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Interdependence and portfolio scheme of emerging industry of Metaverse

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ABSTRACT

The Metaverse industry has attracted global attention and holds significant potential for investment, yet its investment environment and portfolio strategies remain underexplored, particularly in China. This study analyzes the industry's structure and interdependencies using returns from 110 listed Metaverse firms. Employing a Kendall-based network, we identify leaders and peripheral enterprises within the industry. From a micro-perspective, we propose a hybrid Kendall-based investment scheme, showing that portfolios of peripheral firms consistently outperform those of leaders and the overall market. The scheme also proves robust across different network scales, investor preferences, and market conditions. Overall, this research advances understanding of the Metaverse industry by combining a macro view of its industrial environment with a micro focus on portfolio design, offering practical insights for regulators, managers, and investors.

1. Introduction

The Metaverse Industry has rapidly emerged as one of the most strategically significant sectors in the global economy. Since 2021, the Metaverse has been widely envisioned as a next-generation Internet (Web3), characterized by persistence, immersion, and interactivity in three-dimensional environments, and supported by enabling technologies such as virtual reality (VR), augmented reality (AR), mixed reality (MR), blockchain, artificial intelligence, quantum computing, and cloud computing (Kim, 2021). In practice, several of the world's leading firms, including Meta, Microsoft, Amazon, NVIDIA, Epic Games, Apple, and Snapchat, have invested tens of billions of dollars into Metaverse-related technologies and scenarios. In China, this momentum has been particularly strong: more than 10,000 enterprises applied for Metaverse-related trademarks in 2021, and large Internet companies such as Tencent, Alibaba, and Baidu, alongside pan-entertainment platforms such as ByteDance, Bilibili, and Nreal, have all made strategic moves in the sector.

With this growing industrial significance, academic research on the Metaverse has also expanded rapidly. The first stream concerns the foundational elements of the Metaverse, such as XR technologies, avatars, agents, gamification, gaming, blockchain, NFTs, and digital twins (Xi et al., 2023; Yao et al., 2022). The second stream explores development opportunities and application scenarios, ranging from education, tourism, and healthcare to retail, e-learning, hospitality, and manufacturing (David, 2022; Gursoy et al., 2022; Park and Lim, 2023). The third stream emphasizes risks and challenges, including issues of data security, user privacy, governance, and

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the psychological and social impacts of immersive digital environments (Dwivedi et al., 2022; Jaung, 2022). While these streams have significantly advanced our understanding of the Metaverse, the industrial structure and investment environment—particularly in the Chinese context—remain underexplored.

The lack of systematic research on the investment environment of the Metaverse is surprising given the importance of investment analysis in emerging industries. Emerging industries, generally defined as aggregations of enterprises creating disruptive technologies and/or generating substantial new market opportunities (Li et al., 2022), require tailored approaches for investment. Prior studies have examined such investments from both the enterprise and industry perspectives. At the enterprise level, project selection has been assessed through the net present value method (Ohlson, 2003), scoring approaches (Zhao and Vinig, 2017), and mathematical models such as data envelopment analysis (Edirisinghe and Zhang, 2007) and the analytic hierarchy process (Viviana et al., 2022). At the industry level, researchers have increasingly employed network-based approaches to capture systemic dependencies. For instance, Wang et al. (2021) used a Copula-TMFG network to examine the interdependencies of the 5 G industry, while Xu et al. (2022) applied a tail dependence network to analyze systemic risk in the new energy vehicle industry. These studies suggest that a network-based framework provides a powerful tool for analyzing investment environments in emerging industries.

Meanwhile, portfolio selection theory has also been extended through network analysis, which conceptualizes enterprises or assets as nodes and their interrelations as edges. Network approaches have been applied in both physical information networks, such as buyer–supplier linkages, strategic alliances, joint ventures, and lending relationships (Schilling and Phelps, 2007; Carnovale et al., 2017; Kanno, 2020), and financial information networks, including studies of risk spillovers, volatility co-movements, and contagion effects (Wang et al., 2017; Heipertz et al., 2019; Eng-Uthaiwat, 2018). To construct such networks, researchers have employed a range of dependence measures, including Pearson correlation (Wen et al., 2019), partial correlation (Anufriev and Panchenko, 2015), Granger causality (Bonaccolto et al., 2019), Kendall rank correlation (Clemente et al., 2021), tail dependence (Xu et al., 2022), and Copula-based methods (Zhang et al., 2021). These methods have been used either to identify stock portfolios directly from network structures (Clemente et al., 2021) or to optimize traditional portfolio strategies by incorporating network-based restrictions (Peralta and Zareei, 2016; Výrost et al., 2019). As regard to the application of network theory in portfolio selection process, (1) network topology can be applied to identify a portfolio of stocks, with a given cardinality, directly from the dependency structure provided by the financial filtered networks (Clemente et al., 2021); (2) or to optimize traditional portfolio strategies by taking network information as additional restrictions (Clemente et al., 2021; Peralta and Zareei, 2016; Výrost et al., 2019).

However, while prior research has focused on the technological foundations, application scenarios, and risks of the Metaverse, the industrial structure and investment environment have received little attention. On the other hand, although network-driven portfolio selection has been successfully applied to other emerging industries, it has not yet been systematically explored in the context of the Metaverse. Accordingly, this study aims to examines two hypotheses. First, the Metaverse Industry exhibits a heterogeneous dependence structure in which central and peripheral enterprises play complementary roles in maintaining industry stability. Second, portfolio schemes constructed from peripheral enterprises consistently outperform those based on central or mixed enterprises, offering superior risk-adjusted returns.

To bridge these gaps, we propose a hybrid Kendall-based industrial information network to analyze the investment environment of the Chinese Metaverse Industry. Specifically, we construct a Kendall rank correlation network of 110 listed Metaverse enterprises and compute hybrid centrality measures based on five network topological properties, enabling us to capture both macro- and micro-level perspectives. At the macro level, we examine the dependence structure of the industry and identify its leaders, who may be considered "too connected to fail," and its outsiders, who provide diversification benefits aligned with the principle of "not putting all eggs in one basket." At the micro level, we propose a hybrid Kendall-based portfolio scheme and test its robustness across different network scales and rolling windows.

Specifically, we construct industrial information network of 110 listed Metaverse enterprises in China based on Kendall rank correlation, and the hybrid centrality of each enterprise is calculated based on five basic network topological properties. Then, the positions of each enterprise among the whole industrial structure are captured and the leaders (outsiders) are provided in the whole Metaverse Industry. For the micro perspective of investment environment, a hybrid Kendall-based portfolio scheme is recommended from the peripheral enterprises. The empirical results indicate that the portfolio schemes of peripheral enterprises are always superior with central enterprises and all Metaverse enterprises, which are robustness in multi-scale networks with different candidate enterprises and T-period long rolling windows.

It contributes to the literature on the emerging industry investment from several aspects. First, a specific and valuable portfolio scheme of Metaverse Industry, the hybrid Kendall-based investment scheme, is constructed by introducing the hybrid centrality to Kendall network, and the empirical results indicate that the portfolios of peripheral enterprises are always superior with central enterprises and all Metaverse enterprises in the multi-scale networks. Second, the detailed dependence structure among the whole Metaverse Industry is captured, and the leaders and outsiders among all listed Metaverse enterprises are identified, which are vitally important for the stable development of Metaverse Industry because the leaders (such as ZZZ, SAI, TST) are important for the whole industry based on the insights of "too connected to fail", and the outsiders are also important for industrial investors based on the belief of "do not put all eggs in one basket", all found is very important for management of emerging industry investment. Third, it makes up for the gap in the industry environment research of Metaverse from China. The existing research on the Metaverse Industry mainly focuses on the foundations, application scenarios and uncertainty risks but the industrial structure and its investment environment is of great significance, which is currently missing in the theorical research on the Metaverse Industry.

This research is organized as follows. Section 2 proposes a hybrid Kendall-based portfolio scheme for investment environment analysis of Metaverse Industry. The relevant empirical analysis is carried in Section 3. Section 4 provides the detailed discussions and outlines future directions.

2. Methodology

2.1. Hybrid Kendall-based network portfolio scheme

2.1.1. Hybrid Kendall-based network construction

We denote by $G = (V, E)$, a network consists by a set V of N nodes and a set E of edges between nodes of V. A convenient rearrangement of the network information is provided by the n × n adjacency matrix Ω. For unweighted networks, $\Omega_{ij} \in \{0, 1\}$ and therefore only on/off relationships exist (Arcagni et al., 2017). For weighted networks, $\Omega_{ij} \in R$ and the links track the intensity of the interactions between nodes. The Metaverse Industry can be explored through the network approach, where nodes represent each Metaverse enterprise and connected edges account for the returns. In this research, a weekly information as the basic time units, given the price $p_{i,w}$ of stock i at the end of the week w, the continuous weekly return is calculated as:

$$r_{i,w} = \log(p_{i,w}/p_{i,w-1}) \tag{1}$$

The measurement of correlation among listed enterprises is a basic work in the network construction. Pearson coefficient, a common linear measurement, is defined as:

$$\rho_{ij} = \frac{E[r_i r_j] - E[r_i]E[r_j]}{\sqrt{(E[r_i^2] - E[r_i]^2)}\sqrt{(E[r_j^2] - E[r_j]^2)}} \tag{2}$$

where r_i and r_j are the returns of enterprises i and j, $E[r_i]$ indicates the expectation of log return of enterprise i. However, the linear correlation only provides a partial view of enterprises' relationship, and the non-linear correlation is supported in Bouteska et al. (2023) and Hernandez et al. (2022). Therefore, we adopt an alternative scheme to measure the correlation of the edges: Kendall's tau coefficient, which is calculated as:

$$\tau(R_i, R_j) = \frac{\sum_{k=1}^{n}\sum_{l\neq k}\mathrm{sgn}(r_{i,k} - r_{i,l})\mathrm{sgn}(r_{j,k} - r_{j,l})}{n(n-1)} \tag{3}$$

where $(r_{i,1}, r_{j,1}), (r_{i,2}, r_{j,2}), \ldots, (r_{i,n}, r_{j,n})$ is the set of n observations of the joint random variables R_i and R_j in a specific time period (Clemente et al., 2021).

Kendall network is characterized by the weights based on the Kendall's tau coefficient. Formally, a weighted, complete and undirected network G represents the correlations structure, being all enterprises correlated, with edges' weight equal to the correlation between them. Therefore, the elements of the matrix Ω are defined as:

$$\Omega_{ij} = \begin{cases} \tau(R_i, R_j), i \neq j \\ 0, \qquad otherwise \end{cases} \tag{4}$$

After constructing the basic industrial network based on the matrix Ω, the basic topological characteristics, such as degree centrality, betweenness centrality, closeness, eigenvector centrality and eccentricity can be obtained (Huang et al., 2022; Wen et al., 2021) and are shown in Table 1.

To comprehensively measure the positions of enterprises in the whole industrial structure, the hybrid centrality (P) is recommend by Pozzi et al. (2013), which is usually more comprehensive and reliable, and further reduce the potential errors caused by a single metrication (Woods et al., 2022). The hybrid centrality is calculated by the basic network topological metrics and shown as:

$$P = \frac{DC_a + DC_b + BC_a + BC_b - 4}{4(N-1)} + \frac{E_a + E_b + C_a + C_b + EC_a + EC_b - 6}{6(N-1)} \tag{5}$$

where the subscript a and b represents weighted network and unweighted network respectively. These indicators of centrality/peripherality have been sorted in descending order for D, BC, EC, and in ascending order for E, C, then the hybrid centrality of a node (P_i) is calculated. The value of P is small for central nodes in the network, and large for peripheral nodes, which can identify the

Table 1
The basic network centrality metrics.

Metric	Definition	Formula
Degree centrality (DC)	normalization of the number of edges connected to node i	$DC_i = \frac{\deg(i)}{N-1}$
Betweenness centrality (BC)	the fraction of all shortest paths that pass through a given node i	$BC_i = \frac{1}{(n-1)(n-2)}\sum_{k\neq i\neq j\neq k, k\neq j}^{N}\frac{\phi_{jk}(i)}{\phi_{jk}}$
Eccentricity (E)	the maximum length of shortest paths that connect i to any other node	$E_i = \max d_{ij}$
Closeness (C)	the inverse of the average shortest path length from node i to all other nodes in the network	$C_i = \frac{1}{N-1}\sum_{j=1}^{N} d_{ij}$
Eigenvector centrality (EC)	the proportional sum of neighbors' centrality	$EC_i = \lambda^{-1}\sum_j \Omega_{ij} EC_j$

position of each enterprise in whole industry.

2.1.2. Portfolio scheme design

We adopt a rolling window way to assess the effectiveness of the hybrid Kendall network-based portfolio investment scheme, which is characterized by a window width T and a holding period h (Clemente et al., 2021; Hodder et al., 2015). The data of the first sample window of width T (from $w = 1$ to $w = T$) are used to build the network, and m peripheral or central enterprises are selected according to the hybrid centrality P, which is calculated by the basic Kendall network-based model. Then, the selected enterprises are invested in the holding period, from $w = T+1$ to $w = T + h$, where the portfolios' performance is computed. The process is repeated rolling the window h steps forward. Therefore, the selected enterprises are updated in the new subsample (i.e., using data from $w = h+1$ to $w = T+h$ and discarding the first h observations), and the performance is re-estimated using data from $w = T+h+1$ to $w = T + 2h$. These steps are repeated until the end of the dataset is reached.

The design process usually involves parameters as the width T of rolling window and the holding period h. The value of T has a great impact on the dependence network: when the T value is too small, it may lead to insufficient samples, and the correlation between enterprises calculated from the dataset in the T period is unreliable; however, if the T value is too large, historical redundant information will be included in the sample window, resulting in the constructed dependence network cannot accurately match the current industrial environment.

In sum, we have obtained a set of investable enterprises and then adopt the equally weighted portfolio strategy for subsequent allocation of these enterprises. The benchmark scheme is that all N enterprises in the Metaverse Industry are invested, which represent the overall performance of the whole industry. The portfolio performance does not directly rely on the optimization of any specific explicit objective function (for example, a risk measure, such as the portfolio variance, VaR or ES), thus, do not provide optimal weights related to any program linked to financial characteristics of the final investment. Consequently, on one side, the differences in their performance exclusively depend on the information retrieved from obtained network. On the other side, our results are not exposed to any direct source of scheme risk related to portfolio weights. Moreover, naive allocation strategies might anyway be comparable to optimized allocations (Peralta and Zareei, 2016; Výrost et al., 2019). The portfolio characteristics are then used to evaluate the performance of designed investment scheme.

2.2. The Out-of-sample evaluation of portfolio scheme

From the micro-perspective of portfolio performance of Metaverse enterprises, we mainly focus on the measurement of return and risk performance of the selected enterprises. Usually, in the portfolio scheme, the risk-adjusted performance is used to compare with the absolute returns or the relative returns (i.e., excess returns) to the risk taken (Peralta and Zareei, 2016). In this research, we examine the portfolio performance by using the Sharpe Ratio (SR) and the Information Ratio (IR).

As a classic characteristic that considering both return and risk, SR helps investors to obtain the highest return within a certain range of risk, or to seek the minimum risk under the targeted return, which is defined as:

$$SR = \frac{\mu_p - \mu_f}{\sigma_p} \tag{6}$$

where μ_p and σ_p are the average return and the standard deviation of the investment strategy respectively, and μ_f represents the average risk-free rate, which is set as zero in Výrost et al. (2019). The SR measures the mean of excess return per unit of overall risk, and

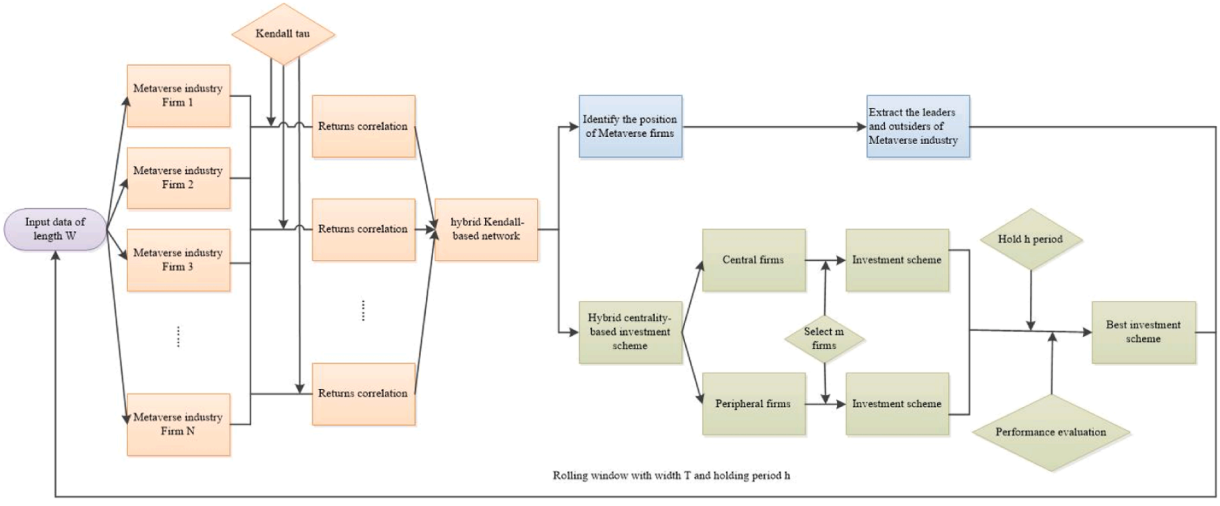

Fig. 1. Analysis framework for hybrid Kendall-based portfolio scheme.

a portfolio inveterate with a higher SR is generally considered to perform better. We use the *SR* to rank different portfolio schemes only in the case of positive portfolio excess return with respect to the risk-free rate.

In line with the literature of Bajeux-Besnainou et al. (2013), the *IR* is considered as another appropriate risk adjusted performance measure. The rationale behind the *IR* is similar to that of the *SR*, but the average portfolio return is compared with a benchmark portfolio return instead of the risk-free rate. The *IR* is defined as:

$$IR = \frac{\mu_\delta}{\sigma_\delta} \tag{7}$$

where $\delta = r_p - r_b$, r_p and r_b represents the out-of-sample time series of optimal investment returns corresponding to the designed portfolio schemes and the benchmark respectively. Usually, the value of the *IR* greater than zero indicates that the scheme is over performing of the benchmark (Clemente et al., 2021).

2.3. Framework for whole industrial portfolio environment analysis

The analytical framework of whole industrial environment for the Chinese Metaverse Industry is presented in Fig. 1, which mainly contains the micro-perspective of hybrid Kendall-based portfolio scheme and the macro-perspective of industrial interdependence structures. The basic experimental steps are as follows:

Step 1: Calculate the continuous weekly return for each Metaverse firm based on Eq. (1).

Step 2: Obtain the adjacency matrix Ω through Kendall's tau coefficient based on Eq. (3).

Step 3: Construct the basic industrial network based on the matrix Ω, and calculating the hybrid centrality of each Metaverse firm based on Eq. (5).

Step 4: Design and conduct the muti-portfolio schemes with different candidate enterprises based on the hybrid centrality of Kendall network (m=20, m=10, m=5), and different T-period long rolling windows (T=52, T=26), and all Metaverse enterprises is the benchmark scheme.

Step 5: Select the optimal portfolio scheme among Metaverse Industry according to the out-of-sample evaluations of SR on Eq. (6) and IR on Eq. (7).

Step 6: Obtain the positions and industrial interdependence structures of each Metaverse enterprise by calculating the cumulative selected times and the mean value of all hybrid centralities during the whole time period under the rolling windows.

3. Results

3.1. Dataset description

To carry out our research, we collect weekly closing prices of listed enterprises in the Metaverse industry from the Shanghai and Shenzhen stock exchanges, using data from the stock market sector of the China Stock Market & Accounting Research (CSMAR) Database (http://www.gtarsc.com), and Metaverse sector of Dongxing Securities (https://www.dxzq.net/). o ensure a sufficiently long sample period, we exclude enterprises listed after 1 January 2020, such as Unionman Technology Co., Ltd. We also exclude firms that

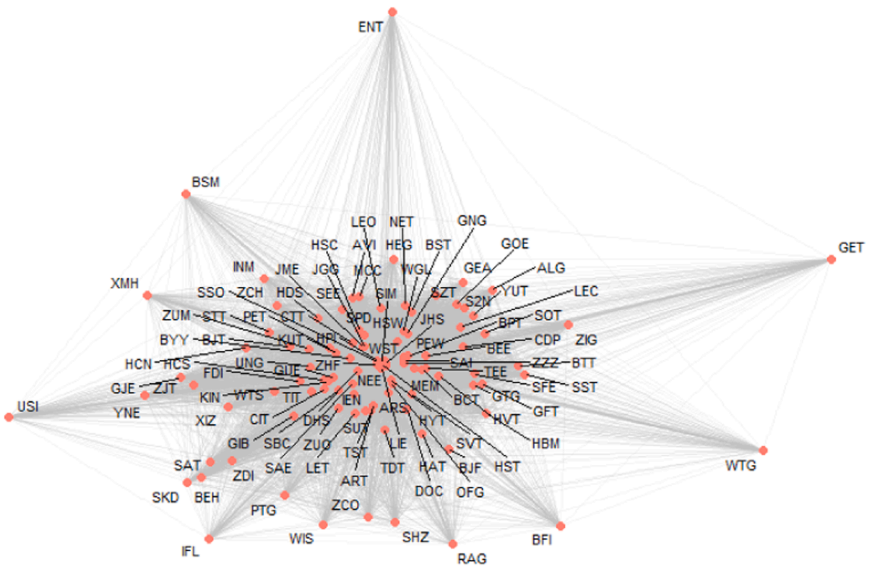

Fig. 2. Interdependence network of the Metaverse Industry (first window-52 weeks).

were listed for fewer than 100 days or delisted for more than one year. The sample period covers 1 January 2020–1 August 2022, as the Chinese Metaverse industry has developed rapidly since 2020. The final sample consists of 110 listed enterprises. The mean and standard deviation of their stock returns are –0.00201 and 0.07262, respectively, and most return series exhibit non-asymmetric and leptokurtic characteristics.

In this research, we use weekly rolling windows with a width of 52 weeks, which provides a balance between overly noisy data from small windows and overly smoothed data from large windows (Clemente et al., 2021; Výrost et al., 2019). We first apply Kendall's tau coefficient to construct the dependence network for the Metaverse industry within the rolling-window framework. To save space, we present only the weighted dependence networks from the first and last 52-week windows, shown in Figs. 2 and 3. The results indicate that enterprises are closely interconnected, with many concentrated at the center of the networks. However, the overall industrial structure and the position of each enterprise change continuously over time.

3.2. Micro perspective of Metaverse portfolio scheme

3.2.1. The portfolio results of peripheral enterprises

First, we select the peripheral Metaverse enterprises based on the hybrid Kendall-based network and compare the return performance with the benchmark (investing in all enterprises). We set $m = 5,\ 10,\ 20$, namely, the 5, 10, and 20 peripheral enterprises with largest hybrid centrality values are selected, respectively, which are used for portfolio construction and perform through the rolling window methodology. We equally weight the selected enterprises in the out-of-sample period of one week and define the investment scheme of peripheral enterprises as "Strategy P". Concerning the returns in Fig. 4, the benchmark provides the worst performance during the period. When 5, 10 and 20 peripheral enterprises are invested respectively, all obtained cumulative returns are higher than the benchmark. In addition, the results indicate the best portfolios' performance is investing in the 20 peripheral enterprises.

To compare the results of different portfolio schemes, the basic out-of-sample portfolio characteristics and the risk-adjusted performance are presented in Table 2. However, it is difficult to identify the best scheme when we only consider the portfolio characteristics. For instance, although we can observe that the network-based portfolios have a higher mean in Strategy P ($m = 5,\ 10,\ 20$), they have a higher variance relative to the benchmark, which implies that investors will face the huge risk. To overcome this issue, we further analyze the risk-adjusted performance. The obtained results of *SR* and *IR* indicate that the hybrid Kendall network-based portfolio schemes all overperform than the benchmark. The results also indicate that it is the best portfolio scheme of 20 peripheral enterprises, which is with the higher *SR* and *IR* than those in 5 and 10 peripheral enterprises.

To test the robustness of obtained results, the width of the rolling window is changed from 52 weeks (a year) to 26 weeks (half a year). Due to the limited space, we only provide the dependence network among whole industrial enterprises in the first and last rolling window respectively, which is shown in Fig. 5 and Fig. 6. We can obverse that the enterprises connect closely, and a large number of enterprises are gathered in the center of the network.

The cumulative returns of benchmark, 5, 10, 20 peripheral enterprises are shown in Fig. 7. Considering that we have already underlined that the *SR* is not an appropriate measure for ranking the portfolios in case of negative excess returns, the *SR* is not reported in Table 3, which can be only compared in *IR*. As for the performance, we can observe that both the benchmark and network-based approach provide worse returns when a shorter rolling window is considered. However, except for the scheme of 5 peripheral enterprises, the network-based approaches of peripheral enterprises all display a better performance than the benchmark. When

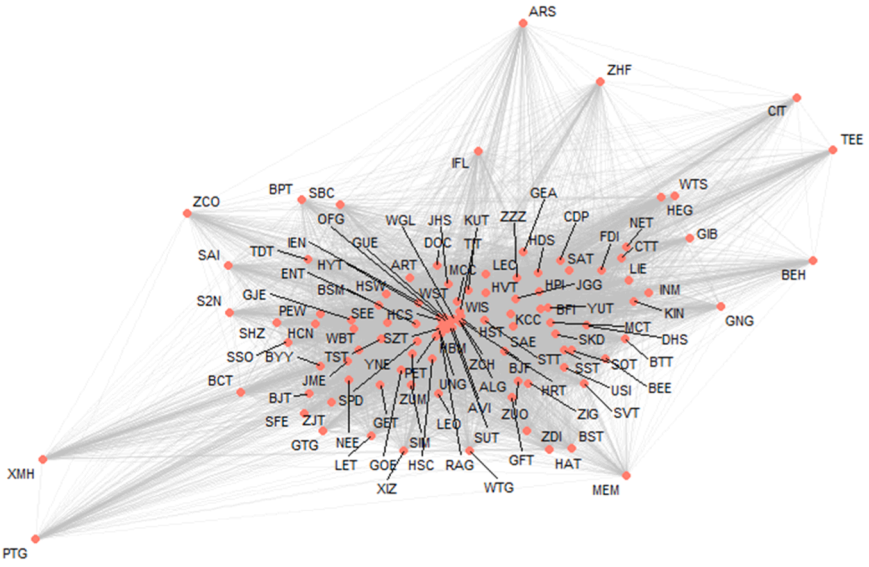

Fig. 3. Interdependence network of the Metaverse Industry (last window-52 weeks).

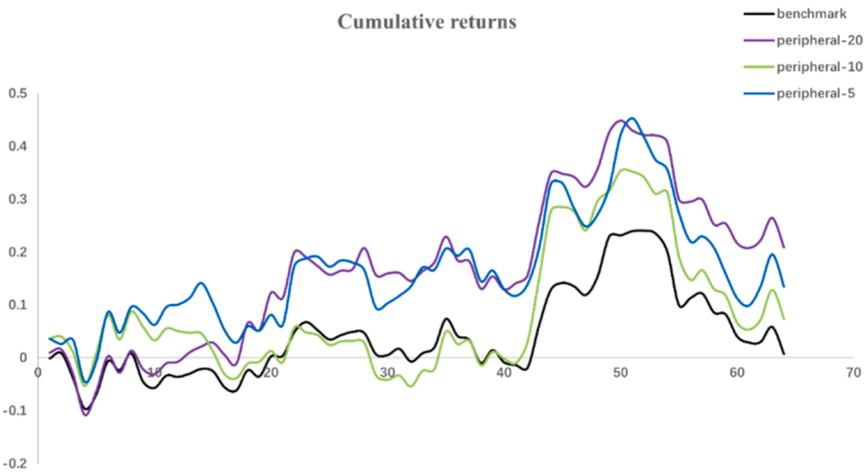

Fig. 4. Cumulative returns of Strategy P (T=52 weeks & h=1 week).

Table 2
Portfolio performance of Strategy P (T=52 weeks & h=1 week).

Investment schemes	Portfolio characteristics			
	μ	σ	*SR*	*IR*
Benchmark	0.00012	0.03306	0.00365	/
Strategy P (m=20)	0.00327	0.03970	**0.08227**	**0.21387**
Strategy P (m=10)	0.00115	0.04237	**0.02716**	**0.04693**
Strategy P (m=5)	0.00211	0.04432	**0.04762**	**0.06985**

Note: Table 2 reports the out-of-sample portfolio characteristics and risk-adjusted performance of different portfolio schemes. The risk-adjusted indicators (SR and IR) demonstrate that the hybrid Kendall network-based portfolio schemes outperform the benchmark, with the portfolio of 20 peripheral enterprises achieving the highest performance across all metrics.

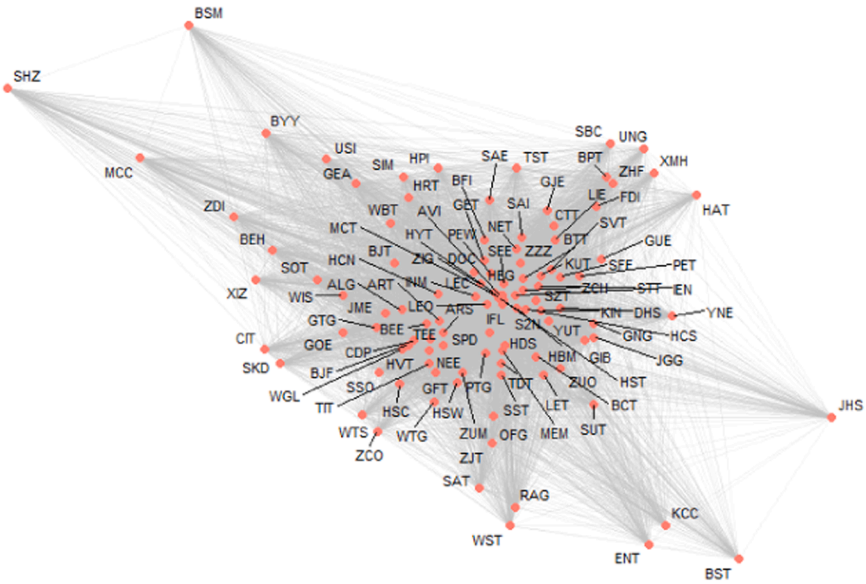

Fig. 5. Interdependence network of the Metaverse Industry (first window-26weeks).

investing in 10 and 20 enterprises, the *IR* are greater than zero, which indicates that there is a significant over-performance with respect to the benchmark strategy. In addition, the results indicate that the best portfolio scheme is always generated from the network-based 20 enterprises.

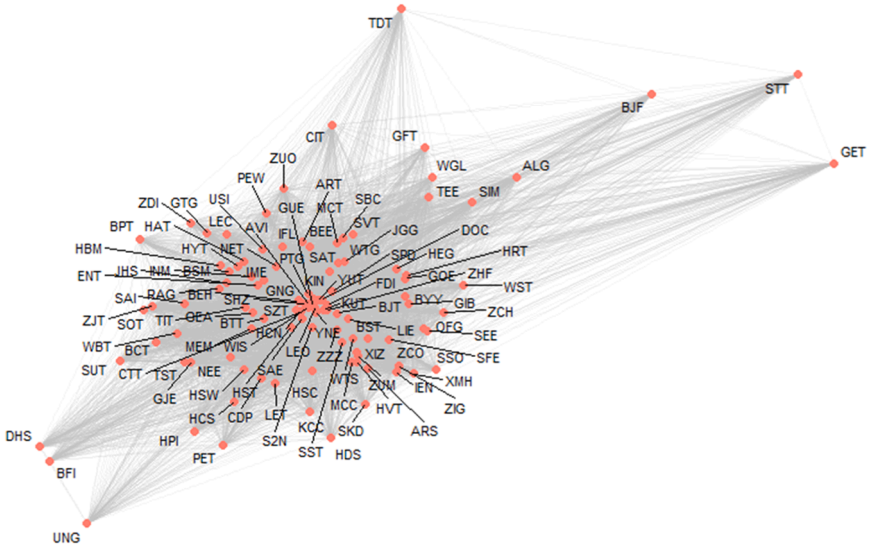

Fig. 6. Interdependence network of the Metaverse Industry (last window-26weeks).

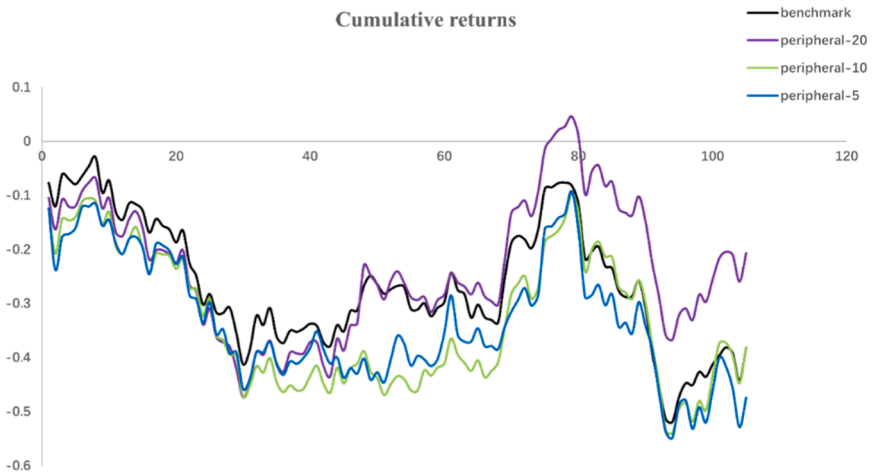

Fig. 7. Cumulative returns of Strategy P (T=26 weeks & h=1 week).

Table 3
Portfolio performance of strategy P (T=26 weeks & h=1 week).

Investment schemes	Portfolio characteristics		
	μ	σ	IR
Benchmark	-0.00363	0.03491	/
Strategy P (m=20)	-0.00197	0.03958	**0.12169**
Strategy P (m=10)	-0.00363	0.03938	**0.00042**
Strategy P (m=5)	-0.00452	0.04287	-0.03629

Note: Table 3 reports the risk-adjusted performance of benchmark and network-based portfolios under different rolling windows. Except for the scheme with 5 peripheral enterprises, network-based portfolios generally outperform the benchmark, particularly those constructed with 10 and 20 peripheral enterprises. Among them, the 20-enterprise portfolio consistently achieves the highest IR, confirming it as the most effective investment strategy.

In particular, at this time, the average return of the benchmark scheme is negative, which indicates that the whole industry may be in a downturn and the overall performance is poor. However, the results show that the investment of peripheral enterprises can obtain smaller losses compared with the benchmark except when investing in 5 enterprises. When 10 and 20 peripheral enterprises are selected, the network-based schemes outperform the classical strategy. This provides several enlightenments: First, the portfolio

scheme is dependent on the whole industrial environment, and we can obtain better returns in a stable period and smaller losses in a downturn through the network-based scheme. Second, one interesting fact is that most firms are small, while they have achieved strong competitive strength and market presence when these small firms agglomerate (Guo, 2011). The performance of peripheral enterprises is relatively stable under any market conditions, which is a safer choice for investors in most cases. Finally, combining the results of rolling windows with different widths, the results of 20 enterprises are the most outstanding with the most excess returns or the smallest losses.

3.2.2. *The portfolio results of central enterprises*

As an alternative portfolio scheme, we then explore the portfolio performance of the returns constructed by the central Metaverse enterprises. The operation is similar in the peripheral enterprises, but the Metaverse enterprises with smallest hybrid centrality are chosen and this portfolio scheme is defined as "Strategy C". More specifically, three schemes are set as follows: (1) we first select top 5, 10, 20 enterprises in the center of the Metaverse Industry respectively by ranking the hybrid centrality in ascending order, and (2) all enterprises in the industry as the benchmark, (3) add the comparison with investing of 5,10, 20 peripheral enterprises.

The empirical results are trained with 52 weeks (rolling window width) in-sample and tested with 1 week out-of-sample and shown in Fig. 8. When the average return of the benchmark is positive, it indicates that the market is stable during this period and the portfolio scheme of the central enterprises can also obtain excess returns. As shown in Table 4, the results of *SR* and *IR* indicate that the investment scheme of 20 central enterprises outperforms the benchmark while the best performance is still generated from the portfolio scheme of peripheral enterprises.

To test the credibility of obtained results, we then transform the rolling window from the width of 52 weeks (a year) to 26 weeks (half a year) and the results are presented in Fig. 9. The returns of the benchmark are negative, indicating that the whole investment environment of Metaverse Industry may be in a downturn, and the results of central enterprises are unsatisfactory with greater losses than the benchmark. This is consistent with our understanding that the central enterprises are more vulnerable to the influence of other enterprises when the whole industry is unstable, because the central enterprises are closely related with other Metaverse enterprises, thus arousing the poor portfolio performance. The compared results can be found in Table 5.

Based on all obtained results, we can draw a basic conclusion that hybrid Kendall-based network portfolio scheme is superior in most cases, especially in the investment scheme of peripheral enterprises. When the whole industry is stable, the hybrid Kendall-based scheme with peripheral enterprises can obtain more excess returns, and also obtain less losses when the whole industry is in a downturn.

3.3. *Macro perspective of industrial interdependence structures*

To analyze the industrial environment of the whole Metaverse Industry more detailed, we investigate the average hybrid centrality of each enterprise by calculating the mean value of all the hybrid centralities under the rolling windows, which reflects the whole interdependence mechanism during the whole time period, and the results are shown in Table 6. Generally, the enterprises in the Metaverse Industry are closely connected and interact with each other intensively, but the dependence and influence of different enterprises across the whole industry are heterogeneous; for example, average hybrid centrality is 1.77380 for SAE while 1.47073 for ZZZ. Additionally, we find that JGG, MEM, SAI, TST and ZZZ have the strongest power to influence with the smallest average hybrid centrality; SAE, CDP, HPI, HBM and LEO have the weakest power to influence with the largest average hybrid centrality.

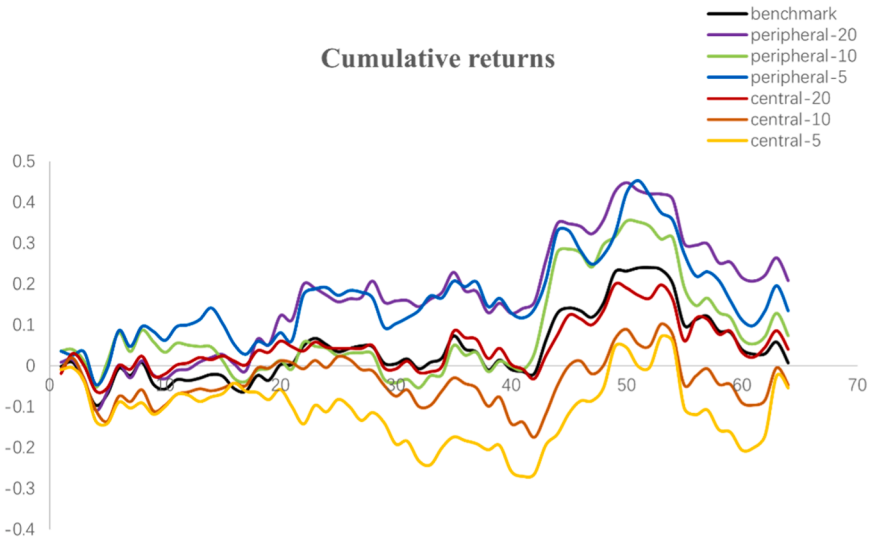

Fig. 8. Cumulative returns of Strategy C (T=52 weeks & h=1 week).

Table 4
Portfolio performance of strategy C (T=52 weeks & h=1 week).

Investment schemes	Portfolio characteristics			
	μ	σ	*SR*	*IR*
Benchmark	0.00012	0.03306	0.00365	/
Strategy P (m=20)	0.00327	0.03970	0.08227	0.21387
Strategy P (m=10)	0.00115	0.04237	0.02716	0.04693
Strategy P (m=5)	0.00211	0.04432	0.04762	0.06985
Strategy C (m=20)	0.00064	0.03397	0.01874	**0.03110**
Strategy C (m=10)	-0.00073	0.03703	/	-0.03811
Strategy C (m=5)	-0.00084	0.04405	/	-0.02856

Note: Table 4 presents the risk-adjusted performance of benchmark, central-enterprise-based, and peripheral-enterprise-based portfolios, using a 52-week in-sample rolling window and 1-week out-of-sample test. The results show that the portfolio of 20 central enterprises outperforms the benchmark in terms of both SR and IR. However, the best overall performance is consistently achieved by the network-based portfolios of peripheral enterprises, confirming their superior risk-adjusted returns across market conditions.

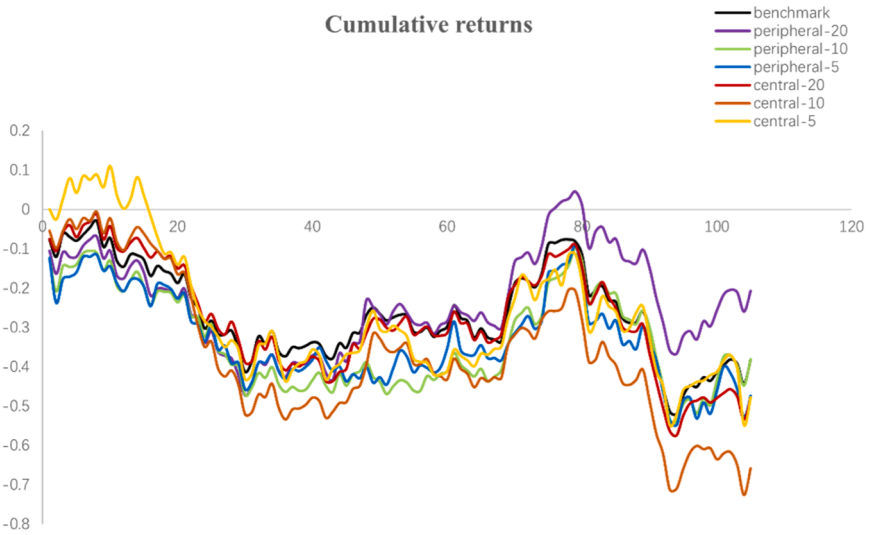

Fig. 9. Cumulative returns of Strategy C (T=26 weeks & h=1 week).

Table 5
Portfolio performance of strategy C (T=26 weeks & h=1 week).

Investment schemes	Portfolio characteristics		
	μ	σ	*IR*
Benchmark	-0.00363	0.03491	/
Strategy P (m=20)	-0.00197	0.03958	0.12169
Strategy P (m=10)	-0.00363	0.03938	0.00042
Strategy P (m=5)	-0.00452	0.04287	-0.03629
Strategy C (m=20)	-0.00455	0.03525	-0.07526
Strategy C (m=10)	-0.00627	0.03862	-0.13879
Strategy C (m=5)	-0.00455	0.04397	-0.03212

Note: Table 5 reports the portfolio performance under a 26-week in-sample rolling window and 1-week out-of-sample test. The results show that portfolios constructed from central enterprises perform worse than the benchmark, incurring greater losses due to their high interconnectivity and vulnerability to contagion effects. By contrast, peripheral-enterprise portfolios demonstrate relative resilience, generating better performance than both the benchmark and central-enterprise schemes, thus confirming the diversification benefits of peripheral firms under adverse market conditions.

Second, we attempt to identify the relative “stable” leaders and outsiders, which always locate in the periphery or center of the Metaverse Industry. For each network, we screen the most central and peripheral enterprises according to the rank of hybrid centrality. Under the rolling window iteration, each dependence network is variable, representing the dynamic industry situation in different periods, and the candidate sets of investable enterprises are also changeable in every periods. Therefore, we calculate the cumulative number of selected times of each enterprise in different time periods, and some enterprises are generally stable with the highest

Table 6
The average hybrid centrality for each Metaverse enterprise.

Ticker	average P	Ticker	average P	Ticker	average P
SAE	1.77380	BEE	1.69085	INM	1.62164
CDP	1.76791	WTG	1.68955	ZCO	1.62120
HPI	1.76148	TEE	1.68901	HST	1.62112
HBM	1.76056	HAT	1.68883	NEE	1.62108
LEO	1.75703	ENT	1.68798	HYT	1.62078
XMH	1.75477	LIE	1.68797	GOE	1.62064
WST	1.75329	BYY	1.68537	HVT	1.61994
SSO	1.75265	WGL	1.68471	KIN	1.61971
PTG	1.74883	MCT	1.68124	FDI	1.61877
BFI	1.74654	HDS	1.67952	DOC	1.61813
SEE	1.74425	WTS	1.67849	BTT	1.60954
NET	1.74348	BCT	1.67651	CIT	1.60736
BSM	1.74330	AVI	1.67167	PEW	1.60287
YNE	1.74202	TDT	1.67142	BST	1.60074
TIT	1.74089	DHS	1.67109	BEH	1.60013
SBC	1.73770	PET	1.67083	JME	1.59262
SUT	1.73666	MCC	1.67080	SIM	1.59013
HSW	1.73633	LET	1.65731	BPT	1.58820
GTG	1.73290	IEN	1.65565	GFT	1.58580
WBT	1.73000	STT	1.65466	USI	1.58444
GUE	1.72863	SKD	1.65396	YUT	1.58093
ZCH	1.72578	BJT	1.64990	SVT	1.57286
GET	1.71902	ZIG	1.64562	HEG	1.56898
KUT	1.71616	WIS	1.64424	ZUO	1.56395
OFG	1.71565	S2N	1.64204	SPD	1.56391
RAG	1.71555	SST	1.64060	SOT	1.56128
KCC	1.71294	ALG	1.64035	ARS	1.55831
GEA	1.71153	HCS	1.63976	ART	1.55718
SAT	1.71105	IFL	1.63950	ZUM	1.54579
BJF	1.71087	ZDI	1.63875	GIB	1.54577
JHS	1.70699	HRT	1.63458	XIZ	1.54407
SHZ	1.70362	HSC	1.63448	JGG	1.54292
UNG	1.70248	HCN	1.63357	MEM	1.53893
CTT	1.70074	ZJT	1.63115	SAI	1.49846
ZHF	1.69872	GJE	1.62906	TST	1.49225
LEC	1.69773	SFE	1.62549	ZZZ	1.47073
GNG	1.69299	SZT	1.62376		

cumulative picks (Wang et al., 2021; Xu et al., 2022). We can observe that ZZZ, SAI, TST are “the most stable” leaders and SAE, HBM, CDP are “the most stable” outsiders.

4. Discussion and conclusion

4.1. Theoretical contributions

We make three contributions to the literature on emerging industry investment. First, we identify the overall interdependence structure of the Metaverse industry, as well as the leaders and outsiders (i.e., peripheral firms), thereby contributing to research on the macro-development environment of the Metaverse. Although previous studies have examined the Metaverse from perspectives such as trust, ownership, privacy, bias, disinformation, and law (Dwivedi et al., 2022; Vidal-Tomasás, 2023), the industrial structure of the Metaverse has largely been overlooked. To address this gap, we identify industry leaders and outsiders and provide meaningful implications for market participants. For example, leaders play a critical role in shaping industry development, as they not only represent broader industry trends but also influence the market more rapidly through network effects (Wang et al., 2021).

Second, a specific portfolio scheme of the hybrid Kendall-based outsiders is recommended, which are always superior with leaders and all Metaverse enterprises in multi-scale networks, and it contributes to the micro-investment environment research of Metaverse Industry. Previous studies on Metaverse from micro perspective mainly focus on users (Jaung, 2022), organizations (Dwivedi et al., 2023), and entrepreneurs (Gupta et al., 2023). However, the analysis of the investment environment of the Metaverse Industry is lacked. We propose a specific portfolio scheme of the hybrid Kendall-based outsiders, and its superiority is verified by a large number of portfolio experiments.

Finally, we construct a new dependence network—the Kendall-based hybrid network—by introducing the comprehensive criterion of hybrid centrality into the Kendall framework, making it suitable for portfolio analysis in emerging industries. Although hybrid centrality was first proposed by Pozzi et al. (2013) to identify the position of each enterprise within the broader economic system via the Pearson network (Clemente et al., 2021; Peralta and Zareei, 2016; Výrost et al., 2019), it has not yet been applied to the Kendall network. In this research, we integrate hybrid centrality into the Kendall network to more accurately capture the structure of the

Metaverse industry and design portfolio schemes by distinguishing between central and outsider enterprises. The results show that portfolios constructed from outsider enterprises identified through hybrid centrality achieve superior performance. This approach not only models the non-linear correlations among all listed firms in the industry but also incorporates multiple topological criteria, thereby providing a concise representation of the industrial structure and its investment environment.

4.2. Practical implications

Some practical insights can also be provided for emerging industry stakeholders, especially for investors, regulators, and managers in Metaverse investment.

For investors, our findings highlight the importance of incorporating network-based portfolio strategies into investment decision-making. Traditional diversification principles (e.g., *not putting all eggs in one basket*) gain new meaning in the Metaverse context, where firm-level connectivity creates heterogeneous risk exposures. Peripheral enterprises, with limited inter-firm linkages, provide relatively stable returns and act as effective hedges in downturns, whereas central enterprises—although more volatile—serve as bellwethers whose shifts strongly influence industry-wide dynamics. Investors can operationalize these findings by embedding centrality measures and network diagnostics into portfolio construction, conducting periodic recalibration of inter-firm dependencies, and adopting adaptive asset allocation strategies that overweight peripheral firms in stable or bearish markets while selectively engaging with central firms in bullish conditions. Such a network-informed approach strengthens resilience and improves the risk-adjusted performance of investment portfolios.

For regulators, the results reinforce the logic of "too connected to fail" and underline the systemic importance of central enterprises. Given that shocks to these firms can rapidly propagate across the entire Metaverse ecosystem, regulators should integrate network dependency assessments into supervisory frameworks and early-warning systems. Practical policy tools may include: (i) periodic stress testing of highly central firms to simulate contagion risks, (ii) targeted disclosure requirements on inter-firm dependencies, (iii) contingency protocols to ensure operational continuity, and (iv) regulatory sandboxes to experiment with industry-specific safeguards. These measures align with international practices such as the EU *Digital Markets Act* and would help prevent systemic instability while fostering sustainable growth of the Metaverse industry.

For managers, understanding a firm's network position provides a strategic lens for risk management and competitive positioning. Enterprises occupying central positions should develop robust risk governance frameworks, including crisis contingency planning, diversified alliances, and real-time monitoring of partner performance, to mitigate contagion risks from industry-wide shocks. Peripheral firms, by contrast, can emphasize their relative stability to attract long-term investment, and strategically adjust connectivity to balance innovation opportunities with controlled risk exposure. More broadly, managers can embed network analytics into strategic planning, using connectivity insights to optimize partnership decisions, capital allocation, and innovation strategies. This network-informed managerial approach enhances organizational resilience, strengthens competitiveness, and promotes sustainable value creation in the rapidly evolving Metaverse ecosystem.

4.3. Conclusion

This research examines the investment environment of the Chinese Metaverse industry from both macro-industrial structure and micro-portfolio perspectives. Importantly, our findings are shaped by China's unique regulatory, cultural, and technological context. The positions of enterprises within the overall industrial structure are captured using the topology of the Kendall-based network, through which industry leaders and outsiders are identified. From the micro-perspective, we recommend a hybrid Kendall-based portfolio scheme based on peripheral enterprises. Future studies could incorporate richer business information, such as actual transactions between Metaverse enterprises (Xu et al., 2022), to enhance understanding of industry interdependencies—particularly when applying this methodology to markets with different cultural and technological settings. In addition, alternative methods of measuring correlations among Metaverse enterprises could be explored (Wen et al., 2019).

Author Statement

Dr. Liukai (Kevin) Wang was responsible for overall project management, coordination of correspondence between co-authors, and distribution of tasks. His contributions included, but were not limited to, writing the original draft, editing, formal analysis, and interpretation of the results.

Yuqing Li was responsible for data handling and analysis. Her contributions included, but were not limited to, writing the original draft, conducting data analysis, interpretation, and visualization.

Dr. Larisa Yarovaya was responsible for conceptualization and interpretation of the results. Her contributions included, but were not limited to, writing the original draft, conceptualization and theory development, and editing. She also served as the corresponding author during submission.

CRediT authorship contribution statement

Larisa Yarovaya: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Liukai Wang:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yuqing Li:** Writing – original draft, Methodology,

Investigation, Formal analysis, Data curation.

Declaration of Competing Interest

Authors have no conflicts of interest to report.

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Appendix 1. List of enterprises in Metaverse Industry

Stock code	Ticker	Stock code	Ticker	Stock code	Ticker
000665	HRT	002717	LEC	300364	CDP
000676	GET	002751	SEE	300413	MEM
000810	SKD	002876	SSO	300418	KUT
000863	SAI	002878	BYY	300433	LET
000909	SOT	300007	HEG	300459	ZJT
000925	ZUM	300017	WST	300494	HCN
000948	YNE	300020	ENT	300496	TST
002036	LIE	300027	HBM	300556	SVT
002045	GUE	300031	WBT	300571	HPI
002047	SBC	300032	JME	300578	BCT
002059	YUT	300036	BSM	300592	HYT
002065	DHS	300043	RAG	300612	SIM
002123	MCT	300052	SHZ	300624	WTG
002195	S2N	300058	BFI	300645	ZZZ
002230	IFL	300071	FDI	300650	TEE
002241	GOE	300075	BEE	300657	XMH
002253	WIS	300079	SUT	300691	ZUO
002273	ZCO	300081	HSC	300756	GJE
002292	ALG	300088	WTS	300781	GIB
002354	TDT	300098	GTG	300793	CIT
002369	SZT	300113	HST	600060	HVT
002373	CTT	300133	ZHF	600208	XIZ
002425	KCC	300134	STT	600410	BTT
002431	PET	300144	SPD	600556	GFT
002456	OFG	300182	BJT	600640	BEH
002467	NET	300213	BJF	600728	PTG
002517	KIN	300220	WGL	600986	ZIG
002555	IEN	300229	TIT	601231	USI
002558	GNG	300232	UNG	603017	ART
002587	SAE	300248	NEE	603081	ZDI
002602	ZCH	300264	AVI	603466	SFE
002624	PEW	300287	BPT	603598	INM
002632	DOC	300296	LEO	603825	HDS
002635	SAT	300322	HSW	603977	JGG
002655	GEA	300323	HCS	688039	HAT
002657	BST	300331	SST	688088	ARS
002699	MCC	300339	JHS		

Data availability

Data will be made available on request.

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