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Artificial intelligence and e-commerce market dynamics: comparative evidence from Europe, China, and the U.S.

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Abstract
The integration of artificial intelligence (AI) technologies into financial systems has fundamentally transformed market dynamics. To address this issue, this study aims to examine the dynamic and asymmetric effects of AI technologies on e-commerce markets by considering cross-country differences. In this context, the relationship between the Global X Artificial Intelligence & Technology ETF (AIQ.Q) index and the CSI Overseas China Internet (CSI), Dow Jones Internet Commerce (DJIC), and Solactive E-commerce (SLCTV) indices is analysed between March 9, 2021, and May 30, 2025, through the Wavelet Quantile-on-Quantile Regression (WQQR) method. The findings indicate that the impact of AI investments varies significantly across countries and market structures. The findings reveal that across all quartiles and periods, an increase in the AI index is connected with an increase in the e-commerce indices, except the Chinese index. Specifically, the effect of AI on the Chinese e-commerce index (CSI) appears weak and negative in the short term, negative and insignificant in most of the quartiles in the medium term, and negative and more pronounced in the long term, while it shows strong and consistent positive effects on the U.S. (DJIC) and European (SLCTV) e-commerce indices across all time horizons. This suggests that the level of technological adaptation, investment in digital infrastructure, and the speed of AI integration play crucial roles in shaping market performance. These findings are of critical importance for both the public and private sectors in developing data driven policies that aim to enhance AI adoption and improve digital market efficiency.

Keywords Artificial intelligence · E-commerce indices · Financial markets: wavelet quantile-on-quantile

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1 Introduction

The adoption of artificial intelligence (AI) technologies within financial infrastructures has led to a profound reconfiguration of market behavior and structural dynamics. Through the widespread use of big data, machine learning, and deep learning models, information asymmetry has decreased, and the price formation process has become more data driven. This transformation represents not only technological progress but also a period in which investor expectations, market confidence, and decision-making speed have been redefined [1, 2]. In this context, AI indices serve as strategic indicators that measure firms' technological adaptation levels and market sensitivity. Increasing AI investment is generally associated with expectations of higher market efficiency, liquidity, and price stability, while during periods of technological uncertainty, investors tend to exhibit risk averse behavior.

The impact of AI on stock markets is multidimensional. On one hand, algorithmic trading increases transaction volume and market depth, while on the other, high frequency trading can trigger short term volatility [3, 4]. This dual structure shows that the market participants' reactions to technology are shaped through information flow, sentiment, and risk perception channels. In particular, in highly digitalized sectors, such as e-commerce, financial services, and technology driven enterprises, the comovement between AI indices and stock performance becomes more pronounced. These sectors not only gain cost advantages through AI based process automation, customer analytics, and forecasting systems but also enhance their valuations through innovation expectations [5, 6].

AI has also transformed the quality of financial decision-making processes. For firms, AI emerges as a tool that enhances the accuracy of financial reporting, strengthens market predictability, and increases investor confidence [7]. Sharma, [8] emphasize that AI makes global stock market movements more predictable and that digital information systems reduce uncertainty for decisionmakers. In this process, investors have begun to take positions not only based on past performance but also on the potential created by technological capabilities. Thus, AI indices have become not only indicators of technological progress but also early signals of market expectations and risk perception.

Within this framework, the relationship between AI indices and stock markets holds strategic importance for understanding the financial reflections of digital transformation. Representatives of the digital economy, such as e-commerce indices, can directly respond to increases in AI investment, reshaping investor behavior, market liquidity, and sectoral performance differentials. The information processing capacity offered by AI increases predictive power in markets while simultaneously strengthening risk transmission channels during periods of high volatility. Therefore, the dynamic relationship between AI indices and stock markets represents not merely a technological development but a new turning point in terms of financial stability, investment behavior, and digital economy integration.

The association between the AI index and e-commerce indices can be evaluated within a multidimensional framework that combines the theories of knowledge-based growth, market efficiency, technological diffusion, and behavioral finance. According to the knowledge-based endogenous growth theory proposed by Romer [9] and

Aghion and Howitt [10], economic growth is fueled by technological innovation, knowledge creation, and innovation capacity. In this context, artificial intelligence accelerates the process of generating and processing knowledge, leading to productivity gains and strengthening competitive advantage, particularly in data driven sectors such as e-commerce. Thus, the increase in the AI index reflects the intensification of knowledge-based innovations and the rising productivity of the digital economy. On the other hand, Fama's [11] efficient market hypothesis argues that market prices reflect all available information. Today, this flow of information is accelerated by AI systems, reducing information asymmetry [1]. This enables price formation in e-commerce indices to become more rational and data driven. Similarly, Rogers' [12] diffusion of innovations theory emphasizes that technological innovations spread through "early adopter" sectors. E-commerce, being one of the fastest and most comprehensive adopters of AI technologies, stands as the pioneer of this process [13]. However, the behavioral dimension of financial markets should not be overlooked. The investor sentiment model developed by Barberis et al. [14] suggests that investor behavior can deviate from rational expectations. In this context, increases in the AI index may enhance investors' confidence in technology driven sectors, leading to positive pricing tendencies in e-commerce indices [2]. In conclusion, the linkage between AI and e-commerce markets is shaped by the interplay of various theoretical foundations, such as knowledge generation, market efficiency, technological adoption, and investor psychology.

The main objective of this study is to examine the impact of the Global X Artificial Intelligence & Technology ETF (AIQ.Q) index on e-commerce markets from a multidimensional perspective. In this context, the CSI Overseas China Internet USD (CSI), Dow Jones Internet Commerce (DJIC), and Solactive E-commerce (SLCTV) indices were analyzed for the period from March 9, 2021, to May 30, 2025. By employing the Wavelet Quantile-on-Quantile Regression (WQQR) method, the relationships between the AI and e-commerce indices were revealed in detail in terms of short, medium, and long term dynamics. Thus, the asymmetric and frequency dependent effects of developments in artificial intelligence technologies on the performance of e-commerce markets were identified across different time horizons and market conditions. This analysis enables a more comprehensive evaluation of the role of artificial intelligence investments in the stability and growth potential of the e-commerce sector during the digital transformation process and examines the dynamic relationship between technology indices and digital market indicators through a multi-frequency and quantile-based approach.

The main motivation of this study is to contribute to the growing literature on artificial intelligence (AI) and digital financial markets by empirically examining the relationship between AI and e-commerce markets, two key components of the digital economy. Although previous studies have extensively discussed the role of AI in financial markets, investment decisions, and stock market forecasting [1, 2, 15, 16], empirical evidence on the interactions between AI-related financial indices and sector-specific equity markets remains limited. Existing research has primarily focused on AI applications in financial forecasting or AI-based investment strategies rather than on how AI-related market dynamics are transmitted to technology-intensive sectors such as e-commerce [17, 18]. In particular, it extends the literature on digital economy finance by examining how artificial intelligence indices are reflected in e-commerce markets and by identifying market-level transmission patterns across these markets. By doing so, this study contributes to the literature by providing new evidence on the financial interactions between AI-driven investment markets and the digital commerce ecosystem. Furthermore, unlike previous studies that mainly rely on conventional linear approaches, this study employs a multi-frequency and quantile-based framework to reveal the time-varying and asymmetric nature of these relationships. The findings are expected to provide valuable implications for policymakers, investors, and e-commerce firms by improving the understanding of how AI-related financial developments influence market dynamics, investment behavior, and the evolution of the digital economy. This study also provides valuable implications for a wide range of stakeholders. For policymakers, it offers insights into how AI investments affect employment, productivity, and competition in the e-commerce sector, which is crucial for shaping digitalization policies. For investors and portfolio managers, identifying the short, medium, and long term impacts of fluctuations in the AI index on e-commerce indices provides a foundation for risk management and diversification strategies. Finally, for e-commerce companies, the findings shed light on how AI integration influences market valuation, investor perception, and the sector's sustainable growth potential. Overall, this research presents an original contribution both theoretically and practically by introducing a dimension underpinned by AI technologies to the relationship between financial markets and the digital economy.

This study consists of five sections. In the first section, the theoretical framework regarding the relationship between AI index and e-commerce indices is presented. In the second section, the existing studies that examine the association between AI and financial markets are reviewed in detail, and a summary of the literature is provided. In the third section, the dataset and econometric method used in the analysis are introduced, and the definitions and sources of the variables are explained. In the fourth section, the findings of the WQQR analysis, which reveal the short, medium, and long term dynamics of the relationship between the AI index and the e-commerce indices, are presented. In the last section, policy recommendations are provided in light of the results, and directions for future research are discussed.

2 Literature review

Although there are limited empirical studies that directly investigate the linkage between AI indices and financial markets, research on the role of AI in the financial system has expanded rapidly in recent years. These studies have examined various aspects of AI, including stock price behavior, investment decision-making, risk management, firm value, and financial stability. One of the early studies, Lingam [18], discussed the potential of AI to improve investment decision-making in the e-commerce context. Ferreira et al. [16] reported that AI models often achieve higher predictive performance than traditional econometric methods in stock market forecasting. Similarly, Chopra and Sharma [2] and Lin and Marques [3] suggested, based on their systematic reviews, that machine learning and hybrid deep learning models may improve stock market prediction performance under certain conditions. Habib et al. [19] applied an LSTM-based deep learning model and reported high predictive performance during periods of market volatility. Arora et al. [20], as well as Pillai and Bi [21], suggested that AI models may better capture complex patterns in financial time series. Rezaei et al. [22] argued that AI has the potential to improve prediction accuracy while contributing to market efficiency and economic sustainability. Chauhan et al. [23] and Annaufal et al. and [24] reported that AI-supported forecasting systems produced competitive forecasting performance in India and Indonesia under rapidly changing market conditions. Najem et al. [25] conducted a comparative analysis of machine learning techniques, while Jain and Vanzara [26] and Sharma [8] identified hybrid predictive frameworks as an emerging area of research. Song and Jain, [4] explored whether AI can "beat the market," finding that algorithmic systems may outperform market indices under specific conditions. Singh and Malhotra [27] proposed a time-series AI prediction framework capable of capturing nonlinear price dynamics.

Following these advances, a significant portion of the literature has focused on the role of AI in investment decisions, portfolio management, and financial behavior. Santos et al. [28] suggested that AI can improve portfolio optimization, asset allocation, and risk-return performance. Miziołek, [29] and Mer et al. [30] indicated that AI may enhance decision speed and analytical efficiency in investment management and banking applications. Alnemer and Al-Sartawi, [5] emphasized AI's strategic role in automated trading, while Hicham et al. [31] proposed an integrated framework for AI adoption in financial decision-making. Koo, [32] examined investors' trust in AI-supported financial advisors and their perceptions of risk. Bas et al. [33] suggested that AI-driven efficiency in stock and supply chain management may indirectly contribute to financial performance. Similarly, Taqi et al. [34] discussed the potential of AI to influence the future of financial trading and market intelligence. Overall, these studies suggest that AI has the potential to influence investment decision-making processes and support strategic adaptation in financial markets.

Research examining the effects of AI investment on firm value, financial risk, and market stability has also become increasingly prominent. Lui et al. [35] found evidence that AI investment is associated with higher firm value by improving data analytics capacity. Zhang et al. [36] and Xiao and Wenyao [37] reported that AI innovation is associated with stock price crash risk depending on governance quality. Zheng et al. [38] suggested that AI investment and executives' digital backgrounds are associated with stronger stock price synchronization. Li et al. [39] provided evidence that AI adoption may contribute to market performance and lower stock price crash risk in emerging economies. Alhazmi et al. [7] found that AI adoption is associated with enhanced financial reporting quality in the Saudi Stock Exchange by reducing information asymmetry. Alex Avelar and Jordão, [40] discussed the role of AI in supporting complex financial analysis and forecasting in major stock exchanges, while Bahoo et al. [15] presented bibliometric evidence on the growing importance of AI research in finance. Similarly, Mohamad et al. [41] highlighted the increasing research interest in AI applications for market analytics. Collectively, these studies suggest that AI may play an increasingly important role in firm performance, financial transparency, and market functioning.

At the macro level, several studies have examined AI's broader impact on the financial system. Rahmani et al. [42] reviewed AI applications in stock trading, market analysis, and risk management. Ahmed et al. [1] documented AI's expanding role in FinTech and digital finance, while Amzile [43] discussed the potential implications of AI for digital currency systems. Kocak and Alnour, [44] reported that AI and green technologies are associated with improved firm returns in the tourism sector, whereas Ghosh and Jana [45] found that explainable AI may improve the predictability of clean energy stock prices. Teplova et al. [46] suggested that AI-based approaches contribute to understanding stock liquidity and ESG performance before and during the COVID-19 pandemic. Jayaprakash and Loganathan, [6] discussed the growing role of AI in the trading infrastructure of the Indian stock market, while Mosleh et al. [47] highlighted the potential contribution of AI to asset performance monitoring and infrastructure finance.

Overall, the existing literature suggests that AI is increasingly being integrated into financial markets through applications in forecasting, investment decision-making, and risk management. While early studies such as Ferreira et al. [16] and Chopra and Sharma [2] focused primarily on market forecasting and automation, recent works including Li et al. [39], Zhang et al. [36], and Zheng et al. [38] have expanded the discussion to include issues related to risk governance and financial sustainability. Nevertheless, despite this growing body of research, empirical evidence directly examining the dynamic relationship between AI indices and sector-based stock market indices remains limited. To address this gap, the present study investigates the relationship between the AI index and e-commerce company indices. By empirically analyzing the interconnections between artificial intelligence technologies and digital commerce market performance, the study provides additional evidence on the interaction between technological innovation and financial market dynamics. Thus, this research contributes to the existing literature by offering new empirical evidence on the financial linkages between AI-related markets and the e-commerce sector within the broader context of the digital economy.

3 Data and methodology

3.1 Data

The study aims to investigate the impact of the Global X Artificial Intelligence & Technology ETF (AIQ.Q) index on e-commerce indices, namely the CSI Overseas China Internet USD (CSI) index, the Dow Jones Internet Commerce (DJIC) index, and the Solactive E-commerce (SLCTV) index from March 9, 2021, to May 30, 2025. AIQ.Q was selected because it tracks the Indxx Artificial Intelligence & Big Data Index, which represents listed firms active in artificial intelligence development, services, hardware, big data analytics, and related infrastructure. The index methodology shows that its constituents are selected from firms positioned to benefit from the development and use of artificial intelligence in products and services, as well as firms producing hardware used in artificial intelligence applications and big data analysis [48]. While AIQ.Q serves as a broad and investable proxy for this technology domain, we distinguish between market based investment intensity and actual firm level adoption. The selection of three e-commerce indices is driven by the objective of capturing regionally differentiated yet thematically aligned segments of global digital commerce markets. For China, one of the world's largest e-commerce markets, the CSI is employed. This index comprises China based companies whose core operations center on internet and internet related technologies. Given that China's e-commerce ecosystem extends well beyond retail platforms alone, this index serves as an appropriate regional proxy representing China's digital platforms, internet services, and online commerce infrastructure (SEC, [49]). For the US, the other major global e-commerce hub, the DJIC index is utilized. This index represents constituents from the Internet Commerce sector within the Dow Jones Internet Composite Index and is constructed to track the 15 largest and most actively traded internet commerce equities [50]. Its concentrated composition of 15 stocks ensures high liquidity and robust market representativeness, making it a suitable comparative benchmark for the US e-commerce landscape. However, the index is more sensitive to large-cap market leaders rather than the broader e-commerce universe. For Europe and the wider global e-commerce space, the SLCTV index is adopted. Its constituent selection relies on natural language processing of publicly available information combined with a minimum 50% revenue threshold from e-commerce related activities. The index encompasses firms that operate online marketplaces, offer e-commerce software, analytics, or services, and predominantly sell goods and services online. Consequently, the SLCTV index functions as a direct thematic proxy for capturing equity market dynamics within the e-commerce ecosystem, rather than merely reflecting broad technology sector movements [51]. Accordingly, the findings are interpreted as market level transmission patterns rather than direct evidence of internal implementation by e-commerce firms. To address concerns about common financial market movements, the study employs the Wavelet Quantile-on-Quantile Regression framework, which allows the relationship to be examined across both market states and time frequencies. This approach helps reduce the risk of interpreting short term financial noise as a uniform long run relationship, although it does not eliminate all sources of co-movement. Prior studies also use artificial intelligence themed ETFs and equity indices to examine connectedness, volatility transmission, and diversification across financial markets, supporting their use as market based indicators of the artificial intelligence investment segment [17, 52–55].

CSI Overseas China Internet USD (CSI) index, and the Dow Jones Internet Commerce (DJIC) index series data were obtained from the official website of S&P Dow Jones Indices (http://www.spglobal.com). Solactive E-commerce Index (SLCTV) data obtained from the official website of Solactive AG (http://www.solactive.com), while Global X Artificial Intelligence & Technology ETF (AIQ.Q) index data obtained from the official website of Investing (http://www.investing.com). Data span depends on data availability, and all data series are transformed into a logarithmic form. These indices capture the performance of major digital economies, including the United States, Europe, and China. They also facilitate the examination of market-level transmission patterns across e-commerce markets that differ in both regional context and structural configuration. The time trend of the logarithmic series is demonstrated in Fig. 1.

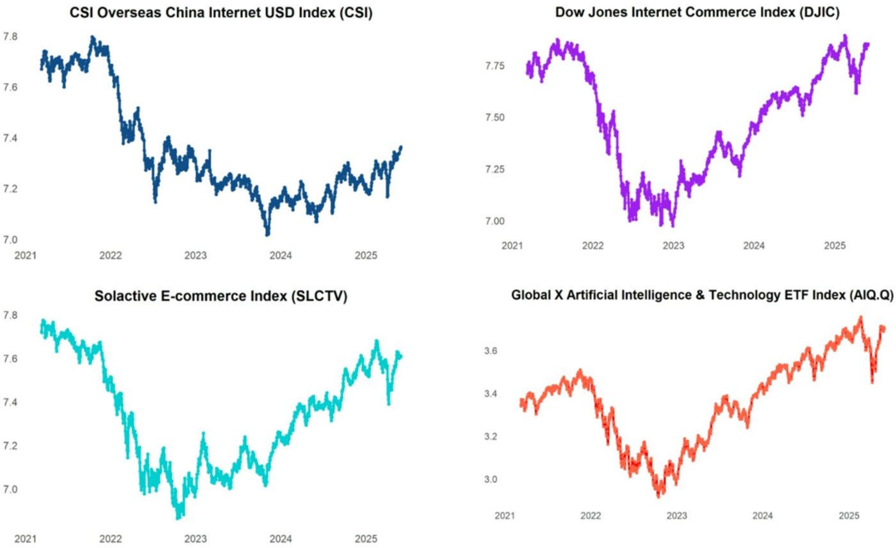

Fig. 1 Dynamic trends of the logarithmic series over time

As illustrated in Fig. 1, all series exhibited a downward trend after 2022, with conjectural fluctuations. Some of the reasons behind this downward trend can be explained by the increasing interest rates in the U.S. after 2022, the rise in inflation due to the Ukraine-Russia war, and the Chinese government's security regulations against technology companies. This pattern suggests a possible parallel movement between the AI technology market and the e-commerce sector.

3.2 Methodology

The ADRL bounds test (augmented Dynamic Regressor Lag bounds test) was introduced by Pesaran et al. [56] and is based on the ARDL (Autoregressive Distributed Lag) model, which is applied to test causality and cointegration in time series econometrics. This test can be formalized as below:

$$\Delta Y_t = \beta_0 + \sum_{i=1}^{p} \vartheta_i \Delta Y_{t-i} + \sum_{i=0}^{q} \delta_i \Delta X_{t-i} + \varphi_1 Y_{t-1} + \varphi_2 X_{t-1} + \epsilon_t \quad (1)$$

This formulation defines Y_t is dependent variable and ΔY_t is first difference of dependent variable. β_0 signifies the constant component of the model and X_t refers independent variable. In addition, φ_1 and φ_2 capture long term dynamic between dependent and independent variable, while ϑ_i and δ_i capture short term dynamics. Moreover, the lag structures of Y_t and X_t are denoted by p and q, also error term is denoted by ϵ_t.

The shortcoming of the ARDL bounds test is that it evaluates the cointegration relationship in a time series model based upon the mean behaviour of the time series dataset. Conversely, a cointegration relationship can exhibit heterogeneity along different segments of the conditional distribution and may differ across various quantiles of the distribution. To overcome this shortcoming, Li et al. [39] developed the Quantile Cointegration (QC) model, which can be formalized as below:

$$Q_\tau\ (\Delta Y_t) ;= \beta_{0,\tau} + \sum_{i=1}^{p} \vartheta_{i,\tau} Q_\tau\ (\Delta Y_{t-i}) + \sum_{i=0}^{q} \delta_{i,\tau}\, \Delta X_{t-1} + \varnothing_{1,\tau} Q_\tau\ (Y_{t-1}) + \varnothing_{2,\tau} X_{t-1} + \epsilon_{t,\tau} \quad (2)$$

In this formulation, Q_τ (.) indicates the conditional quantile function for a given quantile tau (τ), with $\beta_{0,\tau}$ denoting the intercept parameter corresponding to that quantile. The terms $\vartheta_{i,\tau}$ and $\delta_{i,\tau}$ represent quantile-based slope coefficients corresponding to the lagged first differences of dependent and independent variables, respectively, while $\varnothing_{1,\tau}$ and $\varnothing_{2,\tau}$ account for the impact of the lagged levels of these variables at quantile tau (τ). Lastly, at quantile tau (τ) the residual component is denoted by $\epsilon_{t,\tau}$.

3.2.1 Wavelet quantile-on-quantile regression

The methodology of the Quantile-on-Quantile Regression (QQR) was proposed by Sim and Zhou [57], which facilitates an examination of the dependence structure between U.S. equity returns and oil price movements across different quartiles, and this method builds upon the quantile regression framework first formulated by Koenker and Bassett [58]. QQR can be formalized as below:

$$Y_t = \beta_0 (\delta , \varnothing) + \beta_1 (\delta , \varnothing) \left(X_{i,t} - X_i^{\varnothing} \right) + e_t^{\delta} \quad (3)$$

In this formulation, Y_t serves as the dependent variable at time t, and the intercept $\beta_0 (\delta , \varnothing)$ is defined as a function of parameters δ and $\varnothing$. Likewise, the slope term $\beta_1 (\delta , \varnothing)$ may also vary with respect to the parameters δ and $\varnothing$. In this context, the term $X_{i,t}$ identifies the value of the independent variable for observation i at time t, and $X_i^{\varnothing}$ corresponds to its $\varnothing$ -th quantile of the distribution. Moreover, the error component e_t^{δ} is defined at quantile δ .

The QQR method is limited by its static nature; it fails to capture the dynamic relationship between the quantiles of X and those of Y across all periods. In response to this methodological limitation, Özkan et al. [59] introduced the WQQR model. WQQR can be formalized as below:

$$d_j [Y_t] = \beta_0 (\delta , \emptyset) + \beta_1 (\delta , \emptyset) \left(d_j [X_{i,t}] - d_j \left[X_I^{\emptyset} \right] \right) + e_t^{\delta} \quad (4)$$

In this formulation, $d_j [Y_t]$ denotes the wavelet coefficient of the dependent variable at scale j and at time t. Specifically, $\beta_0 (\delta , \varnothing)$ defines the intercept coefficient within the quantile-on-quantile model, while $\beta_1 (\delta , \varnothing)$ represents the quantile-specific slope coefficient. Furthermore, $d_j [X_{i,t}]$ represents the wavelet-decomposed value of the independent variable x for observation i at time t and scale j, while $d_j \left[X_I^{\emptyset} \right]$ indicates the transformation of the $\varnothing$ -th quantile of x using the same wavelet scale. Lastly the resdiual term is expressed as e_t^{δ} .

The study utilized the WQQR method based on Adebayo et al. [60] study, whose methodology deviates slightly from that of Özkan et al. [59] by incorporating relevant values throughout all quantiles and temporal periods, offering a more holistic dynamic analysis. The methodological choice of WQQR is motivated by the economic need to identify how artificial intelligence investment intensity is transmitted to e-commerce markets across both market conditions and investment horizons. Compared with standard wavelet coherence, WQQR does not only show co-movement across frequencies; it also reveals whether the effect differs across lower, middle, and upper quantiles of the variables [61]. This is important because wavelet based financial studies show that market co-movement may vary across time and frequency domains [62], while frequency based connectedness studies indicate that short term and long term shock transmission may have different economic meanings [63]. Compared with QQR, WQQR adds a time frequency dimension, allowing short, medium, and long term transmission patterns to be separated. This extension is useful because QQR identifies how the quantiles of one variable affect the quantiles of another, but does not explicitly distinguish investment horizons [57]. Compared with nonlinear VAR approaches, WQQR provides a more detailed map of how the quantiles of artificial intelligence investment intensity affect the quantiles of e-commerce market indices. Thus, WQQR offers new economic insight by showing whether the artificial intelligence and e-commerce nexus is stronger during bearish, normal, or bullish market states and whether this relationship is temporary or persistent across time horizons. The overall workflow of the study is illustrated below:

4 Results

4.1 Pre-liminary analysis

The logarithmic series of the e-commerce index series and the AI index series (AIQ.Q) are demonstrated in Table 1. The mean statistics reflect the central tendency within the dataset, providing an average measure of the observed values. The DJIC series has the highest average, while the AIQ.Q series has the lowest average. Similarly, the DJIC series exhibits the highest variance, indicating heightened volatility relative to the other series. The skewness values of the DJIC series and the AIQ.Q series are negative, implying a right skewed distribution, with values predominantly concentrated at higher levels. All kurtosis values are below 3, indicating that the

Table 1 Descriptive statistics

	CSI	DJIC	SLCTV	AIQ.Q
Mean	7.344	7.493	7.335	3.367
Median	7.269	7.545	7.350	3.391
Maximum	7.796	7.894	7.774	3.756
Minimum	7.016	6.974	6.863	2.915
Std. Dev.	0.206	0.264	0.244	0.202
Skewness	0.887	−0.266	0.062	−0.255
Kurtosis	2.396	1.708	1.691	2.160
Jarque-Bera	155.597***	86.458***	76.640***	42.709***
Probability	0.000	0.000	0.000	0.000

***$p < 1\%$

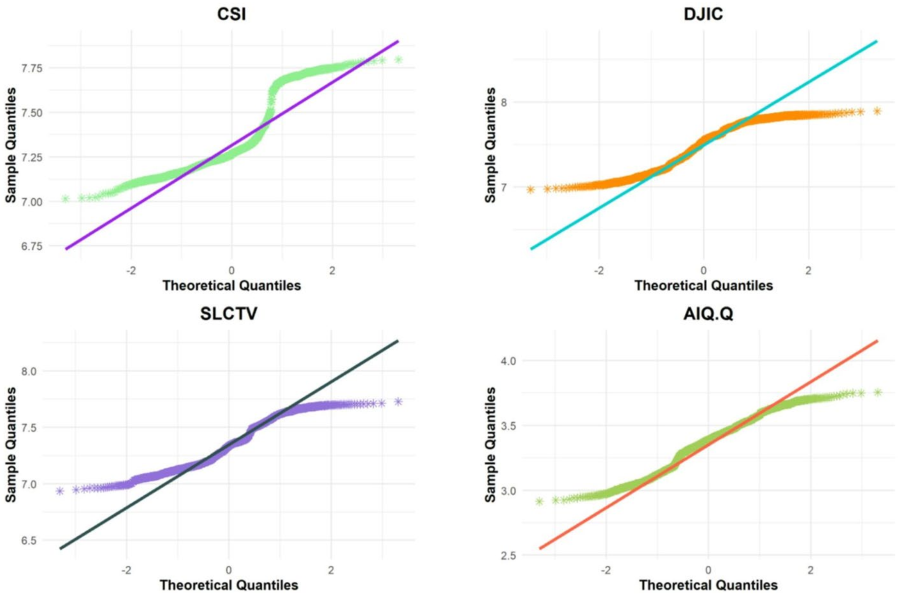

Fig. 2 QQ plot estimations

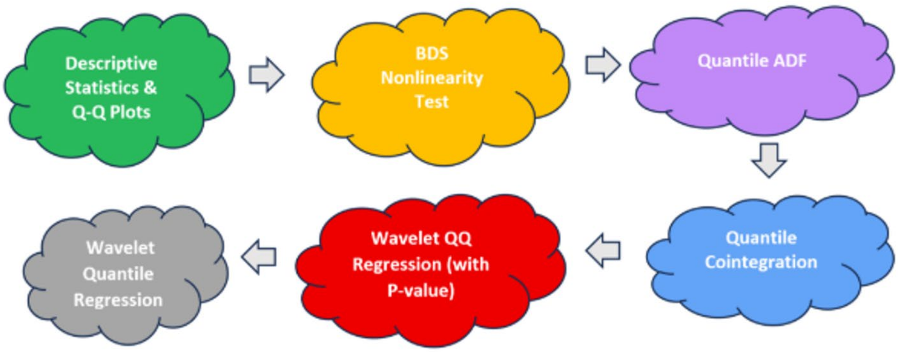

Fig. 3 Overall workflow of analysis

series exhibits properties of normality. Significant Jarque-Bera test statistics suggest that normality is not supported for any of the series.

The Q-Q plots of the log-transformed e-commerce and AI index (AIQ.Q) series are shown in Fig. 2, illustrating the distributional characteristics of the series. The Q-Q plot compares the sample quantiles of the CSI, DJIC, SLCTV, and AIQ.Q series with the corresponding quantiles of a theoretical normal distribution to assess the normality of these series. Figure 3 illustrates that none of the series confirmed this null hypothesis, which assumed that the series are normally distributed. In other words, the CSI, DJIC, SLCTV, and AIQ.Q series are not distributed perfectly normally.

Table 2 BDS test results

Dimensions	CSI	DJIC	SLCTV	AIQ.Q
m2	0.2023***	0.1965***	0.1794***	0.1947***
m3	0.3453***	0.3345***	0.3056***	0.3308***
m4	0.4557***	0.4307***	0.3908***	0.4249***
m5	0.5158***	0.4973***	0.4491***	0.4897***
m6	0.5645***	0.5432***	0.4885***	0.5338***

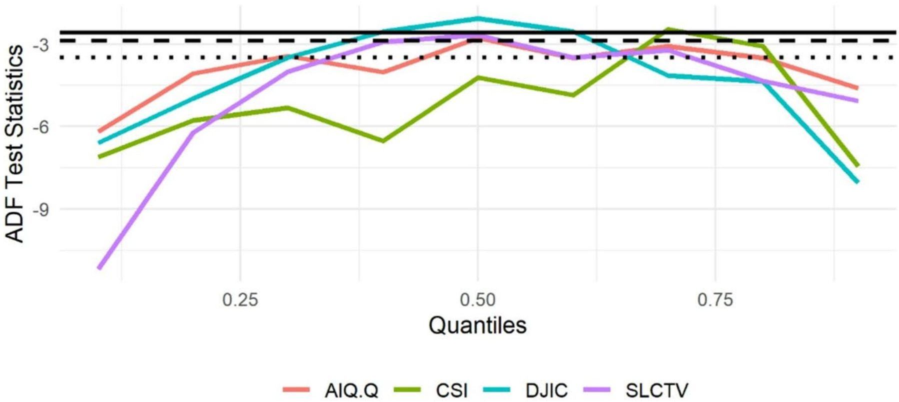

Fig. 4 QADF test statistics across quantiles. QADF test results critical values dotted (1% = 3.49), dashed (5% = 2.89), and solid (10% = 2.58) black lines

To test the nonlinearity properties of indices, we employed the Brock-Dechert-Scheinkman BDS test [64], and test results for the log-transformed e-commerce and AI index (AIQ.Q) series are presented in Table 2. Table 2 illustrates that all series are significant at the 1% level and reject the null hypothesis, which assumes the series demonstrate linear distribution. This indicates that CSI, DJIC, SLCTV, and AIQ.Q are nonlinear over the M2 to M6 dimensions.

Regarding the QQ plot and BDS test results, the CSI, DJIC, SLCTV, and AIQ.Q series do not demonstrate a normal distribution, nor do they exhibit a linear distribution. Consequently, the study applied nonlinear approaches to examine the relationship between these indices.

4.1.1 Quantile unit root

QADF test results of the CSI, DJIC, SLCTV, and AIQ.Q series across the quantiles are illustrated in Fig. 4. The QADF test critical values at the 1%, 5%, and 10% significance levels are shown using dashed and dotted line styles. If the QADF test statistics are below the critical values, it indicates that the data series is stationary; in this case, the null hypothesis is rejected, which assumes the data series has a unit root. Figure 4 reveals that SLCTV and AIQ.Q are stationary across all quartiles, whereas the stationary characteristics of the CSI and DJIC series are quantile-dependent, suggesting variation in stationarity across distinct quantiles of the distribution.

4.1.2 Quantile cointegration

The study aims to examine the impact of the AIQ.Q index on e-commerce indexes, namely the CSI, DJIC, SLCTV, and SPGEC. Before this examination, we investigated the long term cointegration relationship between the AIQ.Q index and the e-commerce indices, and we applied the quantile cointegration within this framework. Figure 2 illustrates the test results, where the F statistics are plotted across the quartiles, and critical values are represented by red, blue, and green dashed lines, indicating the statistical significance level. F statistics above the critical dashed lines indicate a cointegration relationship between variables at that quantile.

Figure 5 illustrates that, however, F statistics are not stable across quantiles; all F statistics are below the red, blue, and green dashed critical value lines. These results reveal a cointegration relationship between CSI & AIQ.Q, DJIC & AIQ.Q, and SLCTV & AIQ.Q.

4.1.3 Wavelet quantile-on-quantile regression (WQQR)

The study utilized WQQR with p-values following the cointegration test to examine the impact of AIQ.Q as an independent variable for the study on e-commerce indices as dependent variables of the study. The impact of AI technologies (AIQ.Q) on the China e-commerce (CSI) index is illustrated in Fig. 6. Panel A presents the short-term effect of AI technologies (AIQ.Q) on the China e-commerce (CSI) index, and it is continuously negative across all quartiles. The results indicate that an increase in AI technologies is associated with a decrease in the e-commerce (CSI) index in the short

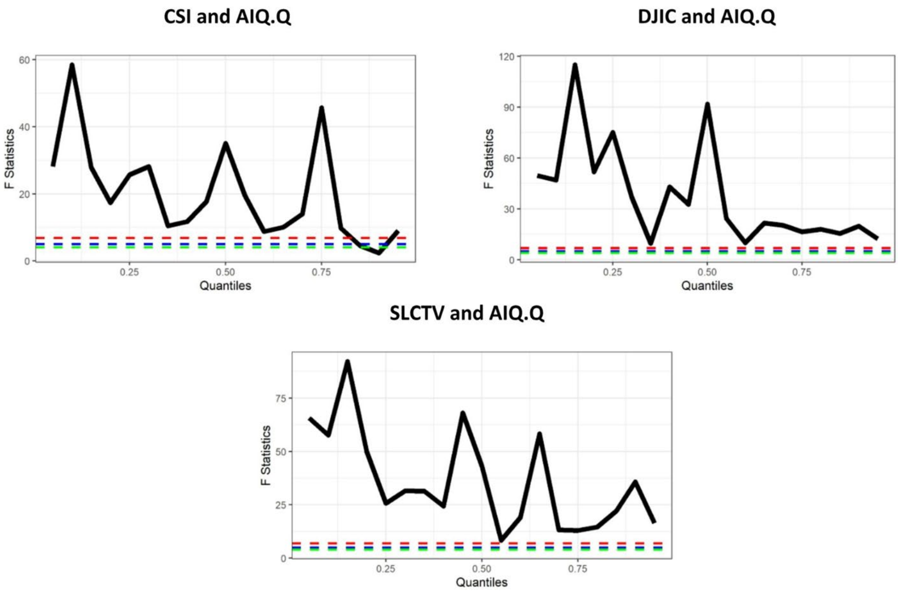

Fig. 5 Quantile PSS bounds test estimates. The upper-bound critical thresholds associated with the 10%, 5%, and 1% significance levels are denoted by the green, blue, and red lines, respectively

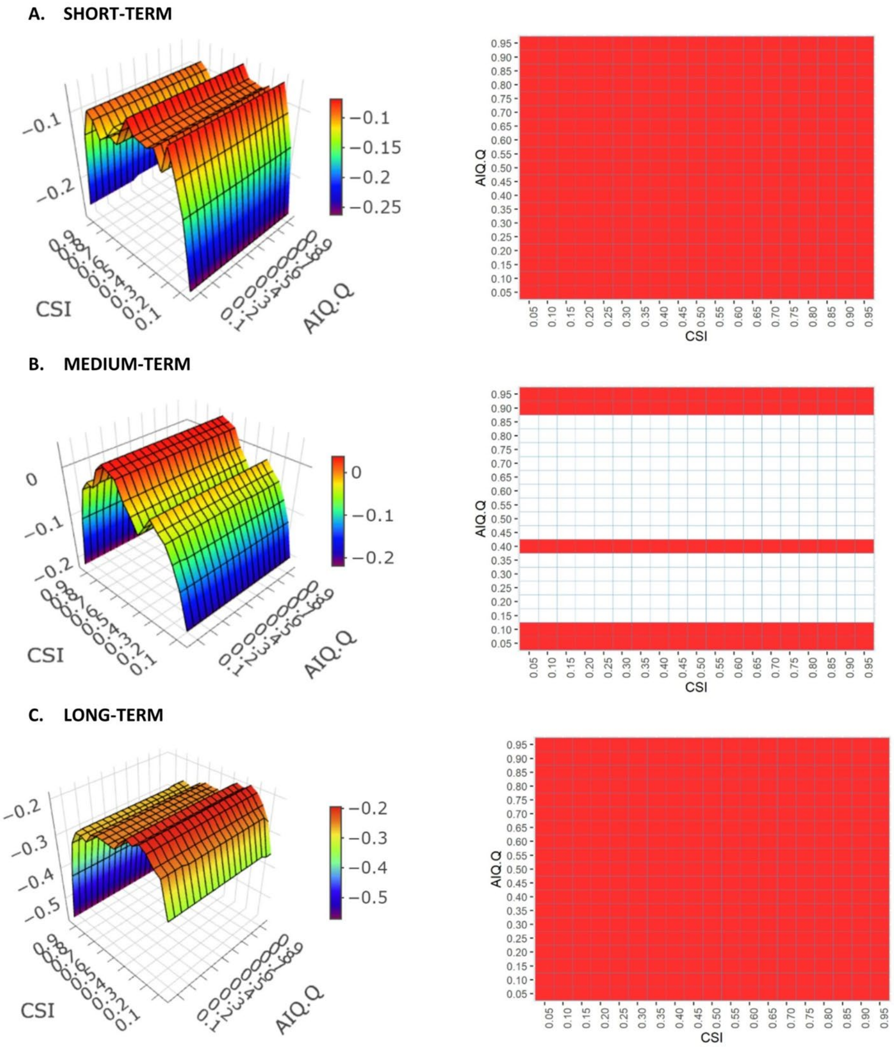

Fig. 6 Wavelet quantile-on-quantile regression results. The left side of the panel displays AIQ.Q's impact on CSI over time and quantiles; the right side of the panel presents corresponding p-values

term. The negative relationships suggest that e-commerce companies that cannot rapidly apply AI technologies may face a loss of market share in the short term. Panel B exhibits the medium term effect of AI technologies (AIQ.Q) on the China e-commerce (CSI) index, and it is also continuously negative across all quartiles. Conversely, the p-values in Panel B demonstrate that the negative relationship between the 15th and 35th quantiles of the China e-commerce (CSI) index, and between the 45th and 85th quantiles of the China e-commerce (CSI) index, is not statistically significant. The results reveal that the impact of AI investment intensity on the e-commerce ecosystem is not homogeneous in the medium term, and that its effects can be weakened depending on specific market conditions and levels of digitalization. Moreover, Panel

C displays the long term effect of AI technologies (AIQ.Q) on the China e-commerce (CSI) index, which remains consistently negative across all quartiles. The color bar shows that the impact is more pronounced in the long term. The pronounced long term negative impact signified that cloud systems, digital logistics networks, and AI driven digital commerce are in sustained demand. Therefore, AI technology innovation leads to negative pressure on China's e-commerce. Lastly, all negative relationships between the AI technologies (AIQ.Q) index and the e-commerce (CSI) index in China can be caused by the fact that the AI technologies (AIQ.Q) index consists mostly of AI technology companies in the U.S., and the improvement in the U.S. technology sector can harm the e-commerce companies in China [65, 66].

The impact of AI technologies (AIQ.Q) on the Dow Jones Internet Commerce (DJIC) index is demonstrated in Fig. 7. The short term impact of AI technologies (AIQ.Q) on the Dow Jones Internet Commerce (DJIC) index, as presented in Panel A, is positive across all quartiles. The results establish that an increase in AI and technology investments leads to an increase in market value and market performance of e-commerce companies in the U.S. Panel B highlights the medium term effect of AI technologies (AIQ.Q) on the Dow Jones Internet Commerce (DJIC) index, which remains consistently positive across all quartiles, and the color bar indicates that the impact has increased steadily in the medium term. Additionally, all statistically significant p-values also pointed out that AI technologies are being increasingly integrated into the business models and operational processes of e-commerce companies. Panel C displays the medium term effect of AI technologies (AIQ.Q) on the Dow Jones Internet Commerce (DJIC) index, which is robustly positive across each quartile of the distribution. Overall, the positive impact of AI technologies (AIQ.Q) on the Dow Jones Internet Commerce (DJIC) index in all time horizons evidenced that technological improvements, which are integrated with AI, support the market performance of e-commerce companies [35, 40].

The impact of AI technologies (AIQ.Q) on the Solactive E-commerce (SLCTV) index is presented in Fig. 8. Panel A presents the short term effect of AI technologies (AIQ.Q) on the Solactive E-commerce (SLCTV) index, which maintains a persistently positive sign across the entire quartiles. The results report that an increase in AI technologies is associated with a rise in the e-commerce (SLCTV) index in the short term. The positive relationships indicate that increasing intensity of investment in AI technologies can create market pressure in the e-commerce sector in the short term. The color distribution shows that the impact is relatively stronger at higher Solactive E-commerce (SLCTV) index levels. The fact that the p-value map is red reveals that the relationship is statistically significant in the short term. Panel B illustrates the medium-term effect of AI technologies (AIQ.Q) on the Solactive E-commerce (SLCTV) index. The results highlighted that, however, the positive impact continues, but the impact has pronounced in some quartiles. Additionally, the p-values in Panel B present that the positive relationship is statistically significant across all quartiles. Panel C displays the long term effect of AI technologies (AIQ.Q) on the Solactive E-commerce (SLCTV) index, which exhibits a uniformly positive relationship throughout all quartiles. The persistence of positive long term impacts highlights that artificial intelligence technologies continue to create permanent structural adjustment costs and infrastructure requirements in the e-commerce sector ([13]; Mer et al. [30].

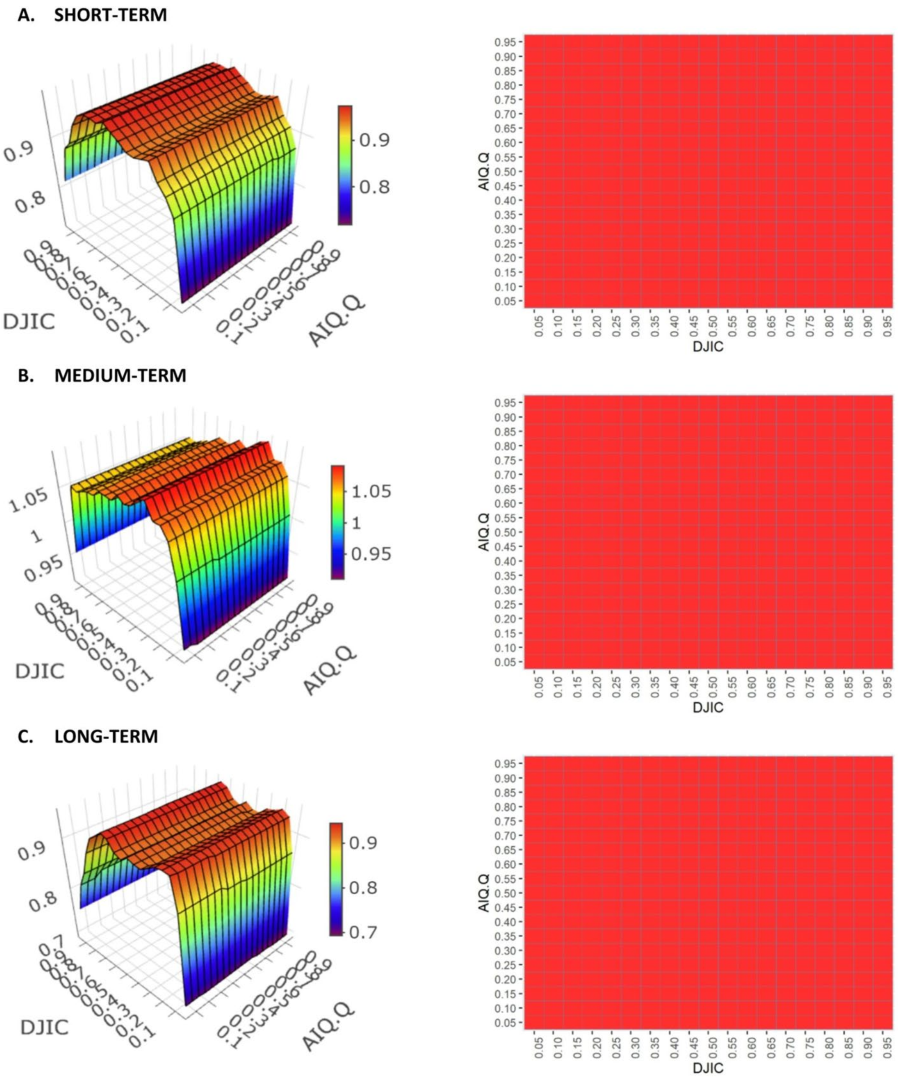

Fig. 7 Wavelet quantile-on-quantile regression results. The left side of the panel displays AIQ.Q's impact on DJIC over time and quantiles; the right side of the panel presents corresponding p-values

4.1.4 Robustness check

To verify the robustness of previous results, the study investigates the differences between Wavelet Quantile Regression (WQR) and Average Wavelet Quantile Regression (AWQQR) analysis results. In this context, the red lines represent AWQQR coefficients and the blue lines represent WQR coefficients in Figs. 9 and 10, and 11. The slope coefficients from WQR and AWQQR analysis are compared in Fig. 9. Figure 9 illustrates that the impact of AI technologies (AIQ.Q) on the China e-commerce (CSI) index varies across quantiles and time horizons, specifically in the short term

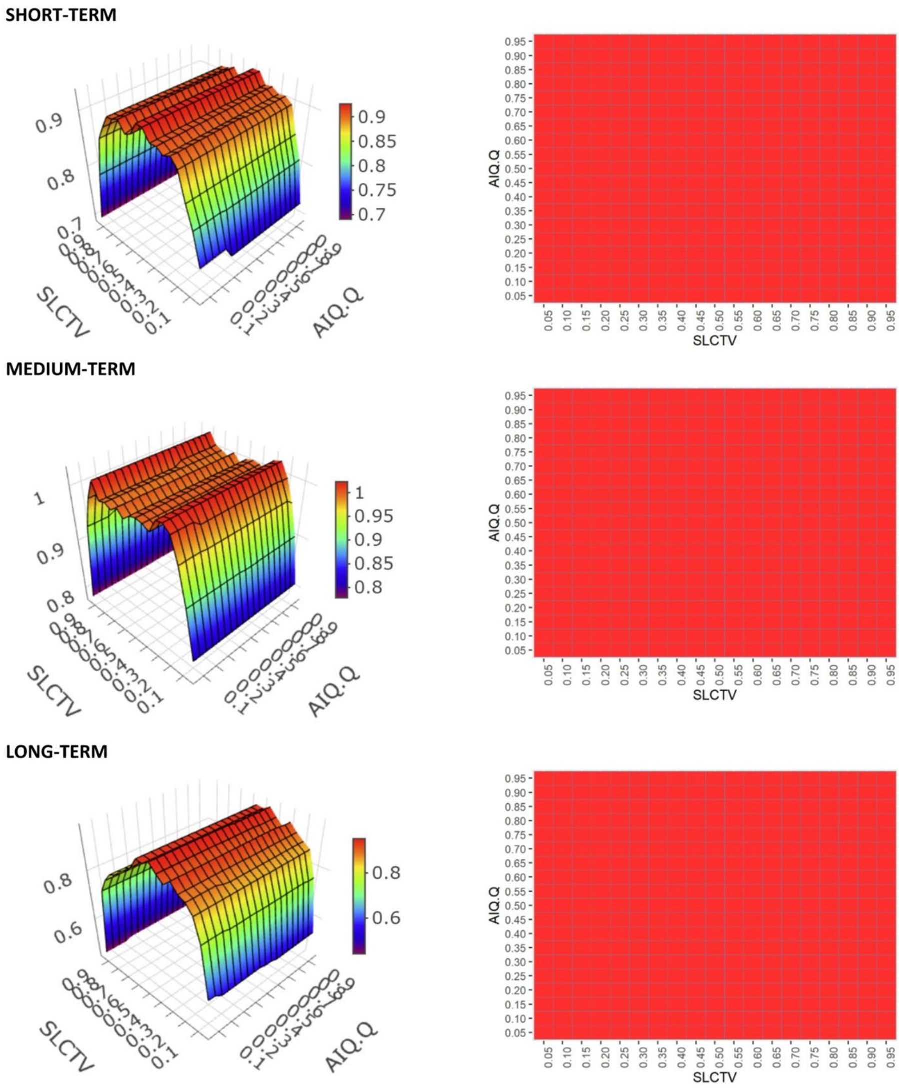

Fig. 8 Wavelet quantile-on-quantile regression results. The left side of the panel displays AIQ.Q's impact on SLCTV over time and quantiles; the right side of the panel presents corresponding p-values

(A), medium term (B), and long term (C) periods. The results demonstrate that AI technologies (AIQ.Q) consistently contribute negatively to the China e-commerce (CSI) index. The parallel behaviour observed in WQR and AWQQR results indicates robustness in the estimated impact.

Figure 10 demonstrates that the impact of AI technologies (AIQ.Q) on the Dow Jones Internet Commerce (DJIC) index varies across quantiles and across short term (A), medium term (B), and long term (C) intervals. The results highlight that there is a positive linkage between AI technologies (AIQ.Q) and the Dow Jones Internet

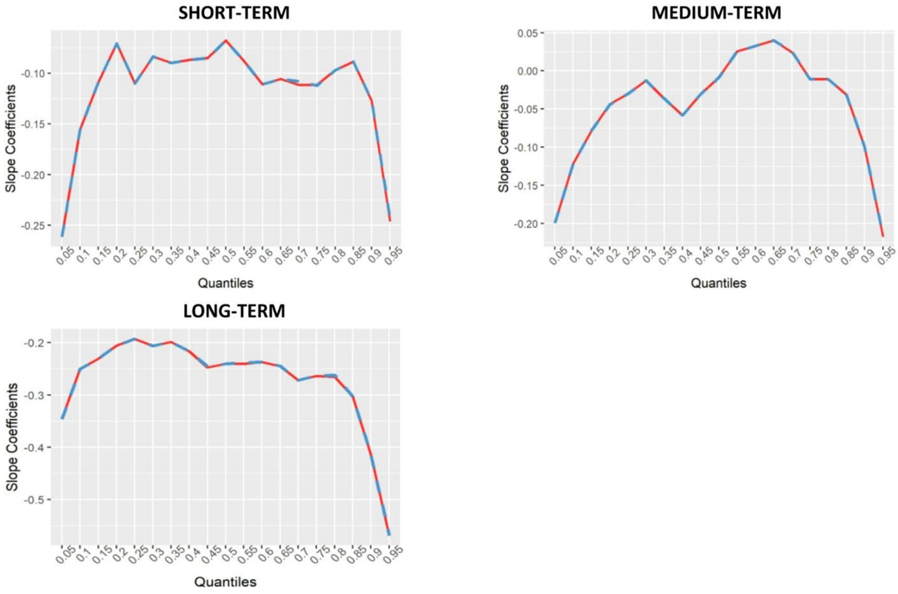

Fig. 9 AIQ.Q's impact on CSI over time and quantiles; slope coefficients from WQR (blue) and AWQQR (red)

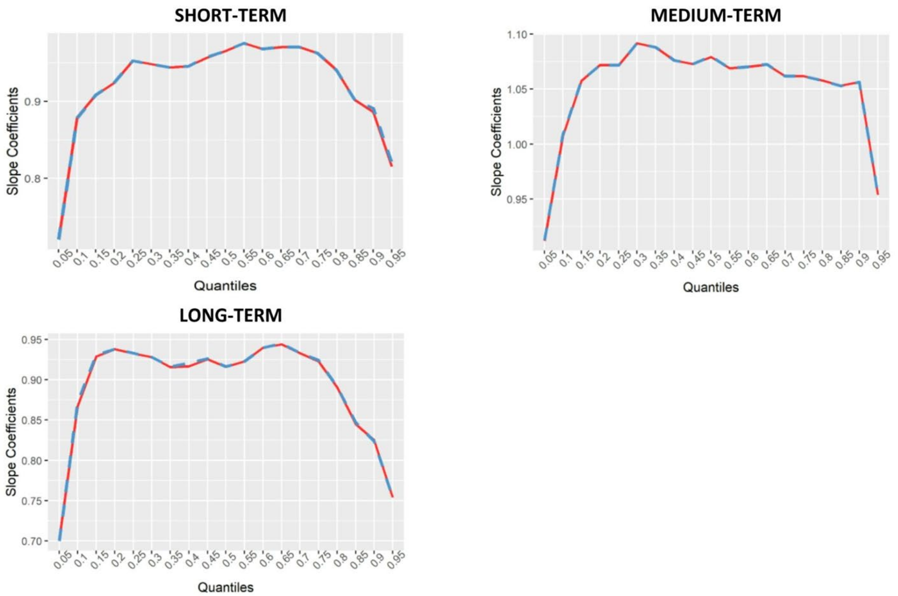

Fig. 10 AIQ.Q's impact on DJIC over time and quantiles; slope coefficients from WQR (blue) and AWQQR (red)

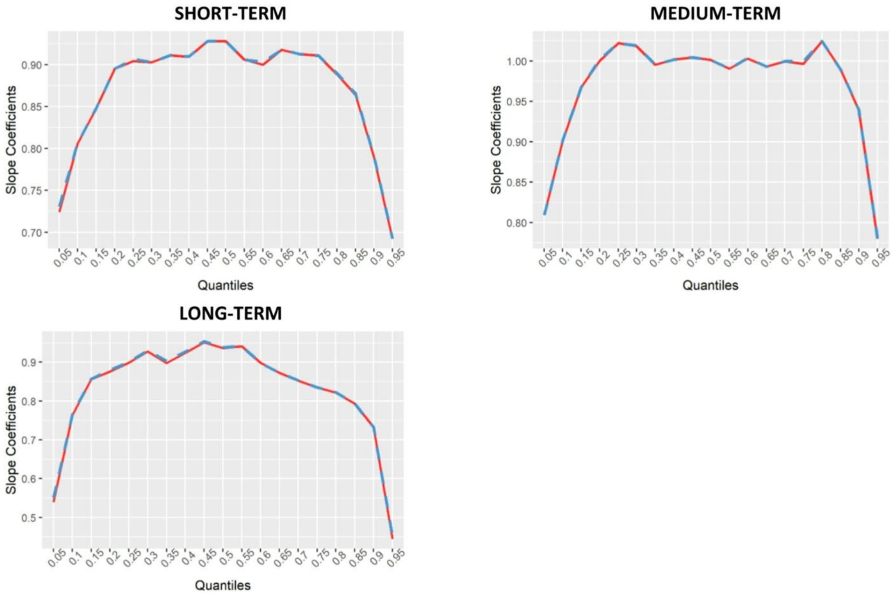

Fig. 11 AIQ.Q's impact on SLCTV over time and quantiles; slope coefficients from WQR (blue) and AWQQR (red)

Commerce (DJIC) index. The positive impact, both captured by WQR and AWQQR analysis, indicates robustness in the estimated impact.

Figure 11 presents that the impact of AI technologies (AIQ.Q) on the Solactive E-commerce (SLCTV) index varies across all quantiles and time frames. The results reveal that the AI technologies (AIQ.Q) exert a positive impact on the Solactive E-commerce (SLCTV) index. The consistency between the WQR and AWQQR results reinforces the reliability of this relationship across different model specifications.

5 Discussion

The findings of the study reveal that the effects of artificial intelligence (AI) technologies on e-commerce markets differ significantly across countries, time horizons, and market structures. This result is consistent with previous studies emphasizing that the effects of AI technologies on financial markets are not homogeneous [1, 15, 67]. In particular, the persistent negative effects of AI investments on the China e-commerce index (CSI) across short-, medium-, and long-term horizons indicate that technological transformation processes do not generate the same economic outcomes across all markets. Similarly, Li et al. [39], Xiao and Wenyao [37], and Zhang et al. [36] demonstrate that AI investments can enhance market performance while, under certain conditions, increasing stock market volatility and stock price crash risk.

The negative effect observed in the Chinese market appears to be driven not only by technological adaptation processes but also by institutional and geo-economic factors. For many years, the Chinese e-commerce sector has followed a growth model based on labor-intensive production, low costs, and economies of scale. During the transition toward knowledge- and capital-intensive technologies such as AI, the financing and human capital requirements faced particularly by small and medium-sized enterprises increase transformation costs. Rogers' [12] diffusion of innovations theory emphasizes that the integration of new technologies into economic systems depends on countries' institutional and technological readiness. From this perspective, China's policy framework regarding data security, cross-border data transfers, and technology regulations may constrain the pace of AI-driven transformation. This interpretation is also consistent with the findings of Chen et al. [65], who document the effects of international competitive pressures on innovation performance in China's ICT sector, and Feng and Yuan, [66], who show that international technology spillovers may contribute to digital inequality in China.

In addition, the AIQ.Q index consists predominantly of U.S.-based artificial intelligence and technology companies, directing global capital flows toward advanced technology markets. The rapid increase in investor interest in AI-themed investment funds and technology stocks in recent years has shifted capital toward markets with higher technological intensity [17, 53]. This situation may limit the ability of Chinese e-commerce firms to attract global investment capital and consequently exert downward pressure on market performance. Therefore, the negative relationship may stem not only from technological adaptation gaps but also from international competition, differences in capital allocation, and digital trade policies. Furthermore, the heterogeneous nature of China's digitalization process means that significant differences exist between advanced technology hubs such as Shanghai and Shenzhen and inland regions, creating spatial variation in the economic effects of AI investments [66].

In contrast, the consistently positive effects of AI investments on the U.S.-based Dow Jones Internet Commerce (DJIC) index indicate that AI technologies have become deeply integrated into the U.S. digital economy. This finding is consistent with the studies of Lui et al. [35], Song and Jain [4], and Kocak and Alnour [44], which conclude that AI enhances firm value and market performance. AI-driven algorithmic advertising, customer behavior prediction, supply chain optimization, and personalized service applications improve the operational efficiency of e-commerce companies and support their market valuations [13, 31]. Moreover, the ability of U.S. capital markets to rapidly price innovation, together with investors' strong confidence in technology firms, enables AI investments to function as a catalyst for market performance and long-term growth [42].

Similarly, the findings for the European Solactive E-commerce (SLCTV) index demonstrate that AI investments generate consistently positive effects. In countries such as Germany, the Netherlands, and France, the widespread adoption of logistics automation, big data analytics, and digital supply chain applications has strengthened the competitiveness of the e-commerce sector. These results are in line with Ferreira et al. [16], Mer et al. [30], and Santos et al. [28], who emphasize that AI applications improve not only financial performance but also operational efficiency and long-term competitive advantage. Accordingly, in advanced economies, AI technologies emerge as a strategic factor that supports not only short-term market performance but also digital infrastructure investments and institutional efficiency.

From a theoretical perspective, the findings provide strong support for knowledge-based growth theory. According to the framework proposed by Romer [9] and Aghion and Howitt [10], knowledge creation and technological innovation are fundamental drivers of long-run economic growth. The positive effects of AI investments observed in U.S. and European markets confirm the role of technological knowledge accumulation in enhancing productivity and market valuations. The results are also consistent with the Efficient Market Hypothesis [11]. By increasing data-processing capacity, AI technologies reduce information asymmetry and enable market prices to respond more rapidly to new information [16, 42]. Nevertheless, behavioral finance offers a different perspective. As suggested by Barberis et al. [14], investors may overreact to technological innovations, potentially leading to asset bubbles and overvaluation. The rapid growth of AI-related investment instruments and the elevated volatility observed in AI-based equities in recent years provide support for this argument [32, 53].

In conclusion, the study demonstrates that the effects of AI technologies on e-commerce markets are asymmetric, country-specific, and highly sensitive to institutional conditions. The negative effects observed in China may be associated with technological adaptation costs, international technological competition, data governance policies, and the level of financial integration, whereas the cases of the United States and Europe indicate that AI-driven digitalization has become one of the main engines of long-term growth in the e-commerce sector. These findings suggest that the economic consequences of AI investments are shaped not only by technological capabilities but also by institutional quality, financial market development, and digital transformation policies, thereby providing new empirical evidence to the existing literature.

6 Policy implications

The findings of this study indicate that the impact of artificial intelligence (AI) investments on e-commerce markets differs considerably depending on countries' institutional structures, market maturity, and levels of technological development. In particular, the consistently negative relationship observed for the Chinese e-commerce index across the short, medium, and long term suggests that AI investments do not necessarily generate the same economic outcomes across all markets. In contrast, the positive coefficients obtained for the U.S. and European e-commerce indices imply that well-developed financial markets and stronger digital infrastructures may enable AI investments to be translated more effectively into market performance. Therefore, country-specific institutional and technological characteristics should be taken into consideration when formulating AI-related policies [1, 12, 15].

The findings for the Chinese market suggest that AI-driven technological transformation may adversely affect market performance, particularly at the lower and middle quantiles. This result indicates that adjustment costs and technological transition pressures may be reflected in financial markets during the digital transformation process. Accordingly, while promoting digital transformation, policymakers may also consider developing financial mechanisms that help firms reduce these adjustment costs. Temporary financial support schemes, digital transformation incentives, and technology programs targeting small and medium-sized enterprises may contribute to a smoother transition process [9, 10].

The positive findings obtained for the U.S. and European markets indicate that AI investments may contribute positively to market performance when supported by favorable financial and institutional conditions. However, the empirical findings also show that the effects of AI investments vary across market conditions and time horizons. Therefore, regulatory authorities may consider continuously monitoring AI-related financial products and algorithmic trading activities, strengthening measures that improve market transparency, and supporting initiatives aimed at increasing investors' awareness of algorithmic risks in order to enhance market stability [34, 42].

The findings further suggest that the impact of AI technologies on financial markets is determined not only by technological developments but also by institutional environments and investor behavior. The fact that the same AI-related shock produces different effects across markets indicates the importance of designing digital transformation policies in accordance with country-specific economic and institutional conditions. Therefore, regulatory frameworks for AI technologies may become more effective when they are developed by considering the characteristics of financial markets and the level of digitalization within each economy [14, 32].

Finally, the empirical findings suggest that AI-related financial developments may spread across internationally connected financial markets. Consequently, in addition to national regulatory measures, the development of common international standards regarding data governance, algorithmic transparency, and AI-related financial products may contribute to the more effective management of potential cross-market spillover effects. Given the increasing integration of cross-border digital markets, stronger coordination among international regulatory authorities may also contribute to the sustainable development of the digital economy [1, 15].

7 Limitations and directions for future research

This study provides original contributions to the literature by revealing the dynamic and asymmetric effects of AI technologies on e-commerce markets; however, it also has certain limitations. Since the analysis includes only three e-commerce indices, it allows for regional comparisons but may not fully reflect the structural diversity and heterogeneity present across global digital markets. In particular, developing economies with limited levels of digitalization and AI diffusion were excluded from the analysis. Future studies that incorporate examples from emerging markets such as India, Southeast Asia, and Latin America would be valuable in testing whether the asymmetric effects identified in this research are also valid across different economic structures.

The Global X Artificial Intelligence & Technology ETF index, used as the independent variable in this study, is largely composed of U.S. based technology companies. This structure introduces certain constraints in capturing the full spectrum of global AI investment, innovation intensity, and technological spillovers. Future research that employs alternative indicators such as patent innovation indices, firm level AI R&D expenditures, or AI adoption rates could provide a more detailed understanding of how AI development shapes sectoral market performance. Such indicators could also help clarify whether the negative effect observed in China stems from technological dependence or from structural differences in market mechanisms.

The standard WQQR framework does not allow control variables to be incorporated in the same way as conventional multivariate regressions; therefore, this study acknowledges that AIQ.Q is used as a market based proxy for artificial intelligence investment intensity, while broader technology shocks and financial conditions cannot be fully separated from the estimated transmission patterns. Future studies may address this limitation by combining WQQR with residualized series, multivariate quantile models, or firm level artificial intelligence adoption measures.

The study period coincides with a time of high volatility in global digital markets. The post-pandemic recovery process, supply chain disruptions, and geopolitical uncertainties have introduced external shocks that may have influenced the relationship between AI and e-commerce indices, particularly in the short term. Therefore, future research should consider longer time spans, incorporate structural break analyses, and account for regime shifts to distinguish the long term impacts of AI from temporary market fluctuations. In addition, the use of firm level microdata or AI news sentiment indices would be beneficial for understanding the behavioral and informational channels through which AI influences financial markets. Furthermore, qualitative case studies examining how major e-commerce platforms adopt AI logistics, recommendation systems, and dynamic pricing algorithms could provide in-depth insights that complement the quantitative findings of this study.

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Data availability The data that support the findings of this study are available on request from the corresponding author.

Declarations

Conflict of interest The authors declare no material or other conflict of interest.

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