1930s, and the technology has evolved significantly. Let's consider the example of portfolio optimization. In 1952, Harry Markowitz published *"Portfolio Selection"* in the Journal of Finance, where he laid out the theoretical foundation for mean-variance optimization, which continues to be taught in colleges today.

Computer-driven quantitative investing began in the 1980s with the formation of several quantitative investment firms, many of which are still thriving today. This fledgling industry benefited from a unique set of conditions:

- Financial data was now available in digital format.
- Computing power allowed them to do quantitative analysis that was previously incredibly tedious.

Today, portfolio optimizers use sophisticated non-linear optimization algorithms, allowing them to handle complex functions and constraints more effectively. The algorithms have also become more efficient, using a technology called parallel processing that enables unprecedented scalability. This allows quant managers to optimize much larger portfolios with thousands of securities in their universes.

Today, we believe that most of the innovation in equity investing is quantitative. The convergence of computing power, novel data sets and new techniques allows portfolio managers to investigate and capture investment signals that were not previously available to them.

Many of these techniques are broadly categorized as "machine learning" (ML), which enables systems to identify patterns and make predictions from data. It also can learn from its experience without being explicitly programmed.

MODERN QUANTITATIVE INVESTING: 100 YEARS IN THE MAKING

1930s – 1980s

- Graham – value factor
- Markowitz – portfolio selection/ optimization
- Ross – arbitrage pricing theory (APT)
- Sharpe – CAPM
- Black / Scholes / Merton
- Bloomberg / IBES / DAIS
- Introduction of quantitative strategies

1990s

- Fama-French three factor model
- Jegadeesh and Titman – momentum investing
- Richard Sloan – quality investing

2000s

- Popularization of "factor" investing
- "Smart beta"
- Extension strategies

2010s

- Natural language processing (LSTM, Transformer Architecture)
- Alternative data sets
- News and sentiment analysis
- Social media data
- Company linkages
- Deep learning (RNN, CNN, ...)

2020s

- Availability of massive computational power
- Large language models
- Generative AI

These technological advancements include:

- **Novel data sets:** Non-traditional sources of data from which investors can generate investment insights.
- **Natural language processing (NLP):** The analysis of text data using computers to extract information from text-based regulatory filings and earnings call transcripts.
- **Large language models (LLM):** AI-powered language models that can be used to query information from a large set of textual data or analysis.
- **Generative AI:** Models that can generate new, original content rather than simply analyzing existing data or making predictions.
- **Cloud computing/GPU computing:** Allow quantitative investors to access to massive computational power that allows quants to achieve in hours what used to take days.

These machine learning technologies all contribute toward the production of non-traditional investment signals. These signals produce scores for each stock in the given universe, which quants add to their investment models to predict future price movements.

Use of quantitative factors and alpha signals

Quantitative factors and investment signals are used to assess the attractiveness of each security. One of the earliest known factors is value, identified by Benjamin Graham in *"Security Analysis"* (1934). Graham introduced the idea of using a number associated with a company (price-to-earnings ratio) to make investment decisions.

In 1992, Eugene Fama and Kenneth French introduced the Fama-French Three-Factor Model, which combined size, beta and value in a model to predict stock returns. The following year, Narasimhan Jegadeesh and Sheridan Titman laid the foundations for momentum investing in *"Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency".*

In the following years, academics and practitioners discovered more factors, falling into broad classifications of factors such as value, momentum, growth, quality and technical. Quants still rely heavily on academically supported factors as inputs to their models, but they increasingly use machine learning and novel-data-set-driven investment signals. The following table compares some common established factors with a few examples of newer investment signals.

The broad range of newer investment signals discovered by quants is driving an increasing portion of the alpha within quantitative models and can also define a quant's competitive edge.

FACTORS VS. INVESTMENT SIGNALS

Established style "factors" with academic support	Newer innovative "investment signals"
Value, Momentum, Quality, Volatilty	Economic linkage, Legislator trading, News sentiment, Earnings call analysis, Employee sentiment

Source: Mackenzie Global Quantitative Equity Team

When researching new factors and investment signals, we believe good candidates for inclusion must have the following attributes:

- ✓ They need to make fundamental and intuitive sense.
- ✓ They need to have statistical significance in the predictive models they are part of.
- ✓ They should have persistent efficacy.
- ✓ They should have widespread efficacy across different geographies and sectors of the economy.
- ✓ They should be as uncorrelated to existing factors as possible.

The last point explains the continuous search for novel sources of data and new investment signals. With a proliferation of factors and signals, quantitative managers must carefully consider the implications of adding them to their models. A crude approach is to equally weight the predictions from multiple factors and then average them. Another simple but more effective approach is to use a linear regression model, which gives more weight to factors that have proven to be more predictive in the past.

Although perhaps counterintuitive, all these rapidly evolving tools, data sets and investment signals require more human oversight, not less. It is critical that quantitative investors apply their experience and expertise to the entire process to help ensure that their outputs make strong fundamental sense and lead to sound investment decisions.

As we continue to push the boundaries the pursuit of alpha will continue, perpetuating the relentless search for new sources of insight and opportunity.

A practitioner's insight on improving quantitative outcomes

As long-term quantitative investors, we have learned many lessons through a wide variety of market environments that have led us to a differentiated approach we define as "holistic" quant. We have channeled our decades of investment experience into process improvements that we believe enhance our ability to consistently achieve alpha targets for our clients.

We believe the following characteristics provide significant advantages to our investors:

- ✓ We believe in a core investment process, without overemphasizing or relying on any single investment style.
- ✓ We adjust investment signal expected payoffs based on company characteristics.
- ✓ We emphasize portfolio construction and implementation as much as investment signal research.
- ✓ We stay nimble by imposing strict AUM capacity limits and rebalancing portfolios daily.
- ✓ We maintain a nimble team to streamline decision making and focus on productivity enhancements over headcount.
- ✓ We evaluate broker trade execution to reduce transaction costs.
- ✓ We keep human oversight in place to ensure output makes intuitive sense and occasionally improve investment outcomes when opportunities present themselves.
- ✓ We always seek ways to improve our model and portfolio construction to reduce the impact of adverse events and maximize alpha.

While each of these concepts is powerful on its own, we believe our advantage comes from combining everything into a comprehensive investment process that is managed by a cohesive and nimble team.

Core process

Many quantitative strategies rely primarily on a narrower group of commonly accepted factors that are supported by well documented academic research. The challenge for these strategies has been that all factors, when viewed individually, experience both periods of outperformance and underperformance.

We believe that a core process that balances a broader array of factors across growth, value and quality dimensions has the potential to generate greater alpha over multi-year cycles.

No investment style outperforms across all market environments. This can be clearly seen in **Figure 3**, which uses the emerging markets large-cap space as an example. It highlights periods when a major investment style like value, growth or quality was in favour (dark green) versus periods when the style was out of favour (dark red). Each major investment style exhibits strong long-term performance with low return correlation with other styles. As such, we expect our core investment philosophy to deliver better performance over reasonable investment horizons versus managers who emphasize any one of these major factors.

FIGURE 3: STYLE EFFICACY IN EM OVER TIME

YEAR	VALUE	GROWTH	QUALITY
2000	0.31	0.75	0.64
2001	1.92	0.73	0.44
2002	0.63	0.52	1.20
2003	1.47	0.75	0.50
2004	0.79	0.66	0.62
2005	0.86	1.87	0.08
2006	0.15	0.95	0.30
2007	0.37	1.22	0.14
2008	0.73	-0.67	0.62
2009	1.61	-0.16	0.44
2010	0.49	0.54	0.57
2011	-0.13	0.86	0.86
2012	0.26	0.50	0.12
2013	0.30	1.09	-0.10
2014	0.02	0.65	0.40
2015	0.11	1.15	0.23
2016	1.17	0.00	0.88
2017	0.54	1.45	0.87
2018	0.53	-0.05	0.62
2019	-0.38	0.68	0.15
2020	-0.59	1.68	-0.14
2021	0.39	0.74	-0.11
2022	0.87	0.00	-0.08
2023	0.86	-0.04	0.17
FULL PERIOD	**0.55**	**0.66**	**0.39**
LAST 10 YEARS	**0.35**	**0.63**	**0.30**

The period since our Emerging Markets Fund's inception has seen major macro-events and associated market volatility, leading to inconsistent performance of common investment styles such as value, growth, or quality individually. Yet the fund has outperformed its Morningstar Peer Group. Our core-style played a key role in this success.

FIGURE 4: MACKENZIE EMERGING MARKETS F VS. MORNINGSTAR PEER GROUP & MSCI EM INDEX

	2019		2020		2021		2022		2023	
	Return	Percentile ranking	Return	Percentile ranking	Return	Percentile ranking	Return	Percentile ranking	Return	Percentile ranking
Mackenzie Emerging Markets F	11.6%	64	18.9%	36	5.4%	7	-13.9%	32	16.4%	6
MSCI EM IMI Index	11.7%	63	16.3%	42	-1.1%	35	-14.0%	33	8.7%	38
Canada Fund Emerging Markets Equity	11.7%	63	12.5%	58	-3.4%	54	-15.2%	44	7.4%	55

	YTD		1 Year		3 Year		5 Year		Since inception	
	Return	Percentile ranking	Return	Percentile ranking	Return	Percentile ranking	Return	Percentile ranking	Return	Percentile ranking
Mackenzie Emerging Markets F	12.7%	19	19.7%	11	0.6%	16	7.5%	2	6.0%	6
MSCI EM IMI Index	11.5%	34	17.4%	25	-0.9%	28	4.9%	24	4.0%	26
Canada Fund Emerging Markets Equity	9.9%	60	13.4%	63	-2.6%	45	2.6%	62	2.3%	60

Source: Morningstar Direct As of June 30th, 2024

Contextualization

Contextualization ensures we are ranking stocks on metrics that are most relevant to the underlying characteristics of each. We find that firm characteristics impact investment signal efficacy. For example, one can reasonably expect valuation measures to be less effective in fast growing businesses or expect price momentum to be more effective in stocks with relatively low liquidity. We systematically test and incorporate such ideas into our model to further increase the predictive power of our forecasts of stock returns. Examples of contextual variables include liquidity, volatility, size and growth.

Portfolio construction and implementation

We emphasize portfolio construction and implementation as much as investment signal research. every member in the team fully understands our model, portfolio construction rules and implementation process. We discuss all aspects of the investment process at our daily morning meetings and regular portfolio positioning reviews. By having one team manage the full investment cycle, from research to portfolio construction to real world implementation, we believe we are well positioned to recommend, evaluate and effectively implement improvements to the investment process.

Continuous portfolio construction research is crucial to our investment success. This helps inform our decisions on:

- sizing stock positions;
- constraining known risk factors;
- managing industry and country exposures;
- monitoring turnover; and
- targeting levels of active risk.

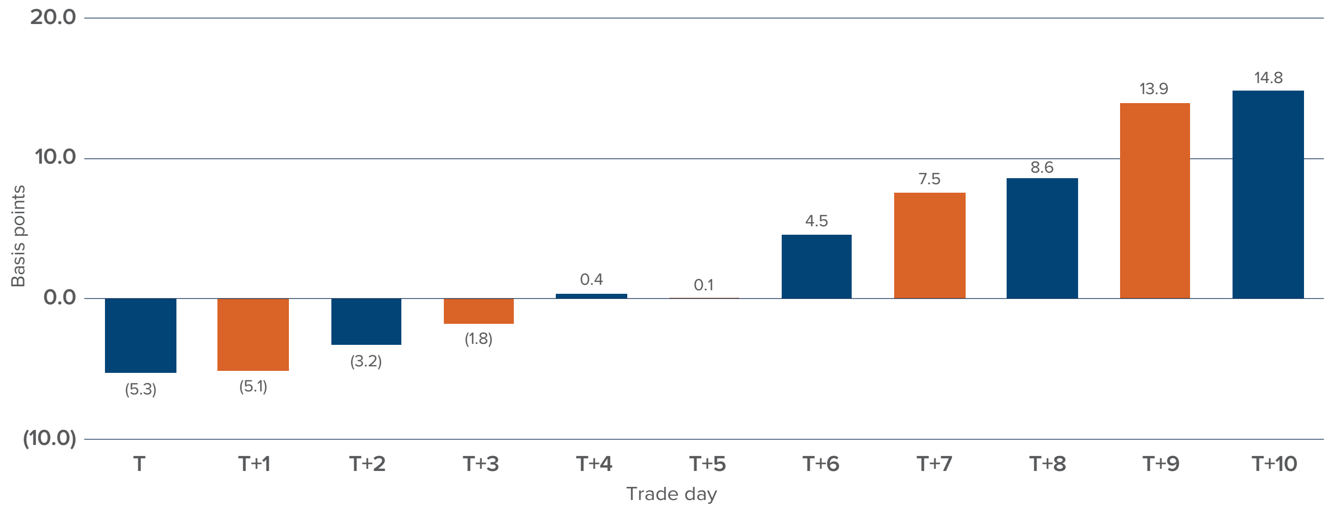
We have also implemented the following practices which enable us to run realistic historical portfolio simulations with daily rebalancing, considering transaction costs, predicted risk and borrow costs:

- Focus heavily on the liquidity of stock positions, transactions costs and borrowing costs for short positions.
- Test the sensitivity of portfolio performance to changes in key portfolio construction parameters.
- Incorporate expected transaction cost models into investment process.
- Impose custom risk models to monitor the risks attributable to proprietary investment signals that we deploy globally.

Importantly, we construct our portfolios in alignment with our alpha model to best capture our investment insights in the live process, which is subject to real world constraints, like transaction costs, limited stock liquidity or controlling risk against a top-heavy benchmark like the S&P 500 Index. By managing all aspects of the investment process, we are well positioned to focus on the relevant portfolio construction rules and to properly evaluate their impact on expected portfolio performance.

Implementation is critical to the success of an investment process. At its core, implementation entails taking the alpha model and portfolio construction rules and applying them live. Poor implementation can destroy any advantages afforded by best-in-class alpha and portfolio construction research. We appreciate the importance of air-tight implementation and have invested heavily in the infrastructure to support daily rebalancing of every portfolio, twice daily for global strategies. This gives us an advantage over competitors who rebalance weekly or even monthly. Those choosing not to rebalance daily are usually constrained by either sub-par infrastructure or excessive assets under management which requires rebalancing groups of portfolios on different days. As **Figure 5** demonstrates, significant excess returns accrue over the first several days following execution of our trades. Rebalancing weekly or monthly would miss out on much of this alpha opportunity.

FIGURE 5: SHORT-TERM PERFORMANCE OF INVESTMENT TRADES



Source: Mackenzie Investments. Performance in bps vs. benchmark for 5/31/2018 - 12/31/2023. Represents all strategies managed by Mackenzie's Global Quantitative Equity team. The information provided is for illustrative purposes only

	Trade #	MktVal USD	Price vs close (bps)	Price vs close+1 (bps)	Price vs close+2 (bps)	Price vs close+3 (bps)	Price vs close+4 (bps)	Price vs close+5 (bps)	Price vs close+6 (bps)	Price vs close+7 (bps)	Price vs close+8 (bps)	Price vs close+9 (bps)	Price vs close+10 (bps)
Buy	160,700	$21,121,710,660	(5.7)	(4.9)	(2.5)	(1.6)	0.5	(0.2)	4.0	7.0	8.6	14.2	14.7
Short	13,020	$789,540,441	6.5	(10.6)	(23.1)	(7.3)	(3.7)	6.7	17.9	21.4	8.3	5.5	17.7
Buy+Short	**173,720**	**$21,911,251,100**	**(5.3)**	**(5.1)**	**(3.2)**	**(1.8)**	**0.4**	**0.1**	**4.5**	**7.5**	**8.6**	**13.9**	**14.8**

To further preserve alpha generation potential, we monitor and quantify our trading experiences with brokers. Any issues we identify are discussed with the offending broker and their trade flow is reduced. If execution slippage continues, we stop trading with that broker altogether. For example, based on such post-trade analysis, we stopped routing trades to Credit Suisse well before that firm failed.

Nimble approach

AUM:

For all our strategies we have strict AUM capacity limits so we can stay nimble in our investment and decision-making process. We believe there is a direct correlation between excessive asset growth and alpha erosion, especially in less liquid markets, such as small-cap and emerging markets.

For small-cap equity strategies across all geographies globally, we have committed to a cap of $4 billion USD.

Excessive strategy assets in these markets can lead to an inability to establish optimal position weightings and can also adversely impact stock price.

Strategies with excessive AUM can cause a manager to:

1. Invest in larger percentages of a stock's daily volume;
2. Spread trades over more days to avoid affecting stock price;
3. Realize worse transaction prices;
4. Decrease desired position sizes;
5. Reallocate capital to less attractive investment opportunities; and
6. Down-weight higher turnover signals.

Team:

We believe team cohesion and culture are vital to producing exceptional results. At our daily morning meetings, our entire team discusses all aspects of our investment process, and makes all decisions in this setting. This ensures uniform understanding of our process, which in turn improves productivity and job satisfaction.

Although our investment staff will continue to grow commensurate with our asset growth, we philosophically believe that larger teams can be counterproductive. Keeping our team nimble enables us to focus on the highest value-added projects and increases the efficiency of our decision-making and ability to deploy new alpha signals or modify risk constraints quickly.

In summary, our "holistic" approach to quantitative investing incorporates each of the following attributes in an attempt to produce stronger and more consistent outcomes for our clients:

- ✓ Core style.
- ✓ Contextualization.
- ✓ Equal emphasis on factor/signal research, portfolio construction and implementation.
- ✓ AUM capacity limits in all strategies.
- ✓ Deliberately nimble team structure.
- ✓ Acute awareness of transaction costs.
- ✓ Intuitive human oversight of all research and implementation processes.

Quantitative approaches to public equity investing continue to introduce new sources of alpha and are now - in select areas - generating research insights in areas formerly reserved for qualitative fundamental analysis. Quantitative methodologies have been enhanced very recently with expanded access to exponentially more powerful computing as well as the rapid evolution of tools such as machine-learning and natural language processing.

These advances have enabled increased analysis of non- traditional data sets that have the potential to provide valuable investment insights and a competitive edge amongst active investors. We believe adopting a more "holistic" approach to quantitative investing can enhance the opportunity for more consistent alpha across a wider array of market environments.

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