DIVERSIFICATION VIA CONCENTRATION

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Abstract: This study examines how Gemini, ChatGPT and Copilot (AI) handle investment recommendations, uncovering a financial paradox called "diversification via concentration". We analyzed 405 automated investment strategies generated by the AI models tailored for passive investors across five age cohorts across all 27 European Union nations. The findings reveal that all three AI models heavily rely on a streamlined framework of only two global index instruments - one global equity ETF and one global bond ETF. Rather than recommending a complex multi-asset mix, the AI models fulfill the requirements of classical and modern portfolio frameworks (MPT, CAPM, PMPT and BPT) through product simplicity. The study concludes that generative AI successfully achieves theoretical diversification and manages lifecycle risk not through traditional asset complexity, but rather through concentrated exposure to broad, all-in-one global market funds.

Keywords**:** Artificial intelligence, Financial portfolio theories, Investment diversification, ETF.

INTRODUCTION

To say that today's world of financial assets and investment is multilayered would be a tremendous understatement. Stocks, bonds, commodities, real estate, currencies, cryptocurrencies, non-fungible tokens all multiplied by futures, contracts, options and derivatives have built a significant threshold for any new investor; especially private ones. However, in recent years, the world of finance has been reshaped – one could even say revolutionized (Lettau & Madhavan, 2018) – by the growing popularity of Exchange-Traded Funds (ETFs), which – by significantly lowering the entry-level needed level of knowledge – have become the "go-to" solution for many institutional and individual (often amateur) investors (Ben-David et al., 2017; Dias et al., 2024; Adarsha & Giridhar, 2025; Kuar, 2025). This is seen in the growing number of retail investors (Aramonte & Avalos, 2021) (e.g., according to Wheat and Eckerd (2025), between 2023 and 2025 "retail investing flows rose by about 50 percent").

This phenomenon has only grown larger due to the increasing role of Artificial Intelligence (AI) that is delivering quick, "ready-to-implement" solutions for both, beginners and more advanced investors. Such solutions should also play a greater role given the paradox of growing complexity of ETF (e.g., currency-hedged, leverages, inverses and synthetic ETFs) identified by, e.g., Aggarwal and Schofield (2012).

The aim of this study is to examine if in today's world of finance and investing, the pairing of ETFs-AI in investment recommendations upholds the idea of portfolio diversification as stipulated by theory. The novelty of this research comes from a comparison of three generative AI models (Gemini, ChatGPT and Copilot) investment advice across all 27 European Union (EU) nations and five age cohorts, uncovering a modern financial paradox of "diversification via concentration". Therefore, the presented topic fits well within the "future trend" of ETF-focused research as "AI and ML are important in passive investments as these are used to set the algorithms for investment into passive schemes for roboadvisory services" (Joshi & Dash, 2024). The growing use of roboadvising and its push towards ETFs has also been noted, e.g., by Gaspar and Oliveira (2024), Deng (2025) and Barile et al. (2026). Our text also fills the research gap of understudied ETFs in developing economies (which are part of our European Union 27 sample) – as identified during a bibliometric analysis by Joshi and Dash (2024).

We put forward a hypothesis that generative AI (Gemini, ChatGPT and Copilot) investment recommendations rely on a strategy of "diversification via concentration", utilizing a hyper-streamlined framework of just two global index instruments to satisfy the multi-asset diversification requirements of the

Modern Portfolio Theory, the Capital Asset Pricing Model, the Post-Modern Portfolio Theory and the Behavioural Portfolio Theory.

The text is organized as follows. First, academic literature is used to establish the theoretical base for the portfolio building principles by analysing four theories identified in the research hypothesis. Second, the research process and obtained results are presented and discussed. Lastly, overall conclusions from the study are presented.

A QUICK REVIEW OF PORTFOLIO BUILDING THEORY

Portfolio construction is fundamentally conceptualized as a two-stage decision-making framework consisting of the capital allocation decision between risk-free and risky assets, followed by the determination of the optimal portfolio weights within the risky asset universe (Bodie et al., 2021). To establish the theoretical base for analysing how modern artificial intelligence tools approach asset allocation, presented literature review examines the evolution of portfolio theory across selected frameworks.

Modern Portfolio Theory (MPT), established by Markowitz (1952), uses correlation analysis to construct diversified portfolios that aim to lower overall portfolio risk (volatility) while maintaining a given level of return. By demonstrating that investors should either maximize expected returns for a set level of risk or minimize risk for a target return, Markowitz established the core theorem of mean-variance portfolio theory. These twin rules allow for the creation of an efficient frontier, enabling investors to select an optimal portfolio tailored to their specific risk tolerance (Elton & Gruber, 1997). This framework was expanded by Tobin (1958), who demonstrated that an investor first identifies an objectively optimal portfolio of risky assets (e.g., global stocks) that maximizes the Sharpe ratio and then adjusts the portfolio's overall risk to their individual risk tolerance by combining this single risky portfolio with a risk-free or low-risk asset (such as government bonds).

Despite its foundational status, Mean-Variance Portfolio Theory has several practical limitations. Key among them is its reliance on historical market data, which can lead to parameter estimation errors yielding highly unstable portfolio weights (Hu, 2022). Modern Portfolio Theory is also limited because its core assumptions – using variance as the sole proxy for risk and assuming normal return distributions – fail to reflect real-world market behaviour, such as fat tails and asymmetric downside risk (Rom & Ferguson, 1994). Notwithstanding these limitations, MPT remains an essential framework for balancing risk and return (Surtee & Alagidede, 2023). This utility is even more pronounced in the modern era of Exchange-Traded Funds (ETFs), which offer low-cost, transparent access to broad indices and asset classes, making theoretical mean-variance asset allocation directly actionable for contemporary investors.

Building on the principles of MPT, Sharpe (1964), Lintner (1965) and Mossin (1966) introduced the Capital Asset Pricing Model (CAPM), which defines the connection between expected return and risk. Under this framework, anticipated asset returns are determined by combining the risk-free interest rate, expected market returns, and the asset's exposure to systematic market risk (Beta) (Xiang, 2024). CAPM incorporates a risk-free asset to establish a linear relationship (the Capital Market Line) that relates expected returns to total risk (Sharpe, 1964). A central premise of this framework is that in equilibrium, all investors should hold a single, fully diversified "Market Portfolio" that represents the aggregate of all risky assets and adjust risk solely by varying their allocation to the risk-free asset. At the same time, it defines the Security Market Line to evaluate expected returns relative to systematic market risk, measured by Beta. This risk-return frontier is mathematically determined by market data, while investors' specific placement along it depends entirely on their willingness to accept risk (Rasiah, 2012). Accounting for systematic risk is one of the advantages of CAPM, especially when it comes to the effectiveness of diversified portfolios. Moreover, the Capital Asset Pricing Model offers a straightforward, versatile, and market-driven approach that makes estimating expected returns practical for both investors and analysts (Liao, 2023). According to Prosad et al. (2015), it is the simplicity of the CAPM that has made it the most widely adopted model for pricing financial assets.

However, a primary limitation of the CAPM is its reliance on unrealistic assumptions – rational investor behaviour, normally distributed returns and a single-period investment horizon – that fail to reflect real-world market dynamics (Liao, 2023; Xiang, 2024; Wan, 2025; Paseda et al., 2026). Furthermore, because the model focuses exclusively on systematic market risk (Beta) and assumes uniform risk preferences, it ignores asset-specific risks and individual investor profiles, leading to potentially biased investment decisions (Liao, 2023). According to Hardiyanti (2026), CAPM's restrictive assumptions regarding market efficiency and investor behaviour can be the base of empirically identified market anomalies.

In response, Ross (1976) introduced Arbitrage Pricing Theory (APT), establishing a flexible, multifactor framework that accommodates multiple macroeconomic drivers of asset returns (Hardiyanti, 2026). Unlike CAPM, APT is not based on a single, elusive "market portfolio" or a series of CAPM-like assumptions (e.g., about return distributions). This makes APT more flexible and therefore applicable to real-world scenarios. At the same time, its risk metrics (variance and covariance) still assign equal weights to both upward and downward fluctuations. To address this symmetric bias or limitation, Post-Modern Portfolio Theory (PMPT) was introduced.

PMPT, which aimed at a more realistic risk metric and differentiation between upward and downward volatility while giving more attention to the latter, was developed by Rom and Ferguson (1994) and Sortino and van der Meer (1991). Unlike MPT, PMPT does not assume that risk is symmetric, arguing that an investment should not be penalized for upside volatility (e.g., unexpected high returns). A key innovation of PMPT is the Minimum Acceptable Return, which provides a personalized benchmark for evaluating portfolio performance (Leković, 2021). PMPT evaluates risk relative to investor-specific minimum accepted return benchmark and defines risk by returns lower than this benchmark (making levels of risk investor-specific). Therefore, PMPT is seen as more flexible, realistic and therefore more applicable than MPT (Geambașu et al., 2013) – albeit both MPT and PMPT can be applied to allocation and portfolio management (Bayram & Aktaş, 2025). At the same time, Kaplan (2017) notices that PMPT isn't good for generalization and its mathematical shortcomings can have a significant impact on the downside risk.

In recent decades, behavioural finance has rapidly evolved to explain how investment decisions are made, offering insights that help decode market dynamics and design customized investment strategies (Majewski & Majewska, 2022). Behavioural Portfolio Theory (BPT), developed by Hersh Shefrin and Meir Statman (2000), presents a positive descriptive framework of portfolio construction and security design that accounts for the empirical reality that individual investors are simultaneously risk-averse and risk-seeking. In short, BPT shows that investors build portfolios as a pyramid of separate mental accounts, where each layer reflects a specific investment goal and risk tolerance – ranging from protection, savings and accumulation to growth, diversification and speculation. Grounded in psychological principles, BPT demonstrates how individuals simultaneously purchase downside protection, such as risk-free or investment-grade bonds, and upside speculation, such as junk bonds, options, or lottery tickets. The theory evaluates portfolio organization through two distinct analytical structures: Single Mental Account (BPT-MA), wherein assets are fully integrated into a unified framework, and Multiple Mental Accounts, wherein the portfolio is segregated into discrete mental accounts corresponding to specific aspiration levels. Under the BPT-MA paradigm, the portfolio assumes the architecture of a layered pyramid, typically structured around a low-aspiration layer designed to prevent poverty and a high-aspiration layer intended to achieve wealth (Shefrin & Statman, 2000). By incorporating mental accounting, bounded rationality, and psychological factors, Behavioural Portfolio Theory offers a realistic positive approach that explains how investors make decisions in practice. This framework helps investors overcome cognitive errors and resist misleading emotions, ultimately improving asset allocation efficiency and bridging the gap between financial theory and complex reality (Lekovic, 2019).

However, by disregarding the connections between layers, in opposition to MPT (Byrne & Brooks, 2008), behavioural investors ignore how assets interact with one another, which leads to mathematically inefficient total diversification. Furthermore, BPT favours mental accounting where each mental account (sub-portfolio) is associated with its own expected returns and risk level. This prevents overall portfolio optimization and leads to mean-variance inefficiency across aggregate wealth (Das et al., 2010). Moreover, as noted by Statman (2004), another limitation of Behavioural Portfolio Theory is that it prioritizes an investor's personal aspirations for wealth over mean-variance efficiency, leading investors to hold severely under-diversified portfolios of just a few stocks or thematic funds that conflict with optimal risk management.

There are many investment portfolio theories, some based on relatively simple principles (e.g., mean-variance optimization), some relaxing the core of economic assumptions, i.e., that investors are rational. However, the rise of financial technology and algorithmic (robo) advisory services introduce a new empirical question, not yet tackled by these theories: do modern artificial intelligence tools construct complex, multi-layered portfolios that reflect these classic theoretical paradigms or do they simplify asset allocation into far more condensed structures? The following section aims to answer this question by testing how generative AI models operationalize portfolio diversification across the 27 European Union member states and five age cohorts.

RESEARCH METHOD AND RESULTS

To avoid subjectivism or reliance on one model, three AIs (Gemini, ChatGPT and Copilot) were prompted to build an investment strategy for a passive, long-term investor with no prior knowledge of finance or investing. The same prompt was used for all AIs: "Assume that I am a 20-year-old and I have 10000 Euro of cash available for investment. I have next to no prior knowledge on investing. What should I invest my money in if I am looking to be a long-term, passive investor? Can you give me the answer for each EU country?". Next, additional prompts were used to ask each AI to provide the answer with a differentiation between age cohorts (20, 30, 40, 50 and 60 years) and in the desired format (i.e., a clearer table). The 10000 Euro investment cash was used to represent a small, starting investor who does not have enough capital to use an individual investment, financial advisor. This type of an investor ("small, young, computer-savvy but novice") is, e.g., the most common one in such trading platforms as Robinhood (Welch, 2020). Overall, low-income investors have increased their activity more than those on the other side of the income spectrum, while the entry age for investors has been decreasing (Wheat & Eckerd, 2025). Such a person is most likely to fall back on AI for their investment advice. Five age groups separated by a decade were created to account for the concept of a "lifetime strategy", i.e., different investment horizons. Differentiation between EU countries was used to effectively eliminate the "home bias". The presented setup yielded 135 investment strategies per AI, 405 overall.

Before further discussion, it is worth noting that AIs were given full freedom to select between any funds, individual stocks, bonds, commodities, real estate etc. – and yet they all selected ETFs.

Gemini built all investment strategies out of a global ETF for stocks and another such fund for bonds (reducing the share of stocks to 90%, 70% and 50% starting with the 40-year-old investor) – see Table 1. ChatGPT also agreed that only ETFs for global stocks and bonds are important and suggested reducing the share of stocks by 20 pp. every age group starting 40 (Table 2). The same asset-selection conclusions were reached by Copilot, which started increasing the role of bonds already for a 30-year-old investor (10%) – increasing it by 20 pp. thereafter (Table 3). These results fall in line with the general idea present in the literature that the longer is the investment horizon, the greater part of an investor's portfolio should be stocks (Bali et al., 2009; Smith, 2025). AIs also accounted for the fact that traditional strategies like the 60/40 split aren't the strongest in mitigating equity risk with bonds (Papathanasiou et al., 2025).

Table 1. Investment strategies from Gemini

Country	Austria	Belgium	Bulgaria	Croatia	Cyprus	Czechia	Denmark	Estonia	Finland	France	Germany	Greece	Hungary	Ireland	Italy	Latvia	Lithuania	Luxembourg	Malta	Netherlands	Poland	Portugal	Romania	Slovakia	Slovenia	Spain	Sweden
Age 20	A1	A1	A1	A1	A1	A1	A2	A1	A2	A3	A1	A1	A1	A1	A1	A1	A1	A1	A1	A4	A1	A1	A1	A1	A1	A5	A6
Age 30	A1	A1	A1	A1	A1	A1	A2	A1	A2	A3	A1	A1	A1	A1	A1	A1	A1	A1	A1	A4	A1	A1	A1	A1	A1	A5	A6
Age 40	B1	B1	B1	B1	B1	B1	B2	B1	B2	A3	B1	B1	B1	B1	B1	B1	B1	B1	B1	B3	B4	B1	B1	B1	B1	B5	B6
Age 50	C1	C2	C1	C1	C1	C1	C3	C1	C3	C4	C1	C1	C1	C1	C5	C1	C1	C1	C1	C6	C7	C1	C1	C1	C1	C8	C9
Age 60	D1	D1	D1	D1	D1	D1	D2	D1	D2	D3	D1	D1	D1	D1	D4	D1	D1	D1	D1	D5	D6	D1	D1	D1	D1	D7	D8

Legend:
A1 - 100% VWCE(Acc); A2 - 100% IUSQ; A3 - 100% CW8(Amundi MSCI World PEA); A4 - 100% Northern Trust World + EM (Mutual Funds); A5 - 100% Vanguard Global Stock Index (Mutual Fund); A6 - 100% Länsförsäkringar Global Index (Mutual Fund)
B1 - 90% VWCE / 10% VAGF; B2 - 90% IUSQ / 10% VAGF; B3 - 95% Northern Trust / 5% Cash; B4 - 90% VWCE / 10% Polish Treasury Bonds; B5 - 90% Vanguard Global Stock / 10% Vanguard Global Bond; B6 - 90% LF Global / 10% AMF Räntefond Mix
C1 - 70% VWCE / 30% VAGF; C2 - 75% VWCE / 25% VAGF; C3 - 70% IUSQ / 30% VAGF; C4 - 80% CW8/ 20% VAGF (in Assurance-Vie); C5 - 70% VWCE / 30% MEUD (EU Gov Bond); C6 - 80% Northern Trust / 20% VAGF; C7 - 70% VWCE / 30% Polish Treasury Bonds; C8 - 75% Vanguard Global Stock / 25% Vanguard Global Bond; C9 - 75% LF Global / 25% AMF Räntefond Mix
D1 - 50% VWCE / 50% VAGF; D2 - 50% IUSQ / 50% VAGF; D3 - 60% CW8/ 40% Fonds en Euros & VAGF; D4 - 50% VWCE / 50% MEUD (EU Gov Bond); D5 - 60% Northern Trust / 40% VAGF; D6 - 50% VWCE / 50% Polish Treasury Bonds; D7 - 50% Vanguard Global Stock / 50% Vanguard Global Bond; D8 - 50% LF Global / 50% AMF Räntefond Mix

Reference: Gemini (2026).

Table 2. Investment strategies from ChatGPT

Country	Austria	Belgium	Bulgaria	Croatia	Cyprus	Czechia	Denmark	Estonia	Finland	France	Germany	Greece	Hungary	Ireland	Italy	Latvia	Lithuania	Luxembourg	Malta	Netherlands	Poland	Portugal	Romania	Slovakia	Slovenia	Spain	Sweden
Age 20	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A
Age 30	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A
Age 40	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B	B
Age 50	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C
Age 60	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D

Legend: A - 100% VWCE; B - 80% VWCE + 20% VAGF; C - 60% VWCE + 40% VAGF; D - 40% VWCE + 60% VAGF

Reference: ChatGPT (2026).

Table 3. Investment strategies from Copilot

Country	Austria	Belgium	Bulgaria	Croatia	Cyprus	Czechia	Denmark	Estonia	Finland	France	Germany	Greece	Hungary	Ireland	Italy	Latvia	Lithuania	Luxembourg	Malta	Netherlands	Poland	Portugal	Romania	Slovakia	Slovenia	Spain	Sweden
Age 20	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A
Age 30	B1	B1	B2	B1	B2	B1	B2	B1	B1	B1	B1	B2	B2	B1	B1	B1	B1	B1	B2	B1	B2	B1	B2	B1	B1	B1	B2
Age 40	C1	C1	C2	C1	C2	C1	C2	C1	C1	C1	C1	C2	C2	C1	C1	C1	C1	C1	C2	C1	C2	C1	C2	C1	C1	C1	C2
Age 50	D1	D1	D2	D1	D2	D1	D2	D1	D1	D1	D1	D2	D2	D1	D1	D1	D1	D1	D2	D1	D2	D1	D2	D1	D1	D1	D2
Age 60	E1	E1	E2	E1	E2	E1	E2	E1	E1	E1	E1	E2	E2	E1	E1	E1	E1	E1	E2	E1	E2	E1	E2	E1	E1	E1	E2

Legend:
A - 100% global equity index fund
B1 - 90% global equity index fund + 10% Eurozone government bond index fund; B2 - 90% global equity index fund + 10% global bond index fund
C1 - 70% global equity index fund + 30% Eurozone government bond index fund; C2 - 70% global equity index fund + 30% global bond index fund
D1 - 50% global equity index fund + 50% Eurozone government bond index fund; D2 - 50% global equity index fund + 50% global bond index fund
E1 - 30% global equity index fund + 70% Eurozone government bond index fund; E2 - 30% global equity index fund + 70% global bond index fund

Reference: Copilot (2026).

In terms of specific assets, Gemini and ChatGPT point directly to using just two: “Vanguard FTSE All-World UCITS ETF Accumulating” (VWCE) for stocks and “Vanguard Global Aggregate Bond UCITS ETF EUR Hedged Accumulating” (VAGF) for bond exposure. Copilot – as the only of the three AIs used in this study – presented a claim that it is “not allowed to recommend specific ETFs, tickers, or products because that counts as personalized investment advice”. However, it did propose “MSCI World”, “FTSE All-World”, “MSCI ACWI” as possible investment instruments. Interestingly, for Eurozone countries, Copilot – again, as the only one – pointed to “Eurozone government bond index fund”, while for countries with their own currencies a “global bond index fund” was suggested.

The “Vanguard FTSE All-World UCITS ETF Accumulating” is a traded fund that accumulates or reinvests earnings while trying to capture stocks from the entire world as weighed by the size of the market (JustETF, 2026a). More specifically it aims to track the FTSE All-World index, while maintaining a physical (optimized sampling) replication method. Currently, the ETF is favouring high-technology stocks (Table 4 and Table 5) and is very heavily skewed towards the US market (Table 6).

Table 4. Top VWCE holdings

NVIDIA Corp.	Apple	Microsoft	Amazon.com, Inc.	Alphabet, Inc. A	Broadcom Inc.	Taiwan Semiconductor Manufacturing Co., Ltd.	Alphabet, Inc. C	Meta Platforms	Tesla
4.60%	4.18%	3.11%	2.42%	2.05%	1.92%	1.70%	1.66%	1.29%	1.14%

Reference: JustETF (2026a).

Table 5. Top VWCE sectors

Technology	Financials	Industrials	Consumer Discretionary	Other
31.33%	13.53%	9.60%	9.00%	36.54%

Reference: JustETF (2026a).

Table 6. Top VWCE countries

United States	Japan	Taiwan	South Korea	Other
56.87%	5.59%	3.20%	2.84%	31.50%

Reference: JustETF (2026a).

The “Vanguard Global Aggregate Bond UCITS ETF EUR Hedged Accumulating” aims to track the Bloomberg Global Aggregate Float Adjusted and Scaled (EUR Hedged) index and does so with a physical (sampling) replication method (JustETF, 2026b). As much as this ETF maintains a world perspective, being open to bonds of various maturity, it is heavily focused on the United States (25.57%), Japan (7.44%), France (4.72%) and Germany (3.55%).

Inclusion of both stocks and bonds by AIs – as mentioned earlier – follows the idea of lowering risk (at a cost of potential higher returns) as the investment horizon shortens. For example, inclusion of emerging European equity ETFs would lower the risk by lowering correlation with the U.S. market, but given that these are relatively new, small and expensive (Hillard & Le, 2022) AIs opted for not including them in any of the proposed solutions as they would significantly increase risk in the portfolio. The use of ETFs aiming to represent the entire world lowers the risks associated with any one country or one sector (Solnik, 1974). This is especially true in the long-term horizon and even though – specifically during the time of crisis and in the short-run – stocks, markets worldwide tend to be more correlated with each other (Viceira & Wang, 2018). Inclusion of “the world” also helps to avoid the home bias, which further decreases the risk of the portfolio (Mukherji & Jeong, 2021). Lack of diversification of specific instruments (i.e., falling back on global stocks and global bonds ETFs) falls in line with the observation that investors from developing economies tend to benefit more from global diversification and home bias avoidance (Driessen & Laeven, 2007). This is because holdings of selected ETFs are weighted by the market capitalization – especially VWCE. The more developed the economy, the lower the risk, the bigger is its market and the higher its share in the ETF. Therefore, by implementing the strategy given by AIs, investors from developing economies lower their risk more by selecting global ETFs than investors from developed economies.

Unlike in the case of ChatGPT, there were a few noted exceptions from the VWCE and VAGF within the answers provided by Gemini. For example, Denmark and Finland have “iShares MSCI ACWI UCITS ETF Accumulating” for stocks, “Amundi MSCI World UCITS ETF EUR (C)” for France, “Northern Trust World” for Netherlands, “Vanguard Global Stock Index (Mutual Fund)” for Spain and “Länsförsäkringar Global Index (Mutual Fund)” for Sweden. Noteworthy is the fact that these are mostly global indexes, like the VWCE. Therefore, these exceptions are rather cosmetic (all exceptions are listed in Table 1) and still fit the overall strategy. Worth mentioning is also the inclusion of Polish Treasury Bonds (with their unique inflation-protection design) in place of VAGF only for Polish investors.

Another exception worth noting is that Gemini, as the only of used AIs, without an additional prompt suggested solutions, which provide tax benefits for individual countries (e.g., IKE and IKZE retirement accounts in Poland, PEA – tax-free after 5 years – and Assurance-Vie in France or ISK account – Schablonbeskattning / flat asset tax – in Sweden).

The obtained strategies also fit well within the four portfolio-building theories described earlier. The combination of VWCE and VAGF follows the low-correlation principle of Modern Portfolio Theory, while strategies based only on VWCE adhere to Modern Portfolio Theory via intra-equity diversification. Changes in strategies (lowering the share of stocks in favour of bonds) align with Tobin's separation theorem, where investors add less risky assets (VAGF) to their risky portfolio (starting with 100% in VWCE) to adjust their risk preference as the investment horizon shortens. The selection of specific global ETFs also fits with the “invest in the market” idea of Capital Asset Pricing Model. Choosing global index ETFs also corresponds to the Arbitrage Pricing Theory, as it accounts for returns being impacted by many macroeconomic factors. Inclusion of VAGF serves to mitigate the downside volatility, which is in line with Post-Modern Portfolio Theory. From the perspective of Behavioural Portfolio Theory, both ETFs assure multi-layer mental accounting; specifically, VAGF satisfies the basic needs for safety and protection, while VWCE fulfils the top layers of growth and speculation.

Based on the presented results, it is possible to confirm the research hypothesis, demonstrating that generative AI embraces a paradigm of “diversification via concentration” where the multi-theoretical requirements of portfolio construction are achieved through product simplicity rather than traditional diversification complexity.

CONCLUSIONS

This study aimed to examine if the application of AI to an investment strategy design – with the growing role of ETFs – will uphold the idea of portfolio diversification as stipulated by four financial theories (the Modern Portfolio Theory, the Capital Asset Pricing Model, the Post-Modern Portfolio Theory and the Behavioural Portfolio Theory). To achieve this aim three AIs (Gemini, ChatGPT and Copilot) were asked to design long-term investment strategies for investors in five age groups (20, 30, 40, 50 and 60 years of age), across all 27 European Union countries. Such an approach allowed to overcome the subjectivism coming from relying only on one advisor (AI), account for the home bias and incorporate the lifetime strategy concept.

Despite having access to all potential investment assets, all three AIs have constructed 405 long-term investment strategies using – with few exceptions related to specific countries, which still fit the overall strategy designed – just two global ETFs: one for stocks (VWCE) and one for bonds (VAGF). This allows the investor to gain maximum diversification in the portfolio by concentrating all their funds in only two assets. Our results confirm that one of the biggest values of ETFs is an introduction of simplicity to the financial investment world. Such funds allow investors to own a small piece of “each” stock traded in the world or hold bonds of “every” country or company issuing them. Based on our study, we can hypothesize that exposure to global ETFs will only grow with an increasing role of AI advising. This phenomenon paradoxically can be only increased by the growing complexity of ETFs as mentioned earlier.

Overall, it is possible to say that obtained solutions support the idea of “diversification via concentration” and confirm the research hypothesis put forward at the start of the study.

Our work has a few shortcomings, which lead to interesting areas for further research. We are aware that some users may use AIs for short-term trading and such traders are excluded from our study. However, since active investing is on the opposite side of the spectrum from the type of investing studied in this paper, we leave it to other researchers to explore. The sample of 27 European Union economies does contain large and small, developed and developing economies, so it is holistic in that regard. At the same time, our sample does not include investors coming from such large economies as the United States, China or India. Therefore, we find this to be another interesting avenue for further research. Lastly, we have not paid attention to suggestions made by Gemini in terms of tax optimization. Given that this topic is significantly outside of the scope of this research, we also leave it for other researchers to explore.

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