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Do AI-powered mutual funds perform better?

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ABSTRACT

We evaluate the performance of artificial intelligence (AI)-powered mutual funds. We find that these funds do not outperform the market *per se*. However, a comparison shows that AI-powered funds significantly outperform their human-managed peer funds. We further show that the outperformance of AI funds is attributable to their lower transaction cost, superior stock-picking capability, and reduced behavioral biases.

1. Introduction

The first artificial intelligence (AI)-powered public fund, AIEQ, was incepted on 18 October 2017. The fund adopts machine learning technologies to actively select stocks in portfolio choices. The AIEQ became one of the most popular funds in 2017 and raised more than $70 million within a few weeks of time.

Algorithmic trading is widely applied to optimize and automate order submissions and executions but only after a portfolio choice is made (Lo et al., 2000; Hendershott et al., 2011). AI, in sharp contrast, makes decisions in the earlier stages of portfolio choices. Moreover, AI-powered funds use proprietary techniques to perform *real-time* prediction and greatly enhance the flexibility and timeliness of traditional quantitative funds (Abis, 2020).

The advantages of AI are multifaceted compared to human beings. First, AI offers super computational power to analyze mass data in a short period of time with decent performance (Donaldson and Kamstra, 1997; Neely et al., 1997; Chouard, 2016; Krauss et al., 2017; Adcock and Gradojevic, 2019). Second, humans have bounded rationality and are susceptible to various cognitive biases (Bazley et al., 2020; Linnainmaa et al., 2021). By contrast, AI optimizes the expected outcome and learns to be more efficient, and is expected to be more rational (D'Acunto et al., 2019). Third, the performance of human managed mutual funds has been on the decline, as the proportion of skilled fund managers is substantially dropping and almost non-existent in the new millennium (Barras et al., 2010; Ratanabanchuen and Saengchote, 2020). As such, the investment community yearns for profits brought by cutting-edge technical innovations (Gencay and Stengos, 1998; Gradojevic and Gençay, 2013; Fischer and Krauss, 2018).

However, the disadvantages of AI-powered funds are equally obvious. The first concern is related to both the achievements of the existing finance literature and the potential incremental contribution by AI techniques. A large number of recent papers examine whether deep learning can predict pricing kernels and the cross-section of stock returns better than "traditional" linear factor models or characteristics (Hutchinson et al., 1994; Fernandez-Rodrıguez et al., 2000; Garcia and Gençay, 2000). The progress to date has been positive but is in no way a breakthrough. Among them, Gu et al. (2020) find that "all (machine learning) methods agree on the same set

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of dominant predictive signals, a set that includes variations on momentum, liquidity, and volatility". It appears that AI techniques have limited marginal predictive power. The second concern is the trading frequency and associated transaction costs. Previous studies have widely documented that actively-managed mutual funds underperform the market after transaction costs and expenses are deducted (Carhart, 1997). As AI continuously optimizes portfolios, whether AI-powered funds can achieve the optimal trade-off between return and turnover calls for additional investigations.

This study performs the first systematic investigation into the performance of AI-powered mutual funds. The preliminary results show that AI-powered mutual funds do not generate significant risk-adjusted returns on aggregate *per se* and only show marginal stock-selection capabilities. For a fair comparison, we proceed to compare AI-powered funds with those that are managed by human beings. Univariate comparisons show that AI-powered funds significantly outperform their human-managed peers by 5.8% per year on a net basis. We further find that AI shows superior stock-selection capability to humans, and AI-powered funds actually have lower turnover and therefore, reduced transaction costs. After controlling for various fund characteristics, AI-powered funds still outperform their human-managed peer funds in multivariate regressions. Finally, AI-powered funds can overcome some of the prevalent cognitive biases such as disposition effect and rank effect.

Our study makes three contributions to the literature. First, our study provides important evidence that favors the application of AI in the mutual fund industry and echoes the surging literature in fintech. Second, our study is related to the vast literature that evaluates mutual fund performance. Whereas researchers have shifted their focus from the aggregate mutual fund industry to searching for a subset of persistently skillful fund managers, our study identifies AI as a subset of effective and skillful fund managers. Third, we add to the behavioral finance literature by showing that AI can overcome cognitive biases.

2. Data and sample

2.1. Data

We obtain mutual fund data from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database from January 2009 to December 2019. We obtain the stock price, stock return, and market capitalization information from the CRSP monthly stock files and the book value of the equity of stocks from the COMPUSTAT dataset.

2.2. Sample description

We collect the prospectuses of 2133 newly issued funds from 2017 to 2019 from the SEC's EDGAR database. We manually read the summary prospectuses filed as Form 497K or 485BPOS to label the funds based on their characteristics. We label (1) AI-powered funds as those that use machine learning technologies to actively select stocks in portfolio choice, (2) quantitative funds as those that use fixed rules and numerical methods to generate computer-driven models and make investment decisions (Abis, 2020), and (3) discretionary funds as those traditional funds that select stocks and make investment decisions mainly through human judgment. AI funds usually include keywords such as "Artificial Intelligence", "Machine Learning", or "Natural Language Processing" in their principal investment strategies. Notably, some self-claimed "AI" funds invest in the AI technology industry and do not use AI to select stocks and thus, are excluded from our sample. In total, we label 15 AI-powered mutual funds. We also label 355 exchange-traded funds (ETF), 300 quantitative funds, and 611 discretionary funds as the pools to identify peers.

These 15 AI-powered funds use a variety of AI techniques to analyze more than one million data and optimize predictive models. They have ten classifications of the Lipper Objective Code, indicating investment in various industries with varying styles. Detailed descriptions of these AI-powered mutual funds are provided in the Internet Appendix.

3. Empirical results

3.1. Performance of AI-powered funds

The first and foremost task is to evaluate the performance of AI-powered mutual funds. We first compare the time-series monthly returns of AI-powered funds and market returns in our sample.[1] As reported in Panel A of Table 1, the performance of the AI-powered fund is statistically indistinguishable from the aggregate market in 25 out of 26 months in our sample period based on both paired *t*-test and Wilcoxon's signed-rank test. We further adopt the model in Jensen (1968) to calculate risk-adjusted alphas and fund betas in the full sample. We use Fama and French (2015) (FF) five-factor model as a robustness check. Panel B of Table 1 reports the aggregated monthly return, market-adjusted return, fund beta, Jensen's alpha, and FF five-factor alpha of the AI-powered funds. The results show that AI-powered funds do not generate significant returns on standalone, market-adjusted, or various risk-adjusted bases. In particular, the annualized Jensen's alpha is 1.6% on an equally-weighted basis[2] and statistically insignificant.

[1] To calculate the value-weighted aggregated market index, the stock market includes all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 in the sample period.

[2] Among these 15 AI-powered funds, AIEQ has a total net assets (TNA) that is higher than 100 million dollars whereas the others TNA are all less than 10 million. AIEQ underperforms on various risk-adjustment bases. If we aggregate the AI-powered funds by using the TNA, the overall performance would be dominated by the AIEQ, which creates a substantial downward bias in the portfolio returns.

Table 1
Performance of AI-powered funds.
Panel A reports time-series monthly returns, *t*-statistics, and Wilcoxon's signed-rank test for AI-powered funds and market returns. Panel B reports aggregated net return, market-adjusted return, and risk-adjusted returns from Jensen and Fama-French five-factor models. Panel C and Panel D report the decomposition statistics of the fund returns. Gross returns are the aggregate stock returns of the fund's monthly holding portfolio. The fund manager's skills measures include stock picking ability (Picking) and stock timing ability (Timing). Panels B, C and D show the equally-weighted (EW) and value-weighted (VW) results by the fund, respectively. *T*-statistics are shown in parentheses and ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. AI-powered fund net returns

Month	No. obs	Fund returns (%)	Market returns (%)	Diff	t-statistics	Wilcoxon
201711	1	2.65	3.20	−0.55		
201712	1	1.42	1.15	0.27		
201801	1	5.91	5.69	0.22		
201802	1	−3.36	−3.54	0.18		
201803	1	−1.53	−2.23	0.70		
201804	8	0.34	0.43	−0.09	−0.11	0.0
201805	8	2.11	2.79	−0.68	−0.80	−7.0
201806	8	2.60	0.62	1.98	1.55	12.0
201807	9	2.57	3.35	−0.78	−0.94	−8.5
201808	9	3.49	3.60	−0.11	−0.12	−0.5
201809	9	1.02	0.21	0.81	1.17	8.5
201810	9	−7.02	−7.49	0.47	0.43	0.5
201811	9	2.05	1.87	0.18	0.21	−2.5
201812	10	−9.15	−9.36	0.21	0.46	4.5
201901	10	9.00	8.62	0.38	0.60	2.5
201902	10	3.01	3.58	−0.57	−1.22	−8.5
201903	10	1.16	1.29	−0.13	−0.18	−1.5
201904	15	3.42	4.17	−0.75	−0.79	−1.0
201905	15	−6.05	−6.73	0.68	0.96	17.0
201906	15	7.07	7.11	−0.04	−0.08	−19.0
201907	15	1.18	1.38	−0.20	−0.44	−2.0
201908	15	−2.12	−2.42	0.30	0.67	10.0
201909	15	0.35	1.61	−1.26	−2.34**	−35.0**
201910	14	2.64	2.21	0.43	0.77	12.5
201911	14	4.65	3.99	0.66	1.35	23.5
201912	14	2.89	2.91	−0.02	−0.09	1.5

Panel B. AI-powered fund returns

	No. obs.	Net returns (%)	Market-adjusted returns (%)	Beta	Jensen's alpha	Five-factor alpha
EW	26	1.16	0.08	0.96	0.13	0.02
t-value		(1.44)	(0.69)		(1.00)	(0.17)
VW	25	1.01	0.02	1.10	−0.07	−0.41
t-value		(1.04)	(0.10)		(−0.35)	(−0.23)

Panel C. Fund manager skills (Monthly average of AI-fund portfolio)

	No. obs.	Gross return (%)	Picking	Timing
EW	26	1.20	0.42*	0.67
t-value		(1.49)	(1.83)	(0.92)
VW	25	1.21	0.39	0.69
t-value		(1.32)	(1.42)	(0.88)

Panel D. Fund manager skills (Cross-funds average of monthly average)

	No. obs.	Gross return (%)	Picking	Timing
EW	15	1.36***	0.18*	0.99***
t-value		(17.30)	(1.83)	(17.26)
VW	15	1.39***	0.14*	0.95***
t-value		(15.62)	(1.85)	(12.31)

Next, we measure the skills of fund managers and quantify the value added by managers according to the investment strategies adopted. We utilize the monthly stock holding data of the fund and follow the approaches in Kacperczyk et al. (2014) to measure manager skills along two dimensions: stock-picking skill (whether the stocks selected by the fund manager perform better than the stock market) and market-timing skill (whether fund managers can predict future market movement and adjust the weight of risky stocks).

Panels C and D of Table 1 report the gross returns and skill components of AI-powered funds. Panel C reports the monthly average of the EW or VW AI-fund portfolio. The AI-powered funds show marginally significant stock-selection skills only by equal-weight and no market-timing skills.[3] Interestingly, when we assign equal weight to the AI-funds with varying historical lengths in Panel D, we obtain significantly positive gross returns, stock-picking, and market-timing skills by both EW and VW basis. This indicates that recently issued AI-funds with a shorter history earn better returns.

Overall, these AI-powered funds do not generate significant net returns or risk-adjusted returns. We find weak evidence that managers of AI-powered funds possess superior stock-picking skills.

3.2. Comparison with human-managed peer funds

In this section, we explicitly compare AI-powered funds with characteristics-matched peers that are managed by humans. We follow the dynamic style-based spatial method in Hoberg et al. (2018) to find customized peers for each AI-fund in each quarter. As the AI-powered funds in our sample are all ETFs, we adopt four criteria (matched fund scale, fund age, Lipper objective, and investment style) to identify peers among the pool of ETFs as the baseline test. Specifically, for each AI-powered fund, we select two ETF peers that are 1) in the same quartile of TNA as AI-power funds, 2) issued after 2009, 3) with Lipper classification codes in the appropriate categories, and 4) with the most similar investment style. Details of the matching procedure are provided in the Internet Appendix.

In total, 14 AI-powered funds are matched with available peer portfolios.[4] We compare the fund performance of AI-powered funds and their human-managed peers during the common period of 2017–2019. Panel A of Table 2 reports the time-series average of the monthly net returns for the AI-funds and their peers. AI-powered funds outperform peer funds in 22 out of 26 months, and the difference is statistically significant in 4 months. In contrast, AI-powered funds underperform peer funds in only 4 months, statistically significant in only 1 month. In terms of equal-weighted portfolios, AI-powered funds outperform their human-managed counterparts by an annualized return spread of 5.8%. The results remain robust while we aggregate funds on a VW basis. Panel B shows the robustness checks for various risk adjustments. Market-adjusted returns are aggregated by month. Jensen's alpha and FF five-factor alpha are estimated by using full sample regressions. Interestingly, while AI-powered funds fail to generate a significant Jensen's alpha, their peers have an even worse performance and generate a significantly negative alpha, thus rendering a significantly positive alpha spread. Panel C shows the difference between the two types of funds based on fund manager skills and the percentage of correctly predicted market movements. Correctly predict market movement is defined as the fund manager increases (decreases) holdings of assets with a high (low) beta before the market rises, or she increases (decreases) holdings of assets with a low (high) beta before the market drops (Kacperczyk et al., 2014). AI-powered funds show better stock-picking skills than their peer funds, while they do not have better timing ability compared with either peer funds or a random walk. Overall, these results demonstrate the value-added by using AI in the mutual fund industry.

To validate the matching results, we calculate the average fund characteristics and report the comparison results. Table 3 shows that AI-funds and their human-managed peer portfolios have similar TNA. As AI-funds have a shorter history than their peer funds in the baseline test, we further match with younger peer funds in the robustness test and the results are qualitatively unchanged. Furthermore, the investment style measured by the characteristics vector (Distance) does not significantly differ. Thus, the matching procedures successfully identify the peers as intended.

We further examine whether AI-funds and their peers differ in other characteristics. Table 3 shows that AI-power funds charge slightly lower expenses than their peer groups. More importantly, AI-powered funds have a lower turnover ratio and typically hold fewer stocks than their human-managed peers. Therefore, the outperformance of AI-funds relative to their human-managed peers is attributable to cost savings from trading fewer stocks and less frequently.

Next, we conduct multivariate analyses to control for the effect of the fund characteristics and report the results in Table 4. We pool the sample of AI-powered funds with their human-managed peer funds and use AI_Dummy to indicate the AI-powered funds. We first regress monthly market-adjusted returns on AI_Dummy and various fund characteristics. We also control the year-month fixed effect. The significantly positive coefficient of AI_Dummy reported in Column (1) shows that AI-powered funds significantly outperform their human-managed counterparts. Alternatively, the Jensen's and FF five-factor alphas at the fund level are used as the dependent variable and significantly positive alpha spreads of the AI-powered funds are found in Columns (2) and (3) as well. Overall, the multivariate regression results support the conclusion that AI-powered funds outperform their human-managed peers.

3.3. Robustness checks

We perform various robustness checks. First, the main findings reported in Section 3.2 are robust to various matching criteria for human-managed peers. Second, we alternatively match AI-funds to quantitative peers only, as the majority of AI-powered funds use complex prediction models. Third, we relax the constraints and search for peers among all of the available human-managed discretionary funds. Last, instead of the full-sample period estimation, we use the 24-month rolling window to estimate the Jensen's and FF-five factor alphas for each fund and accordingly obtain the panel data of fund-month observations of alphas. The results of robustness checks are not reported for brevity. Overall, our robustness tests consistently support the conclusion that AI-powered funds outperform their human-managed peers.

[3] When we use the alternative approaches of Daniel et al. (1997) and Wermers (2000) to decompose fund returns into stock-picking skills, we find that AI-powered funds show robust stock-picking ability.

[4] AIIQ has no appropriate peer due to insufficient stock holdings data.

Table 2
AI-powered funds versus human-managed peer funds.
This table is a comparison of the returns from AI-powered funds versus human-managed peer funds. Panel A shows the time-series and aggregated comparative net return by month. Panel B reports the risk-adjusted returns, including market-adjusted returns, and Jensen's and FF five-factor alphas for AI-powered funds and their peer funds. We calculate the difference between the two based on monthly fund returns. Panel C reports the difference between the two types of funds based on fund manager skills. The gross returns are the aggregate stock returns of the portfolio of the fund. The fund manager's skills measures include stock picking ability (Picking) and stock timing ability (Timing). The *correct market prediction* measures the average percentage of correctly predicted market movements for funds. We report *t*-statistics (in parentheses) and Wilcoxon's signed-rank test and ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	No. obs.	AI Funds ($N = 14$)	Peer Funds ($N = 14$)	Diff (AI-Peer)	t-statistics	Wilcoxon
Panel A. Net returns (%)						
201711	1	2.65	2.45	0.20		
201712	1	1.42	−0.11	1.52		
201801	1	5.91	3.48	2.43		
201802	1	−3.36	−4.50	1.14		
201803	1	−1.53	−0.08	−1.45		
201804	8	0.34	−0.01	0.35	0.51	3.0
201805	8	2.11	1.29	0.82	1.51	10.0
201806	8	2.60	−0.18	2.78	1.84*	16.0**
201807	8	2.88	2.64	0.24	0.23	6.0
201808	8	3.94	2.87	1.08	2.18**	16.0**
201809	8	0.72	0.19	0.53	0.51	7.0
201810	8	−6.88	−8.08	1.20	0.80	2.0
201811	8	2.17	1.99	0.17	0.17	1.0
201812	9	−9.44	−8.88	−0.56	−1.56	−10.5
201901	9	8.85	8.74	0.11	0.16	1.5
201902	9	3.00	2.79	0.21	0.31	1.5
201903	9	1.12	0.96	0.15	0.20	2.5
201904	14	3.51	3.81	−0.30	−0.28	8.5
201905	14	−6.24	−6.85	0.61	0.99	6.5
201906	14	7.10	6.75	0.35	1.07	9.5
201907	14	1.28	0.94	0.34	0.86	22.5
201908	14	−2.20	−2.35	0.15	0.29	3.5
201909	14	0.41	2.41	−2.00	−3.05***	−37.5***
201910	13	2.70	1.45	1.25	1.72*	22.5*
201911	13	4.70	3.39	1.31	1.91*	23.5*
201912	13	2.84	2.76	0.07	0.14	−4.5
Average	26	1.18	0.69	0.48	2.39**	106.5***
t-value		(1.44)	(0.86)			
Panel B. Risk-adjusted returns (%)						
Market-adjusted returns	14	0.06	−0.20**	0.26	2.87***	37.50**
		(0.75)	(−1.96)			
Jensen's alpha	14	0.04	−0.30***	0.34	4.06***	47.50***
		(0.43)	(−3.22)			
Beta	14	1.00	1.03	−0.02		
FF five-factor alpha	14	0.04	−0.26**	0.29	2.10**	27.00***
		(0.27)	(−2.22)			
Panel C. Fund manager skills (%)						
Gross returns	25	1.20	0.84	0.36	1.61	50.50
		(1.49)	(1.08)			
Picking	25	0.42*	0.00	0.42	1.69*	52.50*
		(1.83)	(0.05)			
Timing	25	0.67	0.78	−0.11	−0.86	8.50
		(0.92)	(1.19)			
Correct market prediction	25	52.50	52.86	−0.36	−0.06	6.00
		(0.49)	(0.56)			

3.4. Behavioral biases

In this section, we use the monthly mutual fund holding data from 2017 to 2019 to investigate whether AI-powered funds can overcome a set of behavioral biases documented in Bailey et al. (2011) including disposition effect and rank effect. The former captures the greater tendency of investors to sell winners than losers (Odean, 1998). The latter shows the tendency of investors to sell the best- and worst-performing stocks in their portfolios and neglect those in the middle (Hartzmark, 2015). The comparison results reported in Table 5 imply that applying AI technology to portfolio management helps fund managers to reduce the disposition effect and rank effect.

Table 3
Characteristics of AI-powered funds versus human-managed peer funds.
This table reports the comparison statistics of the fund characteristics between AI-powered mutual funds and their ETF peers. We report the aggregated cross-sectional average of the 12-monthly observations per year of the *TNA* and expense ratio and turnover ratio. Age of fund is the years after its first offering. Distance is the vector length of the fund and is the square root of the sum of the size, book-to-market ratio, and momentum. Fund flow is the monthly percentage change in TNA adjusted by fund returns. Stock Number (*#Stock*) is the number of holdings in the fund portfolio for each month. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Fund Characteristics	AI-funds	Human-managed peer funds	Diff (AI-Peer)	t-statistics	Wilcoxon
TNA($M)	15.49	14.35	1.13	0.58	11.5
Age	1.71	3.88	−2.17	−5.49***	−50.6***
Distance	1.14	1.14	0.00	−0.08	−10.5
Expense (%)	0.37	0.40	−0.03	−0.49	−8.5
Turnover (%)	31.06	72.38	−41.32	−3.02**	−35.5**
Flow (%)	3.91	3.71	0.20	0.17	7.5
#Stock	149.05	197.47	−48.41	−1.67*	−24.5*

Table 4
Multivariate analysis of fund performance.
This table reports the multivariate regression results of funds risk-adjusted returns on AI-powered funds dummy variable and fund characteristics. *AI_Dummy* equals one for AI-powered funds and zero for human-managed peer funds. Fund characteristics are defined in Table 3. *T*-statistics are shown in parentheses and ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
VARIABLE	Market-adjusted returns	Jensen's alpha	FF five-factor alpha
Intercept	−0.31	−1.24	−3.20*
	(−0.30)	(−1.08)	(−1.81)
AI_Dummy	0.39**	0.58***	0.51**
	(2.01)	(3.35)	(1.98)
LogTNA	0.01	−0.06	−0.04
	(0.78)	(−0.64)	(−0.28)
LogAge	−0.09	−0.67	−0.07
	(−0.36)	(−0.23)	(−0.55)
Expense	0.41	0.55	1.22
	(0.58)	(0.88)	(1.19)
Turnover	0.01	−0.40*	−0.15
	(0.14)	(−1.67)	(−0.32)
Flow	0.01**	0.07***	0.05
	(2.43)	(3.50)	(1.50)
Log#Stock	0.22	0.05	0.53
	(1.46)	(0.70)	(1.49)
Observations	627	28	28
Adjusted R-squared	0.760	0.131	0.416

Table 5
Behavioral biases between AI-powered funds and their human-managed peer funds.
This table compares the behavioral biases of the AI-powered funds and their peers. We use the proportion of realized gains minus that of realized losses to measure the disposition effect (*DF*). We use the difference between the number of the best-/worst performing stocks sold and the number of -middle-performing shares sold to measure the rank effect (*RF*). *T*-statistics are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	AI funds	Peer funds	Difference
Disposition effect	−0.68***	−0.53***	−0.15**
	(−10.44)	(−15.68)	(−2.34)
Rank effect-best	0.00	0.03***	−0.03***
	(0.77)	(4.87)	(−3.80)
Rank effect-worst	−0.02**	−0.03***	0.01
	(−2.49)	(−4.46)	(1.07)

4. Conclusion

Our study investigates the performance of AI-powered mutual funds and provides robust evidence that they outperform their human-managed peer funds. We further attribute the outperformance to lower transaction costs and superior stock-picking skills. Such advantages of AI-powered funds could be due to the superior calculation capability that improves the efficiency of data analyses and model predictions. Moreover, the use of AI technology reduces the prevalence of the misbehaviors of traders.

CRediT authorship contribution statement

Rui Chen: Conceptualization, Methodology, Software, Data curation, Formal analysis, Writing – original draft. **Jinjuan Ren:** Validation, Supervision, Writing – review & editing.

Declaration of Competing Interest

None.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2021.102616.

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