systems

MDPI

Article

Artificial Intelligence for Media Ecological Integration and Knowledge Management

Allam Balaram [1], K Nattar Kannan [2], Lenka Čepová [3,*], Kishore Kumar M [4], Swaroopa Rani B [5] and Vladimira Schindlerova [3]

1. Department of Information Technology, MLR Institute of Technology, Hyderabad 500 043, India
2. Department of Artificial intelligence and Machine Learning, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (SIMATS), Chennai 600 124, India
3. Department of Machining, Assembly and Engineering Metrology, Faculty of Mechanical Engineering, VSB-Technical University of Ostrava, 17. Listopadu 2172/15, 70800 Ostrava, Czech Republic
4. Department of Computer Science and Engineering (Data Science), CMR Technical Campus, Hyderabad 501 401, India
5. Department of Computer Science and Engineering (AI&ML), CMR Technical Campus, Hyderabad 501 401, India

* Correspondence: lenka.cepova@vsb.cz

Abstract: Information Technology's development increases day by day, making life easier in terms of work and progress. In these developments, knowledge management is becoming mandatory in all the developing sectors. However, the conventional model for growth analysis in organizations is tedious as data are maintained in ledgers, making the process time consuming. Media Ecology, a new trending technology, overcomes this drawback by being integrated with artificial intelligence. Various sectors implement this integrated technology. The marketing strategy of Huawei Technologies Co. Ltd. is analyzed in this research to examine the advantages of Media Ecology Technology in integration with artificial intelligence and a Knowledge Management Model. This combined model supports sensor technology by considering each medium, the data processing zone, and user location as nodes. A Q-R hybrid simulation methodology is implemented to analyze the data collected through Media Ecology. The proposed method is compared with the inventory model, and the results show that the proposed system provides increased profit to the organization. Paying complete attention to Artificial intelligence without the help of lightweight deep learning models is impossible. Thus, lightweight deep models have been introduced in most situations, such as healthcare management, maintenance systems, and controlling a few IoT devices. With the support of high-power consumption as computational energy, it adapts to lightweight devices such as mobile phones. One common expectation from the deep learning concept is to develop an optimal structure in case time management.

Keywords: media ecology; Q-R hybrid simulation methodology; knowledge management model; artificial intelligence

check for updates

Citation: Balaram, A.; Kannan, K.N.; Čepová, L.; Kumar M, K.; Rani B, S.; Schindlerova, V. Artificial Intelligence for Media Ecological Integration and Knowledge Management. *Systems* **2023**, *11*, 222. https://doi.org/10.3390/systems11050222

Academic Editor: Vladimír Bureš

Received: 24 January 2023
Revised: 19 April 2023
Accepted: 21 April 2023
Published: 26 April 2023

1. Introduction

Due to the growth of mobile internet connectivity, knowledge has never been easier to access. In recent years, video has become increasingly popular, with a wide range of people around the world. In a short film, the information is delivered more comprehensively, making it easier for the viewer to understand. Technologies, such as cloud computing, mobile internet, artificial intelligence, and deep learning, are making algorithms more common in news production [1]. For example, similar algorithms that are popular in deep learning modules, such as auto-encoders, are a kind of trained neural network concept that also replicates particular information between input and output layers. In addition to machine writing and intelligent recommendations, big media companies are using artificial intelligence in a number of ways. This is due to the rapid growth of new media, such as quick hands, volcano videos, and microblog videos. Thus, short films have become more popular than any other form of media for transmission and dissemination. Thus, the use of cutting-edge technology in the production of movies, videos, and audio is referred to as "media ecology" [2]. More people are watching videos than ever before, making videos the most popular sort of content across all major social media platforms right now. To express themselves and gain followers, more and more people are uploading films to social media platforms [3]. The majority of broadcast media is making an effort to concentrate on AI and deep learning algorithms in order to leverage them in producing people's desired entertainment. Making short movies is a terrific method to gain exposure and money. To promote themselves or distribute information, a rising number of people are using video-sharing websites such as YouTube and other services of a similar nature [4]. Given the volume of footage, it is critical to highlight the pertinent material and make it simple for viewers to locate. Making movies more accessible, current, and diverse will help us spend less time looking for and discovering them. In the field of photo depth learning, numerous national and international contests have produced a huge number of outstanding algorithms and models.

Convolutional neural networks are crucial in deep learning applications, as demonstrated by the improvement in video categorization provided by a large number of networks [5,6]. The analysis of video content requires an in-depth knowledge of the video content itself, which implies that a machine camera or video is preferable to an analysis of video content based on a human's identified area. Traditional broadcasting media partners should utilize the implementation of lightweight deep learning modules in the system. A significant part of internet users' media intake has unquestionably benefited from the widespread usage of mobile short video, thanks, in large part, to advances in AI. There was no way anyone could have predicted how far this technology had come or how quickly it had grown. Mobile short video has been shown to have long-lasting and far-reaching effects on culture, commerce, society, and existence [7]. In light of this, when short video content transitions to mobile short video, the mobile short video recommendation algorithm becomes more closely linked to the content. Using mobile devices for short video transmissions, personalized information, and interactive consumption is convenient; nevertheless, longer videos and photos are more difficult to consume [8]. Entrants are one such mandatory thing to be used these days, providing enough advantages and more capabilities in order to create a better method in creating advertisements and other video creation. Apps that allow users to share short videos have became more popular in 2017 due to enhanced mobile internet technology and better network conditions, as well as the introduction of new technologies such as artificial intelligence. Social short video apps are becoming increasingly popular, and there are several difficulties that need to be solved [9]. Due to the availability of more advanced tool qualities and the motivation to do so, social short films have evolved as a unique subtype of short videos in order to compete on the market.

The recent increase in data discovery, management, visualization, and business analytics in the professional context indicates a data-oriented perspective, emphasizing the increasing relevance of information-oriented corporate environments [10]. However, when faced with the vastness of previously existing digital content, human brain processing capacities fall behind in the quest to harness knowledge. As a result, prominent technologies, such as the Internet of Things (IoT), Machine Learning (ML), and artificial intelligence (AI), emerge as important tools for rapidly collecting, analyzing, and transforming vast amounts of data [11,12]. AI has already discovered several approaches to unlock and give new meaning to digital knowledge in order to improve the decision-making processes of commercial organizations through various iteration mechanisms. In most cases, advertisement creators obtain their necessary data through social media. In that case, the collection of such social media performance and utilizing such data with a particular deep learning algorithm would be a great challenge.

Machines process unstructured data and categorize them (commonly known as categories). They can readily connect system-stored concepts with knowledge that is relevant to the same context or environment. The algorithm may learn from these newly discovered connections and gradually improve the detection of existing relationships between digital data, just as the human mind does [13]. Missing linkages within current knowledge cause firms to lose strategic value—information-driven associations are one of the most difficult challenges in dealing with large amounts of digital knowledge. This is the same as how we sometimes read books but then forget about a similar subject covered by an article we read two days ago; the same thing happens with business architectural infrastructures [14]. Businesses frequently fail to build data-friendly settings, making it difficult to identify linkages between the information of different ecosystem components within the organization and between sections of a single component [15]. These relationships are frequently critical in developing a data-driven decision that connects strategy planning to solid analytics insights. They are also the drivers that increase value within an organization's information management environment.

A new ecosystem of smart memory is that, when faced with the term "digital knowledge", many people envision online libraries full of statistics and condensed materials in the form of text or numbers. If anything, knowledge management has demonstrated that the term "data" is a loose one [16]. An AI system capable of grouping together images of similar categories, such as selfies, landscapes, or group photos, is used in the solution. Advanced face recognition and image classification technology simplifies the arrangement of these categories in photobook-ready chapters [17,18]. On the one hand, consumers are relieved of the time-consuming job of scrolling through their phone libraries, categorizing memories, and picking images for printing. On the other hand, many companies can now benefit from useful (anonymous) data derived from the app, which display users' ordering habits. Not only did pattern recognition technology improve the efficiency of the photobook process but the algorithm created from computer vision generated new knowledge. This information is of additional value in the form of data that a corporation use to design its business strategy. AI systems can identify outliers in datasets throughout the data analysis process. Atypical knowledge behavior is extracted from the group of information and regarded as rare or questionable. The environment, such as pattern recognition, can be programmed to improve autonomously through continuous learning from data sources. Data inconsistency can be an indicator of ecosystem failure—in most situations, articles with obvious contextual errors divert readers from the storyline. They recognize something is a mess with the narrative's credibility; the information presented is suddenly untrustworthy. Data pools used by businesses operate in a similar manner [19]. Inconsistencies within datasets can have a direct impact on the knowledge contained within these information pools, causing considerable delays in the workflow of business processes. These are frequently manifested as financial transaction fraud, cybersecurity scams, or production line disruption.

Natural language processing (NLP) alters the game of reimbursement systems. NLP is the core technology that assists AI in interpreting and evaluating human language. Its ability to analyze and categorize online material is critical in the discovery of anomalies in knowledge volumes. The vast amount of information contained in a country's handwritten medical bills might quickly fall victim to data discrepancy. Contextual and environmental factors enhance the likelihood of missing signatures and inaccurate values in documentation. The AI processing system developed an algorithm capable of linking existing categories in medical invoices (such as IBAN, doctors' signatures, or handwritten remarks) with the text included in these papers. The document categorization and validation system readily discovered incomplete or wrong information by filtering the knowledge by content type, whether it was for contracts, orders, or receipts. The NLP's anomaly detection system for reimbursements was the tipping point in reducing the manual processing of paperwork and, hence, the possibility of errors to a simple confirmation of results previously provided by the AI.

Online databases can give AI access to knowledge that is applicable to many different topics and application fields. A properly equipped machine can access real data from a database that grows as a result of human interactions that provide the algorithm with fresh data. It also means that customers or system users will have access to a larger pool of data. Chatbots, artificial technologies built on NLP that analyze and engage with human language through a conversation-like simulation environment, frequently carry out the act of information transmission (or transfer). Knowledge availability is an often-underestimated component that plays a critical influence in service users' satisfaction. Difficulties in obtaining information can result in severe client losses. Readers who are missing portions of a publication may comprehend the paragraph they are focusing on but lose sight of the paper's overall purpose. Similar to this, users who are surfing a website, utilizing an application, or trying out a new service cannot benefit fully from the solution if access to user manuals is difficult. Therefore, failing to facilitate this knowledge transfer can easily lead to users terminating their use of the solution because they believe the support team is not paying attention to them or because they are only using a small number of the available capabilities as a result of inadequate system management communication. Thus, knowledge delivery serves as an informational link between infrastructures and clients. When parts of this bridge are missing, the direct connection between the two parties also breaks, and part of the value transferred within this information ecosystem is lost with it. This study focused on evaluating the performance of a media ecological and knowledge management model employed in the organization using artificial intelligence technology. The media are being described in the case of AI and ML, but one such important thing is to focus on what the viewers expect from a short movie or advertisement. It depends on the method of prediction, for example, analyzing some methods with the help of computer vision and the study of audience's interest and converting such data into an intelligence-based system and serving the actual content expected by the audience. All these roles can be made with the help of deep learning modules, but the important thing is that they are made under lightweight models; then, the system would be compatible with every audience.

2. Motivation of This Work

An interdisciplinary branch of study called Media Ecological Management (MEM) looks at how media technologies interact with their surroundings. It aims to comprehend how society, culture, and the environment are impacted by the media landscape and how this relationship may be handled in a way that is sustainable and advantageous for everyone.

MEM is influenced by a number of academic fields, including media studies, environmental science, communication theory, and corporate management. It looks at how media technologies affect how people see the world, behave, and interact with one another. It also looks at how media creation and consumption affect the environment.

The understanding that media technologies are not objective tools but rather are ingrained in and affected by social, cultural, and environmental settings is one of the fundamental pillars of MEM. Because of this, MEM aims to comprehend the intricate interactions between media technology, society, and the natural world and to create plans for their sustainable management.

MEM includes a variety of methods and tactics for handling the media's impact on the environment, such as the creation of eco-friendly media technologies, the adoption of sustainable media production and consumption methods, and the encouragement of media consumers' media literacy and environmental awareness.

MEM presents a thorough and interdisciplinary perspective on the intricate interplay between media technologies and the environment. It also offers insightful information and management tactics for fostering sustainability and social responsibility. The goal of this work was to investigate the digital technologies that support media ecological management in the inventive industries' customer knowledge management processes. According to the body of articles on the subject, the primary digital technologies used in the media ecological knowledge area of authority were classified as (1) interpersonal tools, (2) marketing tools, and (3) quality scenario tools. In terms of interpersonal tools, it was discovered that firms primarily used conventional digital media ecological technologies. It was a managerial indicator for information system vendors to capitalize on the increasing market desirability defined by media ecological management. On the other hand, it was a strategy indicator to encourage media ecology, which requires economic incentives for digital and technological entrepreneurship. The study proposed a Q-R (Quantity–Record) hybrid model for analyzing the performance of the organization. It is not difficult to train a lightweight deep learning model, but it requires a few parameters, which are satisfactory for intensifying the system's performance, even the model being created on the basis of a recording kit; then, it must require a few discriminators to generate an average feedback system.

Businesses in competitive business environments are constantly striving to provide products and/or services to customers faster and more effectively than competitive products. Supervisors have also learned that they cannot succeed on their own; instead, they must work with other institutions. Although the Q-R hybrid methodology and the eventual results of wireless networking tools are able to compete with the business strategy, media ecological integration, knowledge management, and optimal control tasks are much more complex and difficult. A newly developed judgment tool for evaluating, designing, and trying to improve such supply chains' integration of media, ecology, and knowledge management ensured cutting-edge and user-friendly concepts for modeling, simulation, and enterprise media ecological integration and knowledge enhancement. Media, ecology, and knowledge management are integrated with the aid of wireless networks for data collection, process, and application as each node. While preparing the lightweight deep learning model, the process of generating the system would require an encoding system where the audio, video, or image format is being featured in different methods. At first, the generating system encodes the necessary data that are required for the production and then block separation occurs to train the pre-processed models.

3. Proposed Architecture

Huawei Technologies Co. Ltd. is considered in this research to analyze the result of media ecology utilization in marketing their product on various media, such as Facebook, Twitter, and so on. Using these social media, the company promotes their products and, hence, improves their business by performing various analyses. Using web crawler APIs, they extract the post from Facebook, Twitter, and Instagram. The conversation details will be available at different server nodes, and with the aid of the crawlers, the data are collected through wireless networking technology. The data are collected on a daily basis and the NLP technique is implemented to retrieve positive posts and conduct further processing in the existing system. Media Ecology is a recent technology in which any organization can collect the required information by utilizing social networking websites. Certain social networking websites include Facebook, Instagram, Twitter, and so on. For any analysis of whatever circumstance or scenario, the data collected from the conversations between the persons using Media Ecology are organized and managed for further processes. The database will store the collected and organized data based on the topic, and the user can be given user privileges, depending on the requirement. Not all the data are freely available on the websites. The retrieved data can be implemented in any sector on demand. The information is then shared or transferred and made to learn by the organization's people available at different locations through a wireless network to improve the organization's profit. The analysis results will aid in the creation of new knowledge, and the process is repeated. In this complete process, capturing/acquiring data from the social media networks and organizing the data are grouped as a Management Key in Knowledge Management Model. Access and use/discover are grouped as Application Key, and the last Share/Learn and Create as Users or the people Key. These three keys work as the cyclic process. All these processes do not need be performed at the same node, as it may result in data loss. Hence, each node is provided with each task to perform the process.

Huawei Technologies Co. Ltd. collected conversations from Facebook, Twitter, and Instagram, performed the analysis with the Knowledge Management model, manufactured new products based on the demand, and posted back on the sites. They made announcements to the user regarding the latest product and collected responses with the aid of artificial intelligence technology. The pictorial representation of the process is depicted in Figure 1. The main advantage of using wireless networking technology is faster data transfer among the nodes, which are at remote locations. Additionally, the processes can be performed at any available location with portability and good signal strength. Signal strength plays a dynamic role in each segment of the work as the data transfer is completely dependent on the network signal, irrespective of where the individuals are situated.

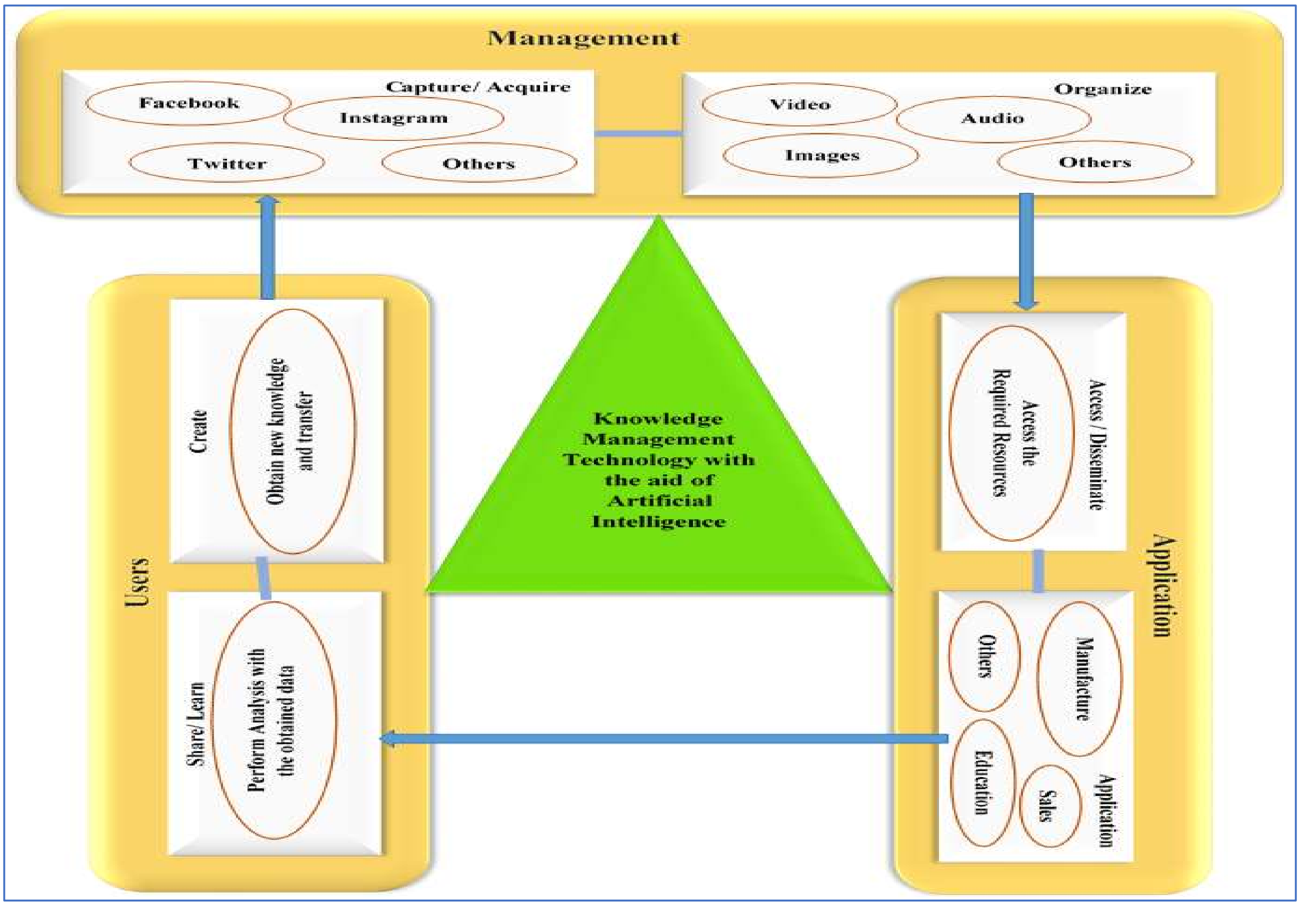

Figure 1. Proposed architecture.

When choosing a tradesperson, the innovative company should consider not just a fundamental understanding of agreement media ecological integration and knowledge media ecological integration but also the knowledge management group's personal parameter estimates and knowledge from enterprise media ecological integration and knowledge media ecological integration and knowledge management modeling techniques. The Economic Order Quantity inventory media ecological integration and knowledge management technique is used to predict the appropriate size of delivery and to choose the least expensive delivery person following Equation (1).

$$MEI = \sqrt{\frac{2 \times G \times Q_x}{R_m \times a}} \tag{1}$$

MEI—is an abbreviation for objective (optimal) response to the requirements. G—the annual requirement for optimized inventories is denoted. R_m—the proportion rate for the cost of production of stockpiling is estimated. Q_x —the expense of stockpiling.

$$Q_{mgnt} = \sqrt{\frac{2 \times G \times Q_n}{Q_r}} \quad (2)$$

Q_r—denotes inventory maintenance operating costs.

Equation (2) is the percentage of conserving deposits, based upon the facts that, now, the expenses of retaining reserve funds have risen in relation to the amount of resources in an enterprise. Its percentage is the total amount of the following options: intermediary, stocking up, logistic support, internal logistics within in the capital sufficiency factory, insurance, and decomposition. Equation (3) is below.

$$GA = \frac{G}{E} \times Q_n + \left(\frac{E}{2} + F_m\right) \times a \times R_m \quad (3)$$

GA—represents the total cost of resources. E—needs to stand again for size of the distribution fraction, and F_m needs to stand with the use of a safety factor, as in Equation (4).

$$QE = \sqrt{\frac{2 \times (1 - D) \times Q_x \times G}{a \times (q + R \times (1 - D))}} \quad (4)$$

q—signifies a different cost. QE—the best amplitude for a money flow in terms of enhancing market capitalization. R—the efficient cost of stock production follows Equation (5).

$$GA = \frac{G}{E} \times Q_r + \left(\frac{E}{2} + m\right) \times a \times R \quad (5)$$

$$QE = \sqrt{\frac{2 \times [(1 - D) \times Q_x^{\#} + Q_x^{*}] \times G}{r \times (q + R^{*} + R^{\#} \times (1 - D))}} \quad (6)$$

where $Q_x^{\#}$ signifies the income expenses associated with creating stock levels, Equation (6). $R^{\#}$ signifies the probability of tax deduction allowed to continue the operating cost of supporting inventories and signifies semi-costs of working to develop inventory levels show in Equation (7).

$$GA = \frac{G}{E} \times Q_x^{\#} + \frac{G}{E} \times Q_x^{*} + \left(\frac{E}{2} + F_m\right) \times a \times R^{\#} + \left(\frac{E}{2} + F_m\right) \times a \times R^{*} \quad (7)$$

R^{*}—Moderate operating costs at an effective rate.

Distinctions in time deliveries have such a substantial impact on numerous phases of supplier's requirement for safety systems, and these are provided, as in the following Equation (8).

$$F_m = \sqrt{-2 \times C^2 \times ln \frac{Q \times E \times C \times a \times \sqrt{\varphi}}{G \times Q_{nm}}} \quad (8)$$

where C represents Equation (9), the standard error for transfer utilization and Q_{nm} represents the cost of not needing stock resources, Equation (10).

$$K = \sum_{i=1}^{m} G_i \times (Q_i - Q)^2 \quad (9)$$

$$C = \sqrt{K} = \sqrt{\sum_{i=1}^{m} G_i \times (Q_i - Q)^2} \quad (10)$$

where G_i denotes the approximate likelihood occurrences of the precise circumstance based on statistics.

It is able to quantify the variability coefficient in Equation (11) in relation to information about what possible advantages may be brought about by lending money to a marketing plan.

$$Q = \sqrt{\frac{C}{G}} = \sum_{i=1}^{m} G_i(Q_{1i} - Q_1) \times (Q_{2i} - Q_2) \tag{11}$$

The next element is a correlation between the advantages of purchasing from a particular supplier and the advantages of acquiring from many other distribution companies. To accurately measure Equation (12), similarity testing is frequently used.

$$\delta_2 = \frac{\sum_{i=1}^{m} G_i(Q_{1i} - Q_1) \times (Q_{2i} - Q_2)}{C_1 \times C_2} \tag{12}$$

δ_2 is the coefficient of correlation here between the advantages of acquiring the first and minute providers; Q_1 reflects the applicable price of economic benefit that can be obtained from the initial supplier; Q_2 denotes the applicable price of economic profit from purchasing from the subsequent provider; and C_1 represents the coefficient of determination for the very first provider. The probability value, again, for the second supplier, is denoted by C_2. Q_{1i} is the possibilities of creating the prospective percentages of economic compensations from products accepted from the initial supplier; Q_{2i} is the possibility of demand for making a possible future percentage of economic benefits from items purchased by the second supplier; and G_i is the possibility of potential rates of economic returns from resources, as represented in Equation (13).

$$C_G = \sqrt{C_n^2 + C_m^2 + 2 \times C_n \times F_m \times \delta_{n\&m}} \tag{13}$$

where C_G is the whole standard error, C_n is the standard error of the very first possible answer, F_m is the standard error obtained from the standard alternative, and $n\&m$ represents the coefficient vectors between the first and second multidimensional data. The initiatives that could be put into action to advance and strengthen the information system will be identified. A constrained and prescribed group of constituent signifiers is signified.

$$K_1 < K_2 < \ldots\ldots < K_n \tag{14}$$

In Equation (14), K_1 arrives within a week of the element, K_2 emerges within a week of element, K_n, etc. The sequence necessity in a set K would be an arithmetical set of resilience learning G of factor initiatives. As a consequence of K_i,

$$G = \{G_i\},\ i = 1, 2, 3, \ldots\ldots n \tag{15}$$

where, in Equation (15), G_i is a significant figure that satisfies the structural divisions for the cumulative plan effectiveness measurement that could be signified as an intricate effectiveness metric in the form of a linear model as in Equation (16).

$$Q = G_1K_1 + G_2K_2 + \ldots + G_nK_n = \sum_{i=1}^{n} G_iK_i \tag{16}$$

The effectiveness of a strategy is simply a function of Equation (16) G that contains n efficiency different factors that are incremental to its performance indicators K_i.

4. Results and Discussion

The study was analyzed using a Q-R hybrid simulation algorithm for evaluating Media Ecological and Knowledge Management Model.

Methodologies can be tailored to individual needs. The store owner always looks at the proportion of income inventory every time a customer walks in. Depending on the total amount of stock on hand, three possible outcomes might be imagined (Figure 2). The first case is when there is sufficient stock on hand to meet consumer demand and the gross stock level is comforting. This shopper needs things desperately. In addition, the shop's stock attitude and total inventory need to be revised. The needs of customers are greater under all conditions, and the media ecology ranks second in terms of information gathering and client satisfaction.

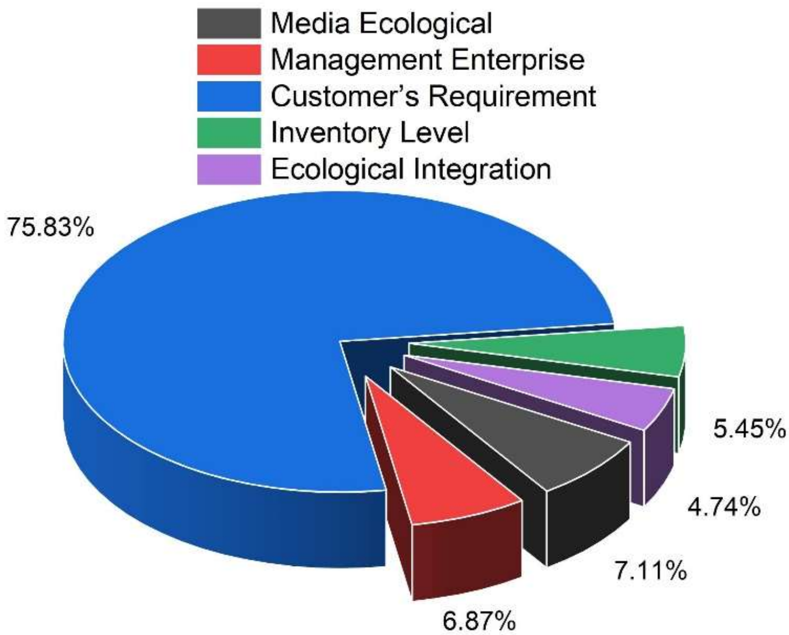

Figure 2. The Media Ecological Integration and knowledge management of customer's requirement.

Total stock is in a good place, but the stock price is too low to fulfill consumer demand. To decide whether or not to place a backorder for the missing items, customers must first satisfy their needs for all currently available products. When there is no available stock, no matter how high the net stock or inventory level, the following occurs (refer to Table 1). In this case, the consumer has two choices: backorder a vacant position item or leave without placing orders. Individuals differentiate consumers within the second and third scenarios, but various market classes have different rearranged probability values. This stock availability can be performed using the on-store method or online method. In the second case, the store's server node will be updated after every transaction in both scenarios that will help the user place orders through online mode, which can decide about a purchase before making a payment. In the current trending technology, online purchase goes with either online payment mode or cash on delivery. In this circumstance, if the client wishes to pay online, the user node will make the payment through the payment gateway node via the billing system on the store's server.

Table 1. Result analysis of Media Ecological Integration and Knowledge Management of customer's requirement.

Media Ecological Size	Probability
Media Ecological	0.3
Management Enterprise	0.29
Customer's Requirement	3.2
Inventory Level	0.23
Ecological Integration	0.2

The impact of the destabilization of a frequency set u on the minimum annualized total cost is analyzed under various interrupted time travel indicator scenarios. We could see that the company's minimum average annual total cost significantly reduces in every scenario. Moreover, as u increases, the amplitude of a decrease becomes bigger. The average destabilization interval in this study is fixed, and the above graph shows that reducing the frequency of disruptions reduces the present minimum overall cost. In addition, as can be seen in Figure 3, when the fault length is brief, there are no appreciable impacts of different interference frequency values necessary only for computing the lowest overall cost.

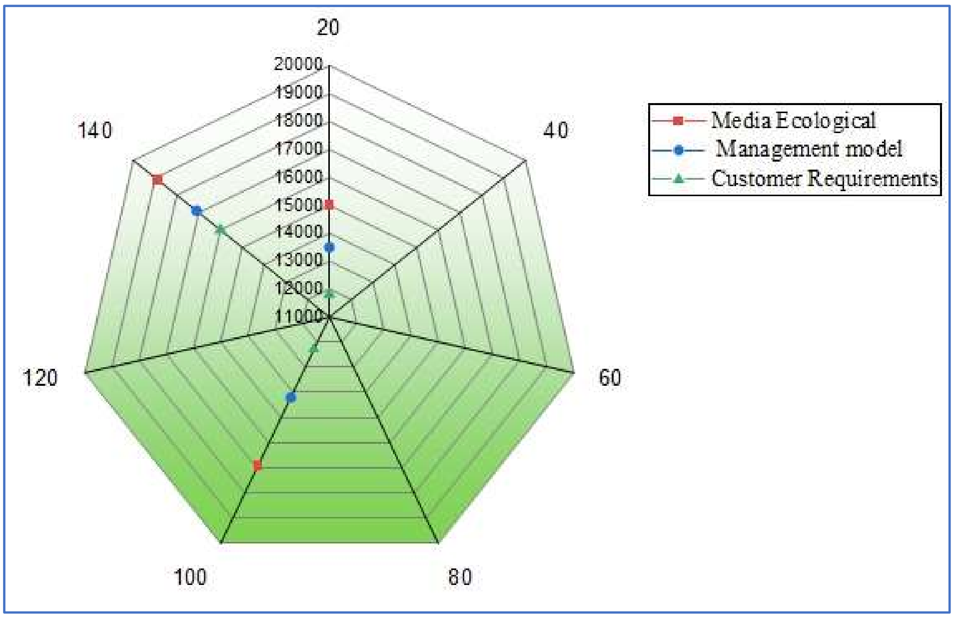

Figure 3. Media Ecological Integration s and Knowledge Management Model construction in different u scenarios.

Distinctions become much more marked when discrimination is utilized. In the case of evaluating the media quality, different qualities or reels are used in order to have sufficient accuracy to form the datasets. From the below analysis, it is possible to analyze both the media management and the ecological prospect of the system.

The impact of customer differences on the required minimum average cost under a destabilization scenario to $q = 75$ and $F = 15$. Equally, four q values and four G_1 and G_2 scenario mixtures are considered. Figure 4 shows that, now, the lowest overall income affects the final tally in q, irrespective of the G_1/G_2 combination. This implies that, if the supply interference scenario is $q = 75$ and $F = 15$, the retail chain has very few class I consumers and the current minimum overall cost is lower. As a result, class I consumers must be reduced. This is the inverse of the previous situation, wherein the provoking scenario is $q = 75$ as well as $F = 15$. This shows how disruptions affect customer distinctions within inventory management systems.

According to the outcomes (refer Figure 5), the continual significantly achieves the other framework in all scenarios to differing q and F values (G value is 0.0002). The major reason for this is that in a given model, timeframes and loss of sale price are lower. Users then compare the two methods that rely on senior time, losing sales data.

The primary goal of an enterprise's Media Ecological Integration and Knowledge Management is to enhance its value. This essential goal should also be helped by the Q-R hybrid simulation. The enterprise value maximization strategy is carried out, with a strong emphasis on uncertainty and risk. It also examines the effect for such a recipient firm of functioning cost attached to delivery capital management by the suppliers. The current article presents an inventory method that uses a Q-R hybrid simulation to produce the best results for customer management, as given in Table 2.

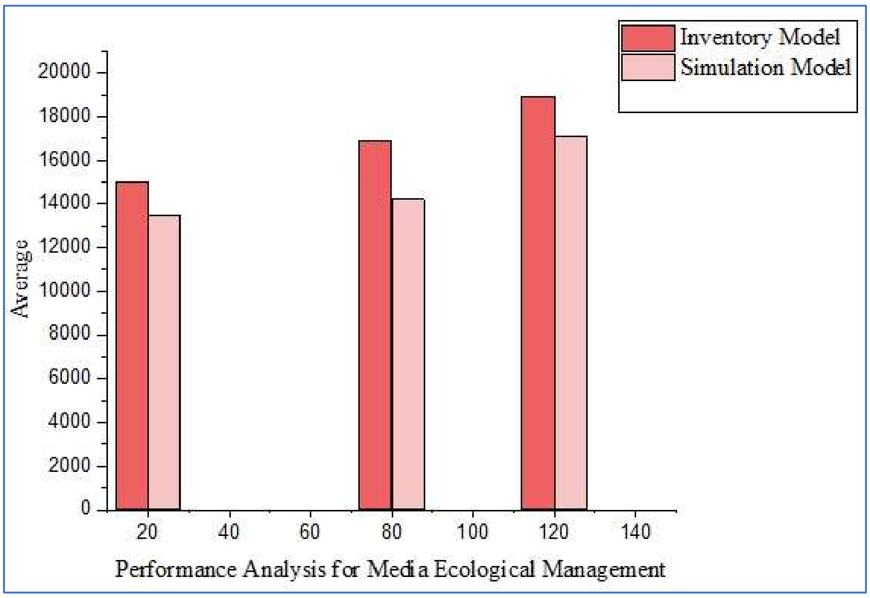

Figure 4. The performance analysis for Media Ecological Management effect of customer segmentation scenario with $q = 65$ and $F = l$.

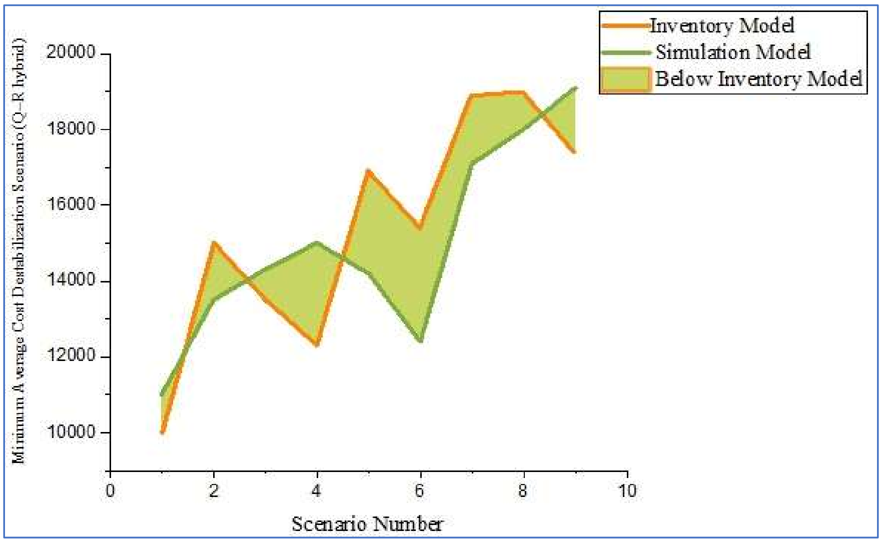

Figure 5. Evaluation of the inventory model to a simulation model under different F and q scenarios.

Table 2. Comparative analysis of inventory model under different v and u scenarios.

Scenario Number	Q	G_1	G_2	Average Annual Total Cost Current Model (E,r)	Average Annual Total Cost Previous Model (r,G)
1	15	98	16	15,500	14,500
2				14,500	12,600
3				12,000	13,200
4				16,500	17,650
5				14,500	14,500
6				17,000	17,600
7				15,750	18,500
8				18,000	18,900
9				16,250	19,000
10				18,500	19,700

Additionally, continuous variation in u and s can significantly be achieved by another model across all scenarios (G value is 0.0006). The primary reason is that the basic model has lead times and lower loss of sales costs (refer to Figure 6). Now, the users compare the two models on the lead time and the loss in sales growth.

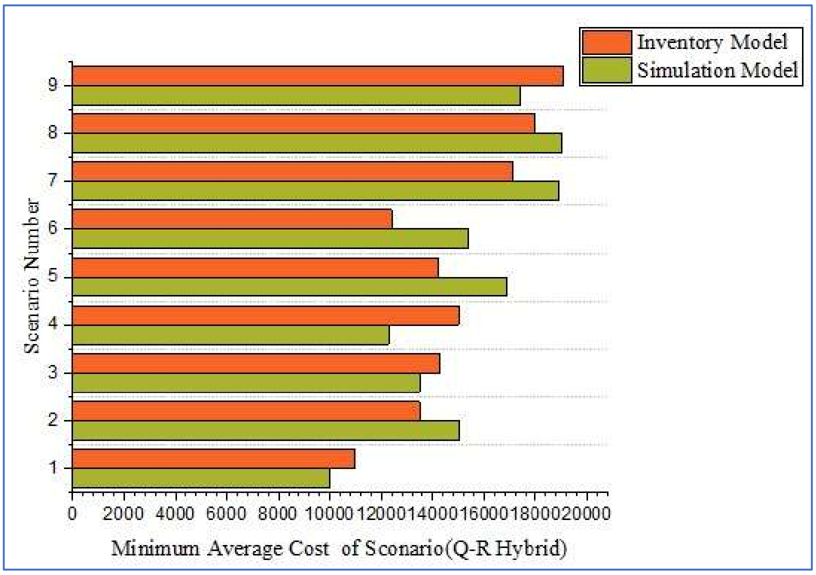

Figure 6. Analysis of the simulation model in the context of customer differentiation.

The finished inventory could use results to compare with specific configurations (refer to Table 3), such as the present condition or possibly reasonable solutions. Furthermore, the completed results can, with high priority, identify the best configuration within the level determined based on the selection of a Q-R simulation. Notwithstanding, it is a good practice to use computation to consider the current situation (if one exists) and other sensible combinations with the suggested ideal level to determine the Q-R simulation for a comprehensive solution.

Table 3. Result for a comparison of the inventory model to the Q-R hybrid simulation under various G and q scenarios.

Scenario Number	Q	G_1	G_2	Average Annual Total Cost	
				Inventory Model (Q,d)	Q-R Hybrid Simulation Model (d,G)
1	16	98	16	12,000	14,800
2				11,000	13,400
3				13,500	12,800
4				12,700	16,250
5				13,600	17,150
6				16,700	18,250
7				17,250	18,700
8				18,300	19,100
9				18,150	18,500
10				18,700	19,800

5. Conclusions

This study focused on determining how Media Ecological Integration and Knowledge Management can enhance the value of an organization. A Q-R hybrid simulation model was used to evaluate the performance of an inventory model. Additionally, the study examined the impact of delivering capital management on the cost of functioning for the recipient firm, and it suggested a strategy for maximizing enterprise value with a focus on uncertainty and risk. The Q-R hybrid simulation model combines two important components, namely queuing theory and simulation modeling, to provide a comprehensive analysis of inventory system performance. The queuing theory component focuses on analyzing the behavior of customers in a queue, such as arrival rate, service rate, and queue length. It allows for the estimation of important performance metrics, such as wait times, queue lengths, and service utilization rates.

The simulation modeling component, on the other hand, models the overall inventory system, including inventory policies, ordering policies, and demand patterns. It allows for the testing of different inventory policies and ordering strategies under various demand scenarios and the analysis of the resulting inventory levels, stockouts, and costs. By combining these two approaches, the Q-R hybrid simulation model can provide a more comprehensive and accurate analysis of inventory system performance than either approach alone.

Furthermore, the Q-R hybrid simulation model can help identify bottlenecks, inefficiencies, and areas for improvement in the inventory system. It can also help determine the optimal inventory policies and ordering strategies to achieve the desired performance outcomes, such as minimizing stockouts or reducing inventory holding costs. Overall, the Q-R hybrid simulation model may be a powerful tool for inventory management, providing valuable insights for decision making and optimization.

A high average service level of at least 98.841% in the supply chain, as demonstrated by the study results, is a strong indication of the effectiveness of the proposed method for improving performance in uncertain environments. This is particularly significant given the potential impact of stockouts on customer satisfaction, sales revenue, and overall business performance. The use of a Q-R hybrid simulation model allows for a more accurate and comprehensive analysis of inventory system performance and the identification of optimal inventory policies and ordering strategies. This can help organizations to minimize stockouts and reduce inventory holding costs, while also improving customer satisfaction and maintaining high levels of service. Overall, the study's findings highlight the importance of effective inventory management in achieving business success, particularly in the context of uncertain demand and supply conditions. It is recommended that future research should evaluate the performance of customer management and capital management, as well as secure data transfer and payment methods in wireless networking. Additionally, it is suggested that researchers compare the performance of normal modules with lightweight deep learning systems, which require fewer parameters and can produce more competitive results.

Author Contributions: Conceptualization, K.N.K.; Methodology, A.B., K.N.K., K.K.M. and S.R.B.; Software, A.B.; Validation, A.B.; Formal analysis, L.Č. and V.S.; Investigation, A.B., K.N.K. and K.K.M.; Resources, K.N.K., K.K.M. and V.S.; Data curation, L.Č., K.K.M. and S.R.B.; Writing—original draft, A.B., K.N.K., K.K.M. and S.R.B.; Writing—review & editing, L.Č. and V.S.; Visualization, S.R.B.; Supervision, L.Č. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available through email upon request to the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Broussard, M.; Diakopoulos, N.; Guzman, A.L.; Abebe, R.; Dupagne, M.; Chuan, C.-H. Artificial intelligence and journalism. *J. Mass Commun. Q.* **2019**, *96*, 673–695. [CrossRef]
2. Shunkov, V.; Shevtsova, O.; Koval, V.; Grygorenko, T.; Yefymenko, L.; Smolianko, Y.; Kuchai, O. Prospective Directions of Using Multimedia Technologies in the Training of Future Specialists. *IJCSNS Int. J. Comput. Sci. Netw. Secur.* **2022**, *22*, 739–746.

3. Wang, H.; Cui, Z.; Liu, R.; Fang, L.; Sha, Y. A multi-type transferable method for missing link prediction in heterogeneous social networks. *IEEE Trans. Knowl. Data Eng.* **2023**, 1–13. [CrossRef]
4. Cheng, W.W.H.; Lam, E.T.H.; Chiu, D.K.W. Social media as a platform in academic library marketing: A comparative study. *J. Acad. Libr.* **2020**, *46*, 102188. [CrossRef]
5. Remli, M.A.; Deris, S. An Approach for Biological Data Integration and Knowledge Retrieval Based on Ontology, Semantic Web Services Composition, and AI Planning. In *Ontology-Based Applications for Enterprise Systems and Knowledge Management*; IGI Global: Hershey, PA, USA, 2013; pp. 324–342.
6. Cao, H. Entrepreneurship education-infiltrated computer-aided instruction system for college Music Majors using convolutional neural network. *Front. Psychol.* **2022**, *13*, 900195. [CrossRef] [PubMed]
7. Hamelink, C. The decent society and cyberspace. In *Mediating Religion: Conversations in Media, Religion And Culture*; 2003; pp. 241–256.
8. Zhang, Q.; Zhou, M.; Li, C.; Zheng, X.; Wang, K.; Yang, S. Case analysis on value creation and sustainable development path of supply chain integrators. In Proceedings of the 2018 15th International Conference on Service Systems and Service Management (ICSSSM), Hangzhou, China, 21–22 July 2018.
9. Owoc, M.L.; Sawicka, A.; Weichbroth, P. Artificial intelligence technologies in education: Benefits, challenges and strategies of implementation. In Proceedings of the Artificial Intelligence for Knowledge Management: 7th IFIP WG 12.6 International Workshop, AI4KM 2019, IJCAI 2019, Macao, China, 11 August 2019.
10. Davenport, T.H.; Harris, J.G.; Morison, R. *Analytics at Work: Smarter Decisions, Better Results*; Harvard Business Press: Cambridge, MA, USA, 2010.
11. Tyagi, K.; Fernandez, T.F.; Mishra, S.; Kumari, S. Intelligent automation systems at the core of industry 4.0. In *Intelligent Systems Design and Applications: 20th International Conference on Intelligent Systems Design and Applications (ISDA 2020), 12–15 December 2020*; Springer International Publishing: Cham, Switzerland, 2021.
12. Li, X.; Sun, Y. Stock intelligent investment strategy based on support vector machine parameter optimization algorithm. *Neural Comput. Appl.* **2020**, *32*, 1765–1775. [CrossRef]
13. Verdejo, D.P.; Mercier-Laurent, E. Video Intelligence as a component of a Global Security system. In Proceedings of the Artificial Intelligence for Knowledge Management: 5th IFIP WG 12.6 International Workshop, AI4KM 2017, IJCAI 2017, Melbourne, VIC, Australia, 20 August 2017.
14. Hohpe, G.; Woolf, B. *Enterprise Integration Patterns: Designing, Building, and Deploying Messaging Solutions*; Addison-Wesley Professional: Boston, MA, USA, 2004.
15. Bekavac, I.; Garbin Praničević, D. Web analytics tools and web metrics tools: An overview and comparative analysis. *Croat. Oper. Res. Rev.* **2015**, *6*, 373–386. [CrossRef]
16. Renzl, B. Trust in management and knowledge sharing: The mediating effects of fear and knowledge documentation. *Omega* **2008**, *36*, 206–220. [CrossRef]
17. Li, Q.-K.; Lin, H.; Tan, X.; Du, S. H_(∞) consensus for multiagent-based supply chain systems under switching topology and uncertain demands. *IEEE Trans. Syst. Man Cybern. Syst.* **2020**, *50*, 4905–4918. [CrossRef]
18. Xiong, Z.; Liu, Q.; Huang, X. The influence of digital educational games on preschool Children's creative thinking. *Comput. Educ.* **2022**, *189*, 104578. [CrossRef]
19. Shang, Y.; Pu, Y.; Yu, Y.; Gao, N.; Lu, Y. Role of the e-exhibition industry in the green growth of businesses and recovery. *Econ. Chang. Restruct* **2023**, 1–8. [CrossRef]