UDC 336.64:004.9:330.322:005.591.6
DOI: 10.15587/1729-4061.2026.356116

DETECTION OF THE IMPACT OF TECHNOLOGY MATURITY ON INVESTMENT ACTIVITY IN THE INDUSTRY USING THE EXAMPLE OF FINTECH

Oleksiy Mints
Doctor of Economics, Professor
SMK College of Applied Sciences
Liepų str., 83B, Klaipeda, Lithuania, LT-92195
ORCID https://orcid.org/0000-0002-8032-005X
Oleh Kolodiziev
Corresponding author
Doctor of Economic Sciences, Professor
Department of International Trade, Customs and Financial Technologies
Simon Kuznets Kharkiv National University of Economics
Nauky ave., 9-A, Kharkiv, Ukraine, 61165
E-mail: kolodizev107@ukr.net
ORCID https://orcid.org/0000-0002-6715-2901
Olena Khadzhynova
Doctor of Economic Sciences, Professor*
ORCID https://orcid.org/0000-0002-7750-9791
Mykhailo Krupka
Doctor of Economic Sciences, Professor, Head of Department**
ORCID https://orcid.org/0000-0002-8775-1397
Nazar Demchyshak
Doctor of Economic Sciences, Professor**
ORCID https://orcid.org/0000-0001-6852-7405
Oleksandr Shchepka
PhD Student*
ORCID https://orcid.org/0009-0003-3616-6395
Pavlo Sidelov
PhD, Senior Lecturer*
ORCID https://orcid.org/0000-0001-5672-8189
Markiian Zaplatynskyi
PhD, Associate Professor
Department of Management and Marketing in Publishing and Printing Business
Lviv Polytechnic National University
Pid Goloskom str., 19, Lviv, Ukraine, 79020
ORCID https://orcid.org/0000-0001-7842-3888
*Department of Finance, Accounting and Banking
State Higher Education Institution «Pryazovskyi State Technical University»
Gogolya str., 29, Dnipro, Ukraine, 49044
**Department of Finance, Money Circulation and Credit
Ivan Franko National University of Lviv
Svobody ave., 18, Lviv, Ukraine, 79008

The financial technology industry and its individual segments have been investigated in this study. The task addressed relates to the insufficient development of methodological tools for quantitatively determining the role of maturity of key technologies as a factor of investment attractiveness, as well as the fragmentation of the analysis of technological drivers of investment activity in FinTech segments.

The methodological basis of this study is the Gartner Hype Cycle model. The information basis is data from global rating and research agencies. The global investment dynamics for 2018–2024 were analyzed, as well as their parameters in the context of individual sectors, which made it possible to identify the main patterns of investment activity.

Based on the rule-based approach, methods for determining score estimates for investment activity and for the technology maturity factor have been proposed. They make it possible to eliminate the nonlinearity critical for the use of correlation analysis, which is inherent in the Gartner model. The results of the analysis of investment activity and maturity factors of key technologies confirmed a high positive correlation (r = 0.8615) between the indicated indicators.

It was determined that the main driver for increasing investment activity is the implementation of key technologies that are near the "peak of inflated expectations" in the Gartner model. It was established that at present such technologies are often associated with artificial intelligence. Thus, taking into account the stages of technology maturity allows one to better explain investor behavior and predict changes in investment activity in FinTech segments.

The results also extend to other sectors of the digital economy with a high share of intangible assets, fast cycles of updating and scaling, network effects, and a global sales model

Keywords: FinTech, technology maturity, Gartner Hype Cycle, drivers of investment activity, investment attractiveness

Received 16.01.2026
Received in revised form 19.03.2026
Accepted 30.03.2026
Published 28.04.2026

How to Cite: *Mints, O., Kolodiziev, O., Khadzhynova, O., Krupka, M., Demchyshak, N., Shchepka, O., Sidelov, P., Zaplatynskyi, M. (2026). Detection of the impact of technology maturity on investment activity in the industry using the example of FinTech. Eastern-European Journal of Enterprise Technologies, 2 (13 (140)), 62–72. https://doi.org/10.15587/1729-4061.2026.356116*

1. Introduction

The emergence of new technologies is often accompanied by increased investment activity of economic entities around them. This is especially clearly observed in industries that are weakly connected with material production, use a global sales model, and can therefore scale up quickly. Among the most known examples are cryptocurrencies, artificial intelligence, non-fungible tokens (NFTs), etc. In such cases, investors' expectations can be formed faster than real financial results, which strengthens the feedback between expectations and investments and leads to the phenomenon of "hype" [1]. Investors, primarily venture capitalists, view such periods as an opportunity for rapid capital growth, but these decisions are associated with increased risk.

The financial technology (FinTech) industry has long been considered promising for investment due to its rapid development and growing role in the digital economy [2]. However, in recent years, there has been a decrease in the volume of financing and the number of deals, which is associated with a combination of macroeconomic and non-financial factors, in particular high interest rates, protracted military conflicts, and general uncertainty [3]. The dependence of investment processes on such factors is also noted in other studies [4, 5]. This influence is most noticeable in industries with short renewal cycles where a transition from investment boom to decline and vice versa is possible in a relatively short period of time [6].

The maturity and perfection of key technologies are considered an important factor affecting investment activity in an industry context. They determine the potential for innovation and investment activity since technological limitations or “bottlenecks” can restrain further technological and industry growth [7].

Work [8] emphasizes that the innovative and technological potential of enterprises is one of the key factors of their investment attractiveness because the level of technological development determines competitiveness and opportunities for attracting investment.

In the early stages of an industry’s development or at the start of a new growth cycle, the technological base is usually still imperfect, and the potential return on investment is combined with high risk. As maturity is reached, the risk decreases, but with it the expected return often decreases. At the same time, this relationship is nonlinear, so it is difficult to directly use it for practical assessments [9].

Therefore, research on determining the role of key technologies as a factor of investment attractiveness in FinTech and other sectors of the digital economy is relevant.

2. Literature review and problem statement

Theoretical research on investment uses the term “investment attractiveness” to characterize the potential of an economic entity to attract investment [10]. Economic entities with high investment attractiveness attract increased interest from investors, which with a certain lag can be transformed into completed investment transactions, that is, into investment activity. Unlike investment activity, investment attractiveness is determined through an indirect assessment of external and internal factors [11]. Thus, investment activity describes the actual flow of capital to the investment object over a period, while investment attractiveness is a latent characteristic of the investment object that reflects the expected return.

In various studies, preference is given to external or internal factors of investment attractiveness. Thus, in [10], external factors are primarily distinguished: political, legal, economic, social, and institutional. This approach allows one to explain the differences in the attractiveness of economic entities depending on the environment in which they operate. However, it does not provide a clear answer to the question of why, within the same industry, and sometimes even in the same market, the investment activity of individual segments changes unevenly. The authors of [12], analyzing methods for assessing the potential return on investment in IT, emphasize the internal factors of technological maturity. In [13], based on a study of a number of enterprises, it was determined that their competitiveness is affected not only by the technological maturity of the production subsystem, but also by the support subsystems (IT, corporate management, decision support). However, in the cited papers, technological maturity is considered mainly as one of the characteristics of enterprise development, without going on to a quantitative assessment of its impact on investment activity in the context of individual segments of the industry.

Separate studies tackle investment processes in FinTech and its individual segments. In [14], mergers and acquisitions between banks and FinTech companies and their impact on the efficiency of buyers in the period 2010–2020 were examined. Based on the calculation of the paired t-test and GMM analysis, a significant positive impact of such transactions on the operational efficiency, liquidity and financial leverage of banks was proven, along with a negative impact in the long term. However, the study focuses on the consequences of already completed transactions and does not provide tools for predicting investment activity due to technological factors. In [15], the dynamics of cryptocurrency markets are considered in the context of dependence on fundamental economic indicators and trends in the global stock market. The authors used correlation analysis and regression models to test the hypothesis about the relationship between the dynamics of major cryptocurrencies and fundamental economic indicators, but the results did not allow it to be unambiguously confirmed or refuted. This suggests that even the application of quantitative methods to individual FinTech segments does not guarantee the identification of stable explanatory factors if the internal logic of technological development is not taken into account.

In parallel, the literature traces a trend that explains investment dynamics through types of technological evolution and the cyclical nature of innovation processes. In [16], the following main types of technological development are distinguished: Discrete Technology Evolution, Continuous Technology Evolution, and Cyclical Technology Evolution. It is emphasized that cyclicality is due to the complex interaction of socio-economic and technological systems. That is why simplified models have limited predictive capabilities [7]. In [9], the perspective of using the Gartner Hype Cycle nonlinear empirical model of technological development to describe FinTech dynamics is shown. It is also noted that each phase of the technology maturity cycle directly affects the investment attractiveness of the economic entity that uses it. However, the authors do not provide tools for quantitative assessment of such an impact. Therefore, the problem is not only in choosing a model but also in the possibility of its practical use for quantitative analysis.

In this context, it is worth noting papers in which the development of FinTech or its segments is interpreted through phase models of innovation maturity. For digital banking, investment activity may decrease due to the gap between the promised benefits and real financial results [17]. Certain problems of predicting the cyclical development of investment activity in such a segment of FinTech as digital banking are explained by the actual set of technologies that are in different phases of their development [18]. The author studies the specification of key aspects of changing the parameters of investment activity by taking into account the phases of the technology life cycle and assessing the threshold value of investment feasibility [19]. In [20], it is shown that FinTech stood out and continued to develop as a separate industry due to the fact that its innovativeness turned out to be very far from the "plateau of productivity" on which the entire banking sector was located. In works devoted to cryptocurrency markets, phase trajectories are used to explain fluctuations in capitalization and recurring cycles with short "plateaus" [21]. This conclusion is confirmed by work [22], which analyzed the development of artificial intelligence systems and proved that they are also characterized by a cyclical model of capitalization changes. These studies are important because they conceptually substantiate the nonlinearity of investment processes in FinTech. However, in most cases, they do not offer a practical procedure that would allow linking the phase of technological development with measurable investment indicators.

In [23] it is shown that blockchain-based technologies, after the hype of 2017–2018, have entered the "Trough of Disillusionment" phase, but have not lost their long-term investment potential. In [24] the impact of hype on the financing of AI and quantum technologies was analyzed and a positive relationship was found between the level of "hype" in expert media and the volume of investments in these technologies. For more mature areas, the relationship turned out to be stronger than for newer ones. This is consistent with the Gartner Hype Cycle concept, according to which investment interest changes unevenly at different phases of development. However, these quantitative studies concern individual technologies, and not FinTech segments as a whole. In addition, they do not offer a consistent approach to translating the phases of technology maturity into quantitative indicators suitable for comparison with investment activity.

Thus, our review of the literature shows that existing studies have already revealed certain aspects of investment attractiveness, investment activity, cyclicality of technological development and the use of phase models in FinTech and related industries. However, these results remain fragmented. First, a consistent approach to quantitative assessment of the maturity factor of key technologies in FinTech segments has not been formed. Second, the issue of quantitative comparison of maturity phases of key technologies with actual investment activity has not been resolved. Third, technological drivers that can support or restore investment activity after a downturn have not been specified. The reason is the predominantly descriptive nature of most studies, the lack of a single procedure for transitioning from qualitative phase models to quantitative assessments, as well as the fragmentation of the analysis, which is most often limited to individual technologies or narrow segments.

All this allows us to argue that it is advisable to conduct a study aimed at devising methodological tools to quantitatively determine the role of maturity of key technologies as a factor of investment attractiveness and specify technological drivers of growth in investment activity in FinTech segments.

3. The aim and objectives of the study

The purpose of our study is to determine the role of the maturity of key technologies, assessed using the Hype Cycle model, as a factor of investment attractiveness in the FinTech industry, as well as to specify the technological drivers of the growth of investment activity of economic entities. This will make it possible to form an appropriate methodological toolkit for the practical search and determination of priority areas of investment in key FinTech segments.

To achieve the goal, the following tasks were set:

– to propose a method for determining the score of investment activity based on statistical data on investment dynamics and to carry out the corresponding calculations for FinTech segments;

– to propose a method for determining the score of the technology maturity factor and to carry out the corresponding calculations for FinTech segments;

– to investigate the relationship between the maturity factor of key technologies and investment activity in FinTech segments and to identify technological drivers associated with the growth of their investment attractiveness.

4. Research materials and methods

4. 1. Object and hypotheses

The object of our study is the financial technology (FinTech) industry and its individual segments.

The subject of this study is the processes of formation of investment activity in FinTech segments and the factors influencing them.

The main hypothesis of the study assumes that the investment attractiveness of FinTech segments is largely related to the maturity phase of the key technologies used in them.

The study adopted the following assumptions. First, within the studied period, the statistical characteristics of investment activity in the main FinTech segments can be considered stable enough for their comparison with each other. Second, the maturity phases of key technologies, determined by the Gartner Hype Cycle, adequately reflect the real state of technological development of the relevant segments. Third, the key technologies allocated for each segment truly determine the core of its products and services and can be used for a generalized assessment of the technological maturity of the segment.

The following simplifications were also accepted: the investment attractiveness of the segment is characterized by one integral indicator; if several key technologies are used in a segment, their contribution to the overall assessment of investment attractiveness is considered the same and is aggregated through a simple average.

4. 2. Conceptual categories

To avoid terminological uncertainty, the term "investment activity" is used in the interpretation of the author of work [8] who writes that it is "the ratio of the current investment volume to the previous one". Therefore, to calculate the investment activity IAc, it is enough to know the actual investment volumes Iv to a certain group of economic entities in the reporting (r) and previous (r – 1) years

$$IAc_r = \frac{Iv_r}{Iv_{r-1}}. \quad (1)$$

Formula (1) enables correct calculation of investment activity only if $Iv_{r-1} > 0$, and there is also a constant capital attraction. If investment flows are zero or episodic, the calculation will be incorrect.

Theoretical research on investment also uses the term "investment attractiveness", which characterizes the potential of an economic entity to attract investments [10]. Economic entities with high investment attractiveness arouse increased interest from investors, which with a certain lag is transformed into completed investment transactions, that is, into investment activity. Unlike investment activity, which is calculated ex post facto based on mathematical relation (1), investment attractiveness can be found only through an indirect assessment of external and internal component factors [11].

Therefore, investment activity describes the actual flow of capital to a particular investment object (technology, company, segment) over a period, while investment attractiveness is a latent characteristic of the investment object that reflects the expected return. The basic conceptual categories that influence investment activity are interconnected in the following logical scheme, shown in Fig. 1.

Fig. 1. The relationship between the main conceptual categories of the study

Our study is based on the empirical model of technological development presented by Gartner [18]. According to the Gartner Hype Cycle model, expectations for each technology follow 5 main phases:

1) innovation trigger;
2) peak of inflated expectations;
3) trough of disillusionment;
4) slope of enlightenment;
5) plateau of productivity.

Each of the Hype Cycles contains a list of key technologies that are assigned by the agency to the corresponding area. For each technology, a phase is shown, as well as a forecast of the time until reaching the plateau of productivity.

4. 3. Research architecture and workflow

The research architecture implements a sequential transformation of metadata scattered across various information sources into quantitative characteristics of the research object with their subsequent comparison. The workflow is organized into three stages: determining the characteristics of investment activity, investment attractiveness factors, and the relationship between them (Fig. 2).

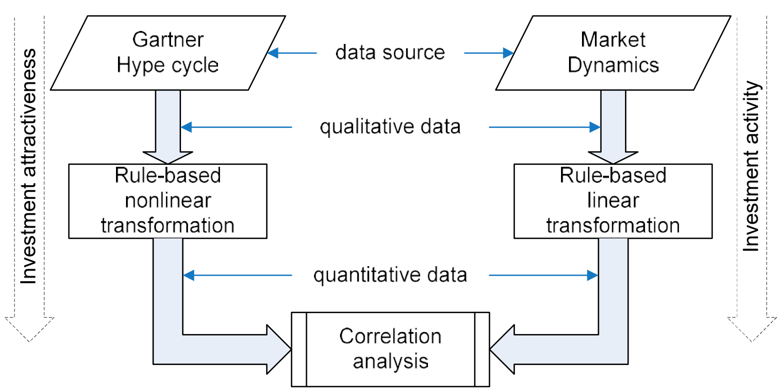


Fig. 2. Research workflow

The main problem that the scenario presented in Fig. 2 solves is that the information sources of the study contain qualitative information, and measuring the strength of the relationship between the characteristics under study involves the use of correlation analysis methods. To solve it, it is necessary to substantiate the methods of transforming qualitative and categorical assessments into quantitative ones, as well as to correct the nonlinearity inherent in the Gartner model.

One of the generally accepted approaches for such transformation is the use of point estimates. This approach is successfully used in various fields, in particular in medicine [25], economics [26], engineering [27]. The idea of recoding the stages of technological development into numerical scores is used in work [28], although unlike the Gartner model, its authors use a simple linear scale.

If it is necessary to reflect nonlinear rules for transforming qualitative characteristics into quantitative values, it is methodologically advisable to give preference to the rule-based approach. Scores are then assigned through formal value and normalization functions (multi-attribute value functions), which reflect the real distances between states recorded in the data or standards [29]. Such computational transformations – including within the framework of multi-criteria decision analysis (MCDA) methods – allow for consistent comparison of categorical or ordinal descriptions with an interval scale and further application of correlation or regression analysis [30]. A similar problem is solved by the Rasch model, which provides mathematically consistent scaling and allows for the correct application of statistical tests of association [31]. In the absence of the possibility of constructing reliable significance functions, structured expert assessment is used, but its results significantly depend on the composition of experts and the quality of the survey protocol [32].

Stage 1 – analysis of available information on the dynamics of investments in individual FinTech segments and determination of quantitative characteristics of investment activity in them.

The information source for such analysis is reports of international agencies that summarize information on investment rounds, M&A procedures and other information related to investments in the industry.

To minimize the impact of industry-wide factors, relative indicators are used for the analysis, reflecting the share of individual segments in the total volume of investments. For the same purpose, along with formula (1), its modification, which is based on relative indicators, is used to calculate investment activity

$$\%IAc_r = \frac{\%Iv_r}{\%Iv_{r-1}}, \qquad (2)$$

where $\%IAc_r$ – investment activity by relative indicators;

$\%Iv(r)$ – share of investments in a certain segment of the industry in the reporting (r) year;

$\%Iv(r-1)$ – share of investments in a certain segment of the industry in the previous ($r-1$) year.

Next, the statistical characteristics of the set of investment activity values are determined, which will later become the basis for determining the dynamics of its changes and transition to point estimates. The distribution of investment activity values based on quartiles is taken as the basis. The transition to descriptive characteristics of investment activity is carried out according to the following rules:

1. R. 1. Stability (investment activity in the segment corresponds to the average in the industry and is in the interval [Q1, Q2]).

2. R. 2. Decrease (investment activity in the segment is less than the average in the industry, and its value is less than Q1).

3. R. 3. Growth (investment activity in the segment is greater than the industry average, and its value is greater than Q3).

As a result, a list of the largest FinTech segments is determined and descriptive information about the dynamics of investment activity in them during the analyzed period is determined. The transformation of this information into a quantitative assessment of the characteristics of investment activity is carried out on the basis of a rule-based approach and linear scaling.

Stage 2 – analysis of current Gartner Hype Cycles and quantitative assessment of the maturity factor of technologies in individual FinTech segments.

The information source of this stage is a set of Gartner Hype Cycles. The need to analyze several models is due to the fact that technologies of one segment can be presented in different Hype Cycles, just as one Hype Cycle can contain technologies of different segments. Thus, in Fig. 3, the Gartner Hype Cycle for Emerging Technologies model [33] indicates technologies that belong to the Cybersecurity Fintech segment and are in the Innovation Trigger phase.

As shown in Fig. 3, the Hype Cycle for Emerging Technologies contains two key Cybersecurity technologies. Both are in the Innovation Trigger phase. For the Cybersecurity Mesh Architecture technology, the performance plateau is predicted to be reached no earlier than in 10 years, which in practice means an increased risk that the technology will not reach development. But for another technology, Disinformation Security, the performance plateau is predicted to be reached in 2–5 years, which means a high probability of its widespread implementation.

To convert the Gartner cycle metadata on the maturity phases of key technologies of an economic entity into quantitative assessments of investment attractiveness factors, a rule-based approach is used. This allows us to take into account the pronounced nonlinear nature of the Gartner model.

Stage 3 – determining the relationship between the characteristics of investment activity and investment attractiveness.

Correlation analysis is applied to the score estimates. In this case, it is important to ensure a sufficient volume of observations. From the estimates given in [34], it is known that at a correlation of 0.9 the minimum required number of observations is 6, and for example at a correlation of 0.7 13 observations are already required.

The results of the correlation analysis are interpreted according to the Chaddock scale, which verbalizes the strength of the correlation from Weak (0.1–0.3) to Very High (0.9–1) [35]. For transparency, the absolute values of the coefficients are also indicated, and the reliability of the results is assessed taking into account the sample size.

Through the analysis of the obtained results of the comparison of key technologies of different Fintech segments and their investment attractiveness, the main technological drivers that contribute to the growth of investments are determined, as well as the general prospects for the development of the industry.

5. Results of investigating the maturity of key technologies as a factor of investment attractiveness in the FinTech industry

5. 1. Determining the score of investment activity based on statistical data on investment dynamics

Fig. 4 shows a chart of global investments in the FinTech business for 2018–2024, which is built on the basis of generalization of information on mergers and acquisitions (M&A) transactions, as well as investments in the form of venture and private capital [3].

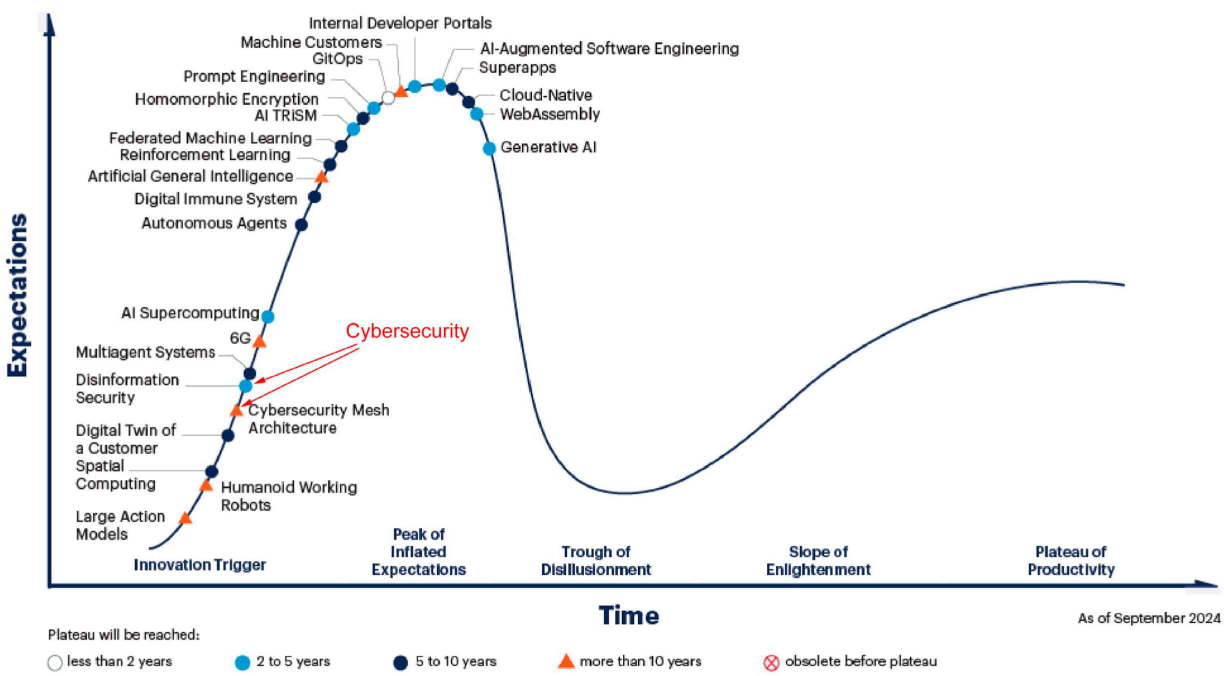


Fig. 3. Key technologies of the Fintech segment Cybersecurity on the Gartner Hype Cycle model for Emerging Technologies
Note: constructed by Authors based on [33]

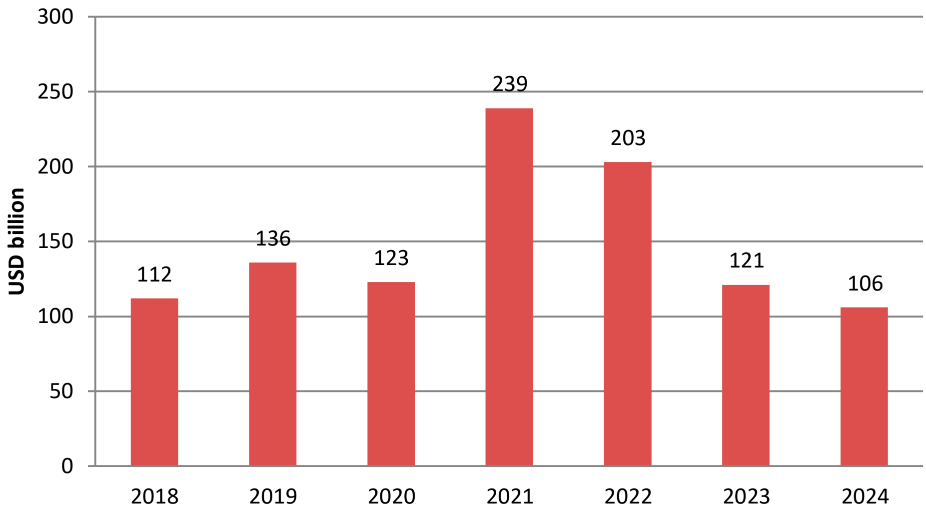


Fig. 4. Global investment in FinTech in 2018–2024, billion US dollars

An analysis of the dynamics of changes in global FinTech investment parameters revealed that after relatively stable indicators in 2018–2020 and a peak in investment in 2021 ($239 billion), investments continued to decline. And in 2024, investment volumes decreased to a seven-year minimum ($106 billion). The number of deals also decreased sharply – there were only 55 large financing rounds with amounts exceeding $100 million for the whole of 2023, while there were 242 in 2021. Among the reasons for the decline, researchers cite both macroeconomic and non-financial factors, in particular high interest rates that increased the cost of capital, protracted military conflicts, general uncertainty and "overheating" after the previous hype.

The structure of investments in Fintech in terms of individual segments of the industry is shown in Fig. 5.

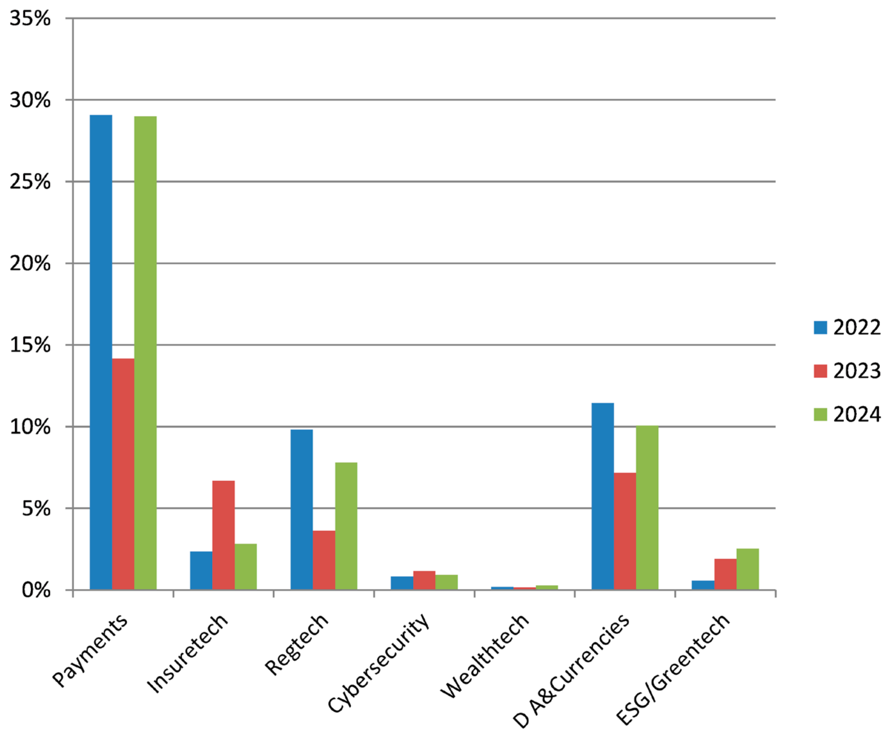


Fig. 5. Share of investments in individual FinTech segments in the total volume of investments in the industry (2022–2024)

Analysis of Fig. 5 reveals that all the segments shown in it were characterized by the so-called "seesaw", when growth alternated with decline and vice versa. A detailed analysis of the prerequisites and reasons for such changes showed that in the context of individual areas, the development of FinTech was very uneven and was accompanied by movements of cash flows. The greatest growth was demonstrated by segments in which reserves for innovative development were found – new business models or technologies [36]. At the same time, the analysis conducted in [36] showed that no capital outflow was observed in any segment, but only stabilization or slowing down of its inflow.

The descriptive characteristics of investment activity are determined on the basis of quartiles of the distribution of its values. To reduce the subjectivity of results, (1) and (2) are used to calculate investment activity.

According to the rules R. 1–R. 3, in each pair of observation periods, three options for the dynamics of investment activity can be distinguished – decrease, stability, and growth. Based on the number of possible placements of these options over 3 observation periods, it is possible to propose rules for transforming its descriptive characteristics into score scores, which are given in Table 1. The graphical interpretation in Table 1 is given only for the first of the descriptive characteristics.

In Table 1 6 different groups of descriptive characteristics of investment activity dynamics are highlighted. They are displayed on an extended 5-point scale with scores from 0 to 5.

The set of methods for calculating investment activity (1) and (2), the rules for determining its descriptive characteristics based on the quartiles of the distribution, and the rules for their further transformation into point estimates form the method for determining the point estimate of investment activity. Further, calculations were made on its basis by FinTech segments.

Based on data on absolute investment volumes by industry segments for 2022–2024, the characteristics of investment activity were calculated using formulas (1), (2), as well as quartiles for each calculation method – absolute (*abs*) and relative (*prc*):

$$Q1^{abs} = 0.373;$$

$$Q1^{prc} = 0.592;$$

$Q3^{abs} = 1.547;$

$Q3^{prc} = 1.796.$

The results of our analysis are given in Table 2.

Table 1

Rules for determining the score of investment activity dynamics

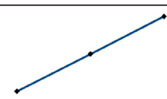
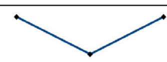
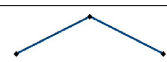
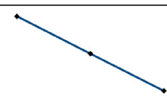
Descriptive characteristics of investment activity	Investment activity rating (0–5)	Graphical interpretation
Constant growth	5	
Growth after decline Growth after stability	4	
Stability Stability after decline Stability after increase	3	
Decline after growth Decline after stability	2	
Constant decline	1	
Critical decline	0	

Table 2

Determining descriptive characteristics and scores of investment activity in FinTech segments

FinTech segment	Investments, billion USD			Investment activity (abs)		Investment activity (prc)		Descriptive characteristics of investment activity	Score
	2022	2023	2024	2023	2024	2023	2024		
Payments	59.2	17.2	30.8	0.291	1.791	0.488	2.045	decrease / increase	4
Insuretech	4.8	8.1	3	1.688	0.370	2.832	0.423	growth / decrease	2
Regtech	20	4.4	8.3	0.220	1.886	0.369	2.155	decrease / increase	4
Cybersecurity	1.7	1.4	1	0.824	0.714	1.382	0.816	stability	3
Wealthtech	0.4	0.2	0.3	0.500	1.500	0.839	1.713	stability	3
Digital assets and currencies	23.3	8.7	10.7	0.373	1.230	0.627	1.405	stability	3
ESG and Greentech	1.2	2.3	2.71	1.917	1.174	3.217	1.341	growth	5
Total FinTech	203.6	121.3	106.2	0.596	0.876	n.a.	n.a.	n.a.	–

It can be noted that the determining descriptive estimates based on calculations of instantaneous investment activity according to formulas (1), (2) gave the same results.

5. 2. Determining the maturity score of key technologies as a factor of investment attractiveness based on the Hype Cycle model

The method of transforming Gartner cycle metadata into quantitative assessments of investment attractiveness factors, which is proposed in the study, is based on a rule-based approach. This involves the synthesis of rules for determining the maturity scores of key technologies. The basis for this is the results of quantitative analysis of their investment attractiveness, which were performed by other authors for technologies related to Fintech. Among these are artificial intelligence, quantum computers [24], and blockchain [23].

The analysis conducted in [24] revealed that in the "Innovation Trigger" phase, real capital inflows are very weak. These statistics confirm that for the whole of 2023, global investments in quantum technologies, which are a typical example for this phase, barely reached $2 billion. which, according to pessimistic estimates, is approximately 10% of future values. The difference of 7–10 times, compared to the next phase, is also observed for other analyzed technologies and determines the appropriateness of using a 10-point scale.

The implementation of an accurate score is complicated by the fact that the "Innovation Trigger" phase is characterized by the greatest scope in the Hype Cycle model. Therefore, technologies at the beginning and end of this phase differ greatly in risk and impact on investment attractiveness. Depending on the degree of technology development, their impact on investment attractiveness is estimated from 0 to 4 points. Technologies that are at the beginning of the phase usually do not yet have investment potential and are estimated at 0 points. Technologies that are in the middle of the phase are estimated at 2 points. A score of 4 points is given to technologies that are close to the end of the first phase of the Gartner model and may soon move on to the next one.

When the technology reaches the "Peak of Inflated Expectations" phase, investments become maximum, and almost all institutions, including venture and corporate funds, private investors, ICOs, etc., participate in the investment process. Quantitative analysis shows that in this phase, according to the Review Report (2025) [37], for the field of artificial intelligence, an increase in investments is recorded in 5 years by 7 times – from $12.4 billion in 2016 to a peak of $87.5 billion in 2021. Paper [23] notes a similar progress in investments (almost 10 times) for blockchain technology. Thus, the "Peak of Inflated Expectations" phase should be assessed at the upper level of the scale – 10 points. In the "Trough of Disillusionment" phase, using the example of blockchain [23], a decrease in investment volumes to a level of approximately 25–30% of the maximum in the hype phase is determined. Therefore, the investment attractiveness of technologies in this phase should be estimated at 3 points.

If the industry technologies overcome the shortcomings and move to the "Slope of Enlightenment" phase, then an increase in investment activity is observed again, but not as strong as in the hype phase. For example, blockchain technologies can be seen as an increase in investment by 1.5–2 times compared to the lowest indicators of the "Trough of Disillusionment" [23]. As for the "Innovation Trigger" phase, the actual assessment will strongly depend on where the technology is located – closer to the beginning or to the end of the phase. Depending on this, we shall set it at 5–6 points.

Finally, in the "Plateau of Productivity" phase, financing levels off and remains stably at a high level. The review conducted in [9] shows that in this phase the average market capitalization continues to grow already due to profits from industry technologies, and the level of investment attractiveness is second only to the hype phase. Therefore, it can be estimated at 7 points.

The generalization of these results makes it possible to propose rules for transforming Gartner cycle metadata into scoring, which are given in Table 3.

Table 3

Rules for determining the score of maturity of key technologies as a factor of investment attractiveness of an economic entity

Maturity phase of key technologies	Assessment of investment attractiveness by maturity phase (0–10 points)
Innovation Trigger	0–4
Peak of Inflated Expectations	10
Trough of Disillusionment	3
Slope of Enlightenment	5–6
Plateau of Productivity	7

In practice, not one but n key technologies, which are in different phases of maturity, may be used simultaneously in individual FinTech segments. In such a case, the overall assessment of the investment attractiveness of the IA segment by the technology maturity factor is calculated as the average assessment of individual key technologies (kta_i)

$$IA = \frac{\sum_{i=1}^{n} kta_i}{n}. \quad (3)$$

The set of rules given in Table 3, as well as the technique for calculating the score for segments where key technologies are in different phases of maturity (3) forms a method for determining the score of the technology maturity factor. Further, calculations were made on its basis for FinTech segments. The FinTech segments indicated in Fig. 5 were analyzed in terms of the key technologies used in them and the maturity phases of these technologies. Since none of the published Hype Cycles includes all FinTech technologies, several such cycles published in [17, 18, 33] were analyzed. The results of calculating the scores are given in Table 4.

It should be noted that the different investment attractiveness ratings given to the "Payments" and "Digital assets and currencies" segments are different, although both are in phase 4 of the "Slope of Enlightenment". However, the first of them is closer to phase 5 of the "Plateau of Productivity", and the second is closer to phase 3. Therefore, according to Table 3, their attractiveness is rated at 6 and 5 points, respectively. The situation is similar with the technologies of the Wealthtech segment, which are close to the beginning of the "Innovation Trigger" and "Slope of Enlightenment" phases and are rated at 1 and 5 points, respectively.

5. 3. Analysis of the relationship between the maturity factor of key technologies and investment activity in FinTech segments

The input data for the analysis are the results of determining the score estimates of investment activity (Table 2) and the maturity factor of key technologies (Table 4). The summarized results of calculating the score estimates are given in Table 5.

Table 5

Input data for correlation analysis

FinTech segment	Scores by segment	
	Key technology maturity factor (0–10)	Investment activity (0–5)
Payments	6	4
Insuretech	4	2
Regtech	10	4
Cybersecurity	6	3
Wealthtech	5.3	3
Digital assets and currencies	5	3
ESG/Greentech	10	5
Mean score	6.61	3.43

A graphical interpretation of the relationship between the input data in the form of a scatterplot is shown in Fig. 6.

Analysis of Fig. 6 allowed us to establish that the form of the relationship between the studied parameters is close to linear, which meets the requirements for using the linear correlation method for further calculations.

Table 4

Determining descriptive characteristics and maturity scores of key technologies in individual FinTech segments

FinTech segment	Technology maturity phase	Score		Source: Hype Cycle for:
		kta	*IA*	
Payments	4. Slope of Enlightenment	6	6	Digital Banking Transformation
Insuretech	1. Innovation Trigger	2	4	Digital Life and P&C
	4. Slope of Enlightenment	6		Insurance Fintech VC
Regtech	2. Peak of Inflated Expectations	10	10	Cyber-Risk Management
Cybersecurity	1. Innovation Trigger	2	6	Emerging Technologies
	2. Peak of Inflated Expectations	10		Cyber-Risk Management
Wealthtech	1. Innovation Trigger	1	5.3	Emerging Technologies
	2. Peak of Inflated Expectations	10		Fintech VC
	4. Slope of Enlightenment	5		Fintech VC Emerging Technologies
Digital assets and currencies	4. Slope of Enlightenment	5	5	Web3 and Blockchain
ESG and Greentech	2. Peak of Inflated Expectations	10	10	Digital Banking Transformation

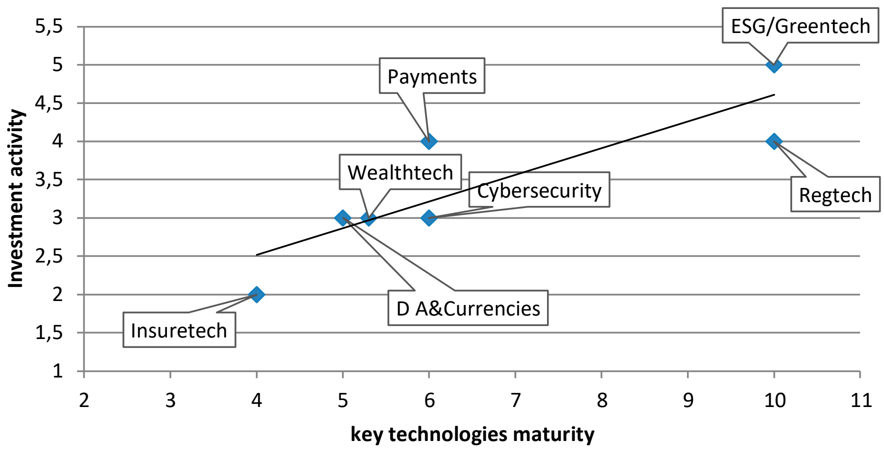


Fig. 6. Diagram of the relationship between investment activity and technology maturity factor in individual FinTech segments

Correlation analysis revealed that there is a correlation between the maturity factor of key technologies and investment activity in FinTech segments at the level of $r = 0.8615$. According to the Chaddock scale, this level of correlation is assessed as high.

6. Discussion of results related to the relationship between the maturity phase of key technologies and investment activity in the FinTech industry

The results (Tables 2, 4, 5, Fig. 6) allowed us to conclude that investment activity in FinTech is largely related to the maturity phase of key innovative technologies used in the industry. The high level of correlation ($r = 0.8615$), calculated on the basis of Table 5, indicates a strong direct relationship between the parameters under study. This means that the behavior of investors is generally consistent with the phase patterns of development described by the Hype Cycle model. Investors are more willing to invest in those segments where key technologies are closer to the "Peak of Inflated Expectations" or to the "Plateau of Productivity". Therefore, the maturity of key technologies can be considered as one of the most important factors of investment attractiveness.

Compared with previously published studies, our result quantitatively confirms qualitative observations made earlier by other authors. Papers [17, 19] used the Hype Cycle model to explain the cyclicality in the development of individual segments, in particular digital banking. Work [9] emphasizes that the phases of technology maturity affect investment attractiveness but does not offer tools for its measurement. The proposed methods provide a transition from descriptive analysis to quantitative assessment through scoring scales (Tables 1, 3) and further statistical verification of the relationship (Table 5, Fig. 6).

It should be noted separately that the recovery of investment activity may be associated with the emergence of new key technologies in the segment that are closer to the "Peak of Inflated Expectations". This was most noticeable in the Wealthtech segment, which received a higher investment attractiveness rating due to the active use of artificial intelligence technologies to improve approaches to capital management (Tables 3, 4). According to (3), the addition of a key technology with a high *kta* score increases the average *IA* score for the segment. Therefore, the introduction of new technologies that are close to the peak of inflated expectations can be considered as a technological driver of growth or recovery of investment activity in FinTech segments. However, (3) implies that if there are a large number of key technologies in the segment, the marginal effect of adding another technology decreases. This observation is consistent with the conclusions in [38] about the key role of artificial intelligence in increasing the attractiveness of FinTech. This also explains the "swings" in investment dynamics observed in Fig. 5, when segments that seem to be losing their attractiveness can quickly regain it through innovation.

The results and conclusions obtained are valid not only for FinTech but also extend to other sectors of the digital economy with a high share of intangible assets, fast cycles of renewal and scaling, network effects, and a global sales model. Overall, the results of our study confirm that the Gartner Hype Cycle model can be used not only as a descriptive concept but also as a working tool for analyzing and forecasting investment activity in industries for which Emerging Technologies are key.

It is necessary to recognize the limitations of the research. The developed methods for translating descriptive characteristics of investment dynamics and maturity phases of key technologies from the Gartner descriptive model into quantitative score scales (Tables 1, 3) are empirical approximation. Although these methods are based on the analysis of the results of works [8, 23, 24], their use inevitably simplifies the complex reality and contains an element of subjectivity. The accuracy of the conclusions and recommendations depends on the correctness of the assignment of points and can be specified in further research.

In addition, our study is limited only to large FinTech segments, and their number, equal to 7, is close to the minimum sufficient to detect a strong correlation. According to estimates [34], with a correlation of 0.9, the minimum required number of observations is 6, and with a correlation of 0.7, 13 observations are already required. Formal expansion of the sample due to niche areas can increase the number of observations but creates additional problems. For niche areas, episodic investment flows are more often observed, which complicates calculations for (1) or (2). In addition, the factors of development of niche areas may differ significantly from the factors that shape investment activity in large FinTech segments.

The disadvantages of the study include the fact that the scoring scales (Tables 1, 3) are set empirically and require further verification of the stability of the results. Also, in calculating the integral assessment of the investment attractiveness of the FinTech segment, a simple averaging of the assessments of key technologies (3) was used, which does not take into account their possible different weight for a separate segment.

Further development of our study may be associated with the expansion of the time base of observations and the detailing of data, in particular, the transition to more frequent intervals (quarterly) if such data are available. It is also promising to refine the scoring scales and check the sensitivity of the results to alternative scaling rules. The main difficulties on this path are the incompleteness of data for niche areas, the difference in approaches to the classification of segments and technologies in the sources, as well as the non-stationarity of investment series during periods of sharp changes in the economic situation.

7. Conclusions

1. For quantitative measurement of the parameters of the dynamics of investment activity of economic entities, a method for determining a score has been proposed, in which the characteristics of the dynamics of changes are calculated on the basis of quartiles. According to the results of the calculations, the following threshold values were obtained: $Q1^{abs} = 0.373$; $Q3^{abs} = 1.547$; $Q1^{prc} = 0.592$; $Q3^{prc} = 1.796$. That has made it possible to identify zones of stability, decline, and growth of investment activity and, on this basis, determine the score estimates of investment activity in FinTech segments.

2. The proposed method for determining the score estimate of the technology maturity factor based on the rule-based approach allowed us to obtain a quantitative assessment of this factor of investment attractiveness in FinTech. The results of the calculations confirmed that the investment attractiveness of FinTech as an industry as a whole remains high. The average maturity score (6.61 points) places the industry between the "slope of enlightenment" and "plateau of productivity" phases, and the average investment activity score of 3.43 points is between the descriptive scores "investment stability" and "growth after decline". This explains that the decline in total financing volumes is not a sign of the decline of the industry, but reflects its transition to a maturity phase, where growth increasingly depends on the real profitability of economic entities, rather than on speculative capital.

3. A quantitative relationship has been established between investment activity in FinTech segments and the maturity factor of key technologies. The high level of correlation ($r = 0.8615$), which was calculated in the study, indicates the presence of a strong direct relationship between the parameters under study. The calculations made it possible to confirm the principal hypothesis of the study that the investment attractiveness of economic entities in FinTech is largely related to the maturity phase of the key technologies they use. This means that investors are willing to invest in those segments where key technologies are close to the peak of inflated expectations or to the plateau of performance, and investor behavior largely follows the patterns of the Hype Cycle model. The key technological driver capable of supporting or restoring investment activity in individual segments is the introduction of technologies close to the "Peak of Inflated Expectations". Currently, such a technology is artificial intelligence. Thus, taking into account the stages of technology maturity allows us to better explain investor behavior and predict changes in investment activity in FinTech segments.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study and the results reported in this paper.

Funding

The study was conducted without financial support.

Data availability

All data are available, either in numerical or graphical form, in the main text of the manuscript.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

Authors' contributions

Oleksiy Mints: Conceptualization, Investigation, Writing – original draft, Formal analysis, Supervision; **Oleh Kolodiziev:** Conceptualization, Methodology, Writing – review & editing, Validation, Project administration; **Olena Khadzhynova:** Data Curation, Validation, Investigation, Visualization; **Mykhailo Krupka:** Investigation, Writing – original draft, Project administration, Funding acquisition; **Nazar Demchyshak:** Writing – review & editing, Resources, Supervision, Funding acquisition; **Oleksandr Shchepka:** Investigation, Formal analysis, Resources, Funding acquisition; **Pavlo Sidelov:** Software, Data Curation, Writing – original draft, Visualization; **Markiian Zaplatynskyi:** Software, Resources, Funding acquisition.

References

1. Cloft, H. J. (2008). What is All of the Hype About? American Journal of Neuroradiology, 29 (9), 1604–1604. https://doi.org/10.3174/ajnr.a1228
2. Alt, R., Beck, R., Smits, M. T. (2018). FinTech and the transformation of the financial industry. Electronic Markets, 28 (3), 235–243. https://doi.org/10.1007/s12525-018-0310-9
3. Pulse of Fintech H1 2025: Global analysis of fintech funding (2025). KPMG. Available at: https://assets.kpmg.com/content/dam/kpmgsites/xx/pdf/2025/08/pulse-of-fintech-h1-2025.pdf
4. Mints, A., Kolodiziev, O., Krupka, M., Vyshyvana, B., Yastrubetska, L. (2022). A cross-impact analysis of the bank payment card market parameters and non-financial sectors' indicators in the Ukrainian economy. Banks and Bank Systems, 17 (2), 163–177. https://doi.org/10.21511/bbs.17(2).2022.14
5. Ogawa, E., Luo, P. (2022). Macroeconomic effects of global policy and financial risks. International Journal of Finance & Economics, 29 (1), 177–205. https://doi.org/10.1002/ijfe.2681
6. Zeng, T., Wei, L., Reniers, G., Chen, G. (2024). A comprehensive study for probability prediction of domino effects considering synergistic effects. Reliability Engineering & System Safety, 251, 110318. https://doi.org/10.1016/j.ress.2024.110318
7. Benkenstein, M., Bloch, B. (1993). Models of Technological Evolution: Their Impact on Technology Management. Marketing Intelligence & Planning, 11 (1), 20–27. https://doi.org/10.1108/02634509310024146

8. Levchenko, Y. (2018). Assessing and ensuring enterprise investment attractiveness in the context of regional development. Mykolo Romerio Universitetas. Available at: https://gs.elaba.lt/object/elaba:29698767
9. Dedehayir, O., Steinert, M. (2016). The hype cycle model: A review and future directions. Technological Forecasting and Social Change, 108, 28–41. https://doi.org/10.1016/j.techfore.2016.04.005
10. Gavrysh, O., Kukharuk, A., Gavrysh, I. (2022). Innovative Determinants of the Investment Attractiveness of a Country: The Case of Ukraine. Marketing of Scientific and Research Organizations, 44 (2), 21–40. https://doi.org/10.2478/minib-2022-0007
11. Amosha, O., Velychko, V., Troian, V. (2023). Strategies for managing the company's potential to increase the enterprise's investment attractiveness. Baltic Journal of Economic Studies, 9 (2), 34–39. https://doi.org/10.30525/2256-0742/2023-9-2-34-39
12. Lin, C., Huang, Y. A., Cheng, M. S., Lin, W. C. (2007). Effects of information technology maturity on the adoption of investment evaluation methodologies: A survey of large Australian organizations. International Journal of management, 24 (4), 697. Available at: https://www.semanticscholar.org/paper/Effects-of-Information-Technology-Maturity-on-the-A-Lin-Huang/5051dfcaf161e266dd2b3a36cd687a124d437323
13. Shpak, N., Vytvytska, O., Martynyuk, O., Kylaec, M., Sroka, W. (2022). Formation of management and technological maturity levels of enterprises for their dynamic development. Engineering Management in Production and Services, 14 (3), 1–12. https://doi.org/10.2478/emj-2022-0022
14. Akhtar, Q., Nosheen, S. (2022). The impact of fintech and banks M&A on Acquirer's performance: A strategic win or loss? Borsa Istanbul Review, 22 (6), 1195–1208. https://doi.org/10.1016/j.bir.2022.08.007
15. Baranovskyi, O., Kuzheliev, M., Zherlitsyn, D., Serdyukov, K., Sokyrko, O. (2021). Cryptocurrency market trends and fundamental economic indicators: correlation and regression analysis. Financial and Credit Activity Problems of Theory and Practice, 3 (38), 249–261. https://doi.org/10.18371/fcaptp.v3i38.237454
16. Grodal, S., Krabbe, A. D., Chang-Zunino, M. (2023). The Evolution of Technology. Academy of Management Annals, 17 (1), 141–180. https://doi.org/10.5465/annals.2021.0086
17. Experiences and future perspectives in digital banking. Architecht. Available at: https://architecht.com/en/corporate/blog/technology/experiences-and-future-perspectives-in-digital-banking/
18. Gartner. Available at: https://www.gartner.com/
19. Griffiths, P. D. R. (2021). Fintech and Its Historical Perspective. The Palgrave Handbook of FinTech and Blockchain, 19–50. https://doi.org/10.1007/978-3-030-66433-6_2
20. Li, G., Au, C. H. A., Chou, C.-Y. (2025). Exploring the trend of the cryptocurrency market – an extended hype cycle perspective. SAIS 2025 Proceedings. Available at: https://aisel.aisnet.org/sais2025/28/
21. Lee, K.-F. (2018). The four waves of A.I. FORTUNE. Available at: https://fortune.com/2018/10/22/artificial-intelligence-ai-deep-learning-kai-fu-lee/
22. Kolodiziev, O., Chmutova, I., Biliaieva, V. (2016). Selecting a kind of financial innovation according to the level of a bank's financial soundness and its life cycle stage. Banks and Bank Systems, 11 (4), 40–49. https://doi.org/10.21511/bbs.11(4).2016.04
23. Ellul, J. (2021). Blockchain is dead! Long live Blockchain! The Journal of The British Blockchain Association, 4 (1), 1–11. https://doi.org/10.31585/jbba-4-1-(8)2021
24. Akwue, I. A. (2024). Financing futures: How hype shapes the funding and progression of quantum computing and AI. University of Twente. Available at: https://purl.utwente.nl/essays/100360
25. Cnattingius, S., Johansson, S., Razaz, N. (2020). Apgar Score and Risk of Neonatal Death among Preterm Infants. New England Journal of Medicine, 383 (1), 49–57. https://doi.org/10.1056/nejmoa1915075
26. Asif, M., Saxena, A., Bhardwaj Padmaja, S., Tiwari, S., Chaturvedi, S. (2024). A study of altman z-score bankruptcy model for assessing bankruptcy risk of national stock exchange-listed companies. Proceedings on Engineering Sciences, 6 (2), 789–806. https://doi.org/10.24874/pes06.02a.006
27. Kim, K. O., Zuo, M. J. (2018). General model for the risk priority number in failure mode and effects analysis. Reliability Engineering & System Safety, 169, 321–329. https://doi.org/10.1016/j.ress.2017.09.010
28. Salazar, G., Russi-Vigoya, M. N. (2021). Technology Readiness Level as the Foundation of Human Readiness Level. Ergonomics in Design: The Quarterly of Human Factors Applications, 29 (4), 25–29. https://doi.org/10.1177/10648046211020527
29. Keeney, R. L., Raiffa, H. (1993). Decisions with multiple objectives: preferences and value trade-offs. Cambridge University Press, 569.
30. Brans, J. P., Vincke, Ph. (1985). Note—A Preference Ranking Organisation Method. Management Science, 31 (6), 647–656. https://doi.org/10.1287/mnsc.31.6.647
31. Bond, T. G., Fox, C. M. (2013). Applying the Rasch Model. Psychology Press. https://doi.org/10.4324/9781410614575
32. Saaty, T. L. (2008). Decision making with the analytic hierarchy process. International Journal of Services Sciences, 1 (1), 83. https://doi.org/10.1504/ijssci.2008.017590
33. Get Grounded With the 2025 Gartner Hype Cycle™ for Emerging Technologies. Gartner. Available at: https://www.gartner.com/en/articles/hype-cycle-for-emerging-technologies
34. Bujang, M. A., Baharum, N. (2016). Sample Size Guideline for Correlation Analysis. World Journal of Social Science Research, 3 (1), 37. https://doi.org/10.22158/wjssr.v3n1p37
35. Chaddock, R. E. (1925). Principles and methods of statistics. Houghton Mifflin, 471. Available at: https://openlibrary.org/books/OL6680442M/Principles_and_methods_of_statistics
36. Mints, O., Yankovets, A. (2025). The Investment Attractiveness of FinTech Businesses in the Context of Global Technological Trends. Economic Herald of the Donbas, 1 (79), 141–147. https://doi.org/10.12958/1817-3772-2025-1(79)-141-147
37. Artificial intelligence (AI) startup funding worldwide from 2011 to 2023 (in billion U.S. dollars), by Quarter (2025). Review Report. Available at: https://reviewreport.co/artificial-intelligence-ai-startup-funding-worldwide-from-2011-to-2023-in-billion-u-s-dollars-by-quarter
38. State of European FinTech 2024 (2024). FinchCapital. Available at: https://finchcapital.com/archive/state-of-european-fintech-2024