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# THE DIGITAL LEAP OF E-LEARNING IN HIGHER EDUCATION

Kaikai Liu[1], Marja Liisa Tenhunen[2,*], Jun Chen[1], Hui Chen[3] and Jingjing Liang[1]
*[1]SHU-UTS SILC Business School, Shanghai University, Shanghai, China*
*[2]Shanghai University, Shanghai, China*
*[3]Henkel Co. Ltd., China*
*[*]Corresponding Author*

**ABSTRACT**

COVID-19 pandemic has led to the confrontation of higher education system with enormous challenges. This necessitated the urgent transition from face-to-face teaching to online teaching. A comparative study of digital education in seven different countries was conducted. This study established grey comprehensive evaluation model based on entropy weight method, which was successfully validated by reliability test. In general, developed countries tend to have high comprehensive evaluation value while Finland, South-Korea and Latvia have relatively low grey correlation coefficient in several certain indicators, leading to a sharp drop in the overall score. Romania ranked last while China ranked second as a developing country as well. This is followed by model optimization though input-output analysis method based on the upgrading of higher education system due to the pandemic's influence. The study launched a conclusion that research and development personnel, infrastructure funds and university financial investment in digital education have relatively more obvious effects on improving the quality of higher education system.

**KEYWORDS**

E-learning, Higher Education, Grey Comprehensive Evaluation Model, Sensitivity Analysis

## 1. INTRODUCTION

Online-teaching opens up as a smart solution for future education. In the field of education, a digital leap has been made in a short notice which has encouraged universities in the development of creative solutions. Concerns about educational inequality have risen in the process especially in the countries with short prior experience in online education. Despite the limitations in technological conditions, all possible efforts should be made when pursuing equality in online-education.

The global emergency of the COVID-19 pandemic confronts all people with unpredictable, disruptive situations which has changed our daily lives, economies, political decisions and universities. Important changes have been made in terms of online-teaching, admission and exam schedules, which have stirred discussions about future prospective in university landscape after the pandemic is over. Amid all the uncertainty and shock, universities are obliged to stick to their basic values and ethical responsibilities, which give academics a sense of direction and credibility. In any case, remote online teaching and learning cannot fully replace a face-to-face teaching and learning environment where teachers and students discuss with each other. Generally, online-teaching has been used to supplement the classroom teaching, which is called "blended learning". As the saying goes, "When there is a risk, there should be an opportunity". The late Austrian-American economist Joseph Schumpeter introduced the "creative destruction theory". The COVID-19 pandemic has been destructive, but it also, in a sense, has created some creative destruction. In the best scenario, teachers and students have got some benefits from online-teaching, which will equip them for the future learning and communication. For instance, teachers should consider the issues such as how to motivate students and encourage them to be proactively participate in real-time video class discussions, how to implement innovative teaching concepts more effectively, how to maintain care and guidance for individual students, and how to share and integrate online-teaching experiences with other colleagues. Teachers' creativity with online teaching can be a vital factor for stimulating students' autonomous learning, turning the epidemic "crisis" into an "opportunity" whilst reforming teaching and learning concepts. The university management should provide support in this process.

Throughout history, education has rarely been reformed or benefited from technological advances. Nowadays, with digital teaching allowing real-time interaction, many innovative teaching and learning methods can be attempted and implemented. The most powerful part of this new generation of real-time interactive teaching and learning is that it can simultaneously accommodate in scaling and personalized learning, which traditional classroom teaching cannot do. In traditional large classes, it is difficult for teachers to know how many of the students understand or master the contents of a class. However, if the teaching and learning activities are carried out online in real time, teachers' understanding of students' progress can change. For example, teachers can review the distribution of answers to certain multiple choice questions. They can recognize the number of students who answered incorrectly and where they went wrong through the interactive polling function. Based on a real-time data, teachers can better understand students' immediate responses and provide suitable assistance as quickly as possible in order to improve learning efficacy. The system can also guide students to review more challenging content. With the benefit of this experience, teachers can use similar functions in their traditional classroom teaching in the future to better understand students' personal progress and needs. The "flipped classroom" teaching method that has emerged in recent years is particularly applicable in a real-time video teaching environment. Students can watch the relevant teaching materials and videos in advance before the live online class so that the teacher can make better use of live class hours and focus on interactive discussion. This reduces the portion of unidirectional lecturing. During online teaching and learning, it is possible to reduce some of the limitations of traditional classrooms, which gives room to rethink how teachers can turn "classes" into better learning experiences and enhance teachers' mentoring and coaching roles.

## 2. AIM OF THE STUDY

COVID-19 created a digital leap in all around the world, including higher education. The starting point has varied from country to country and therefore, the changes that took place in the spring of 2020 vary. In some countries, a system for providing e-learning has been acquired on a fast schedule. Teachers have been introduced to new types of teaching, and only then has provision been introduced. Other countries have expanded only their previous offerings of courses. It will be interesting to compare the seven selected countries, China, Latvia, Mexico, Romania, Finland, South Korea and the United States at different levels of online education and to gather experiences of change for operational development. There is no return to yesterday, so institutions need to start from first principles, creating a vision for life after the pandemic, making hard choices based on data, creating new models, realigning priorities and entering a post-covid-19 world not in isolation but collaboration. The aim of this study is to compare the implementation, quality and quantity of online-education by a questionnaire method in seven different countries. The countries selected are China, Latvia, Mexico, Romania, Finland, South Korea and the United States. The countries have been selected on the basis of the researchers' teaching experience. The first electronic survey will be conducted for the management of every university and the second electronic survey will also be conducted for the academics including program directors. The third electronic survey in the study will be conducted simultaneously for groups of students of the same size in business administration.

## 3. THEORETICAL FRAMEWORK AND RESEARCH PROBLEM

There is no single or core theory which support online education. Research is linked to educational theories, mainly constructivism or exploratory learning. Constructivism is an international concept, so it is used is this research. Exploratory learning is actually a manifestation of constructivism. E-learning is implemented in as an opportunity to individualize teaching and it provides the preconditions for the realization of a constructivist view of learning better than mass-based teaching. The main research problem is as follows: The realization of a constructivist view of e-learning at universities in seven different countries. In the constructivism, knowledge and learning are related to action. Knowledge does not pass from the outside into the human mind, but each student constructs his or her own knowledge. Understanding cannot be transferred it is always the output of the student's own thinking. It is the student's own active knowledge construction process, in which the student selects and interprets information based on what he or she has previously learned and expectations. Learning includes, for example, self-perceived questions, self-experimentation, problem-solving, and understanding. According to the constructivism, the key to learning is the understanding and thinking. Learning is thus the active interpretation of an individual's observations and experiences and the construction of new meanings associated with them. Learning is situational and based on interaction. The student must be able to direct his or her own selective attention to what is relevant to what he or she is learning, and the student must also feel that the questions that arise are important and meaningful to him or her. Only then does learning happen. The results of the work of the different students form the basis for the teacher's own analysis of the matter.

The most important skill of a teacher is to create functional, appropriate learning environments that raise questions in the student's mind and help him or her construct answers by understanding what is being sought. In the learning environment created by the teacher, appropriate questions arise, the answers to which are sought under the guidance of the teacher on the basis of the student's own experimentation, understanding and thinking. The teacher trains students' thinking and comprehension skills by giving them the widest possible opportunities to receive feedback on their own operational processes. The learning environment includes situations of uncertainty (confrontations) initiated by the teacher. Through these, the student gets the opportunity to develop their own abilities to learn to learn. The appropriateness of the learning environment should be a conscious goal for all involved in the process.

Skills are developed through long-term and goal-oriented training at a variable, gradually decelerating pace. There are occasionally different levels of skill learning, during which a certain aspect of a skill is automating, but overall performance suffers. The development of skills at the highest level means the persistent continuation of practice even after the pace of skill development has slowed down. Peak performance can be achieved by avoiding the formation of rigid routines. The student has to face challenges that break with familiar patterns and force the student to stretch his/her own skills. Simply maintaining the level of performance achieved is not enough. The most difficult of these skills are often thinking skills. In order to develop, the student must constantly and consciously refine both his/her own actions and his/her own thinking. Action and thinking develop intertwined. A well-developed and unified way of acting and thinking is typical of an expert. Self-assessment skills (metacognitive skills) are needed to develop expert thinking. The student cannot get them naturally, because the assessment and development of student's own internal models and skills requires acceptance that the student does not yet know everything.

New creative and evolving expertise is needed when the operating environment changes and old and proven models do not work. An innovative expert constantly strives to invest in learning new things and is also willing to question his or her own previous beliefs. It is impossible to teach different core skills such as problem solving and interaction skills in isolation. Also, the ability to collaborate, creativity, knowledge of different learning styles, assessment of one's own learning and the use of knowledge never arise in a vacuum, but are best learned in a relevant context. E-learning is implemented in as an opportunity to individualize teaching and it provides the preconditions for the realization of a constructivist view of learning better than mass-based teaching. If e-learning is used only to share material and tasks used in face-to-face teaching without pedagogical vision and reflection, e-learning does not take advantage of the new opportunities to apply constructivism that e-learning offers to interactive learning. It could also be stated that not only a new kind of pedagogical approach, e-learning also requires more work from the teacher than lecture-based contact teaching. A priori reflection on the preconditions of constructivism in e-learning provides subjects to the theoretical part and the surveys.

# 4. METHODS

## 4.1 Data Collection

Data collection of this study was conducted as digital surveys. Target survey-takers were divided into 3 groups: (1) University management: What role does e-learning play in the current strategy of the university? How do they see the change in the future? Also management was asked about their views on learning and whether they relate to some general theories or whether they exist at all. (2) Academics including program leaders: What kind of experience have they had with e-learning technical solutions, software, content, and guidance? What is the key feedback from academics and program teachers? What are the key successes, what about failures? How do program managers and academics see the connection of e-learning to students working life after graduating? How have been the reactions of the partner companies to e-learning? (3) Students: What kind of experience have they had with e-learning technical solutions, software, content and guidance? How has their studies progressed? What are the key successes and failures? How do students see the connection of e-learning to working life after graduation? The collection of questionnaire data plays a significant role on the application of our model. The extensiveness and reliability of the data could ensure the model feasible with practical significance. This study selected managers, students and academics engaged in higher education as investigation objects. The survey was conducted from August 2020 to March 2021, finally collecting data from the selected countries including China, Finland, Latvia, Mexico, Romania, South-Korea and the United States of America. A total of 160 questionnaires were issued in this survey. After eliminating 4 invalid questionnaires, 156 valid ones were obtained with an effective recovery rate of 97.50%.

## 4.2 Variable Description

This study selected 17 indicators from *Scale of e-learning in higher education*, *Input of digital education during the COVID-19 crisis* and *Impacts of e-learning on higher education during the COVID-19 crisis* to accurately evaluate the implementation, quality and quantity of digital education in each country. First, *Scale of e-learning in higher education* reflects the basic development of digital education. Enrollment number of graduate students and number of doctor students could represent this index. Second, *Input of digital education during the COVID-19 crisis* is the core reflecting the driving force of digital education development under the influence of the pandemic. Among them, number of R & D personnel has attracted our special attention in terms of manpower investment in scientific research. Last, *Impacts of e-learning on higher education during the COVID-19 crisis* could reflect the ability of digital education to serve the current community. Wen's article (2013), one of the most cited articles in this field, mentions that intensity of students' performance evaluation, grade for academics' online teaching skills and grade for managers' digital working efficiency are important indices to measure the significance of digital technologies in higher education. Table 1 provides the list of variables.

Table 1. Parameter list

| Primary variable | Secondary variable | Symbol |
|---|---|---|
| **Scale of e-learning in higher education** | Enrollment | $X_1$ |
| | Number of graduate students | $X_2$ |
| | Number of doctoral students | $X_3$ |
| **Input of digital education during the COVID-19 crisis** | Proportion of e-leaning in higher education | $X_4$ |
| | Number of teachers implementing online-teaching | $X_5$ |
| | Number of R & D personnel in digital education | $X_6$ |
| | Infrastructure funds | $X_7$ |
| | Financial investment provided by universities | $X_8$ |
| | Online education expenditure per capita | $X_9$ |
| | Research funds on digital technologies | $X_{10}$ |
| | Inherent assets | $X_{11}$ |
| **Impacts of e-learning on higher education during the COVID-19 crisis** | Total use frequency of digital technology | $X_{12}$ |
| | Intensity of students' performance evaluation | $X_{13}$ |
| | Grade for academics' online teaching skills | $X_{14}$ |
| | Grade for managers' digital working efficiency | $X_{15}$ |
| | Number of temporary forms of academic employment | $X_{16}$ |
| | Opportunities for equity, diversity and inclusion | $X_{17}$ |

## 4.3 Factor Analysis

Due to the considerable number of indicator selection, there might be high internal correlation between different indicators and unstandardized structure of observation data resulting in inconsistent analysis results. In order to facilitate the subsequent data analysis, we hope to reduce the number of variables and improve the model accuracy through factor analysis. The basic principle is to find out the representative factors that can reflect the overall characteristics in multi-dimensional variables, and classify the same essential variables into one factor. These unobservable synthetic indicators are public factors. The model is as followed:

$$X_i = \mu_i + a_{i1}F_1 + \cdots + a_{iq}F_q + \varepsilon_i \qquad (1)$$

*Note:* $X = (X_1, X_2, X_3, \ldots, X_p)'$ *is a p-dimensional random vector with a mean value of* $\mu$ . $F = (f_1, f_2, \ldots, f_q)'$ *is a q-dimensional random vector.* $\varepsilon_i$ *is a special factor.* $E(F) = 0$ , $E(\varepsilon) = 0$ ; $Cov(F, \varepsilon) = 0$; $D(F) = 1$.

## 4.4 Grey Comprehensive Evaluation Model Based on Entropy Weight

After the dimensionality reduction by factor analysis, grey comprehensive evaluation method was conducted to test. This method assesses the pros and cons of each comparison sequence by calculating the similarity between the comparison sequence and the reference sequence. However, the traditional grey comprehensive evaluation method simply samples the average value of the correlation coefficient of each index when solving the sample correlation degree, which obliterates the heterogeneity between the indexes. While in accordance to the background of this topic, different elements of the data have different significance to digital education system. Therefore, it is of great priority to distinctly set the reasonable and scientific weights for these indicators so as to represent different elements' value. To improve the traditional one, this study integrated the entropy weight method and the grey comprehensive evaluation method to analysis the quality of digital education in various countries.

### 4.4.1 Dimensionless Processing of Data

The standardization of data to solve the error caused by the disunity of measurement units was conducted. We use semi-ascending trapezoidal fuzzy membership function for non-dimensionalization where $r_{ij}$ is the actual value of the $j^{th}$ index in the $i^{th}$ province, $x_{ij}$ is its fuzzy membership value, $r_{min}$ and $r_{max}$ are the minimum and maximum values of the $j^{th}$ index respectively.

$$x_{ij} = \begin{cases} 0, & r_{ij} \le r_{min} \\ \frac{r_{ij} - r_{min}}{r_{max} - r_{min}}, & r_{min} \le r_{ij} \le r_{max} \\ 1, & r_{ij} \ge r_{max} \end{cases} \qquad (2)$$

### 4.4.2 Entropy Method

Entropy method and Analytical Hierarchy Process (AHP) are regarded as the most commonly used methods in the field of scientific empowerment. Since AHP method has the subjective and optional drawbacks, we choose entropy method which overcomes the subjectivity in determining the weight and is more appropriate in this case. Entropy weight method is usually used in comprehensive evaluation problems to carry on the weight analysis to the importance of the assessment index.

Firstly, we calculate the information entropy of each index, and its formula is as follows:

$$E_j = -\ln(n)^{-1} \sum_{i=1}^{n} p_{ij} \ln p_{ij} \qquad (3)$$

$$p_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{n} Y_{ij}} \qquad (4)$$

Then we determine the weight of each index. According to the calculation formula, the information entropy of each index is $E_1$, $E_2$, $E_3$……$E_k$. The weight of each index is calculated by information entropy, and the formula is as follows:

$$W_i = \frac{1 - E_i}{k - \sum E_i} (i = 1,2,3 \ldots \ldots k) \qquad (5)$$

### 4.4.3 Grey Comprehensive Evaluation Method

In this method, we firstly select the optimal sequence. Since the indexes described above are positive indicators, the maximum value of the same index for each evaluation object is taken as the optimal value of the index. The sequence composed of the optimal values of each indicator is called the optimal sequence, and is denoted as $X_0 = (x_{01}, x_{02}, \ldots x_{0n})$. Secondly, to figure out the grey correlation coefficient, we set the comparison sequence and the reference sequence respectively. Continue to the previous step, the optimal sequence is taken as the reference sequence. And the sequence composed of the index values of each evaluation object as the comparison sequence, denoted as $X_i = (x_{i1}, x_{i2}, \ldots x_{in})$, i=1, 2, …m. The grey correlation coefficient between the $i^{th}$ evaluation object and the $j^{th}$ index in the reference sequence is denoted as $\gamma_{ij}$, which is expressed as:

$$\gamma_{ij} = \frac{\min_i \min_j |x_{ij} - x_{0j}| + \rho \max_i \max_j |x_{ij} - x_{0j}|}{|x_{ij} - x_{0j}| + \rho \max_i \max_j |x_{ij} - x_{0j}|} \tag{6}$$

In formula (6), ρ is the resolution coefficient, $\rho \in [0,1]$. Here, we take ρ as 0.5.

Last step is to calculate the grey correlation degree which reflects the closeness of the comparison sequence to the reference sequence. The greater the degree of association, the closer the comparison sequence is to the optimal value. Therefore, the pros and cons of each evaluation object can be evaluated according to the degree of grey correlation of each comparison sequence. Taking into account the heterogeneity between different indicators, different weights are assigned to the indicators according to the relative importance of each indicator. The grey correlation degree of the $i^{th}$ evaluation object is defined as:

$$\gamma_{i0} = \sum_{j=1}^{n} \omega_j \cdot \gamma_{ij} \tag{7}$$

Among them, $\omega_j$is the weight of the jth index. The index weight is determined by the above-mentioned entropy weighting method. Then we calculate the grey correlation degree of each country based on this.

# 5. RESULT ANALYSIS

## 5.1 Evaluation Results

Before factor analysis, it is necessary to judge whether the variables selected are suitable for factor analysis. According to the data, a group of observations with 5 related variables and 12 sample size are obtained for analysis. In order to prevent the occurrence of multicollinearity, we need to estimate the correlation between the selected variables before factor analysis. In this study, we use SPSS 25.0 statistical software to test the collected data. The test results are shown in Table 2. Although the significance level of Bartlett sphericity test is less than 0.01, the KOM value is 0.495, less than 0.6, which does not pass the KMO test indicating that the selected variables are not suitable for factor analysis.

Table 2. Results of KMO and Bartlett's test

| | | |
|---|---|---|
| **Kaiser-Meyer-Olkin Measure of Sampling Adequacy** | | .495 |
| **Bartlett's Test of Sphericity** | Approx. Chi-Square | 58.196 |
| | Df. | 10 |
| | Sig. | .000 |

When the index data does not meet the KMO test, the factor analysis method is not applicable. Fortunately, the grey correlation analysis does not require the distribution of sample data, nor does it require sample data to meet statistical tests, which can make up for the defects of the above methods. Therefore, we directly evaluate all these seventeen indicators adopting grey comprehensive evaluation model based on the entropy weight. Using the collected data of 7 countries in the questionnaire, the entropy weighting of each evaluation index is carried out according to the steps of solving the entropy weight. The weight of each indicator is shown in Table 3.

Table 3. Results of weight calculation

| Index | Weights | Index | Weights |
|---|---|---|---|
| $X_1$ | 4.160% | $X_{10}$ | 4.123% |
| $X_2$ | 4.357% | $X_{11}$ | 6.732% |
| $X_3$ | 4.048% | $X_{12}$ | 3.040% |
| $X_4$ | 4.301% | $X_{13}$ | 11.589% |

| | | | |
|---|---|---|---|
| $X_5$ | 11.296% | $X_{14}$ | 5.055% |
| $X_6$ | 9.562% | $X_{15}$ | 4.615% |
| $X_7$ | 1.924% | $X_{16}$ | 4.804% |
| $X_8$ | 4.822% | $X_{17}$ | 3.549% |
| $X_9$ | 12.024% | | |

According to formula (6), first obtain the grey correlation coefficient matrix of each country, as shown in Table 4. According to formula (7), the grey correlation degree of each country is calculated, that is, the comprehensive evaluation value of the development level of digital education. Table 5 demonstrates the value and rank.

Table 4. Grey correlation coefficient matrix

| Index | U.S. | South-Korea | Romania | Mexico | Latvia | Finland | China |
|---|---|---|---|---|---|---|---|
| $X_1$ | 1.00 | 0.33 | 0.33 | 0.35 | 0.39 | 0.35 | 0.45 |
| $X_2$ | 0.35 | 0.33 | 0.33 | 0.34 | 0.47 | 0.37 | 1.00 |
| $X_3$ | 1.00 | 0.33 | 0.33 | 0.33 | 0.49 | 0.37 | 0.47 |
| $X_4$ | 0.59 | 0.49 | 0.33 | 1.00 | 0.58 | 0.36 | 0.75 |
| $X_5$ | 0.59 | 0.33 | 0.34 | 0.34 | 0.36 | 0.35 | 1.00 |
| $X_6$ | 1.00 | 0.37 | 0.36 | 0.33 | 0.45 | 0.98 | 0.34 |
| $X_7$ | 0.66 | 0.38 | 0.47 | 0.41 | 0.47 | 1.00 | 0.71 |
| $X_8$ | 1.00 | 0.33 | 0.34 | 0.41 | 0.40 | 0.34 | 0.34 |
| $X_9$ | 1.00 | 0.56 | 0.38 | 0.39 | 0.55 | 0.37 | 0.36 |
| $X_{10}$ | 0.40 | 0.66 | 0.37 | 0.34 | 1.00 | 0.35 | 0.33 |
| $X_{11}$ | 1.00 | 0.68 | 0.36 | 0.35 | 0.40 | 0.40 | 0.35 |
| $X_{12}$ | 1.00 | 0.33 | 0.34 | 0.38 | 0.34 | 0.45 | 0.43 |
| $X_{13}$ | 1.00 | 0.33 | 0.34 | 0.43 | 0.34 | 0.48 | 0.57 |
| $X_{14}$ | 1.00 | 0.33 | 0.34 | 0.33 | 0.34 | 0.36 | 0.35 |
| $X_{15}$ | 0.43 | 0.33 | 0.34 | 0.35 | 0.34 | 0.53 | 1.00 |
| $X_{16}$ | 0.35 | 0.34 | 0.35 | 0.33 | 0.33 | 0.89 | 1.00 |
| $X_{17}$ | 0.35 | 0.35 | 0.33 | 0.33 | 0.34 | 0.95 | 1.00 |

Table 5. Comprehensive evaluation value

| Country | Comprehensive evaluation value | Rank |
|---|---|---|
| **U.S.** | 0.7709 | 1 |
| **China** | 0.5387 | 2 |
| **Finland** | 0.4988 | 3 |
| **Latvia** | 0.4751 | 4 |
| **South-Korea** | 0.4192 | 5 |
| **Mexico** | 0.3786 | 6 |
| **Romania** | 0.3495 | 7 |

## 5.2 Analysis of Results

It is widely accepted that developed countries tend to have high comprehensive evaluation value, including the United States, Finland, South-Korea and Latvia. However, Finland, South-Korea and Latvia have relatively low grey correlation coefficient in several certain indicators such as “Research funds on digital technologies” with heavy entropy weight, leading to a sharp drop in the overall score. Notably, Romania ranks last. This is because Romania’s digital education penetration is still relatively low. It can be found from the Table 4 that the number of enrolled students (number of undergraduates, graduate students and doctoral students) is particularly low.

In general, as a developing country, all digital education evaluation index values in Mexico seem to be tremendously low. The number of academic staff implementing online-teaching continues to decrease and their quality could not be guaranteed significantly. On the other hand, what is puzzling is that China ranks second as a developing country as well while the various evaluation index values have a relatively large gap, showing that China has an unbalanced level of resource development when the digital education system has obvious room for improvement.

In terms of that, Liu and Ru (2018) demonstrate that for the large number of students in China, the phenomena of uneven distribution in higher education resources are increasingly obvious. For example, the resources of scientific research personnel attracted by various schools and the financial resources invested by the state are uneven. Jiang (2020) discovers that only a few universities are considered to be highly efficient in digital R&D. Since schools without national key construction projects lack national financial support, the research efficiency is relatively low. According to the analysis of China's grey correlation coefficient, it can be found that the statuses of scientific research, university construction investment as well as university financial investment are far below the optimal sequence. Furthermore, the entropy weights of R&D personnel, university financial investment and digital research funding are relatively large. Therefore, we select China whose digital education system has room for amelioration as the object for further optimization and evaluation with focus on the mentioned five aspects.

# 6. MODEL OPTIMIZATION

COVID-19 pandemic has led to the confrontation of higher education system with enormous challenges. This necessitated the urgent transition from traditional teaching mode to e-learning. Therefore, redesigning a more appropriate model to evaluate the improvement of digital education is deemed necessary for the provision of quality online-education without compromising the established standards amidst rampant outbreaks. Specifically, the model is mainly optimized from five dimensions which were extensively improved during the pandemic, namely number of R&D personnel in digital education, research funds on digital technologies, infrastructure funds, inherent asset investment and financial investment provided by universities. For different aspects, we have selected adjusted indicators as the basis for optimization. The descriptions and explanations of each index are shown in Table 6.

Table 6. Descriptions and explanations of optimization basis index

| Optimization | Index | Symbol | Explanation |
|---|---|---|---|
| Number of R&D personnel in digital education | $X_6/X_2$ | A1 | It represents the selection probability of talents cultivated by higher education for scientific research. The larger the proportion, the more attractive the digita technology research work. |
| Research funds on digital technologies | $\frac{X_{10}}{(X_{16}+X_{17})}$ | A2 | The ratio of scientific research funding input to output of achievement. It indicates the effectiveness of scientific research funding. The smaller the input-outpu ratio, the more efficient the use of research funding on digital technologies. |
| Infrastructure funds | $X_7/X_1$ | A3 | Per capita infrastructure funding, inherit asset investment and university financial investment indicate the campus resources available to each student, whethe it is electronic facilities or online help. The more digita resources available to each student, the better. |
| Inherent asset | $X_{11}/X_1$ | A4 | |
| Financial investment provided by universities | $X_8/X_1$ | A5 | |

The original data is used to calculate the values of these five indicators in seven countries, and the results are shown in Table 7. According to published peer-reviewed literature, under the principle of realizability, we conduct following analysis and optimization.

A1: Developed countries pay more attention to technology and craftsmanship and have a sound intellectual property system. Funds are guaranteed in the transformation of scientific and technological achievements (Cheng et al. 2020). The lack of these resources in China has led to fewer people willing to continue to do research on digital education, especially under the the pressure of economic contraction during the pandemic. Therefore, we use the index value of the United States as a major technological power considering its value is not too high for China to reach the level.

A2: R&D expenditure has an important position in the digital world, and especially research funds of universities have a positive impact on employment (Baş & Canöz 2020). The original data demonstrates that

China's R&D expenditure is relatively high. In addition, it is found that China has the highest digital research funding input-output ratio, according to further optimization basis index calculations. Therefore, we maintain the value of China's research funding or keep with a little fluctuation.

A3&A4: In order to build a research university that is in line with international education and research standards, the Romanian government focuses on upgrading existing higher education institutions to adopt online-teaching. In the context of the Belt and Road Initiative, China-Romania multilateral education cooperation has become closer (Liu & Yan 2020). Therefore, it has realizable reference significance in terms of university's infrastructure construction and the proportion of available inherent asset resources.

A5: In many developed countries, government expenditure on higher education accounts for a particularly important part of government expenditure, which makes it one of the elements of national competitiveness. Therefore, we choose the number of indicators in the Finland as the optimized value. This is not only the standard of major developed countries, but it can also be achieved under China's economic conditions.

Based on the current situation of higher education system adapting to the pandemic, while the values of other indicators remain unchanged, we adjust the number of R&D personnel in digital education to grow threefold (0.18/0.06) when infrastructure funding, inherent asset investment and university financial investment respectively increase by 24%, 4.5 times and 3.2 times. In addition, it would be the relatively ideal state that the research funding could keep remind when we suggest that the quality of digital technological research output should be improved. The optimization of selected indicators is listed in Table 7 as well.

Table 7. Calculation results and optimization results

| Country | A1 | A2 | A3 | A4 | A5 |
|---|---|---|---|---|---|
| **U.S.** | 0.18 | 38634.40 | 609.40 | 16.93 | 8036.84 |
| **South-Korea** | 3.76 | 277321.98 | 42284.57 | 2439.35 | 6475.04 |
| **Romania** | 1.19 | 26087.95 | 74772.35 | 370.44 | 32116.82 |
| **Mexico** | 0.09 | 50964.19 | 3857.52 | 19.43 | 28104.57 |
| **Latvia** | 3.04 | 946737.27 | 1923.56 | 20.63 | 9718.12 |
| **Finland** | 0.39 | 720.99 | 13971.89 | 74.74 | 2470.46 |
| **China** | 0.06 | 240.46 | 1613.44 | 4.33 | 756.62 |
| **Optimization** | **0.18** | **240.96** | **3857.52** | **19.43** | **2470.46** |

According to the optimization index value calculated in the previous section, we change the value of $X_6$, $X_7$, $X_8$ and $X_{11}$ in turn. The obtained indicators are substituted into the entropy weight and grey comprehensive evaluation model to recalculate the score in turn, and the new score is compared with the original data to calculate the change rate. The results are shown in the Table 8.

Table 8. The score and rate of exchange of the optimized objective

| The optimized variable | Score | Rate of change |
|---|---|---|
| Initial value | 0.5388 | - |
| $X_6$ | 0.5565 | 3.29% |
| $X_7$ | 0.5462 | 1.37% |
| $X_8$ | 0.5691 | 5.62% |
| $X_{11}$ | 0.5706 | 5.90% |

It can be found that the original data in $X_6$, $X_7$, $X_8$ and $X_{11}$ are all improved. And the change of inherent assets has the greatest impact on the score of digital education system with a 5.90% increase in the evaluation score. The inherent assets of colleges and universities are the hardware guarantee and basic conditions for the running of digital education, which may determine the essential material basis of the development of digital education. Therefore, when facing teaching restrictions resulted from the COVID-19 pandemic, increasing the investment of inherent assets can continuously promote the ability of online-teaching and scientific research activities, thus increasing the output of digital education and optimizing the whole higher education system. Secondly, the score increasing rate of digital education system caused by the increase of university financial investment is 5.62%. Generally speaking, the sufficient balance of investment funds can provide more opportunities for recovering and developing digital education system during the pandemic. Meanwhile, it could also improve the income of online-teaching staff. As a consequence, the quality and quantity of academics would be positively affected to a certain extent, therefrom improving the education output and the overall level of higher education (Trostel, 2009).

## 7. SENSITIVITY ANALYSIS

To improve the accuracy of the data and avoid being affected by extreme values, this section takes the mean value of each variable to process. The comprehensive score is calculated by using grey comprehensive evaluation model. According to the basic principle of sensitivity analysis, this section mainly studies the sensitivity of a systems' state to the change of system parameters, which is equivalent to the method of controlling variables. The parameters needed for analysis are increased or decreased by a range, such as 5%, 10%, etc. When the control parameter value $X^k$ remains unchanged, the sensitivity response of overall function $F_j(X)$ to the variable $X^i$ can be calculated by the formula：

$$S_{ji} = \frac{\partial F_j(X)}{\partial X_i} \quad X = X^i \quad (j=1, 2, \ldots, m; i=1, 2, \ldots, n) \tag{8}$$

$|S_{ji}|$ is the sensitivity level of function $F_j(X)$ to $X_i$. The higher the value of $|S_{ji}|$, the more sensitive of the effect of $X^i$ on the function.

This section uses the monofactor change method of sensitivity analysis to test the response of higher education level to $X_6$, $X_7$, $X_8$, $X_{10}$ and $X_{11}$. Set the initial value of each variable as shown in Table 9.

Table 9. The initial value

| Variable | Value | Variable | Value |
|---|---|---|---|
| $X_1$ | 7263217 | $X_{10}$ | 17730716.35 |
| $X_2$ | 1982246 | $X_{11}$ | 23108306.06 |
| $X_3$ | 320913 | $X_{12}$ | 548959 |
| $X_4$ | 17.5083 | $X_{13}$ | 537064 |
| $X_5$ | 2286878 | $X_{14}$ | 53994 |
| $X_6$ | 31899 | $X_{15}$ | 408624 |
| $X_7$ | 11588547175 | $X_{16}$ | 863610.8333 |
| $X_8$ | 5789665133 | $X_{17}$ | 110129.8333 |
| $X_9$ | 3104.3226 | | |

Firstly, $X_6$ is selected for sensitivity analysis, while keeping other variables unchanged. This index is set to be increased and decreased by 5%, 10% and 20% respectively. Each time the parameters are changed, the model is run and the corresponding digital higher education level score is output as the basis of sensitivity analysis. The calculation process of other variables is similar to the sensitivity calculation process of $X_6$, according to which the sensitivity coefficients of each factor can be calculated respectively. The results are shown in the Table 10.

Table 10. The Sensitivity coefficients of selected variables

| | Sensitivity coefficients | | | | | |
|---|---|---|---|---|---|---|
| **Parameters** | **-20%** | **-10%** | **-5%** | **5%** | **10%** | **20%** |
| $X_6$ | -0.184 | -0.146 | -0.0739 | 0.0760 | 0.154 | 0.137 |
| $X_8$ | -0.060 | -0.045 | -0.015 | 0.015 | 0.031 | 0.061 |
| $X_7$ | -0.045 | -0.018 | -0.009 | 0.007 | 0.014 | 0.025 |

The sensitivity coefficients of digital technology research funds and inherent assets are close to 0, which indicates that these two variables have little influence on the digital higher education system. The changes of $X_6$, $X_7$ and $X_8$ are in direct proportion to the changes of the level of higher education system, which shows that with the increase of input in these aspects during the COVID-19 pandemic, the higher education system has a certain improvement. Among all the selected variables, $X_6$ has the greatest impact. The higher education system has a greater change in $X_6$, and the sensitivity order is $|S_{X_6}|>|S_{X_8}|>|S_{X_7}|$, while the effects of $X_{10}$ and $X_{11}$ are not obvious. Controlling other variables unchanged, we make the value of $X_6$ and $X_8$

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fluctuate by 20% and calculate the corresponding score of higher education level after fluctuation. Then we draw the diagram between $X_6/X_8$ and higher education level by using MATLAB software. As shown in figure 1 and figure 2, the more intuitive performance of the improvement of higher education level is more sensitive to these two variables. Therefore, during the outbreak of the pandemic, the increasing input on the number of R&D personnel in digital education, university financial investment and infrastructure investment may have a positive influence on higher education, while that of promoting the digital technology research funds and inherent assets is relatively ineffective.

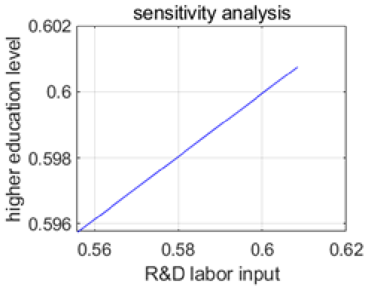


Figure 1. Sensitivity of $X_6$

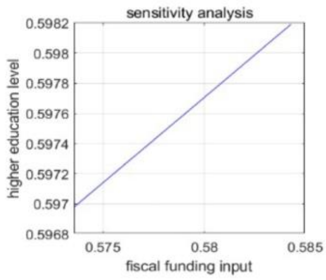


Figure 2. Sensitivity of $X_8$

## 8. VALIDATING THE MODEL

Reliability refers to the consistency of the evaluation results, that is, how many people can trust the evaluation score. This section mainly selects the reliability test method $\mathrm{L.J.\,Cronbach}-\alpha$, which tests the reliability based on the consistency of all internal items. The mathematical model is:

$$\alpha = \frac{k}{k-1}\left(1-\frac{\sum S_i^{\,2}}{S_k^{\,2}}\right) \qquad (9)$$

K is the number of indicators. $S_i^{\,2}$ is the variance of the score of an evaluation index. $S_k^{\,2}$ is the variance of the total score. When α is between 0.95 and 0.99, the reliability of the index system is high, but it is not common. It is usually a good result when α is between 0.8 and 0.94. It can be used when α is between 0.7 and 0.79. However, if α is below 0.7, it indicates that the error is large, and the index system cannot be used.

We use SPSS25.0 statistical software to obtain the reliability analysis results according to the score coefficient matrix, as shown in Table 11 and Table 12.

Table 11. Reliability coefficient table

| **Reliability Statistics** | | |
|---|---|---|
| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
| .817 | .837 | 17 |

Table 12. Results of variance analysis

| **ANOVA** | | | | | | |
|---|---|---|---|---|---|---|
| | | Sum of Squares | df | Mean Square | F | Sig |
| Between People | | 5.655 | 11 | .514 | | |
| Within People | Between Items | 5.273 | 16 | .330 | 3.499 | .000 |
| | Residual | 16.577 | 176 | .094 | | |
| | Total | 21.849 | 192 | .114 | | |
| Total | | 27.504 | 203 | .135 | | |
| Grand Mean = .367569756356655 | | | | | | |

It can be seen from Table 11 that the reliability coefficient α of the evaluation system is 0.817, and the standardized α is 0.837, which indicates that the evaluation system has high homogeneity reliability and the evaluation results have high reliability. In addition, in the results of ANOVA in Table 12, F is 3.499, P is less than 0.001, which is quite significant. It indicates that the re-use effect of the digital education evaluation system is good.

## 9. CONCLUSION

Economic and cultural globalization has ushered in a new era in higher education. Because of its immersion in knowledge, higher education plays a particularly important role in global knowledge economies. However, the current Covid-19 pandemic is making it trapped in a development burden. To cope with the challenges posed by this crisis, transformation from traditional face-to-face teaching to online-teaching should be timely implemented in higher education system. This research offered insightful analysis and established grey comprehensive evaluation model based on entropy method, which followed by model optimization according to the improvement of higher education system due to the pandemic's influence. Although COVID-19 has restricted mobility, the research result promotes the development work and internationalization of higher education institutions, which could serve as a credible reference for the higher education reform. In the future, more cross-border e-learning will be offered and implemented. The expansion of e-learning across national borders implements internationalization in an economic and efficient way. In particular, the study is likely to stimulate discussion with business representatives on issues related to employability as well as on the achievement of lifelong learning objectives.

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