Можно выделить основные признаки, согласно которым разработку, внедрение и эксплуатацию веб-приложения можно считать успешными:

- разделение ответственности – компоненты программы имеют определенные обязанности и занимаются ограниченным набором задач;
- применение архитектурных шаблонов, позволяющих сделать приложение структурированным, исходный код более читаемым и расширяемым;
- разбиение приложения на слои – помогает упорядочить структуру и улучшить процесс повторного использования кода;
- высокая скорость обработки запросов пользователя;
- достаточный уровень отказоустойчивости в зависимости от решаемых системой задач;
- оптимальное соотношение затрат на систему и уровень эффективности ее эксплуатации.

Таким образом, процесс выбора архитектуры и разработка современных веб-приложений являются неразрывными понятиями. Правильно выстроенная архитектура в долгосрочной перспективе позволит поддерживать программный продукт в соответствующем рынку и запросам пользователей состоянии. Каждая из вышеописанных архитектур веб-приложений решает определенный спектр задач, который является специфичным для отдельно взятого проекта и организации, в рамках которой будет функционировать приложение.

В современной экономике компании, занимающиеся разработками ПО, веб-ресурсов обеспечивают нашу экономику цифровыми ресурсами и в современном мире становятся важнейшими представителями сектора экономики. Учитывая современные тенденции развития экономики России можно сказать, что развитие электронной сети, цифровых технологий, веб-технологий будут способствовать развитию технологий проектирования ПО, росту квалификации специалистов, экономить средства и затраты времени создания программных продуктов.

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МЕТОДОЛОГИЧЕСКИЕ ПОДХОДЫ К НОРМАЛИЗАЦИИ ДАННЫХ В КОНТЕКСТЕ ФОРМИРОВАНИЯ ИНДЕКСА ФИДЖИТАЛИЗАЦИИ ФИНАНСОВОГО СЕКТОРА

METHODOLOGICAL APPROACHES TO DATA NORMALIZATION IN THE CONTEXT OF DEVELOPING THE PHYGITAL INDEX OF FINANCIAL SECTOR

Аннотация. В рамках представленного исследования проведен сравнительный анализ различных методов нормализации данных, применяемых при формировании индекса фиджитализации финансового сектора. В условиях стремительного развития финансового сектора и диджитализации услуг, расчет интегральных индексов, отражающих уровень развития цифровой и физической финансовой инфраструктуры определенных территорий, требует использования точных и надежных методик нормализации данных. В рамках статьи исследуются основные методы нормализации данных такие, как масштабирование Min-Max, нормализация Z-оценки, категориальное масштабирование и др., с акцентом на их влияние на точность и интерпретируемость интегрального индекса. В результате исследования было выявлено, что не существует универсального метода нормализации данных, который бы превосходил другие методы. В связи с этим рекомендуется экспериментировать с различными методами нормализации во время первичной обработки данных.

Abstract. The presented study provides a comparative analysis of various data normalization methods used in the formation of the phygital index of financial sector. In the context of the rapid development of the financial sector and the digitalization of services, the calculation of integral indices reflecting the level of development of the digital and physical financial infrastructure of certain territories requires the use of accurate and reliable data normalization methods. The article examines the main data normalization methods such as Min-Max scaling, Z-score normalization, categorical scaling, etc., with an emphasis on their impact on the accuracy and interpretability of the integral index. The study revealed that there is no universal data normalization method that would be superior to other methods. In this regard, it is recommended to experiment with various normalization methods during the initial data processing.

Ключевые слова: нормирование данных, интегральный индекс, сравнительный анализ.

Keywords: data normalization, integral index, comparative analysis.

1. Introduction

Phygital (combination of physical and digital) is a new form of «hybrid consumption experience» [1], which eliminates the gap between the physical and digital worlds. The objective of phygitalization is to transfer the best physical customer experience into digital reality and vice versa [2]. Even though e-commerce has become an increasingly popular mode of consumption, the supply of goods and services has not completely separated from the physical supply channel. Moreover, the supply of goods and services is often provided in the mixed form of physical and digital channels, i.e., phygital channels. Suppliers aim to create a seamless and integrated experience that includes physical and digital advantages to engage customers through a combination of the virtual and real [3-4] due to the exploitation of smart technologies [5].

The trend of phygitalization is observed in almost all sectors of the economy. The extensive use of digital technology in the financial sector has resulted in a new phygital finance. Phygitalization of financial sector refers to the blending of physical and digital experiences in the financial sector. This concept has emerged as technology continues to evolve and consumer expectations shift towards more digitally integrated experiences. Phygitalization can provide several benefits to both financial institutions and their customers. For financial institutions, it can help reduce operating costs, attract more customers, and provide more personalized services. For customers, it can offer greater convenience, faster service, and a more seamless experience. Financial development depends on the physical and digital infrastructures. It is worth pointing out that the unbalanced development of inclusive finance among countries (regions) is a frequently addressed topic by both academics and practitioners, which is relevant for policymakers to formulate economic policies for balanced development.

The development of an integral index is an effective tool that can be adopted to measure the development of phygital finance across countries or regions. Existing indexes regarding the development of the financial sector focus on a particular industry (banking, insurance, or financial market respectively) or on a particular aspect of the financial sector, such as measuring the level of financial sector digitalization or the level of financial inclusion, etc. There are no indicators on phygital finance that consider both the digital and physical dimensions of the financial sector. Therefore, it is of theoretical and practical significance to develop an indicator to measure the level of phygitalization of the financial sector.

We have referred to existing empirical studies and instructive publications from authoritative official organizations for creating the integral index [6]. A proposed methodology consisting of the following five main steps is implemented: (i) theoretical framework; (ii) variable selection; (iii) normalization; (iv) weighting; and (v) aggregating indicators. Preprocessing of data is an essential step in the process of creating an integral index, which includes data discretization, dealing with missing data, removing outliers, and normalization. Data normalization is a necessary preprocessing technique that converts the data measured on different scales to a comparable array [7]. Normalized data provide comparability across features, making data analysis more accurate and interpretable. The bias of features that have a high numerical contribution can be minimized by normalization [8]. In existing quantitative studies, z-normalization is commonly considered the default method to rescale the original data without any experimental evidence [9]. The purpose of this study is to conduct a comparative analysis of different normalization methods to examine their impact on creating an integral index. In the framework of research, the development of the phygital index is used as an example.

The main contents of the study are organized as follows: Section 1 is the introduction. Section 2 summarizes different normalization methods based on related empirical studies. Section 3 describes the data and different normalization methods for creating the integral index. Empirical results using different normalization methods are presented in Section 4. The main conclusions of the study are presented in Section 5.

2. Literature Review

In quantitative analysis, different variables usually have different quantitative scales and units, which may affect the results of data analysis and modelling. To eliminate the influence of the different scales between the indicators, it is necessary to normalize raw (un-normalized) data. Data normalization is one of the pre-processing approaches that enable the indicators to the same level of scale. Empirical studies indicate that there is no normalization method that provides the optimal performance in each case, the selection of an adequate normalization method depends on the features of the dataset, the characteristics of the research subjects, and the purposes of the research [8-10].

Adel S. Eesa and Wahab Kh. Arabo [11] applied different normalization methods on several datasets to find the most adequate normalization method for the backpropagation artificial neural network model. The result of this comparative study shows that the most suitable normalization methods depend on different datasets. Mean-Mad and Median-Mad normalizations have better performance.

Vafaei, N. et al [12] provided a comparative analysis of six selected normalization techniques within the framework of the multicriteria decision-making approach. The outcomes of the comparison suggest that Max-Min normalization is the most fitting technique for the selected case study.

Felipe Lima and Vinicius Souza [9] also compared ten normalization methods for rescaling time series data. The normalization methods being compared in this paper include Z-normalization, Min-max normalization, Mean normalization, Max absolute scaling, Median normalization, Decimal scaling, Sigmoid normalization, Tanh normalization, Quantile transform (uniform), Quantile transform (normal) and Power transform (or Yeo-Johnson transform). Based on the experimental comparison results, the authors recommend that researchers consider maximum absolute scaling as an alternative to z-normalization and then select the appropriate validated method for the specific research subject.

Pan et al. [10] compared the impact of normalization methods on predicting stock indices and their movements with un-normalized data. The experimental results suggested that no method emerged as superior over all others. Dalwinder Singh and Birmohan Singh [8] came the same conclusion using fourteen data normalization methods to rescale or transform the data and to compare their effect on classification performance. The empirical evidence on 21 publicly available real and synthetic datasets illustrates that no single normalization method outperforms others. The authors have suggested a set of the best and the worst performers. Z-score and Pareto scaling have the better performance, while Mean centered, Variable stability scaling and Median and median absolute deviation methods are the worst performers.

3. Research methodology

3.1. The characteristics of phygital index of financial sector

The dataset used in this study is collected by the author for the 2016 year. It covers 31 provinces in China, which has relatively comprehensive and open data on the regional finance at the provincial level. Mention, that the structure of the data released before and after 2016 is inconsistent, hence only the data for 2016 is used as an example. Data are collected from the People's Bank of China, China Statistical Yearbooks and CSMAR databases. Table 1 presents the main components for measuring the phygitalization level of provincial financial sector infrastructure.

Table 1 – Components of phygital index of financial sector

Infrastructure	Components	Units
Physical	Number of banking institutions	units
	Number of bank cards	ten thousand units
	Number of insurance branches	units
	Number of securities company branches	units
Digital	Number of broadband subscribers	units
	Number of mobile phones users	units
	Number of internet users	percentage
	Number of financial risk monitoring platforms	units
	Number of bank accounts	ten thousand units

The original data are rescaled by considering provincial population. We used various methods to normalize the data, which will be discussed in the next section. Phygital index of financial sector is calculated by two approaches – geometric aggregation or additive method using equal weights. Geometric aggregation is used for Optimal region scaling, Min-Max scaling and Categorical scaling, since they result in non-negative values. Additive method is used for Z-score normalization, Median-Mad normalization and Mean-Mad normalization, since their outcomes include negative values.

3.2. Methodology

As mentioned in the literature review there are various possible approaches used for the data normalization. According to the features of dataset and the purposes of the research, we selected six commonly used normalization methods for comparative analysis. Table 2 summarizes the different normalization methods used in this study.

Table 2 – Selected normalization methods

Normalization methods	Formula	Range of outcomes
Optimal region scaling	For benefit criteria: $x_{scaled} = \frac{x_i}{x_{max}}$ For cost criteria: $x_{scaled} = \frac{x_{min}}{x_i}$	(0,1]
Min-Max scaling	For benefit criteria: $x_{scaled} = \frac{x_i - x_{min}}{x_{max} - x_{min}}$ For cost criteria: $x_{scaled} = \frac{x_{max} - x_i}{x_{max} - x_{min}}$	[0, 1]
Categorical scaling	Each region is assigned a categorical score based on the percentiles of the distribution of the indicator value across the regions.	[0,1]
Z-score normalization	$x_{scaled} = \frac{x_i - \mu}{\sigma}$, where μ is the mean value and σ is the standard deviation of data.	$(\mu - 3\sigma, \mu + 3\sigma)$
Median-Mad normalization	$x_{scaled} = \frac{x_i - Median(x_i)}{MAD(x)}$, where $MAD(x) = \frac{1}{n}\sum_{i=1}^{n}\lvert x_i - Median(x_i)\rvert$	(Median – 3MAD, Median + 3MAD)
Mean-Mad normalization	$x_{scaled} = \frac{x_i - Mean(x_i)}{MAD(x)}$, where $MAD(x) = \frac{1}{n}\sum_{i=1}^{n}\lvert x_i - Mean(x_i)\rvert$	(Mean – 3MAD, Mean + 3MAD)

(i) Optimal region scaling (Distance to a reference region)

Optimal region scaling refers to taking the region that has the optimal value (maximum for benefit criteria and minimum for cost criteria) as a reference and then normalizing the values of the metrics for the other regions. The normalized outcomes are distributed within the interval (0,1], with 0 meaning the worst performance and 1 being the best.

(ii) Min-Max scaling (Re-scaling)

Min-Max scaling applies the difference between the maximum and minimum values instead of the standard deviation. Even though the method is the most commonly used normalization technique, it may have distorting effects on the normalization outcomes in the presence of extreme outliers in the minimum or maximum values.

(iii) Categorical scaling

Categorical scaling involves categorizing regions and converting initial data to categorical scores. Each region is assigned a categorical score based on the percentiles of the distribution of the indicator value across the regions. Table 3 shows the distribution of regions and their corresponding categorical scores.

Table 3 – Distribution of regions and categorical scores

Distribution of regions	Number of regions	Categorical score
top 5 % regions	2	100
the 85th - 95th percentiles	3	80
the 65th - 85th percentiles	6	60
the 35th - 65th percentiles	9	50
the 15th - 35th percentiles	6	40
the 5th - 15th percentiles	3	20
bottom 5 % regions	2	0

When the values of the various regions are relatively different, the categorical scaling facilitates the categorization of the regions, which enables further analyses. However, if the difference between the original values of the regions is very small, the percentile bands force the data to be categorized, which may lead to imprecise categorization.

(iv) Z-score normalization (Standardization)

Z-score normalization is the most commonly used normalization technique, which converts initial values to a common scale with an average of zero and a standard deviation of one. Its main application is to measure how many standard deviations the initial values differ from the overall mean of the data, approximately 99.7% of the values lie within three standard deviations of the mean after normalization.

(v) Median-Mad normalization

Median-Mad normalization is based on the calculation of the Median Absolute Deviation. Median Absolute Deviation as an estimator of scale. The median is, like the mean, a measure of central tendency but offers the advantage of being very insensitive to the presence of outliers. In addition, MAD is independent of sample size [13-15]. The data normalized by the Median Absolute Deviation method are distributed within the interval of the median plus or minus three times the MAD.

(vi) Mean-Mad normalization method

Mean-Mad normalization is similar to the Median-Mad normalization, which also can be used for normalizing the data [10, 14]. The data normalized by the Mean Absolute Deviation method are distributed within the interval of the mean plus or minus three times the MAD.

After normalizing, the next step is to assign weights to the submatrices and aggregate the integral indicator. Commonly used methods for weighting include equal weights method and weights based on statistical models. We consider physical infrastructure and digital infrastructure to be equally important for the financial sector at present, hence the equal weights method used in this paper to integral phyigital infrastructure index. Geometric aggregation is considered a less compensatory approach for aggregating subindexes. Geometric aggregation is used in the case of optimal region scaling, Min-Max scaling, and categorical scales. The additive method is used for Z-score normalization, Median-Mad normalization, and Mean-Mad normalization since the output of the last three methods contains negative values.

4. Results

This section presents descriptive statistics after normalizing the variables with different methods and compare the effects of different normalization methods on integral index. Figure 1 and 2 illustrate the dispersion and symmetry of the distribution of the data normalized by the different methods in box plots, along with the outliers of the data.

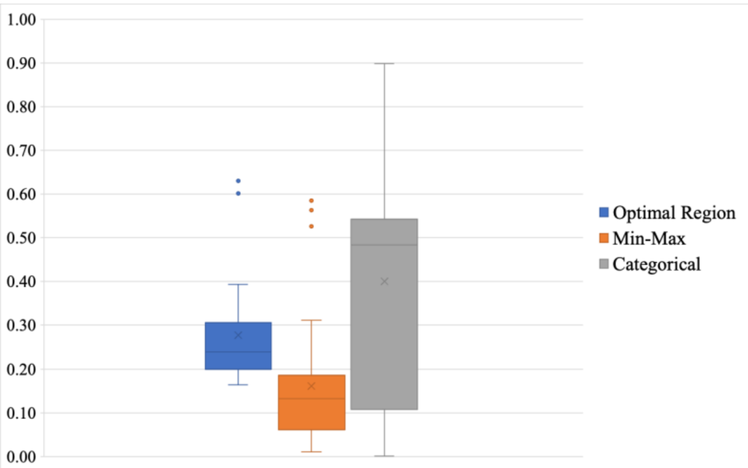

Figure 1 – Box plots of phygital index of financial sector normalized by optimal region scaling, Min-Max scaling and Categorical scaling.

Figure 1 shows that the phygital index of financial sector integral after normalization with optimal region scaling, Min-Max scaling and Categorical scaling has a range of values between 0 and 1. The median of the data normalized by optimal region scaling is 0.24, the upper limit is 0.39, the lower limit is 0.16, and there are three outliers above the upper limit, which refer to Zhejiang (0.64), Beijing (0.63), and Shanghai (0.60). Normalized data with Min-Max scaling has a median of 0.13, an upper limit of 0.31, and a lower limit of 0.01, with three outliers higher than the upper limit, and the outliers come from Beijing (0.59), Zhejiang (0.56), and Shanghai (0.53). With Categorical scaling the median of the normalized data is 0.48, the upper limit is 0.90, the lower limit is 0.00, and no outliers are shown.

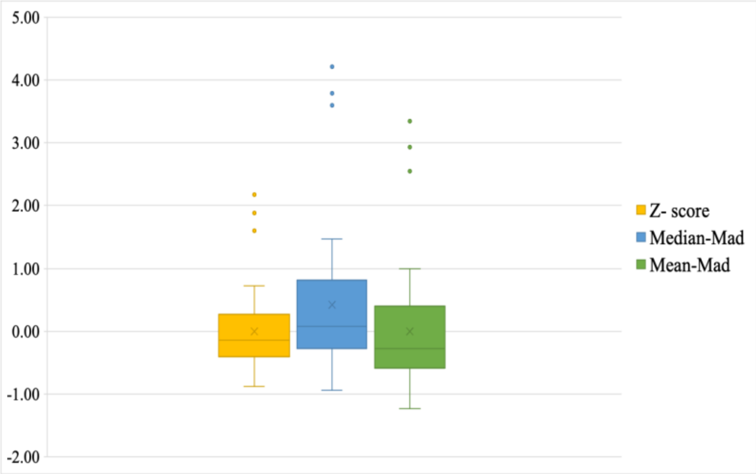

Figure 2 – Box plots of phygital index of financial sector normalized by Z-score normalization, Median-mad normalization and Mean-mad normalization

Figure 2 illustrates that values of phygital index of financial sector integral using Z-score normalization, Median-mad normalization and Mean-mad normalization have a relatively large range of values compared to the previous three approaches. Except for the outliers, the values of phygital index of financial sector are distributed between -1.24 and 1.47. The median of the data normalized by Z-score normalization is -0.14, the upper limit is 0.72, the lower limit is -0.88, and there are three outliers higher than the upper limit, which belong to Beijing (2.18), Shanghai (1.89) and Zhejiang (1.60). With Median-mad normalization, the median of the normalized data is 0.08, the upper limit is 1.47, and the lower limit is -0.94. The outliers originate from the three regions listed previously, from Beijing (4.21), Shanghai (3.79) and Zhejiang (3.60) respectively. With Mean-mad normalization, the median of the data is -0.27, the upper limit is 1.00, the lower limit is -1.24. There are three outliers greater than the upper limit, which come from the same three regions as before: Beijing (3.34), Shanghai (2.93) and Zhejiang (2.55).

5. Discussion and Conclusions

Based on the values of phygital index of financial sector formulated by various post-processing data and normalization methods, different normalization approaches rescale the data to a particular interval. As shown in Figure 3, normalization methods generate different distribution intervals, however the trend of the final integral index across provinces is generally similar.

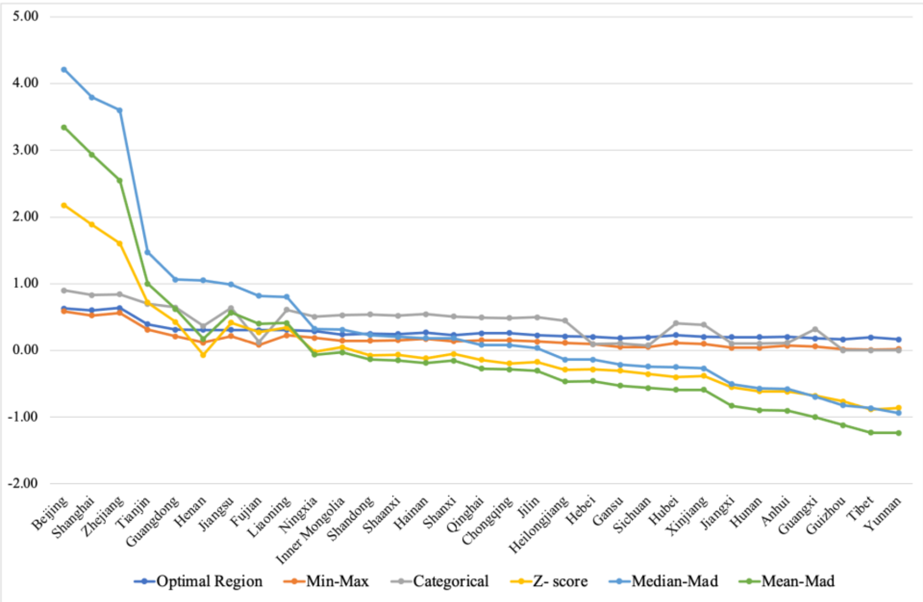

Figure 3 – Phygital index of financial sector for China's provinces

It can be observed from Figure 3 that the results of Z-score normalization are basically the same as the results obtained through Mean-Mad normalization since the two normalization methods have similar calculation formulas. The distribution of the index across provinces resulting from the Median-mad normalization method is generally consistent with these two methods. All the results show that Beijing has the highest value of phygital finance, followed by Shanghai and Zhejiang, which are as the top three provinces (or cities) that have relatively high values compared to the other provinces (or cities). In contrast, the results obtained with optimal region scaling show that Zhejiang province is the best province for most sub-indexes, and therefore it has the highest phygital index of financial sector (0.64), followed by

Beijing (0.63) and Shanghai (0.60), which are the three provinces (cities) with the leading position with very little difference in values. There is a significant difference between the values of these three provinces (or cities) with Tianjin (0.39), which is ranked in the fourth place. The results obtained by Min-Max scaling and Categorical scaling similarly demonstrate the leading status of these three provinces (or cities), with similar distribution of results for the other provinces. It is worth pointing that the results obtained in the case of Min-Max scaling have relatively small differences among provinces (except Beijing, Shanghai and Zhejiang), the value of Tianjin is 0.31, which is in the fourth place, and the values of the other 27 provinces are distributed in the interval of [0.01,0.23]. In the case of Categorical scaling, the results have a large range of values and are consistently distributed within the interval of [0.00,0.90].

This paper analyzes the impact of six different normalization methods on the index that is obtained by normalizing the raw data and composing the index based on them. As proposed in the literature review section, there is no single normalization method that performs best on all cases. Although many empirical studies in economics consider Z-score normalization as the most used method, we have observed that there are other normalization methods that could be used in comparison to Z-score normalization, providing more insights on the interpretation of economic statistics. Categorical scaling method is more preferable in the context of analyzed index. Figure 4 presents the Phygital index of financial sector for China's provinces using Categorical scaling.

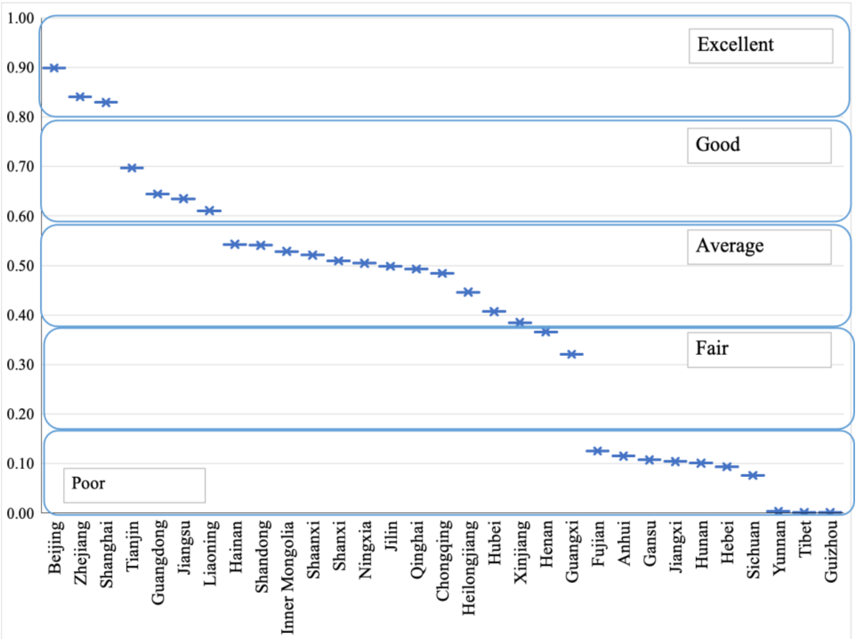

Figure 4 – Phygital index of financial sector for China's provinces using Categorical scaling

The National Bureau of Statistics of China classifies the country's economic regions into four main groups: eastern, central, western and north-eastern regions, with the aim of accurately reflecting the socio-economic development of the different regions of China. In this context, the eastern part of the country refers to the provinces and cities that were the first to implement the opening up policy and have a high level of economic development, the central and north-eastern part refers to the developing regions, and the western part refers to the underdeveloped regions [16]. As shown in Figure 4, the results obtained by implementing Categorical scaling can more accurately reflect the real situation of the phygitalization level of financial service in China's provinces. We classified the different development level of phygitalization into five levels based on the phygital index score:'Poor ' (0.0-0.2), 'Fair' (0.2-0.4), 'Average' (0.4-0.6), 'Good' (0.6-0.8) and ' Excellent' (0.8-1.0). Our findings are consistent with the reports of the Central Bank of China and state-owned commercial banks [17; 18]. Researches in related fields have drawn similar conclusions [19; 20]. The level of financial development varies widely across provinces. The eastern regions have relatively high levels of development in both the physical and digital dimensions of the financial sector with leading positions in the country. Most of the central and north-eastern regions have a medium development level of phygitalization. The relatively low levels of phygitalization are found in part of the central and western regions.

Our paper contributes to the literature on normalization methods in the field of economics, developing an integral index for evaluating the phygitalization level of finance sector, using the latest comprehensive publicly available data on China's financial industry. The comparative analysis reveals that in addition to the most commonly used Z-score approach, Categorical scaling could offer relatively more straightforward and reliable results in considering indicators that capture differences in the development levels of different regions. This paper takes the data of China's financial sector as an example for developing the integral index, it is a limitation of this study. As one of the future directions, the methodology for compositing index could be applied to measure and compare the development level of phygital finance in other countries or regions, which is relevant in the context of the digital economy.

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ОПЫТ И РЕЗУЛЬТАТЫ ИСПОЛЬЗОВАНИЯ КЛАСТЕРНОГО ПОДХОДА К ОБЕСПЕЧЕНИЮ УСТОЙЧИВОСТИ РЕГИОНАЛЬНЫХ СОЦИАЛЬНО-ЭКОНОМИЧЕСКИХ СИСТЕМ

EXPERIENCE AND RESULTS OF UTILIZING A CLUSTER APPROACH TO ENSURING THE SUSTAINABILITY OF REGIONAL SOCIOECONOMIC SYSTEMS

Аннотация. В статье представлен анализ эффективности кластерного подхода к обеспечению устойчивости региональных социально-экономических систем. На основе изучения зарубежного и отечественного опыта, авторами были выявлены ключевые факторы, влияющие на успешность реализации кластерной политики в регионах. Особое внимание уделено оценке результатов внедрения кластерного подхода в различных регионах, включая анализ экономических, социальных и экологических показателей. Автор статьи приходит к выводу, что кластерный подход может стать эффективным инструментом для повышения устойчивости региональных социально-экономических систем, но требует тщательного планирования, координации и мониторинга.

Abstract. This article presents an analysis of the effectiveness of the cluster approach to ensuring the sustainability of regional socioeconomic systems. Based on the study of foreign and domestic experience, the authors identified key factors influencing the success of cluster policy implementation in regions. Particular attention is paid to the assessment of the results of cluster approach implementation in various regions, including an analysis of economic, social, and environmental indicators. The author concludes that the cluster approach can be an effective tool for enhancing the sustainability of regional socioeconomic systems but requires careful planning, coordination, and monitoring.

Ключевые слова: кластерный подход, устойчивое развитие, региональные социально-экономические системы, экономический рост, социальное развитие.

Keywords: cluster approach, sustainable development, regional socioeconomic systems, economic growth, social development.

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Одним из актуальных и эффективных организационно-экономических механизмов обеспечения устойчивости региональных социально-экономических систем, в том числе в сфере туризма, можно признать создание и последующее развитие кластерных структур, ориентированных на межотраслевое и, в отдельных случаях, межрегиональное взаимодействие хозяйствующих субъектов. К очевидным преимуществам кластерных образований с точки зрения обеспечения устойчивости региональных социально-экономических систем, как это отмечается трудах таких авторов, занимающихся вопросами эффективной кластеризации на территориальном