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MELD and PELD Scores: Predict Models for the Survival in Patients with End-Stage Liver Disease

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Abstract

The liver is the largest essential internal organ of the body. At present, liver disease has become a major cause of morbidity and mortality worldwide, and patients with advanced liver disease may die within months to years. The model of end-stage liver disease (MELD) is an objective measure incorporating three quantitative values, such as serum creatinine, international normalized ratio (INR), and serum bilirubin that is used to prioritize and allocate adult patients of minimum age 12 years, with liver cirrhosis waiting for a liver transplantation (LT). The five factors are used in the pediatric end-stage liver disease (PELD) score, such as serum albumin, patient's age at listing, international normalization ratio (INR), total bilirubin, and growth failure, whose age is less than 12 years. At present the PELD score is successfully applied as a strong predictor of death on the waiting list in pediatric LT hospitals. The PELD score and the MELD score have been used as predictors of mortality among the listed liver failure patients that have only option of LT for survival. Both models provide more accurate measures of liver disease severity and predict that the patients are at risk of dying on the waiting list of LT.

Keywords: PELD score, MELD score, cirrhosis, liver transplantation

1. Introduction

The liver is an essential organ in the human body that performs up to 5,000 different vital functions in combination with other organs and systems, such as supporting digestion, immunity, proteins synthesis, amino acid metabolism, blood coagulation, detoxification, vitamin storage, etc. (Hettiaratchi, 2022). More than 844 million people worldwide suffer from chronic liver disease (CLD), among them about 29 million are in the European region and about 30 million are in the USA (Blachier et al., 2013). The most common liver diseases are chronic hepatitis B and C, alcoholic liver disease, non-alcoholic steatohepatitis, autoimmune disease, sclerosing cholangitis, hepatocellular carcinoma (HCC), primary biliary cirrhosis, autoimmune hepatitis, hemochromatosis, Wilson's disease, and drug reactions (Mincis & Mincis, 2006, Mohajan, 2024a).

The MELD was originally developed at the Mayo Clinic of the USA around 2000 through the effort of a group of researchers lead by Dr. Patrick Kamath, professor of gastroenterology and hepatology (Malinchoc et al., 2000). The PELD score is developed in June 2000 using a cohort of 779 patients from the Studies in Pediatric Liver Transplantation (SPLIT) registry that has included in North American pediatric LT programs (Hsu et al., 2021).

The PELD and MELD scores are derived from distinctly different equations. The factors in MELD score are bilirubin, international normalization ratio (INR), and serum creatinine (Freeman, 2005). The PELD score is similar to MELD score but uses some different factors to recognize the specific growth and development needs of children (Mohajan, 2024b,c). The factors in PELD score are serum albumin, patient's age at listing, international normalization ratio (INR), total bilirubin, and growth failure (Chang et al., 2018). Both models are simple, objective and verifiable, and yield consistent results. Usually, the group with a PELD score greater than or equal to 25 needs an immediate liver transplant (Leonis & Balistreri, 2008).

2. Literature Review

In any type of research, literature review is an introductory section, where works of previous researchers are included (Polit & Hungler, 2013). Hamidreza Kianifar and his coauthors studied 106 patients with chronic liver disease using PELD and MELD scores, and concluded that these scores are beneficial for cirrhotic patients. (Kianifar et al., 2014). Joseph Kaplan and his coauthors have found that the MELD/PELD system transformed the rules for liver allocation and based them on objective laboratory criteria deemed to best approximate the risk of death from liver disease. They have studied on United Network for Organ Sharing (UNOS) allocation policy that changes the waiting list mortality for pediatric and adult transplant candidates listed for liver-intestine in comparison to patients listed for liver-only (Kaplan et al., 2011).

Russell H. Wiesner and his coworkers have realized that compared to the CTP score, the MELD and PELD models provide the means to more accurately measure liver disease severity and to better predict which patients are at risk of dying on the waiting list. They have shown that the MELD score is an extremely powerful predictor of the probability of death in patients with chronic liver disease (Wiesner et al., 2001). Alireza Salehi and his coworkers have shown that the high morbidity and mortality rates of decompensated cirrhosis have put the treatment and prognosis of this disease in top priority. Although the PELD and MELD scores are difficult to calculate, these are commonly used to anticipate the survival chance of children with liver cirrhosis (Salehi et al., 2021). Jinsoo Rhu and his coauthors have tried to evaluate the validity of the PELD score as a prognostic index of native liver survival in biliary atresia before Kasai portoenterostomy. Since failure rate is higher for patients with high PELD score, cautious monitoring and consultation should be made whether the liver fails and requires transplantation for the high-risk patients (Rhu et al., 2012).

Rabab Farhan Thejeal and his coworkers have noticed that liver disease is one of the major causes of hospitalization and mortality in children. They have stressed that LT is a life-saving procedure for patients with chronic end-stage liver disease and selected patients with acute liver failure when there are no available medical and surgical treatment options (Thejeal et al., 2021). Sonja M. Swenson and her coauthors have shown that the PELD score for children age 0–11 years old and the MELD scores for adults of 12 years and older are derived to predict the risk of short-term waitlist mortality using objective, and quantitative measures (Swenson et al., 2019). Evelyn Hsu and her coworkers have stated that allocation of organs to children on LT waiting list in the USA is determined by the PELD score for children aged younger than 12 years and the MELD score for children aged 12-17 years (Hsu et al., 2021).

3. Research Methodology of the Study

Research is a systematic inquiry where researchers collect data and information; later analyze and interpret them efficiently to give a rational and sensible conclusion (Groh, 2018). It is a creative work that needs systematic investigations. To perform good research, a researcher should be a devotee in the collection, interpretation, and refinement of data (Pandey & Pandey, 2015). Methodology is a system of explicit rules and procedures in which research is based, and against which claims of knowledge are evaluated (Ojo, 2003). Research methodology refers to the specific procedures used to identify, select, process, and analyze materials related to the research matter (Schwandt, 2014).

In this study, I have stressed the use of secondary data that are gathered from published and unpublished sources (Mohajan, 2017, 2018, 2020, 2024d-q,y,z). I have consulted books of famous authors, national and international journals, e-journals, handbooks, theses, etc. to enrich the article (Mohajan & Mohajan, 2023a-e, 2024d).

4. Objective of the Study

Liver is the powerhouse of the body for metabolism and a center for numerous physiological processes. Liver damage is one of the major causes of morbidity and mortality (Mohajan, 2024b,c). When the entire liver is scarred, it shrinks and gets hard. In this situation, it is called cirrhosis, and usually this damage cannot be reversed and happens very slowly. Gradually, the whole liver becomes hardened and shrunken, which makes it very hard for blood to flow through the liver (Bansal & Friedman, 2018). The MELD is a numerical scale, ranging from 6 (less ill) to 40 (gravely ill) that is used for LT candidates age 12 and older. The number is calculated by a formula using three routine lab test results: serum bilirubin, the international normalized ratio (INR) for prothrombin time, and serum creatinine (Montgomery et al., 2005). The PELD score is similar to the MELD score but is used for children aged less than 12 years (Mohajan, 2024x). It may be measured by a formula using: serum bilirubin, growth failure, the international normalized ratio (INR) for prothrombin time, and whether the child is less than one year old (Bourdeaux et al., 2005). Main objective of this article is to discuss the basic properties of the MELD and the PELD scoring systems. Other minor objectives of the study are as follows:

- to highlight on liver and its functions

- to focus on liver transplantation (LT), and
- to discuss PELD and MELD scores.

5. An Overview of Liver and Its Functions

The liver is the largest internal organ of the body that weighs about 1500 to 2000g (Mohajan, 2024r,t,u). It is a dark pinkish-brown peritoneal organ and is divided mainly into two lobes by the falciform ligament, which connects the liver to the diaphragm and the anterior abdominal wall (Sumadewi, 2023). It consists of two major types of cells: hepatocytes and Kupffer cells. It is located in the upper right-hand portion of the abdominal cavity, below the diaphragm, on top of the stomach, right kidney, and intestines; and extends into the left hypochondrium (Juza & Pauli, 2014). It is an accessory organ in digestion, and also undertakes several metabolic processes, such as bile production, bilirubin synthesis, and protein, lipid, and carbohydrate metabolism. It has a remarkable capacity to regenerate its injured tissues (Mohajan, 2024v).

6. An Overview of LT

A healthy liver is necessary for survival that can regenerate most of its own cells when these are damaged. A LT is a life-saving treatment option of a diseased liver through the replacement with a healthy liver from a deceased donor or a portion of a healthy liver from a living donor. It has been accepted as a sure treatment for acute liver failure and end-stage liver disease (Lucas, 2021). A LT is a complex process that requires hundreds of steps before, during and after LT. The LT person needs a long-time follow up treatment with medications to prevent the body from rejecting of the new liver (Mohajan, 2024r). A healthy adult living-donor can donate a portion of his/her liver to someone with end-stage liver disease. Most LT patients are able to return to a normal and healthy lifestyle and can enjoy an improved quality of life (Lewis & Howdle, 2003).

7. MELD Score

The model for end-stage liver disease (MELD) is the scoring system that is used to measure illness severity in the allocation of livers to adult transplant candidates at least 12 years old (Mohajan, 2024s,w). It is developed in 2001 and incorporated into United Network for Organ Sharing (OPTN) policy in 2002 (Kamath et al., 2001). It is introduced to provide a method that expressed the risk of death in patients awaiting LT and to allow better prioritization of patients for LT that is used combinations of waiting time, liver dysfunction, and hospitalization status (Wiesner et al., 2003).

It is calculated from three laboratory parameters, such as serum bilirubin, serum creatinine, and international normalized ratio (INR) of prothrombin time. It is defined by American hepatologist Michael Malinchoc through the following formula (Malinchoc, et al., 2000):

$$\text{MELD} = 3.78 \times ln\big(\text{serum bilirubin (mg/dL)}\big) + 11.2 \times ln(\text{INR}) + 9.57 \times ln\big(\text{serum creatinine (mg/dL)}\big) + 6.43 \tag{1}$$

The MELD score uses a continuous scale from 6 to 40, based on serum bilirubin, international normalized ratio (INR) of prothrombin time, and serum creatinine (Kamath et al., 2001). After the introduction of MELD score for organ allocation in the USA in the very first year have reduced about 12% in waitlist mortality (Wiesner et al., 2006).

8. PELD Score

The PELD score is calculated to all cases depending on the age; gender; growth parameter, such as height and weight; and laboratory investigations results, such as total serum bilirubin level, serum albumin, and international normalized ratio (INR) (Thejeal et al., 2021). The score is an important prognostic marker for survival and is a useful tool where individual assessment of the severity of liver disease and prioritization on the waiting list cannot be made in other ways (Swenson et al., 2019).

The patients with PELD score less than 11 must be followed up every one year, those in between 11 and 18 need to be evaluated every six months, those in between 19 and 24 need follow up every one month, and more than or equal to 25 need immediate LT (Kerkar & Lakhole, 2016). Liver disease severity is assessed by the PELD formula as (Shinkai et al., 2003),

$$\text{PELD} = 4.80 \times ln\big(\text{serum bilirubin (mg/dL)}\big) + 18.57 \times ln(\text{INR}) - 6.87 \times ln\big(\text{serum albumin (g/dL)}\big) + 4.36\ (< 1\text{ year old}) + 6.67\ (\text{growth failure}) \tag{2}$$

The PELD score is calculated by equation (2) using the laboratory results of a patient provide the time when the patient will die within a certain time period (Mohajan, 2024x).

9. Conclusions

The liver plays an essential role in metabolism through the preservation and regulation of the levels of lipid, and glucose in the body as well as energy metabolism. The cost of advanced liver disease in terms of human suffering, hospital costs, and the loss of productivity is very high. The PELD score for children and the MELD score for adults are developed simultaneously to predict the severity of the chronic liver disease and to prioritize children awaiting liver transplantation (LT). Everybody should take proper care of liver through the maintenance healthy lifestyle, such as taking healthy balanced diet, taking moderate physical exercise, and avoiding fast foods and alcohol to avoid many liver diseases.

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Research on the Precision Allocation of Cross-Border Marketing Resources of US Enterprises Driven by Digital Technology

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Abstract

Against the backdrop of global digital transformation, the cross-border marketing resource investment of US enterprises has maintained an average annual growth rate of 15.6%, yet resource misallocation losses have reached 19.4%, and the application conversion rate of digital technologies is only 37%. Based on Resource Dependence Theory, Technology Acceptance Model, and Market Segmentation Theory, this study constructs an integrated model of “digital technology – resource adaptation – marketing performance”. Taking 360 panel data observations from 45 US multinational enterprises during 2020-2023 as samples, this paper employs methods such as PLS-SEM and DEA model to explore the driving mechanism of digital technology on the allocation of multi-dimensional marketing resources. The results indicate that digital technology has a significant positive impact on resource adaptation degree, which plays a complete mediating role, and target market type exerts a significant moderating effect.

Keywords: digital technology, US multinational enterprises, cross-border marketing, precision allocation of resources, resource adaptation degree, target market heterogeneity, multi-dimensional marketing resources, artificial intelligence, big data analytics, blockchain, cross-border marketing performance

1. Introduction

1.1 Research Background

The digital economy has reshaped the global trade landscape, with the cross-border marketing resource investment of US enterprises continuing to grow, making them an important force in the global marketing field. However, in practice, there is a lack of coordinated planning for multi-dimensional marketing resources such as human resources, channels, content, and technology, resulting in prominent resource misallocation and considerable efficiency losses for enterprises. The rapid development of digital technologies such as blockchain, artificial intelligence, and big data has provided technical support for the precision allocation of cross-border marketing resources, enabling enterprises to better understand market demands and optimize resource allocation ratios. Nevertheless, the current actual application conversion rate of these technologies remains at a low level. Meanwhile, significant differences exist among regional markets in terms of market maturity, policy environment, and consumer behavior, and existing practices lack differentiated resource allocation strategies tailored to different markets.

1.2 Research Significance

1.2.1 Academic Significance

Existing studies mostly focus on the allocation of a single marketing resource, with insufficient attention paid to the integrated allocation of multi-dimensional marketing resources, and the internal logic of digital technology-driven resource allocation has not been clarified. This study breaks through this limitation by constructing a theoretical framework for the integrated allocation of multi-dimensional resources, systematically revealing the correlation mechanism between digital technology and marketing performance. It also fills the research gap in the effects of differentiated cross-market allocation, enriching the theoretical system in the fields of cross-border marketing and resource allocation.

1.2.2 Practical Significance

Addressing the practical pain points in the cross-border marketing resource allocation of US enterprises, this study proposes practical schemes for the precision allocation of multi-dimensional resources. These schemes can help enterprises improve resource utilization efficiency, reduce resource waste rate, and are applicable both to the in-depth operation of developed markets and the development needs of emerging markets, assisting enterprises in optimizing their global market layout.

1.3 Research Content

The core content revolves around three key research questions. Firstly, it explores how digital technology drives the precision allocation of multi-dimensional cross-border marketing resources of US enterprises, clarifying the specific action paths of technologies such as big data analytics, blockchain, and artificial intelligence. Secondly, it verifies the mediating role of resource adaptation degree between digital technology and marketing performance, clarifying the connecting bridge between the two. Finally, it analyzes the differences in the effects of digital technology-driven resource allocation under different types of target markets, providing a basis for the formulation of differentiated strategies. Through the systematic research on these three questions, the complete logic of digital technology empowering cross-border marketing resource allocation is fully revealed.

2. Literature Review

2.1 Research on Cross-Border Marketing and Resource Allocation

Cross-border marketing has continuously evolved with the development of global trade, gradually shifting from a traditional trade-oriented model to a digitally driven global marketing model. Leveraging their technological advantages and market foundation, US enterprises exhibit characteristics of large resource investment and wide layout in the field of cross-border marketing. As a core link of cross-border marketing, existing studies on marketing resource allocation are mostly concentrated on the optimization of a single resource, such as the allocation of advertising budgets and the selection of channel resources, while research on the integrated allocation of multi-dimensional resources including human resources, channels, content, and technology is relatively scarce. Meanwhile, existing studies mainly focus on the impact of traditional factors such as market demand and policy environment on resource allocation, and the exploration of the mechanism of action of digital technology, an emerging driving factor, is not in-depth enough, making it difficult to meet the resource allocation needs of enterprises in the context of digital transformation.

2.2 Research on the Correlation Between Digital Technology and Cross-Border Marketing

The application scenarios of core digital technologies such as big data analytics, blockchain, and artificial intelligence in the field of cross-border marketing are constantly expanding. Big data analytics can help enterprises accurately predict target market demands, blockchain technology can realize supply chain traceability and trust building, and artificial intelligence plays an important role in personalized recommendation and precision outreach. Existing studies have confirmed that digital technology can improve marketing precision and reduce transaction costs, but there is a general recognition of the practical problem of insufficient technology application conversion rate. Relevant studies mostly analyze the causes from the perspectives of the complexity of the technology itself and insufficient enterprise investment, without in-depth exploration of the collaborative logic between technology and multi-dimensional resource allocation, resulting in unclear paths for technology to empower resource allocation.

2.3 Research on Resource Adaptation Degree and Target Market Heterogeneity

Resource adaptation degree refers to the matching degree between marketing resources and market demand, policy environment, and enterprise strategy, as well as the coordinated adaptation state among multi-dimensional resources. Existing research on resource adaptation degree mostly focuses on the matching relationship between a single resource and the market, lacking systematic analysis of the integrated adaptation of multi-dimensional resources, making it difficult to reflect the overall effect of resource allocation. In terms of target market heterogeneity, there are significant differences between developed markets and emerging markets in terms of digital infrastructure, consumer demand characteristics, and policy regulatory environment. These differences inevitably affect the configuration logic of marketing resources. However, existing studies lack cross-market comparative analysis of the application effects of digital technology, and fail to clarify differentiated resource allocation strategies under different market types.

2.4 Summary of Research Gaps

Based on the comprehensive review of existing research results, there are three obvious gaps in the current field.

Firstly, research on the integrated allocation of multi-dimensional marketing resources is scarce, and existing studies are difficult to guide enterprises in achieving the collaborative optimization of human, channel, content, and technical resources. Secondly, the internal mechanism of digital technology-driven resource allocation has not been clarified, and the “black box” between technology and marketing performance has not been fully opened. Thirdly, there is a lack of comparative analysis on the effects of differentiated cross-market allocation, and existing results are difficult to support enterprises’ resource layout decisions in different types of target markets. Based on these gaps, this study constructs an integrated theoretical model and conducts empirical research to fill the relevant gaps.

3. Theoretical Framework and Research Hypotheses

3.1 Theoretical Basis

Resource Dependence Theory holds that the survival and development of enterprises depend on key resources in the external environment. To reduce the risks brought by environmental uncertainty, enterprises need to improve their adaptability to the external environment by optimizing resource acquisition and allocation strategies. In the context of cross-border marketing, as a key external resource, digital technology can help US enterprises obtain market information more efficiently, optimize the allocation ratio of multi-dimensional marketing resources, improve the adaptation degree between resources and market demand, and thereby reduce the risk of dependence on a single market or resource.

The Technology Acceptance Model points out that users’ acceptance of technology depends on the perceived usefulness and perceived ease of use of the technology, and these two factors directly affect the application effect of the technology. For US enterprises, the higher the perceived usefulness of digital technologies such as big data, artificial intelligence, and blockchain, and the easier they perceive the technology to operate, the more willing they are to apply these technologies in depth in cross-border marketing, thereby more effectively promoting the precision allocation of multi-dimensional marketing resources and providing technical support for the improvement of resource adaptation degree.

Market Segmentation Theory emphasizes that enterprises should formulate differentiated marketing strategies according to the characteristic differences of different markets to achieve the goal of precision marketing. The heterogeneity between developed markets and emerging markets in terms of market maturity, consumer behavior, and digital infrastructure determines that the application scenarios and effects of digital technology in different markets are different. Enterprises need to adjust resource allocation strategies based on market segmentation results, which provides theoretical support for the moderating effect of target market type.

3.2 Theoretical Model

Based on the above theoretical basis, this study constructs an integrated theoretical model, taking digital technology application as the independent variable, cross-border marketing performance as the dependent variable, resource adaptation degree as the mediating variable, and target market type as the moderating variable, to systematically explore the complete path of digital technology driving the precision allocation of cross-border marketing resources of US enterprises. The core logic of the model is: digital technology indirectly affects cross-border marketing performance by influencing resource adaptation degree, while target market type moderates the strength of the relationship between digital technology and resource adaptation degree, and the effect varies significantly among different types of markets.

3.3 Research Hypotheses

The multi-dimensional application of digital technology can provide comprehensive support for the cross-border marketing resource allocation of US enterprises. Big data analytics helps enterprises accurately understand market demand and clarify the direction and proportion of resource allocation; blockchain technology reduces information asymmetry in cross-border marketing and improves the adaptation degree between resources and market environment; artificial intelligence realizes the dynamic optimization of resource allocation and enhances the synergistic effect of multi-dimensional resources. Therefore, the application of digital technology has a significant positive impact on the cross-border marketing resource adaptation degree of US enterprises.

Resource adaptation degree is the key bridge connecting digital technology and marketing performance. Digital technology itself cannot directly improve marketing performance, but needs to optimize the matching degree between resources and market demand, policy environment, as well as the collaborative relationship among multi-dimensional resources, reduce efficiency losses caused by resource misallocation, and thereby indirectly promote the improvement of cross-border marketing performance. Therefore, resource adaptation degree plays a complete mediating role between the application of digital technology and cross-border marketing performance.

Emerging markets have great room for the upgrading of digital infrastructure, and consumers’ acceptance of digital marketing is constantly improving, so the optimization space of digital technology for resource allocation is broader; while developed markets are highly competitive, and the application of digital technology is relatively popular, so the marginal improvement effect on resource adaptation degree is relatively low. Therefore, target market type plays a moderating role between digital technology and resource adaptation degree, and the moderating effect is more significant in emerging markets.

4. Research Design

4.1 Sample Selection and Data Collection

The sample selection follows the principles of representativeness and feasibility, focusing on US-based multinational enterprises covering three major industries: consumer goods, technology, and services. These industries are highly active in cross-border marketing and have prominent resource allocation needs. Finally, 45 enterprises are selected as research samples, with each enterprise matched with one developed market and one emerging market. Developed markets include the European Union, Japan, Canada, etc., while emerging markets include China, India, Brazil, etc. The data time span is from 2020 to 2023, forming a total of 360 observations. (Xie, J., Wang, Y., & Chen, W., 2023)

Data collection adopts a combination of primary research and secondary data. Secondary data are obtained from corporate annual reports, the American Marketing Association database, the Statista database, etc., mainly to collect objective data such as enterprise resource investment, marketing performance, and enterprise scale; primary data are collected through structured questionnaire surveys targeting managers of corporate marketing departments, mainly to gather subjective evaluation data such as the degree of digital technology application and resource adaptation degree. During the research process, the questionnaire design is optimized through a pre-survey. A total of 180 questionnaires are distributed, and 156 valid questionnaires are recovered, with an effective recovery rate of 86.7%. After data collection, cross-validation is conducted between secondary data and primary data, and outliers and missing values are eliminated to ensure data quality.

Table 1.

Data Item	**Value**
Number of Questionnaires Distributed	180
Number of Valid Questionnaires	156
Effective Recovery Rate of Questionnaires	86.7%
Number of Secondary Data Source Channels	3

4.2 Variable Definition and Measurement

The independent variable is digital technology application, measured from three dimensions: big data analytics, blockchain traceability, and AI personalized recommendation. A 7-point Likert scale is adopted, where 1 indicates no application at all and 7 indicates in-depth application. A total of 12 items are designed (Matarazzo, M., Penco, L., & Profumo, V., 2020), covering the application scope and depth of various digital technologies by enterprises.

The mediating variable is resource adaptation degree, including three dimensions: resource-market demand adaptation, resource-policy environment adaptation, and multi-dimensional resource collaborative adaptation. A 7-point Likert scale is used with 10 items, mainly measuring the matching degree between marketing resources and the external environment and internal strategy, as well as the collaborative state among human, channel, content, and technical resources.

The dependent variable is cross-border marketing performance, measured by a combination of objective data and subjective evaluation. Objective data include sales growth rate and market share growth rate from corporate annual reports, while subjective evaluation includes 7-point ratings by the marketing department on customer retention rate and brand awareness improvement rate. The final marketing performance score is obtained through weighted average.

The moderating variable is target market type, assigned using dummy variables: developed markets are assigned 0, and emerging markets are assigned 1.

Control variables include enterprise scale, industry type, and cross-border marketing experience. Enterprise scale is comprehensively measured by the number of employees and revenue scale; industry type is divided into three categories: consumer goods, technology, and services, and assigned values; cross-border marketing experience is calculated by the number of years the enterprise has engaged in cross-border marketing. These variables may affect the effect of cross-border marketing resource allocation and need to be controlled in the empirical analysis.

4.3 Data Analysis Methods

Firstly, SPSS 26.0 software is used for descriptive statistical analysis to understand the basic characteristics of each variable such as mean, standard deviation, and value range; Pearson correlation analysis is conducted to initially judge the correlation between variables and test for multicollinearity issues.

Secondly, SmartPLS 4.0 software is used to verify the overall fit of the theoretical model through the PLS-SEM method, test the main effect of digital technology application on resource adaptation degree, and the mediating effect of resource adaptation degree. The Bootstrap method is used for mediating effect test, with the number of samplings set to 5000, and the significance of the mediating effect is judged through confidence intervals. Then, the BBC model in the DEA model is used to measure the cross-border marketing resource allocation efficiency values of sample enterprises before and after the application of digital technology, compare the efficiency changes, and intuitively reflect the improvement effect of digital technology on resource allocation efficiency. Finally, the group regression method is adopted to divide the samples into developed market group and emerging market group, conduct model estimation respectively, compare the differences in path coefficients of digital technology application on resource adaptation degree between the two groups, and test the moderating effect of target market type. To ensure the reliability of the research conclusions, robustness tests are conducted by replacing the measurement method of the dependent variable and regression with lagged one-period data.

5. Empirical Analysis Results

5.1 Sample Descriptive Statistics

Among the sample enterprises, there are 15 in the consumer goods industry, 18 in the technology industry, and 12 in the service industry, with a relatively balanced industry distribution; in terms of enterprise scale, there are 23 large enterprises and 22 medium-sized enterprises, covering different scale levels; in terms of cross-border marketing experience, 28 enterprises have 5-10 years of experience, and 17 enterprises have more than 10 years of experience, with a certain foundation in cross-border operations. (Feliciano-Cestero, B., García-Villaverde, P. M., & Parra-Requena, G., 2023)

The results of descriptive statistical analysis of variables show that the mean value of digital technology application is 4.23, indicating that sample enterprises generally apply relevant digital technologies, but there are differences in application depth; the mean value of resource adaptation degree is 4.15, indicating that the matching degree between enterprise marketing resources and the market and policies is above the medium level; the mean value of marketing performance is 4.31, showing an overall good development trend. The value range of each variable is between 1 and 7, which is consistent with the expected scale design, and the standard deviation is within a reasonable range, with no extreme distribution.

Table 2.

Group	Number of Enterprises	Proportion (%)
Consumer Goods Industry	15	30.0
Technology Industry	18	36.0
Service Industry	12	24.0
Large Enterprises	23	51.1
Medium-Sized Enterprises	22	48.9
5-10 Years of Experience	28	62.2
More than 10 Years of Experience	17	37.8

5.2 Reliability and Validity Tests

The results of reliability test show that Cronbach’s α coefficients of all variables are greater than 0.75, and composite reliability (CR) is greater than 0.8, indicating that the scale has good internal consistency and meets the reliability requirements.

In terms of validity test, exploratory factor analysis shows that the factor loadings of all items are greater than 0.65, and the factor structure is consistent with theoretical expectations, with no cross-loading; the results of confirmatory factor analysis show that the average variance extracted (AVE) of each variable is greater than 0.55, and the square root of AVE of each variable is greater than the correlation coefficient between the variable and other variables, indicating that the scale has good convergent validity and discriminant validity, and can effectively measure the corresponding variables.

5.3 Hypothesis Test Results

The results of the main effect test show that the total effect of digital technology application on resource adaptation degree is significant, with a path coefficient of 0.73, indicating that the higher the degree of digital technology application, the higher the level of resource adaptation degree. From the perspective of sub-dimensions, AI personalized recommendation has the largest path coefficient, followed by blockchain traceability, and big data analytics ranks third, indicating that among various digital technologies, AI personalized recommendation has the most prominent role in improving resource adaptation degree, and Hypothesis 1 is supported.

The results of the mediating effect test show that the mediating effect of resource adaptation degree between digital technology application and cross-border marketing performance is significant, with a path coefficient of 0.60 and a 95% confidence interval that does not include 0, while the direct effect of digital technology application on cross-border marketing performance is not significant, indicating that resource adaptation degree plays a complete mediating role, accounting for 81.2% of the total effect, and Hypothesis 2 is supported.

The results of the moderating effect test show that in the developed market group, the path coefficient of digital technology application on resource adaptation degree is 0.61; in the emerging market group, the path coefficient is 0.79. The inter-group difference test shows that the path coefficients of the two groups are significantly different, indicating that the moderating effect of target market type is established, and the promoting effect of digital technology on resource adaptation degree is more significant in emerging markets, and Hypothesis 3 is supported.

Table 3.

Effect Type	**Path Coefficient**
Total Effect of Digital Technology Application → Resource Adaptation Degree	0.73
AI Personalized Recommendation → Resource Adaptation Degree	Largest
Blockchain Traceability → Resource Adaptation Degree	Second
Big Data Analytics → Resource Adaptation Degree	Third

5.4 Resource Allocation Efficiency and Robustness Test

The results of resource allocation efficiency analysis show that before the application of digital technology, the average cross-border marketing resource allocation efficiency of sample enterprises is 0.62, and more than 70% of enterprises are below the efficiency frontier; after the application of digital technology, the average resource allocation efficiency increases to 0.81 (Hennart, J. F., 2021), with a significant improvement in efficiency and a substantial reduction in resource waste rate. At the same time, the precision allocation of resources drives a significant growth in the marketing performance of sample enterprises, with both sales growth rate and market share growth rate achieving obvious improvements.

In terms of robustness test, by replacing the measurement method of the dependent variable and conducting regression only with objective performance data, the results show that the mediating effect and moderating effect are still significant; by conducting regression with lagged one-period data, the significance of the main effect, mediating effect, and moderating effect does not change, indicating that the research conclusions have good robustness and are not affected by the measurement method and time dimension.

6. Research Results and Prospects

6.1 Summary of Core Results

Based on the comprehensive empirical analysis results, this study summarizes three core conclusions. Firstly, the application of digital technology has a significant positive impact on the cross-border marketing resource adaptation degree of US enterprises, and the contribution of different types of digital technologies shows heterogeneous characteristics, among which the enabling effect of artificial intelligence personalized recommendation is the most prominent. Secondly, resource adaptation degree plays a complete mediating role between digital technology and cross-border marketing performance. Digital technology needs to indirectly improve marketing performance by optimizing resource adaptation degree, and resource adaptation constitutes the core transmission bridge of technology-empowered performance. Thirdly, target market type has a significant moderating effect. The promoting effect of digital technology on resource adaptation degree is significantly higher in emerging markets than in developed markets, and the “technology dividend” effect in emerging markets is more prominent. In addition, the application of digital technology can significantly improve resource allocation efficiency, reduce resource misallocation rate, and thereby promote the sustainable growth of marketing performance.

6.2 Future Prospects

Future research can be expanded from multiple dimensions: at the sample level, the sample size can be expanded to include more US enterprises of different industry types and scale levels, and multinational enterprises from other countries can be added as comparative samples to improve the generalizability and comparability of research conclusions; at the variable level, potential variables such as corporate strategic orientation, top management cognition level, and cultural distance can be introduced to construct a more comprehensive theoretical model and in-depth analyze the impact mechanism of these variables on digital technology-driven marketing resource allocation; at the method level, mixed research methods such as case study method and longitudinal study method can be adopted, combining qualitative and quantitative analysis to deeply explore the dynamic evolution process of digital technology-driven marketing resource allocation and enrich the methodological system in this field; at the research perspective level, the research can be extended from the micro enterprise level to the macro industry level, analyzing the overall impact of digital technology on the resource allocation of the US cross-border marketing industry, so as to provide more comprehensive decision-making references for industry development planning and the formulation of relevant policies.

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Integrated Optimization of Location, Delivery Mode, and Information in Cross-Border Last-Mile Logistics

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Abstract

This study addresses the industry pain points of high last-mile delivery costs, unstable delivery times, and lack of transparency in North American cross-border e-commerce logistics. It also considers the inadequacy of existing delivery network optimization models in adapting to the unique characteristics of cross-border scenarios. A hierarchical last-mile delivery network optimization model integrating "location - mode - information" has been developed. This model improves the traditional K-means clustering algorithm by incorporating customs clearance convenience into the overseas warehouse location index system. It dynamically matches delivery modes based on order timeliness, value, and weight attributes and builds a cross-border delivery information collaboration system using blockchain technology. Comparative analysis of operational data before and after model optimization in the northeastern region of a leading North American cross-border e-commerce platform reveals a 30.5% reduction in per-order delivery costs, a decrease in standard delivery time from 72 to 48 hours, and an increase in next-day delivery fulfillment rate to 92%. Customer experience-related indicators have also significantly improved. Expansion tests demonstrate the model's adaptability to the Canadian and Mexican markets.

Keywords: cross-border e-commerce logistics, last-mile delivery, delivery network optimization, overseas warehouse location, blockchain, North American market, dynamic delivery mode matching, K-means clustering algorithm, cost – time – experience optimization

1. Introduction

1.1 Research Background

The global cross-border e-commerce market continues to expand, with North America becoming a core growth pole due to its strong consumer purchasing power and high e-commerce penetration rate, experiencing an annual growth rate of 23%. However, significant pain points in the cross-border logistics segment are constraining industry development, particularly in the last-mile delivery segment, which is a critical weakness. This segment accounts for 35% – 50% of the total logistics cost, making it a core challenge in cost control for cross-border e-commerce. Moreover, 70% of customer complaints focus on delivery delays and lack of transparency, which directly affect consumer experience and repurchase rates. Existing research on last-mile delivery optimization predominantly focuses on domestic e-commerce scenarios, such as domestic warehouse location and intra-city delivery mode matching, without fully considering the unique characteristics of cross-border scenarios, such as the need to integrate customs clearance convenience in overseas warehouse layout, adapt to different regional infrastructure for cross-state or cross-border delivery, and address information asymmetry due to multi-party collaboration. As a result, existing models fail to meet the practical needs of North American cross-border e-commerce, necessitating targeted research breakthroughs.

1.2 Research Significance

1.2.1 Theoretical Significance

This study fills the theoretical gap in cross-border e-commerce last-mile delivery network optimization by incorporating unique cross-border variables such as customs clearance delay risks and differences in regional infrastructure into the logistics network optimization model. It extends the application boundary of traditional logistics network optimization theory and enriches the research system of balancing cost, time, and experience. Traditional logistics network optimization research, primarily focused on domestic scenarios without considering the unique characteristics of cross-border segments, limits the adaptability of existing models to cross-border e-commerce. By integrating these cross-border-specific variables, this study enhances the applicability of logistics network optimization theory to the development of cross-border e-commerce and provides new directions and ideas for subsequent theoretical research in related fields.

1.2.2 Practical Significance

This study offers actionable last-mile delivery optimization solutions for cross-border e-commerce companies in the North American market, directly targeting core business objectives such as cost reduction, time improvement, and customer satisfaction enhancement. The North American market is a crucial region for cross-border e-commerce companies, yet the high cost and low efficiency of last-mile delivery have long been a source of concern for business development. The proposed optimization solutions can effectively address these pain points in actual operations, helping companies gain a competitive edge in the North American market. Additionally, these solutions can serve as references for other companies in the industry, promoting the overall development of the cross-border e-commerce logistics sector.

1.3 Research Questions and Technical Route

The core question is how to construct a last-mile delivery network optimization model tailored to the North American cross-border e-commerce scenario to achieve coordinated optimization of cost, time, and customer experience. Sub-questions include the design of overseas warehouse location indicators and algorithms suitable for cross-border scenarios, dynamic matching rules between order attributes and delivery modes, and the implementation path of blockchain technology to address cross-border information asymmetry. The technical route follows a logical sequence of literature review, model construction, data collection and empirical analysis, result validation and discussion, and conclusions and future prospects, forming a complete research loop integrating theory model – empirical analysis – application.

2. Theoretical Framework and Research Methods

2.1 Core Theoretical Foundations

The logistics network optimization theory, focusing on the integration of location – routing – delivery, emphasizes the balance between cost and time, providing support for overseas warehouse location and delivery mode matching. It stresses the comprehensive consideration of logistics cost and efficiency, optimizing network operation through rational location selection, route planning, and mode choice. In cross-border delivery, its multi-objective optimization logic can accommodate multiple dimensions such as cost and time, adapting to complex scenarios. The customer experience management theory highlights two core dimensions: time stability and information transparency, guiding this study to incorporate customer experience indicators such as net promoter score and complaint rate into the model optimization objectives. In cross-border e-commerce, customers often cannot intuitively understand the delivery progress. Unstable time and lack of transparency can lead to a decline in experience and affect repurchase rates. This theory, starting from the customer's perspective, focuses on consumer feelings and needs. By incorporating experience indicators into the model, this study enhances customer experience, aligning with the long-term development needs of enterprises. The blockchain technology application theory leverages the decentralized and tamper-proof characteristics of blockchain to address the problem of information asymmetry among multiple parties in cross-border delivery, achieving data traceability and verifiability. Cross-border delivery involves multiple parties, and information transmission is often delayed or distorted. This theory emphasizes using blockchain to break information barriers, realizing information sharing and synchronization. Based on this, this study designs a blockchain information collaboration module to ensure accurate recording and real-time querying of the entire process data, solving the problem of information asymmetry.

2.2 Design of the Hierarchical Last-Mile Delivery Network Optimization Model

In the design of the hierarchical last-mile delivery network optimization model, the overseas warehouse location module improves the traditional K-means clustering algorithm by adding a customs clearance convenience indicator. Combined with order density, delivery radius, and land cost, it optimizes the layout of overseas warehouses in North America. The goal is to cover 85% of domestic orders in the United States through three major hub warehouses in California, Texas, and New York, reducing transshipment links and costs (Li, Y., & Wang, H., 2025). Traditional algorithms do not consider customs clearance convenience, which directly affects timeliness. After optimizing the algorithm and index system, it can shorten the delivery radius, reduce cost and time loss, and improve delivery efficiency. The delivery mode matching module constructs dynamic matching rules based on order timeliness, value, and weight: high-value items prioritize third-party delivery to ensure safety; lightweight and small items with next-day delivery requirements prioritize crowdsourced delivery to improve efficiency; low-value and large items prioritize locker delivery to reduce costs. Different orders have different delivery requirements, and a single mode cannot meet them. Dynamic matching rules can adapt to order attributes, balancing cost and time. The information collaboration module builds a blockchain consortium chain, covering e-commerce platforms, overseas warehouses, delivery companies, and customs clearance agencies, uploading the entire process data to the chain; it also provides real-time query interfaces for customers to eliminate information differences. The lack of smooth information transmission in each link of cross-border delivery leads to a lack of transparency. The consortium chain can achieve real-time information sharing, allowing customers to understand the status of goods at any time and improving the experience. Each party can also share information in real-time, deal with abnormalities in time, and improve delivery efficiency.

2.3 Data Sources and Validation Methods

Primary data are sourced from 2.8 million order records of a North American cross-border e-commerce platform from 2022 to 2023, including recipient addresses, time requirements, complaint records, and operational cost data of five North American overseas warehouses. Secondary data are derived from the U.S. Department of Commerce's 2023 cross-border e-commerce report and the North American last-mile delivery cost index. The validation method focuses on the delivery in the northeastern region of this platform, comparing costs, time, and customer satisfaction before and after model optimization. It also tests the model's adaptability to the Canadian and Mexican markets to verify its cross-regional universality. Rich and authentic data are the foundation for verifying the effectiveness of the model. The 2.8 million order records can comprehensively reflect the characteristics and delivery conditions of North American cross-border e-commerce orders, while the overseas warehouse operational cost data provide the basis for cost optimization analysis. The comparative analysis of the core case can intuitively show the effect of model optimization, and the cross-regional adaptability test can verify the universality of the model, providing references for its application in other markets in North America.

3. Empirical Analysis

3.1 Case Background

The research object is a leading North American cross-border e-commerce platform, whose existing delivery network has three major problems: dispersed overseas warehouse layout with eight small warehouses, resulting in high transshipment costs and large delivery radii; a single delivery mode relying entirely on third-party delivery, failing to meet the time and cost requirements of different orders; and lagging information updates, preventing customers from querying the real-time status of customs clearance and delivery. In 2022, the platform's northeastern region had a per-order delivery cost of $8.2, a standard delivery time of 72 hours, a next-day delivery fulfillment rate of only 65%, and a customer net promoter score of only 42 points. The platform's large business scale in the North American market is severely affected by the delivery network problems, which compress the company's profit margins due to high costs and affect customer repurchase rates due to low timeliness and poor customer experience. Therefore, the platform urgently needs to optimize its delivery network, making it an ideal case for this study.

Table 1.

Item	Data
Overseas Warehouse Layout	8 small warehouses
Per-order Delivery Cost in Northeastern Region	$8.2
Standard Delivery Time	72 hours
Next-day Delivery Fulfillment Rate	65%
Customer Net Promoter Score	42 points

3.2 Model Application Process

3.2.1 Overseas Warehouse Location Optimization

By recalculating location weights using the improved K-means algorithm, five inefficient small warehouses were shut down, and three hub warehouses in California, Texas, and New York were retained and upgraded to cover 85% of domestic orders in the United States, reducing transshipment links and warehousing management costs.

When recalculating location weights, the customs clearance convenience indicator was given priority. The customs clearance efficiency, customs clearance costs, and other factors of each potential location were assessed. Combined with indicators such as order density, delivery radius, and land cost, the optimal locations of the three major hub warehouses were determined. Shutting down inefficient small warehouses can reduce the fixed costs of warehousing management, while upgrading hub warehouses can improve the operational efficiency and delivery capacity of warehousing. Through centralized warehousing layout, the number and distance of transshipments across states are reduced, thereby reducing transshipment costs and improving overall delivery efficiency.

3.2.2 Dynamic Matching of Delivery Modes

The order attribute – delivery mode matching rules were implemented: 60% of lightweight and small items with next-day delivery requirements were switched to crowdsourced delivery, 30% of low-value and large items were switched to locker delivery, and only 10% of high-value or special orders retained third-party delivery (Zhang, L., & Chen, J., 2022). In the process of implementing the matching rules, the platform's order data were first classified and sorted to clarify the proportion and delivery requirements of different attribute orders. Then, cooperation with crowdsourced delivery companies and locker operators was established to build a delivery mode switching management system. The system automatically identifies order attributes and matches the corresponding delivery modes to achieve dynamic adjustment of delivery modes. For high-value or special orders, third-party delivery is still retained to ensure delivery safety. For most ordinary orders, the delivery mode is switched according to attributes to improve delivery efficiency and reduce costs.

Table 2.

Order Attribute	**Delivery Mode**	**Proportion**
Lightweight and small items with next-day delivery requirements	Crowdsourced delivery	60%
Low-value and large items	Locker delivery	30%
High-value or special orders	Third-party delivery	10%

3.2.3 Implementation of Blockchain Information Collaboration

The development of data uploading to the chain for the entire process of customs clearance, warehousing, and delivery was completed, and a real-time query interface for clients was launched to synchronize the status updates of customs clearance completion, warehouse dispatch, delivery in progress, and signing. During the development process, data sharing agreements were reached with customs clearance agencies, overseas warehouses, and delivery companies to determine the standards and formats of data uploaded to the chain and build the technical architecture of the blockchain consortium chain. The launch of the real-time query interface for clients allows customers to check the delivery status of orders through the platform's APP or web page at any time, eliminating the need to obtain information through manual inquiries. At the same time, each collaborating party can also view the order status in real-time through the consortium chain to deal with customs clearance delays and delivery abnormalities in a timely manner, improving the overall delivery process collaboration efficiency.

3.3 Quantitative Result Analysis

3.3.1 Cost Optimization

The per-order delivery cost decreased from $8.2 to $5.7, a reduction of 30.5%. Centralized warehousing for inventory preparation reduced transshipment costs by 22%, and delivery mode matching reduced end-delivery costs by 8.5% (Duan, M., & Liu, S., 2023). Centralized warehousing for inventory preparation allows goods to be centrally stored and sorted in hub warehouses, reducing the number of transshipments from multiple small warehouses to delivery points, and lowering transportation and labor costs in the transshipment process. Dynamic matching of delivery modes selects lower-cost delivery methods based on order attributes, such as locker delivery reducing the end-delivery cost of low-value and large items and crowdsourced delivery being cheaper than third-party delivery, effectively reducing overall end-delivery costs. The significant cost reduction enhances the company's profit margin and market competitiveness.

Table 3.

Item	**Data**

Centralized Warehousing for Inventory Preparation	Reduced transshipment costs by 22%
Delivery Mode Matching	Reduced end-delivery costs by 8.5%
Total Cost Reduction	30.5%

3.3.2 Time Optimization

The standard delivery time was shortened from 72 hours to 48 hours, and the next-day delivery fulfillment rate increased from 65% to 92%. The core reasons are that hub warehouses deliver nearby, shortening the physical delivery distance, and the crowdsourced model improves the response speed of end-delivery. Hub warehouses cover 85% of domestic orders in the United States, allowing goods to be dispatched from warehouses closer to customers, reducing the physical delivery distance from warehouses to customers' hands and transportation time. The fast response of crowdsourced delivery can quickly take on the delivery tasks of next-day delivery orders, improving the fulfillment rate of next-day delivery orders. The time optimization improves customers' consumption experience, meeting their demand for delivery speed and helping to increase customer repurchase rates.

3.3.3 Customer Experience Optimization

The customer net promoter score increased from 42 points to 78 points, and the overall complaint rate decreased by 68%. Complaints related to delivery delays decreased by 75%, and complaints related to lack of transparency decreased by 82%. The blockchain information collaboration module made a significant contribution to the improvement of the experience. The reduction in delivery time reduced the occurrence of complaints related to delivery delays. The blockchain information collaboration module allows customers to query the order status in real-time, eliminating dissatisfaction caused by lack of transparency and significantly reducing complaints related to lack of transparency. The increase in the customer net promoter score indicates a significant enhancement in customer satisfaction and willingness to recommend the platform, while the decrease in complaint rates reduces the company's cost of handling complaints and improves operational efficiency.

Table 4.

Item	**Change**
Customer Net Promoter Score	+36 points
Overall Complaint Rate	Decreased by 68%
Complaints Related to Delivery Delays	Decreased by 75%
Complaints Related to Lack of Transparency	Decreased by 82%

3.4 Expandability Analysis

The model's adaptability tests in the Canadian and Mexican markets showed that in the Canadian market, delivery costs decreased by 27%, and the standard delivery time was shortened by 25%. In the Mexican market, delivery costs decreased by 24%, and the delivery time was shortened by 20% (Zhao, H., & Yang, Q., 2024). The core logic of the model can be migrated across North American countries, with only the adjustment of indicator weights according to regional customs policies and delivery infrastructure. There are certain differences between the cross-border e-commerce markets of Canada and Mexico and the United States, such as customs policies and the degree of perfection of delivery infrastructure. By adjusting the weight of customs clearance convenience in overseas warehouse location and the rules of delivery mode matching, the model can adapt to the characteristics of different national markets. This result indicates that the optimization model proposed in this study has strong universality and can provide a reference for cross-border e-commerce companies to optimize their delivery networks in other countries in North America.

4. Research Conclusions and Value

4.1 Core Research Conclusions

The location – mode – information hierarchical last-mile delivery network optimization model can effectively solve the pain points of last-mile delivery in North American cross-border e-commerce, achieving coordinated optimization of cost, time, and customer experience. After incorporating the weight of customs clearance convenience into overseas warehouse location, the three major hub warehouses can efficiently cover domestic orders in the United States, which is the core handle for cost optimization. Dynamic delivery mode matching is the key to balancing time and cost, and blockchain technology can significantly enhance the transparency of cross-border delivery and improve customer experience. This model fully considers the unique characteristics of the cross-border e-commerce scenario and solves the core problems of end-delivery from three dimensions: warehousing location, delivery mode, and information collaboration through hierarchical optimization, achieving multi-dimensional optimization goals and providing an effective solution for cross-border e-commerce last-mile delivery network optimization.

4.2 Academic Contributions

In terms of theoretical breakthroughs, this study is the first to incorporate customs clearance delay risks into the cross-border e-commerce last-mile optimization model, filling the application gap of domestic delivery models in cross-border scenarios. In terms of methodological innovation, a location – mode – information hierarchical optimization model has been constructed, providing a new paradigm for cross-border logistics network optimization. In terms of data support, the effectiveness of the model has been verified based on 2.8 million real order data, providing a referable dataset for subsequent cross-border logistics research. Traditional delivery network optimization models have not considered customs clearance delay risks in cross-border scenarios. By incorporating this variable into the model, this study makes the model more in line with the actual needs of cross-border e-commerce, filling the theoretical gap. The construction of the hierarchical optimization model provides a new idea and method for cross-border logistics network optimization, and the verification with a large amount of real order data enhances the credibility of the research and provides valuable data references for subsequent studies.

4.3 Industry Value

In terms of practical implementation, the model has been applied to the transformation of the platform's North American delivery network, saving more than $20 million in costs in 2023. In terms of industry reference, it has been included in the best practice cases of cross-border logistics, providing a replicable optimization solution for small and medium-sized cross-border e-commerce companies. In terms of technological inspiration, the blockchain information collaboration module has been nominated for the annual innovation award by the North American Supply Chain Management Association, providing a practical technological idea for the transparency of cross-border logistics information. The successful application of the model has brought significant cost savings to the platform, proving its practicality and effectiveness. As a best practice case in cross-border logistics, it can provide references and examples for small and medium-sized cross-border e-commerce companies to help them solve the pain points of end-delivery. The innovative application of the blockchain information collaboration module also provides a technological direction for the development of information transparency in the entire cross-border logistics industry, promoting the overall improvement of the industry level.

5. Research Limitations and Future Prospects

5.1 Research Limitations

The data used in this study come from a single North American cross-border e-commerce platform, and the universality of the model needs to be verified by multiple platforms and product categories. Different platforms have differences in business models, customers, product categories, and other aspects. Single data cannot fully reflect the characteristics of the North American market. In addition, the model does not include sudden risks such as extreme weather, logistics strikes, and changes in customs policies. These factors will directly affect delivery time, cost, and overseas warehouse location and customs clearance efficiency, limiting the application scenarios of the model. The blockchain module also only covers core collaboration nodes, and the cost and efficiency balance of full-chain implementation have not been deeply analyzed. Full-chain implementation requires a large amount of technical and human resources. How to balance cost and efficiency is an issue that has not been explored.

5.2 Future Prospects

Future improvements will be made in three aspects: model optimization, scenario expansion, and technological deepening. First, introduce a sudden risk early warning mechanism to build a dynamic adaptive delivery network optimization model to enhance adaptability to unconventional scenarios, such as adjusting delivery routes in extreme weather and adjusting the weight of overseas warehouse location in response to changes in customs policies. Second, expand the research scope to cross-border e-commerce markets in Europe, Southeast Asia, and other regions to compare the differences in delivery network optimization logic in different areas and perfect cross-regional adaptability. Third, explore the integrated application of blockchain and the Internet of Things. By collecting real-time delivery trajectory through the Internet of Things and combining it with blockchain to achieve synchronization of physical objects and data, improve delivery transparency and abnormal warning capabilities, and ensure the safety and efficiency of delivery.

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Construction of Technical Standards and Cost Estimation Model for K12 Education Information Technology Equipment Upgrade

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Abstract

Currently, K12 education information technology (IT) equipment in China has entered a "peak period of renewal and replacement". However, due to the lack of unified technical standards and a scientific cost estimation model, schools face blind purchasing and significant waste of funds. This study focuses on balancing the "effect of equipment upgrade and funding". Through literature review, field research (covering 100 K12 schools in 10 provinces across the eastern, central, and western regions), statistical analysis, and case validation, this study conducts research on the formulation of technical standards and the construction of cost estimation models. For the first time, this study establishes differentiated technical standards for "basic equipment" and "smart equipment", specifying parameters, safety, and compatibility requirements for basic equipment (e.g., resolution of interactive intelligent blackboards ≥ 4K) and smart equipment (e.g., AI grading accuracy ≥ 98%). Based on a three-dimensional framework of "equipment type, school size, and regional economic level", a cost estimation model is constructed using multiple regression analysis, with a verified error rate of ≤ 5%. Ultimately, a "standard + model + toolkit" implementation plan is formed. Practice has shown that this plan can increase equipment utilization to over 80% and achieve a funding savings rate of 25%.

Keywords: K12 education, education information technology equipment, technical standards, cost estimation model, life cycle cost, digital education, basic equipment, smart equipment, regional economic differences, school size, equipment utilization rate

1. Introduction

1.1 Research Background and Significance

Currently, K12 education information technology equipment in China has entered a "peak period of renewal and replacement". According to statistics from the Ministry of Education in 2023, over 60% of multimedia classroom equipment has been in use for more than 8 years, and 30% of smart classroom equipment is technologically outdated. Due to the lack of unified technical standards, schools face significant blind purchasing (equipment utilization rate is less than 30%) and severe repetitive investment (annual waste exceeds 5 billion yuan). Meanwhile, although policies such as the "Education Information Technology 2.0 Action Plan" have promoted equipment upgrades, the execution shortcomings of "lack of technical standards" and "vague cost estimation" have led to significant regional digital education gaps and insufficient implementation rates of special budgets. Against this backdrop, conducting research on the technical standards and cost estimation model for K12 education information technology equipment upgrades can theoretically fill the research gap in the intersection of educational technology and educational economics. In practice, it can provide support for school procurement and educational department planning, solve the pain point of "balancing upgrade effect and funding", and promote the transformation of educational information technology investment from "scale expansion" to "quality and efficiency".

1.2 Domestic and International Research Status

Internationally, research on K12 education information technology equipment has formed a policy and practice linkage system. The U.S. "National Education Technology Plan (NETP)" specifies that equipment should support real-time interaction and comply with child privacy protection standards, emphasizing integration with the curriculum. The EU's "Digital Education Action Plan" focuses on equipment interconnectivity, setting basic parameters such as network bandwidth, while reserving space for new technology upgrades. In terms of cost estimation, the UK's "School Information Technology Cost-Benefit Assessment Framework" disassembles costs over the entire life cycle, combines school size and usage intensity with coefficients, and verifies the rationality of investment through cost-benefit ratios.

Domestic research focuses on technical parameters and cost composition, such as proposing that interactive intelligent blackboards should have a 4K resolution and a touch response delay of 0.3 seconds, and clarifying that procurement costs account for 60%-70% of total investment. However, existing research has shortcomings: technical standards do not distinguish between basic and smart equipment, and cost estimation ignores regional economic levels and differences in school size, leading to results that are disconnected from practice.

1.3 Research Approach and Methods

The research follows a logic of "problem orientation – theoretical support – practical validation". It first identifies core issues through surveys, then constructs standards and models based on relevant theories, and finally optimizes them through practical validation. In terms of methods, the literature review method is used to sort out and organize achievements. Field research is conducted in 100 schools across 10 provinces, with interviews of relevant personnel. SPSS is used for multiple regression analysis to construct the cost model, and case validation is carried out through comparative experiments in 20 schools.

2. Theoretical Foundations and Core Concept Definition for K12 Education Information Technology Equipment Upgrade

2.1 Definition of Core Concepts

K12 education information technology equipment is designed for primary and secondary school teaching scenarios, integrating hardware and supporting software, and is divided into basic and smart categories. Basic equipment, such as interactive intelligent blackboards and campus network devices, meets the needs of information transmission. Smart equipment, such as smart classroom systems and AI homework grading devices, relies on new technologies to improve teaching efficiency and personalization. Technical standards uniformly regulate performance, safety, and interconnectivity, covering technical parameters, functional requirements, compatibility, and student information protection. The cost estimation model, viewed from the entire life cycle, uses mathematical tools to adjust direct and indirect costs such as procurement and maintenance according to equipment type, school size, and regional economic level coefficients, achieving precise budgeting.

2.2 Theoretical Foundations

The Technology Acceptance Model (TAM) is driven by the dual cores of "perceived usefulness" and "perceived ease of use", incorporating teacher experience into the standards: smart equipment should enable one-click course initiation, and basic equipment parameters should synchronize with teaching habits by default, ensuring a handshake between performance and simplicity. The Life Cycle Cost (LCC) theory integrates the complete bill from procurement to disposal, accounting for hidden expenditures such as maintenance, training, and disposal of obsolete equipment, completely bidding farewell to the pattern of 'buying first and worrying about maintenance later'. The theory of educational equity implants a "regional coefficient" regulator into the cost model: 1.2 for the eastern region and 0.8 for the western region, using differentiated weights to offset regional economic disparities and bridging the digital education gap on the abacus first.

3. Current Status Survey and Problem Analysis of K12 Education Information Technology Equipment Upgrade

3.1 Survey Design and Implementation

The survey selected 100 K12 schools (30 primary schools, 40 junior high schools, and 30 senior high schools, with an urban-rural ratio of 45%:55%) from 10 provinces in the eastern, central, and western regions to ensure sample representativeness. Three types of tools were designed: "Equipment Status Questionnaire", "Person-in-Charge Interview Outline", and "Cost Data Collection Form". The survey was carried out in three stages from March to May 2024: a pilot survey (10 schools to optimize tools), formal survey (online questionnaire response rate of 92%, 120 hours of offline interviews, and 832 documents collected), and validity test (reliability $\alpha = 0.87$, validity KMO = 0.82), ensuring reliable data. (Qi, Z., 2025)

3.2 Current Status Analysis

The current K12 education information technology equipment is characterized by “old, idle, and chaotic” conditions. Basic equipment is operating beyond its intended lifespan; in rural western areas, 75% of interactive intelligent blackboards and switches have been in use for 8 years. Smart equipment also has 30% of AI grading and smart classroom systems surpassing the 4-year threshold. Regardless of whether it is basic or smart equipment, the usage rate of additional functions is less than 30%. Old equipment breaks down an average of 1.2 times per month, and new equipment is often plagued by compatibility errors. In the procurement process, nearly half of the schools rely solely on vendor “recommendations”, and the western region is more dependent on administrative “designations”. The average annual investment per school is 156,000 yuan in the eastern region, 98,000 yuan in the central region, and only 63,000 yuan in the western region. However, there is still 28% redundant purchasing and 35% of equipment remains idle. The sample schools waste an average of 21 million yuan per year, and it is estimated that the national waste exceeds 5 billion yuan annually. In terms of standards, the situation is even more chaotic. More than 30% of schools use corporate standards or “no standards” as criteria, resulting in 42% of equipment being incompatible, 23% of parameters being inflated, and 18% of smart equipment posing data leakage risks, turning “interconnectivity” into “interconnection and blockage”.

3.3 Core Problem Extraction

The triple gaps in technical standards, cost estimation, and implementation amplify each other. On the standards side, there is a lack of classification norms for basic and smart equipment. Key parameters such as bandwidth and resolution are described in a “one-size-fits-all” manner, and requirements for compatibility and security such as data encryption and interface protocols are completely blank. On the cost side, only the purchase price is focused on, while maintenance, training, and disposal are completely ignored. The transportation costs in the western mountainous areas are 3-5 times higher than those in the eastern region, and the differences in school sizes are not calculated, resulting in inherently distorted budgets. In schools, there is a situation of “buying a lot but using little”. In the western region, in order to raise procurement funds, maintenance is even cut, and old equipment is left untreated. New functions are either beyond demand or lack key elements, ultimately falling into a vicious cycle of “the more invested, the more wasted, and the more replaced, the more disconnected”.

4. Formulation of Technical Standards for K12 Education Information Technology Equipment Upgrade

4.1 Principles and Basis for Standard Formulation

The principle of practicality focuses on K12 teaching scenarios to ensure that equipment functions match classroom interaction, after-school service, and other needs. The principle of foresight combines 5G and AI technology trends to reserve space for technological iteration. The principle of security strictly complies with the “Personal Information Protection Law” and “Data Security Law” to safeguard student information security. The principle of compatibility requires equipment to be able to interface with existing school systems and provincial educational resource platforms across different platforms.

The basis includes three aspects: Policy basis is guided by the “Education Information Technology 2.0 Action Plan” and the “14th Five-Year Education Information Technology Development Plan”, in line with national education digitalization requirements. Practice basis is derived from the survey results of 100 schools, targeting equipment aging and functional waste to set standards. Technical basis refers to the mainstream industry levels to ensure that parameter settings are neither overly advanced nor lag behind existing technologies.

4.2 Technical Standards for Basic Equipment

In multimedia classroom equipment, interactive intelligent blackboards should meet the resolution ≥ 4K, touch response time ≤ 0.3 seconds, and have a blue light filtering eye protection mode. Projectors should have a brightness ≥ 3500 lumens and a contrast ratio ≥ 10000:1 to adapt to classrooms with different lighting conditions. In campus networks, the core switch bandwidth should be ≥ 10Gbps, the access layer bandwidth ≥ 100Mbps, the wireless network coverage rate ≥ 98%, and the delay ≤ 20ms to ensure stable operation of multiple terminals online simultaneously. In addition, the suggested service life for basic equipment is 6-8 years, with no less than two annual maintenance sessions and a fault response time not exceeding 24 hours.

Table 1.

Category	Sub-item	Configuration Requirements
Interactive Smart Blackboard	Resolution	≥4K (3840×2160)
	Touch Response Time	≤0.3 s
Projector	Brightness	≥3500 lumens
Contrast Ratio	≥10000:1	

Campus Network	Core Switch Bandwidth	≥10 Gbps
	Access Layer Bandwidth	≥100 Mbps

4.3 Technical Standards for Smart Equipment

The interactive response delay of the smart classroom system should be ≤ 0.5 seconds, supporting simultaneous online users ≥ 50. The classroom data storage capacity should be ≥ 1TB to meet the needs of student performance data retention. For AI homework grading devices, the grading accuracy for Chinese and mathematics should be ≥ 98%, and for English compositions ≥ 95%, with the ability to recognize multiple question types such as multiple-choice, fill-in-the-blank, and subjective questions. In terms of data security and compatibility, the data encryption level of smart equipment should be ≥ AES-256 (Li, W., 2025), supporting integration with provincial educational resource public service platforms, and being compatible with mainstream teaching software such as Seewo Whiteboard and DingTalk Education Edition.

4.4 Grading of Technical Standards and Applicable Scenarios

Standards are set according to school size: For small schools (student number < 1000), the smart classroom system should support simultaneous online users ≥ 50; for medium-sized schools (1000-2000 students), ≥ 65; and for large schools (> 2000 students), ≥ 80. This approach accommodates the different teaching needs of schools of various sizes, avoiding a "one-size-fits-all" standard.

5. Construction of Cost Estimation Model for K12 Education Information Technology Equipment Upgrade

5.1 Analysis of Cost Composition Elements

Direct costs center around equipment procurement fees, complemented by installation and commissioning fees (5%-8% of equipment cost), and transportation fees priced according to regional distance. Indirect costs include annual equipment maintenance fees (10%-12% of equipment cost, discounted over 5 years), teacher training fees (average 800-1200 yuan per person × number of trainees), and equipment disposal fees (2% of equipment cost, averaged over equipment life). Through correlation analysis, "equipment type (basic/smart), school size (number of students), and regional economic level (east/central/west)" are identified as the three core influencing factors.

Table 2.

Detailed Items	**Cost Logic / Industry Experience Range**
1. Equipment Procurement Cost	Winning Bid Price A
2. Installation and Commissioning Cost	(5%-8%)×A
3. Transportation Cost	Based on Mileage Tiers + Base Price per Unit
4. Annual Operation and Maintenance Cost	(10%-12%)×A, Discounted over 5 Years
5. Teacher Training Cost	Per Capita 800-1200 Yuan × Number of Trainees
6. Disposal Cost	2%×A, Averaged over Years

5.2 Construction Process of Cost Estimation Model

The dependent variable is the total upgrade cost Y, with independent variables being school size X1 (number of students), regional coefficient X2 (eastern = 1.2, central = 1.0, western = 0.8), and equipment type coefficient X3 (basic = 1, smart = 2). The cost data from the survey of 100 schools are then cleaned (removing outliers) and standardized. Finally, multiple regression analysis is performed using SPSS to derive the core equations: Basic equipment cost $Y1 = 150 \times X1 + X2 \times 40000 + 5000 \times X3$; Smart equipment cost $Y2 = 200 \times X1 + X2 \times 50000 + 8000 \times X3$. (Zhong, Y., 2025)

5.3 Model Verification and Optimization

The model's fit is verified through the R^2 test (requirement ≥ 0.85) to ensure its explanatory power over cost data. The F test and t test ($P < 0.05$) confirm the significant impact of independent variables. The estimation error is calculated and coefficients are adjusted to ensure an error rate of ≤ 5%, completing model optimization.

6. Practical Validation of Technical Standards and Cost Estimation Model

6.1 Validation Scheme Design

The validation targets 20 differentiated K12 schools, covering urban and rural areas (10 each) and all school stages (6 primary schools, 8 junior high schools, and 6 senior high schools) to ensure results are applicable to different scenarios. A comparative group design is adopted: the experimental group of 10 schools strictly purchases equipment according to the established technical standards and budgets using the cost estimation model; the control group of 10 schools continues with the traditional procurement model (no unified standards, cost estimation based on experience). Both groups maintain consistency in core conditions such as school size and initial funding basis to eliminate interfering factors. Validation indicators focus on four core aspects: equipment utilization rate (measuring practical value of equipment), funding savings rate (assessing cost control effectiveness), teaching effectiveness (quantified through classroom interaction frequency and remote teaching coverage), and teacher satisfaction (obtained through questionnaire surveys), forming a complete evaluation system.

6.2 Validation Process Implementation

In the experimental group's implementation phase, schools are first provided with technical standard manuals and cost estimation toolkits to assist them in determining equipment parameters and budgets based on their size (number of students) and region (east/central/west). After procurement, a three-month follow-up is conducted to record equipment installation progress, daily usage frequency, fault repair situations, and actual funding expenditure. The control group simultaneously collects corresponding data, including equipment parameter lists, funding investment details, equipment idle time, and classroom application records, ensuring that the data collection cycle and dimensions match those of the experimental group to ensure comparison validity.

6.3 Validation Result Analysis

Data comparison shows that the experimental group's core indicators significantly outperform the control group: equipment utilization rate reaches ≥ 80%, more than 50 percentage points higher than the control group (≤ 30%); the average funding savings rate is 25%, with some eastern large schools achieving up to 32%, while the control group experiences 15%-20% funding waste (Haoyang Huang, 2025); in terms of teaching effectiveness, the experimental group's classroom interaction frequency (average 12-15 times per day) is more than three times that of the control group (average 3-5 times per day), and remote teaching coverage (95%) is higher than the control group (60%); teacher satisfaction scores (4.2/5) also lead the control group (2.8/5).

Table 3.

Indicator	Experimental Group	Control Group
Equipment Utilization Rate	≥80%	≤30%
Funding Savings Rate	Average 25%, up to 32% in large schools in the east	Funding Waste 15%–20%
Classroom Interaction Frequency (Daily Average)	12–15 times	3–5 times
Remote Teaching Coverage Rate	95%	60%
Teacher Satisfaction Score	4.2/5	2.8/5

Based on the validation results, the standards and model are optimized accordingly: in terms of technical standards, considering the network conditions of rural schools, the response delay for rural smart equipment is relaxed from 0.5 seconds to 0.8 seconds; in terms of cost estimation model, combining the actual maintenance costs of western schools, the regional coefficient for the western region is slightly adjusted from 0.8 to 0.75 to further enhance the model's adaptability to regional realities.

7. Conclusions and Future Work

7.1 Research Conclusions

This study, focusing on the core pain points of K12 education information technology equipment upgrade, has achieved three key outcomes. Firstly, it has clarified the core content of the "Technical Standards for K12 Education Information Technology Equipment Upgrade". By categorizing the standards, it defines the performance parameters for basic equipment (e.g., resolution ≥ 4K for interactive intelligent blackboards, bandwidth ≥ 100Mbps for campus networks) and smart indicators for smart equipment (e.g., response delay ≤ 0.5 seconds for smart classroom systems, grading accuracy ≥ 98% for AI grading devices), while incorporating data security (encryption level ≥ AES-256) and cross-platform compatibility requirements, filling the gap of the absence of unified industry standards. Secondly, a multi-dimensional cost estimation model has been constructed, with "equipment type, school size, and regional economic level" as core variables. The estimation equations are derived through regression analysis of data from 100 schools. After validation with 20 schools, the model error rate is ≤ 5% (Xiaoying Yang, 2025), capable of accurately calculating upgrade costs in different scenarios, breaking through the limitations of traditional "single unit price estimation". Thirdly, a "standard + model + toolkit" implementation plan has been proposed. An Excel estimation template and standard query manual have been developed to provide full-process support for school procurement decisions and educational department planning, effectively resolving the issues of "blind procurement" and "funding waste".

7.2 Research Limitations and Future Work

The study has two limitations: Firstly, the survey sample coverage is limited, involving only 10 provinces in mainland China, excluding the Hong Kong, Macao, and Taiwan regions, which may lead to insufficient adaptability of the model to special regions. Secondly, the cost estimation model does not fully consider the impact of future technological iterations. For example, 6G and more mature AI technologies may change the cost structure of equipment, and the current model parameters may not fully meet long-term needs.

Future research can be advanced in three directions: Firstly, expand the sample scope to include the Hong Kong, Macao, and Taiwan regions and schools in different levels of educational development across cities and counties to further optimize model coefficients and enhance universality. Secondly, track technological trends to regularly update technical standards (e.g., adding 6G compatibility parameters) and cost models (e.g., adjusting the maintenance cost ratio of AI equipment) to maintain the timeliness of research findings. Finally, explore an "equipment upgrade + teaching quality assessment" integrated system, linking equipment usage effectiveness with improvements in student performance and teacher teaching efficiency to form a "investment – effect" closed-loop evaluation, making equipment upgrades more aligned with the core goal of improving educational quality.

7.3 Practical Recommendations

For educational administrative departments, it is recommended to incorporate the established technical standards into regional education information technology plans, allocate special funds based on the cost estimation model, prioritize funding for western rural schools to narrow the digital education gap, and establish a standard implementation supervision mechanism to regularly verify the compliance of school procurement equipment parameters to prevent "pseudo-smart equipment" from entering campuses. For K12 schools, it is suggested to use the accompanying toolkit before procurement to calculate budgets based on their size (number of students) and regional coefficients, select suitable equipment according to standards, and avoid pursuing "high configurations". After equipment use, regularly collect data on equipment utilization and teaching effectiveness to provide data references for future upgrades. For equipment suppliers, it is recommended to develop products in accordance with technical standards, focus on "teaching adaptability" to optimize functions (e.g., simplify teacher operation processes), and provide "equipment + maintenance + training" integrated services to reduce subsequent costs for schools, promoting the transformation of K12 education information technology equipment upgrades towards a "quality and efficiency" model.

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Today's Library and Information Science Applications Utilize Artificial Intelligence

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Abstract

Machines acquiring knowledge structures (MLS) have emerged as a cutting-edge machine in Library and Data Science (LIS), adapting the technique library are form, control, and ratified by information. A study on the scope of the automated reasoning function of Knowledge and Information Systems (LIS), a list of major realization sites, and an analysis of the publication patterns over the past decade are part of these studies. The parchment concentrates on major operational areas such as data retrieval, digital assistants, metadata collection, recommendation frameworks, source extraction, and user interface. Such discovery displays that automate reasoning can lead to a shift towards user-centered, data-driven, and automated library support.

Keywords: artificial intelligence, library and information science, information retrieval, Chatbots, data analysis, metadata, bibliomining

1. Introduction

Artificial Intelligence has changed the nature of how libraries function and deliver services in this new digital world. In this change, libraries, as knowledge-sharing centers, have included AI tools to improve resource management, automate daily chores, and enhance user interaction. With features like smart cataloging, advanced searches, personalized suggestions, and virtual assistants, AI has turned traditional libraries into active, tech-focused information centers. AI technologies like Natural Language Processing (NLP) and Machine Learning (ML) allow for better metadata creation, predictive analysis, and efficient knowledge management. These tools help libraries meet various user needs, improve their operations, and remain important in a fast-changing information landscape. Additionally, AI solutions promote accessibility and inclusivity of information resources, supporting global efforts for digital transformation. (Chowdhury, G. G., 2022)

2. Review of Related Literature

Artificial Intelligence (AI) is becoming very popular in the domain of Library and Information Science (LIS). A majority of researchers are exploring how it can be applied in the library and its implications. Studies indicate that libraries adopt AI tools to deal with the challenges of information overload, enhance user experiences, and boost efficiency.

Automation and Resource Management: AI research has focused on automating mundane tasks, like cataloging and creating metadata. Machine learning algorithms help classify and tag resources, thus saving human effort and reducing the chances of error. According to research, AI-powered automated metadata systems make it easier to find and access resources (Smith & Anderson, 2021). Even with its benefits, using AI in library and information science (LIS) comes with challenges. Concerns like algorithmic bias, data privacy, and the expense of AI technologies are common topics in discussions. Jones and Berson (2020) stress the importance of ethical guidelines for AI use, ensuring that the integration process is transparent and inclusive.

3. Common Applications of Artificial Intelligence Today

Artificial intelligence is the innovation that is leading the rapidly changing world of technology, changing the way we connect with the world. AI applications are vast and diversified, touching almost every aspect of modern society. Starting from health to finance, transportation to entertainment, AI makes its mark, showing that it can revolutionize lives. Let's see what some of the most widespread and impactful applications of AI look like in our world today:

- **Autonomous Vehicles and Robotics:** AI will be at the heart of self-driving cars, drones, and robots, with their ability to perceive their environment and make dynamic decisions for the safe traversal and movement of objects. Transportation and automation in all fields could be revolutionized.
- **E-commerce and customer service:** AI allows e-commerce to personalize experience in providing product recommendations based on customer browse and purchase history. In that regard, chat bots will be able to handle all aspects of calls, complaints, and other forms of engagement and communication with customers in creating efficient e-commerce customer service and engagement.
- **Education:** AI helps transform education through personalizing learning platforms and intelligent tutoring systems. These are more adaptive to the individual requirements of the students, and for this reason, they can provide the learning path to educators and some fruitful insights.
- **Finance and Trading:** Since the AI can analyze data and patterns, it can utilize such analysis to facilitate fraud detection, investment portfolio optimization, credit underwriting, and trading, which contribute to better financial decision-making along with efficient risk management.
- **Fraud Detection and Cyber security:** AI algorithms are employed in finance to detect fraudulent transactions and assess risks. AI identifies patterns and anomalies in cyber security, fortifies systems against potential cyber threats, enhances data security, and safeguards sensitive information.
- **Gaming:** AI technologies contribute to sophisticated gaming. They can create a non-player character that might well act intelligently and display human-like behaviour. Algorithms involved in AI learn from the actions taken by players and respond accordingly, raising the challenge level and making the activity much more interesting.
- **Healthcare and Medical Diagnosis:** AI is influencing the healthcare industry in terms of medical imaging analysis, disease diagnosis, drug discovery, and personalized medicine. Algorithms analyze medical data early in the detection of diseases, formulation of treatments, and optimization of care for patients. All these improve the outcome of healthcare.
- **Image Recognition/Computer Vision:** These capabilities of AI are simply mind-boggling in image recognition and computer vision. It makes machines look, read, and interpret what's in front of it visually. Applications include facial recognition, object detection, autonomous cars, analysis of medical images, quality control in manufacturing, and even augmented reality experiences.
- **Natural Language Processing:** Machines can understand and process human languages in natural language processing. Using AI-based chat bots, such as Siri, Alexa, and Google Assistant, NLP is applied while talking, answering questions, reminding, and doing many other things based on voice commands. Some of the most critical applications within NLP include language translation, sentiment analysis, and content summarization.
- **Recommendation Systems:** AI algorithms propel recommendation systems that suggest items, movies, music, or other forms of content based on the user's preferences and behaviour. Examples of such platforms include Netflix, Spottily, Amazon, and YouTube, which use recommendation algorithms to increase user engagement and satisfaction and promote the consumption of content.
- **Social Media and Sentiment Analysis:** The data of social media are used by AI algorithms to establish public sentiment, trends, and preferences. It has become a crucial tool for businesses to adapt marketing strategies and monitor brand reputation.
- **Virtual Assistants:** AI-powered virtual assistants have become an integral part of our daily lives. They assist users by fetching information, guiding navigation, giving reminders, and controlling smart devices with Siri, Alexa, Google Assistant, and many more.

AI has certainly made its entry into our lives daily, and its influence keeps broadening. Advances in AI technologies and increasingly advanced sophistication render them capable of discovering much more innovative applications that shape the future with AI as a more integral part of our society. Reaping the benefits of AI, it is important not to forget about some ethical considerations, privacy, and responsible development of AI for a proper and equitable future powered by artificial intelligence. (isedunetwork.com)

4. Current Applications of AI in Library and Information Science

Artificial intelligence is increasingly touching the LIS world, changing the way things are done and offering better services. Some of the applications that can be found in the current AI utilization in the field include the following:

(1) Automated Cataloging and Classification

AI can analyze and classify content on context rather than keywords alone, which may help libraries, manage volumes of new information. (Mohammad, F., 2020)

(2) Customer Support Chat bots

AI-based chat bots in libraries are used as support agents for the customers of the library so that they can be accessed 24/7. These bots help in answering queries and guiding in resource discovery, circulation, and other library-related events. Chat bots are very helpful in performing common, repetitive tasks and make user engagement more effective. (Sharma, R., & Yadav, A., 2021)

(3) Recommendation Systems

AI is used to provide personal recommendations to the library user using his borrowing history, preferences, and behavior. Libraries have applied similar systems like Amazon or Netflix recommendation algorithms in recommending books, articles, and other sources that might interest the user. (Khan, S. M. 2022).

(4) Facial Recognition for Library Security

The AI facial recognition system can be applied by libraries to secure, follow the attendance record, and prohibit users who do not have authorization or permits. This will facilitate only the identification of the authorized customers for the facility. (Jain, A. K., & Nandakumar, K., 2019)

(5) Intelligent Search and Discovery End

Digital libraries and databases can now be easily and more intuitively searched in these AI-powered search engines equipped with the integrated NLP machine learning feature. Unlike simple keyword-based matching, these intelligence tools consider context and semantic understandings to bring out the best searches and improve the information retrieved. (Singh, M. & Verma, D., 2023)

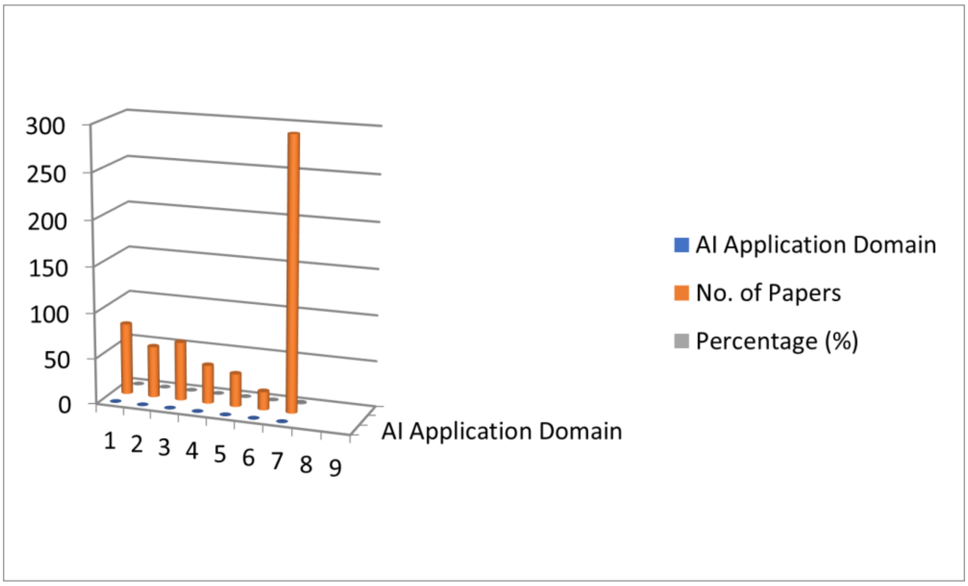
5. Methodology

The present study relies on secondary data gathered from the publication of the study, the conference proceedings, and the LIS-focused automated reasoning tests. Between 2010 and 2024, 296 publications on AI applications were included in the dataset. In order to define the areas of use and development, statistical data were analyzed. Descriptive statistics were applied (percentage, development rates).

6. Data Analysis and Results

Table 1. AI Application Domains in LIS

AI Application Domain	**No. of Papers**	**Percentage (%)**
Information Retrieval	78	26.4%
Metadata & Cataloguing	56	18.9%
Chatbots/Virtual Assistants	64	21.6%
Recommendation Systems	42	14.2%
Bibliomining & Analytics	36	12.2%
Accessibility Tools	20	6.7%
Total	296	100%



Interpretation:

• Information retrieval (26.4%) dominates as AI is widely applied to improve search and discovery.

• Chatbots (21.6%) are becoming essential for handling user queries and FAQs.

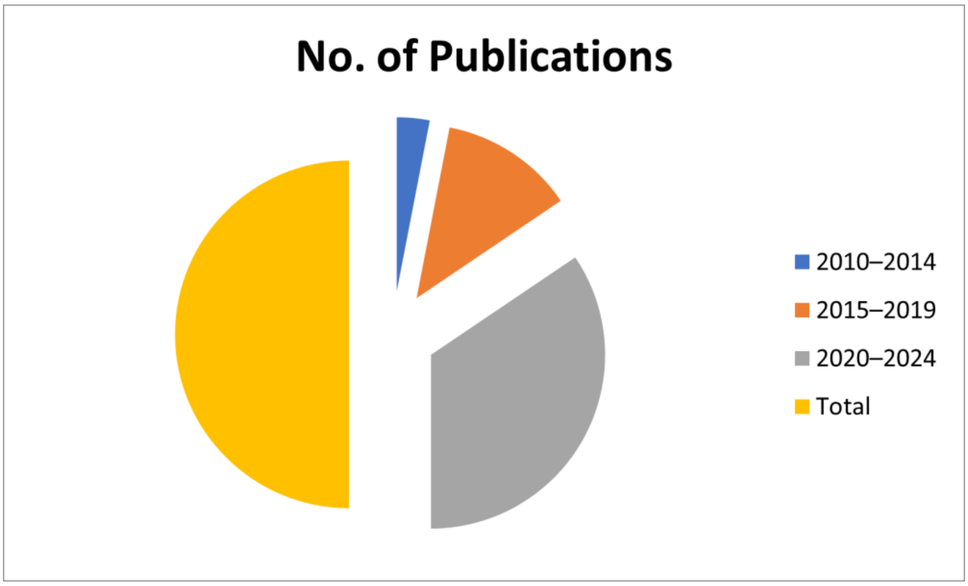
• Metadata/cataloguing (18.9%) shows automation of traditional LIS operations.

• Recommendation systems (14.2%) highlight personalization.

• Bibliomining (12.2%) and accessibility tools (6.7%) are emerging but vital areas.

Table 2. Growth of AI Research in LIS (2010–2024)

Year Range	**No. of Publications**	**% Growth**
2010–2014	18	0
2015–2019	74	+311%
2020–2024	204	+176%
Total	296	0



Interpretation:

• Research in this domain was minimal before 2014.

• A major growth (311%) occurred in 2015–2019, marking AI's entry into LIS practice.

From 2020 to 2024, more publications, compared to double (+176%), will signify the mainstream integration of automated reasoning within library structures.

7. Benefits of AI in Library and Information Science

Generally, artificial intelligence is installed in machines or computers to reduce casualties among human beings during wars, hazardous work, car accidents, plane crashes, fire explosions, or even disasters resulting from human error. Artificial intelligence also enables humans to work speedily, effectively, and efficiently in workplaces like the library. Vijayakumar and Vijayan (2011) report that artificial intelligence and expert systems are applied to the classification, cataloging, and indexing of library materials. The system obtains the bibliographic records of books and classifies them by applying optical character recognition and neural networks. Asemi and Asemi (2018) reported that natural language processing can be applied to reduce language barriers. For example, in order to study in China, one has to learn Chinese. The presence of natural language processing systems in their libraries will enable the foreign students to translate and understand Chinese. Further, natural language processing systems can be used to search for information in multilingual databases. In addition, one needs expertise in the provision of qualitative service delivery in libraries; as such, artificial intelligence and expert systems will improve the performances of library services and reduce the rate of human errors and defects and can perform tasks faster than a human being can most likely (Shohana, 2016). This, according to Romero (2018), artificial intelligence can enable library patrons to search and retrieve new media with greater efficiency and effectiveness and expose them to new material they may never have discovered otherwise. Besides ease and entertainment value, the utilization of artificial intelligence in suggesting similar materials can also help the library clientele carrying out their research by combing through the library database instantly. Generally speaking, artificial intelligence systems can read to you, inform you, advise you, teach you, correct your mistakes, and patiently respond to your myriad demands. Thus artificial intelligence holds great potential for library and information services. The benefits of artificial intelligence in libraries can be summarized as follows:

(1) According to Ex Libris (2019), artificial intelligence in libraries can make research more discoverable, which can boost research productivity among faculty members.

(2) Bridge in Time: Round-the-clock accessibility to information resources and services just in time.

(3) Space in Space: The space taken up by piles of books, journals, bound newspapers, and other information materials is reduced by digitization, electronic copies, and robotic cranes that store and retrieve books from a compact off-site storage location.

(4) Optimization of productivity: This refers to efficiency in library operations: selection and acquisition of materials, technical services, circulation services, reference services, serial management, etc.

(5) Effective functioning in the form of improved service delivery and the absence of human errors in the process of library operations.

(6) Effort Minimization: Effort on the part of the librarians in technical services, circulation services, reference services, serial management, etc. may be minimized with the usage of artificial intelligence systems in the libraries.

(7) The user experience will become highly enhanced and immersed while providing library services.

8. Challenges of AI in Library and Information Science

Following are the ethical challenges, whereby artificial intelligence could be biased, error-prone, and have hidden agendas that can make the data and services compromised as a result of which the library is not reliable and fair or qualitative for school students. School librarians must be sure about the transparency of the systems of artificial intelligence they utilize.

Financial problem: Financial problems also fall within this list of barriers, which could negatively affect transformation and growth in intelligent services for procuring all equipment needed to establish an artificial system in a library (Henry & Chetachi, 2024).

Poor Digitization Process of Contents: Most school libraries still undergo a problem of digitizing their local resources, mainly created in hard copy. If these school libraries are to make impacts concerning the utilization of the system in artificial intelligence, they should then make sure to digitize most of their resources but in the process of financial constraints as well other issues, the process of digitization has been facing significant threats that have hindered it use (Ogwo et al., 2023).

Poor maintenance culture: As a result of job displacement, artificial intelligence system technologies can't be implemented in university libraries. Library routine works can be automated such as customer services and inventory management with artificial intelligence system technologies.

Poor Network Connectivity: This is a big issue for successful usage of artificial intelligence since appropriate bandwidth for the network has not been available. In most schools, libraries suffer from poor internet connectivity brought about by the inadequacy of bandwidth to access and download needed datasets.

Social issue: Artificial intelligence systems may become the center of many aspects of society and, therefore open more digital divides or may even form the attitudes and actions of the students. In this aspect, school librarians need to consider and ensure human dignity, diversity, and inclusion as they critique the social impact the technologies might create when used or developed.

Technical challenge: Technical limitations of artificial intelligence systems include complexity, unpredictability, or vulnerability. Thus, school librarians should identify the advantages and disadvantages of the current systems in place or being developed to ensure that the artificial intelligence systems used are reliable, solid, and secure.

9. Futures of AI in Library and Information Science

Traditionally, librarians have gathered tremendous amounts of data about the ways in which library resources are used in order to inform better internal decision-making and in order to illustrate the library's relevance to institutional priorities. Several factors are combining to make gathering library data more challenging but also more critical. Libraries now offer far more different types of resources than the books, journals, newspapers, etc., that have been historic (Konkiel 2016). This can be movies, tapes, DVDs, CDs, databases, eBooks, collections of digital images, music scores, and digitized audio files. Digitization of scholarship could mean that users would generally access library resources at farther-off locations, henceforth making it difficult to monitor. The Ithaka S+R library survey for 2019 revealed that nowadays most of the materials budget in a library is spent on online digital journals, online databases, and eBooks. Less than 10% is spent on print books (Frederick, 2020). As Konkiel puts it, "… it would come as no surprise to anyone who has worked with digital collections to say that digital library content is heterogeneous and, in many cases, complicated to measure (Konkiel, 2016)." In the event where the data is retrieved from various systems that do not have easy compatibility, it can be challenging to analyze. Artificial intelligence can assist in making this information better presentable. It is increasingly important to explain the rationale for campus resources' investment in scarce campus funds for library materials. Such requests become particularly relevant when the campus budget is tight. Historically, libraries have only reported on internal utilization of library services or external material. Now, librarians also track the reach of campus scholarship, counting the external uses of content created on campus by calculating uploads of research output to citation systems such as Mendeley, CiteULike, or Zotero and mentions in blogs, Twitter, Facebook, Wikipedia, and other places on the web.

The growing use of open-access resources may mean that more users are accessing material not owned by the library. These measures, known as altmetrics, are used as a supplement to traditional citation metrics (Glänzel 2015). The new capabilities will allow librarians to monitor not only usage patterns from the past and present but also information about how systems are changing and why these changes are occurring. This latter function is called observability. It is hoped that this type of data analysis, facilitated by artificial intelligence, will allow the library to identify changing information needs earlier and respond faster and more efficiently to these changes.

10. Findings

(1) AI applications in LIS have expanded rapidly, especially in information retrieval and chatbot services.

(2) Traditional services like cataloging and metadata management are increasingly automated.

(3) Recommendation systems show a shift toward user-centered personalization.

(4) Bibliomining and analytics enhance scholarly communication and decision-making.

(5) The increasing number of publications shows that machine acumen will move from the experimental phase between 2010 and 2014 to the feasible phase between 2020 and 2024.

11. Conclusion

In brief, AI implementation within today's LIS environment portrays the total turnaround in which the service of a library gets managed and delivered. With AI-based technologies, machine learning, natural language processing, and automation enhance traditional approaches in cataloguing and classification while developing sophisticated retrieval methods. As libraries increasingly implement AI more and more, they need to be bold innovators weighed against risk, as long as the approach ensures easy access, transparency, and inclusiveness. Basically, AI is transforming libraries from static, less responsive structures to dynamic and user-based institutions that are better structured to serve the needs of a digital society. The future of LIS would, therefore, be

AI-driven, providing tremendous scope to improve services and management in a library.

Library support has been transformed by intelligent automation into a hybrid environment of automation, personalization, and high-tech examination. The fact finding revealed that machine intelligence plays an important role in data retrieval, colloquial support, and catalog automation. The rapid increase in publication over the past decade is intended to increase organized and feasible enthusiasm for machine learning-based LIS solutions. Given the prognosis for systematic examination, expert graph, intrigue innovations, and the virtuous obstacles to the adoption of AI, it is expected that an extroverted study will be ordered.

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