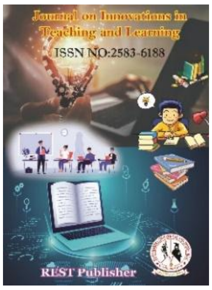
Journal on Innovations in Teaching and Learning

Vol: 4(1), March 2025

REST Publisher; ISSN: 2583 6188

Website: http://restpublisher.com/journals/jitl/

DOI: https://doi.org/10.46632/jitl/4/1/14



Key Factors Influencing Learning Outcomes in Distance Education: A Comprehensive Analysis

***Zeba perween**

Teacher training and Non formal education,Jamia Millia Islamia New Delhi, India.

*Corresponding Author Email: zeba.ahad01@gmail.com

Abstract: *Distance learning has become a viable alternative to conventional face-to-face teaching methods, gaining widespread adoption by governments worldwide in response to the COVID-19 pandemic. The enforcement of lockdowns and social distancing measures necessitated the rapid implementation of distance learning, often termed Emergency Remote Teaching (ERT) in crisis situations. This abrupt and large-scale transition to online education has brought several challenges to the forefront, including technological adaptation, student engagement, parental involvement, increased workload for educators, organizational restructuring, and the need for governments to formulate new policies and frameworks for monitoring and assessing learning outcomes. The objective of this paper is to examine various distance learning alternatives and their effects on students' academic performance and retention. The study first explores how different stakeholders leverage distance learning to fulfill educational goals. It then assesses multiple options and the criteria that influence distance learning, analyzing their interdependencies to identify the most effective approaches. Despite the growing popularity of online education over the past decade, many aspects of students' online learning strategies remain inadequately understood. This research focuses on uncovering the 'invisible' collaboration patterns among students within online learning environments, using assignment submission timing as a basis for detecting these connections. After identifying key criteria, a second survey was conducted using the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method within the context of distance learning education. This approach helped assess the significance of each criterion and establish causal relationships among them. The study's findings suggest that trusted data-driven distance learning, along with students' professional competence, plays a pivotal role. Additionally, it was found to have a reciprocal impact on the effectiveness of service personnel, particularly in their communication and problem-solving abilities.*

1. INTRODUCTION

The rapid advancement of artificial intelligence (AI) and big data, driven by the continuous evolution of computer and communication technologies, has ushered in a new era of education. Emerging trends such as mobile education and the fragmentation of learning are becoming increasingly prevalent. Furthermore, AI and mobile network technology are gaining traction as key research areas in the educational sector. Despite the benefits of distance education, several scientific and engineering challenges remain unresolved. Addressing the issues related to education-based information technology, particularly in the context of mobile networks, is crucial. Additionally, the application of AI and big data in distance learning continues to pose significant engineering challenges, necessitating further research efforts. A major concern with data-driven learning (DDL) is whether it fulfills its promises or falls short due to difficulties such as lack of motivation, irrelevance, or inefficiency. Boulton (2009a) explores these barriers, highlighting that while learners generally find DDL beneficial, working teachers often express concerns. These concerns stem from a perceived threat to their roles, loss of authority, and a lack of communication between research and teaching communities. Another challenge involves the suitability of educational resources, such as corpora and software, which may not always be user-friendly for learners (Kosem, 2008). Furthermore, inadequate infrastructure—such as poorly equipped computer labs or lack of technical support—can hinder the effective implementation of DDL. Teachers' resistance to new technologies, often due to the time required to master them, parallels students' "technophobia" (Seidlhofer, 2000). The range of activities possible with DDL is extensive and largely dependent on user creativity (Breyer, 2006). The choice of DDL implementation depends on factors such as the learning context, students' proficiency levels, and the topics being studied. Research increasingly focuses on how students directly engage with corpora, rather than merely using corpus analysis to inform teaching materials (Johns, 1988). Technological advancements have led to a socio-material paradigm shift in online education, empowering students to take greater control of their learning experiences (11, 16). Modern educational settings prioritize flexibility, allowing students to learn at their own pace, choose their collaborators, and select relevant information to meet their objectives (7, 11). However, while massive open online courses (MOOCs) provide a wealth of learning opportunities, they also pose challenges in fostering meaningful engagement within learning communities (12, 10). Studies on traditional and online learning emphasize the value of small group collaboration in enhancing student success and developing essential communication skills (25, 9). MOOCs have also demonstrated that students who enroll with friends tend to achieve higher completion rates and better results (6). Pedagogy encompasses both the theoretical and practical aspects of education, with the primary goal of leveraging students' prior knowledge to enhance their skills and attitudes (Coccia, 2019; Dommet, 2019). Data-driven pedagogy relies on internet-based collaboration between students and facilitators, where digital tools and network accessibility play vital roles (Hamid et al., 2015). With the widespread adoption of personal, portable, and wirelessly connected devices, technology-enhanced learning is entering a new phase (Reynard, 2017; Bozkurt, 2017). Despite technological advancements, challenges persist in training educators and students in the effective use of these tools in open and distance e-learning (ODeL) (Ahn, 2020; Brandao & Algarvia, 2020; Bozkurt & Keefer, 2017). The COVID-19 pandemic further complicated teaching methodologies, introducing two primary challenges to data-driven decision-making (DDDM): the shift from traditional classrooms to remote teaching and the increased importance of emotional aspects in learning (Usher et al., 2021; Roman et al., 2021; Yang et al., 2021). These challenges have required educators to reassess their pedagogical strategies and adapt their approaches to support students effectively. Online learning environments are continuously evolving due to advancements in technology and pedagogical approaches. For example, mobile technology has facilitated the development of multi-device learning systems (Wu et al., 2012), while affective computing has enabled automated feedback systems that recognize and respond to students' emotional states (Picard, 1997). As educational systems grow in complexity and user diversity, addressing emerging design challenges and adapting to new contexts becomes increasingly difficult. Identifying recurring issues and implementing effective design solutions are critical for ensuring a seamless learning experience. The paper introduces a data-driven decision-making methodology to assess the suitability, acceptance, and effectiveness of innovative technologies in enhancing student motivation and educational quality. According to Visvizi et al, quality education is a powerful tool for social empowerment and poverty alleviation. The proposed evaluation framework places emphasis on social business and innovation, providing a comprehensive approach to modern educational challenges.

2. MATERIALS AND METHOD

Data-Driven Algorithm Design and Its Applications: Selecting the most suitable algorithm for a particular application is a significant challenge in contemporary data science and algorithm design. Rather than relying solely on pre-existing algorithms with worst-case performance guarantees, practitioners often fine-tune algorithm parameters based on the typical problems they encounter within their domain. The objective is to ensure that the chosen algorithm performs effectively on future tasks. However, traditional approaches to algorithm selection have generally lacked formal performance assurances. In a ground breaking study, Gupta and Rough garden introduced a distributional learning framework for algorithm selection. They proposed modelling an application domain as a probability distribution over common problem instances, demonstrating that the complexity of an algorithm family determines the number of samples required to achieve a close match between an algorithm's empirical and expected performance. This research advances the understanding of algorithm selection by addressing two critical aspects: online and private algorithm selection. In an online setting, problem instances arrive sequentially, possibly in an adversarial manner. The aim is to adjust algorithm parameters for each instance to minimize regret, which is the gap between the cumulative performance of selected parameters and the best possible parameters determined in hindsight. The study also explores private algorithm selection, which seeks to optimize algorithm parameters over a dataset without exposing sensitive information, a crucial factor when dealing with personal data such as medical records or purchasing habits.

Big Data-Driven Education: Educational institutions utilize data in numerous ways. In traditional schools, teachers and administrators use student data to make instructional decisions, assess performance, assign grades, and generate transcripts. The advent of high-speed internet and cloud computing has enabled interactive virtual learning environments, allowing students to engage with modular video lessons, problem sets, and supplementary materials at their convenience. Many schools integrate these platforms into their curricula to create blended learning experiences, combining online and in-person components, or to implement flipped classrooms, where students review lectures at home and participate in discussions during class time.

Massive Open Online Courses (MOOCs) initially aimed to provide free access to high-quality content from prestigious universities, earning 2012 the title "The Year of MOOC" by *The New York Times.* Over time, leading MOOC providers such as Coursera, edX, and Udacity shifted their focus to vocational and professional training, introducing participation fees and certification programs. Meanwhile, emerging educational technology providers continue to develop innovative learning tools such as adaptive e-textbooks, mobile applications, and educational games.

Advantages and Disadvantages of Data-Driven Activity Recognition

Advantages:

1. **Uncertainty Handling:** Data-driven approaches, which rely on probabilistic and statistical modeling, effectively manage sensor uncertainties. This is essential because sensors can produce unreliable information or fail.
2. **Temporal Information Modeling:** Techniques such as Dynamic Bayesian Networks and Hidden Markov Models inherently capture time-related aspects of activities, including delays between sensor readings, activity durations, and start times.
3. **Integration of Heuristics:** Discriminative models allow the incorporation of heuristics to supplement data-driven approaches, reducing complete dependence on raw data.
4. **Dynamic Adaptation:** Since learning is an ongoing process, activity models can evolve over time as user habits change.
5. **Personalized Models:** By learning directly from user data, these models are tailored to individual activity patterns, ensuring a high degree of customization.

Disadvantages:

1. **Cold-Start Issue:** Data-driven models require initial data collection and training, leading to delays in deployment as they cannot function immediately without sufficient data. Transfer learning offers partial solutions but does not completely eliminate this issue.
2. **Limited Reusability:** Since models are personalized based on specific users, they lack generalizability and cannot be easily applied to other users.
3. **Challenges in Data Annotation:** Supervised learning approaches require extensive annotated datasets, which are costly and time-consuming to produce. On the other hand, unsupervised methods may result in lower semantic accuracy and activity granularity.
4. **Lack of Interpretability:** The statistical and probabilistic nature of data-driven models makes them difficult to understand, posing challenges for applications that require human-readable insights, such as behavior modelling and anomaly detection.
5.

DEMATEL method: The Decision Making Trial and Evaluation Laboratory (DEMATEL) method has been widely utilized to analyze the interdependencies among criteria and to identify key factors that contribute to overall effectiveness. This method has been applied in various domains, including marketing strategies, control systems, safety management, competency development for global managers, and group decision-making. Furthermore, hybrid models that integrate DEMATEL with other methodologies have been extensively employed in areas such as e-learning assessment, airline safety evaluation, and policy innovation for Taiwan's SIP Mall. To enhance the development of global managerial competencies, Wu and Lee proposed a hybrid approach combining fuzzy logic with DEMATEL, effectively addressing the uncertainty associated with human judgment. Similarly, Yang et al. used DEMATEL to detect intricate relationships, construct an impact-relation map (IRM), and determine influence levels of various criteria. These influence values were then utilized as inputs for a normalized supermatrix in the Analytic Network Process (ANP), which provides a more comprehensive analysis of the relative importance of factors. The ANP, which extends the traditional Analytic Hierarchy Process (AHP), has proven effective in practical decision-making applications such as project selection, product planning, green supply chain management, and scheduling optimization. Unlike simpler systems where a fixed value can represent the influence degree between factors, complex systems often involve multiple interdependent influences. For example, in supply chain management, upstream enterprises affect downstream enterprises through product supply, while downstream enterprises impact upstream counterparts through financial settlements. Additionally, mutual collaboration efficiency presents another layer of interaction, each with varying degrees of influence depending on the perspective considered. Traditional DEMATEL approaches have not explicitly addressed these multiple influence types.

Applications of DEMATEL: DEMATEL provides several key advantages that make it a valuable tool in decision-making. It effectively illustrates the overall influence of factors, visualizes causal relationships, and identifies interdependencies among criteria. These capabilities have led to its application across various industries to facilitate strategic decision-making by pinpointing critical factors and establishing cause-and-effect relationships. One fundamental application of DEMATEL is in identifying critical factors to help prioritize improvement initiatives. For example, Shieh, Wu, and Huang applied the method to determine the key success factors for service quality in hospitals. Similarly, Büyüközkan and Güleryüz used DEMATEL to select the most suitable renewable energy resources to optimize energy investment costs in the environmental protection industry. Mathiyazhagan, Sengupta, and Poovazhagan leveraged the method to recognize key challenges related to sustainable manufacturing practices in the automotive industry. Another significant application of DEMATEL is the creation of causal-effect relation diagrams, which serve as intuitive tools for decision-makers. For instance, Horng, Liu, Chou, and Tsai used DEMATEL to analyze relationships among six dimensions and 27 sub-dimensions of creativity for future restaurant space design. Similarly, Quezada, Lopez-Ospina, Palominos, and Oddershede applied the method to identify causal links within strategic maps in the manufacturing industry. DEMATEL continues to play a crucial role in complex decision-making processes, helping organizations and stakeholders better understand the relationships among various factors and prioritize actions effectively.

- **Motivation to Learn:** The drive or willingness of students to engage with and commit to their learning process.
- **Effectiveness of Distance Learning:** The extent to which online education meets learning goals and provides value to students.
- **Anxiety Level:** The degree of stress or nervousness experienced by students or teachers in a learning environment.
- **Enjoyment in Teaching Distance Learning:** The level of satisfaction and pleasure educators experience while conducting online classes.
- **Satisfaction Level:** The overall contentment of students and teachers with the learning or teaching experience.
- **Learning Environment:** The physical or virtual setting in which students engage with educational materials and interact with instructors.
- **Teaching Environment:** The resources, tools, and support available to educators to facilitate effective teaching.
- **Ability to Understand Curriculum:** The capacity of students to grasp and comprehend the course content effectively.
- **Participation:** The involvement and engagement of students in learning activities and discussions.
- **Professional Development Training:** Opportunities for teachers to enhance their skills and knowledge through training programs.
- **Opportunity to Demonstrate Learning:** Chances for students to showcase their knowledge and skills through assessments or practical applications.

3. RESULT AND DISCUSSION

TABLE 1. Alternative

Motivation to learn	ML
Efectiveness of DL	EDL
Anxiety level	AL
Enjoyment in teaching DL	ETDL
Satisfaction level	SL
Learning environment	LE
Teaching environment	TE
Ability to understand curriculum	AUC
Participation	PA

Table 1 presents the alternatives considered in the study, each representing key aspects of the learning and teaching experience. Motivation to Learn (ML) refers to the intrinsic drive of students to engage with their studies. Effectiveness of Distance Learning (EDL) evaluates how well online education achieves its intended outcomes.

Anxiety Level (AL) measures the stress or nervousness experienced by students and educators in the learning process. Enjoyment in Teaching Distance Learning (ETDL) captures the level of satisfaction teachers derive from conducting online classes. Satisfaction Level (SL) represents the overall contentment of both students and teachers with the educational experience. Learning Environment (LE) encompasses the physical or virtual settings that facilitate effective learning. Teaching Environment (TE) focuses on the conditions and resources available to educators for delivering instruction. Ability to Understand Curriculum (AUC) assesses how well students can comprehend and apply the course content. Finally, Participation (PA) reflects the extent to which students actively engage in learning activities and discussions.

TABLE 2. Decision Matrix

	ML	EDL	AL	ETDL	SL	LE	TE	AUC	PA	**Sum**
ML	0	0.5	0.5	0.5	0.33	0.5	0.5	0.2	0.33	3.03
EDL	2	0	0.33	0.5	0.5	0.25	0.2	0.33	0.5	4.11
AL	2	3	0	0.5	0.5	0.5	0.5	0.33	0.33	7.33
ETDL	2	2	2	0	0.25	0.5	0.5	0.5	0.5	7.75
SL	3	2	2	4	0	0.5	0.25	0.25	0.5	12
LE	2	4	2	2	2	0	0.25	0.5	0.25	12.75
TE	2	5	2	2	4	4	0	0.5	0.33	19.5
AUC	5	3	3	2	4	2	2	0	0.33	21
PA	3	2	3	2	2	4	3	3	0	20

Table 1 presents the decision matrix, which evaluates the interrelationships between various alternatives related to the learning and teaching experience. Each row and column represent an alternative, with values indicating the level of influence one alternative has on another. The diagonal values are zero, as an alternative does not influence itself. Motivation to Learn (ML) has a total influence sum of 3.03, indicating a relatively lower impact compared to others. Effectiveness of Distance Learning (EDL) shows a moderate influence with a total sum of 4.11. Anxiety Level (AL) and Enjoyment in Teaching Distance Learning (ETDL) have significant influences, with sums of 7.33 and 7.75, respectively, suggesting their critical roles in the learning process. Satisfaction Level (SL) and Learning Environment (LE) exhibit higher influence sums of 12 and 12.75, emphasizing their importance in the overall educational experience. Teaching Environment (TE) and Ability to Understand Curriculum (AUC) demonstrate substantial influence, with sums of 19.5 and 21, respectively, highlighting their essential roles in facilitating effective learning. Lastly, Participation (PA) also holds a significant influence with a sum of 20, indicating the importance of student engagement. This decision matrix provides valuable insights into the dependencies and contributions of each factor in the educational process.

TABLE 3. Normalisation of direct relation matrix

	ML	EDL	AL	ETDL	SL	LE	TE	AUC	PA
ML	0	0.02381	0.0238	0.02381	0.01571	0.02381	0.02381	0.00952	0.0157
EDL	0.09524	0	0.0157	0.02381	0.02381	0.0119	0.00952	0.01571	0.0238
AL	0.09524	0.14286	0	0.02381	0.02381	0.02381	0.02381	0.01571	0.0157
ETDL	0.09524	0.09524	0.0952	0	0.0119	0.02381	0.02381	0.02381	0.0238
SL	0.14286	0.09524	0.0952	0.19048	0	0.02381	0.0119	0.0119	0.0238
LE	0.09524	0.19048	0.0952	0.09524	0.09524	0	0.0119	0.02381	0.0119
TE	0.09524	0.2381	0.0952	0.09524	0.19048	0.19048	0	0.02381	0.0157
AUC	0.2381	0.14286	0.1429	0.09524	0.19048	0.09524	0.09524	0	0.0157
PA	0.14286	0.09524	0.1429	0.09524	0.09524	0.19048	0.14286	0.14286	0

Table 3 presents the normalized direct relation matrix, which standardizes the influence values between the various alternatives in the decision-making process. Each value in the matrix represents the relative influence of one alternative over another, normalized to ensure comparability across different factors. Motivation to Learn (ML) exerts relatively low influence across other factors, with values such as 0.02381 on Effectiveness of Distance Learning (EDL) and Enjoyment in Teaching Distance Learning (ETDL), and an even lower influence of 0.00952 on Ability to Understand Curriculum (AUC). Effectiveness of Distance Learning (EDL) has a slightly stronger influence, with its highest impact of 0.09524 on Motivation to Learn (ML), indicating its importance in fostering student motivation. Anxiety Level (AL) and Enjoyment in Teaching Distance Learning (ETDL) display moderate levels of influence, with values of 0.14286 and 0.09524, respectively, suggesting their interdependent relationships with other criteria. Satisfaction Level (SL) and Learning Environment (LE) exhibit notable influence over various factors, with values reaching up to 0.19048, highlighting their crucial roles in shaping the educational experience. Teaching Environment (TE) has the highest influence on Effectiveness of Distance Learning (EDL) with a value of 0.2381, demonstrating its pivotal role in enhancing distance education. Similarly, Ability to Understand Curriculum (AUC) shows strong influences on multiple alternatives, especially on Motivation to Learn (ML) and Satisfaction Level (SL), with values of 0.2381 and 0.19048, respectively. Participation (PA), while influential, maintains a balanced impact across other factors, signifying its supportive yet essential role in the overall learning process. The normalized values in this matrix provide a clearer understanding of how each factor contributes to and is influenced by others within the system.

TABLE 4. I= Identity matrix

1	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0
0	0	0	0	1	0	0	0	0
0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	1	0
0	0	0	0	0	0	0	0	1

Table 4 represents the identity matrix, a fundamental concept in linear algebra. In this matrix, the diagonal elements are all set to 1, and all off-diagonal elements are 0. The identity matrix plays a critical role in various mathematical operations, particularly in systems involving matrix multiplication. When any matrix is multiplied by an identity matrix, the result is the original matrix itself, making the identity matrix the multiplicative identity in matrix algebra. In the context of decision-making and modeling, the identity matrix often serves as a baseline or reference point, allowing for the calculation of influence or impact relationships between various alternatives or factors within a system. Here, the matrix serves as the foundation for subsequent calculations and transformations in the decision-making process.

TABLE 5. Y values

0	0.02381	0.02381	0.02381	0.015714	0.02381	0.02381	0.009524	0.015714
0.095238	0	0.015714	0.02381	0.02381	0.011905	0.009524	0.015714	0.02381
0.095238	0.142857	0	0.02381	0.02381	0.02381	0.02381	0.015714	0.015714
0.095238	0.095238	0.095238	0	0.011905	0.02381	0.02381	0.02381	0.02381
0.142857	0.095238	0.095238	0.190476	0	0.02381	0.011905	0.011905	0.02381
0.095238	0.190476	0.095238	0.095238	0.095238	0	0.011905	0.02381	0.011905
0.095238	0.238095	0.095238	0.095238	0.190476	0.190476	0	0.02381	0.015714
0.238095	0.142857	0.142857	0.095238	0.190476	0.095238	0.095238	0	0.015714
0.142857	0.095238	0.142857	0.095238	0.095238	0.190476	0.142857	0.142857	0

Table 5 presents the Y values, which represent the normalized direct influence relationships between the various alternatives in the decision-making system. Each entry in this matrix reflects the degree of influence one factor (represented by the rows) has on another (represented by the columns) within the system. The values range from 0, indicating no influence, to higher values, signifying a stronger impact between the corresponding criteria or alternatives. These normalized values are crucial for further analysis and calculations, such as determining the cumulative impact of each factor or constructing a causal relationship map. They help decision-makers understand the interdependencies between the criteria, allowing for a more informed decision-making process. The Y values also contribute to deriving influence scores and constructing matrices for evaluating the relative importance of the criteria in the context of the overall decision-making model.

TABLE 6. I-Y

1	-0.02381	-0.02381	-0.02381	-0.01571	-0.02381	-0.02381	-0.00952	-0.01571
-0.09524	1	-0.01571	-0.02381	-0.02381	-0.0119	-0.00952	-0.01571	-0.02381
-0.09524	-0.14286	1	-0.02381	-0.02381	-0.02381	-0.02381	-0.01571	-0.01571
-0.09524	-0.09524	-0.09524	1	-0.0119	-0.02381	-0.02381	-0.02381	-0.02381
-0.14286	-0.09524	-0.09524	-0.19048	1	-0.02381	-0.0119	-0.0119	-0.02381
-0.09524	-0.19048	-0.09524	-0.09524	-0.09524	1	-0.0119	-0.02381	-0.0119
-0.09524	-0.2381	-0.09524	-0.09524	-0.19048	-0.19048	1	-0.02381	-0.01571
-0.2381	-0.14286	-0.14286	-0.09524	-0.19048	-0.09524	-0.09524	1	-0.01571
-0.14286	-0.09524	-0.14286	-0.09524	-0.09524	-0.19048	-0.14286	-0.14286	1

Table 6 shows the matrix of the identity matrix (I) subtracted by the normalized direct relation matrix (Y), resulting in the I-Y matrix. This matrix highlights the differences between the identity matrix and the influence values, showing the degree of deviation from the baseline identity (where values are 1 for the diagonal and 0 for off-diagonal elements) based on the normalized relationships between the alternatives. The negative values indicate a reduction in the influence compared to the identity matrix, while the magnitude of these negative values reflects the strength of the deviation. This matrix serves as a tool to analyze the influence of each factor in relation to others, allowing for a deeper understanding of the system's dynamics by emphasizing how the interrelations differ from the initial assumption of independence.

TABLE 7. (I-Y)-1

1.0334	0.0588	0.0457	0.0445	0.0348	0.0404	0.0330	0.0178	0.021523
0.1288	1.0355	0.0411	0.0474	0.0433	0.0311	0.0227	0.0254	0.03061
0.1479	0.1865	1.0330	0.0561	0.0521	0.0482	0.0390	0.0285	0.02721
0.1555	0.1542	0.1288	1.0353	0.0455	0.0530	0.0428	0.0385	0.03578
0.2240	0.1762	0.1486	0.2271	1.0372	0.0595	0.0382	0.0333	0.041984
0.1896	0.2676	0.1483	0.1487	0.1316	1.0351	0.0367	0.0435	0.031938
0.2515	0.3813	0.1914	0.1994	0.2553	0.2377	1.0368	0.0562	0.04687
0.3905	0.3035	0.2416	0.2039	0.2641	0.1630	0.1333	1.0343	0.04859
0.34498	0.313926	0.274525	0.225065	0.218902	0.280736	0.194328	0.179952	1.037004

Table 7 presents the inverse of the matrix (I-Y), denoted as (I-Y)^(-1). This matrix provides the reciprocal of the differences between the identity matrix (I) and the normalized direct relation matrix (Y). Each element in this table reflects how the relationships between the alternatives have been adjusted after inverting the differences. The values indicate the degree of influence and the interplay between each pair of alternatives within the system, with higher values suggesting a stronger relationship or influence. The diagonal elements show the inverse of the self-influence values, which can be interpreted as the self-adjustment of each alternative within the decision-making process. This matrix is a crucial step in understanding the revised interactions between the alternatives after considering their normalized relations. It provides an analytical foundation for further calculations or decision-making steps, offering insights into the structure and strength of the connections within the evaluated system.

TABLE 8. Total Relation matrix (T)

ML	0.03345	0.058808	0.045678	0.044452	0.034817	0.040355	0.032975	0.017778	0.021523
EDL	0.12878	0.035459	0.041108	0.047406	0.043272	0.031111	0.022717	0.025442	0.03061
AL	0.14791	0.186541	0.033024	0.056095	0.052076	0.048244	0.039025	0.028494	0.02721
ETDL	0.15545	0.154229	0.128792	0.035299	0.045455	0.052979	0.042838	0.038512	0.03578
SL	0.22397	0.176157	0.148576	0.22711	0.03724	0.059513	0.038182	0.033315	0.041984
LE	0.18957	0.267566	0.148278	0.148744	0.131564	0.035129	0.036731	0.043531	0.031938
TE	0.25147	0.381272	0.191396	0.199446	0.255265	0.237686	0.036843	0.056223	0.04687
AUC	0.39048	0.303543	0.241553	0.203926	0.26409	0.162958	0.133323	0.03428	0.04859
PA	0.34498	0.313926	0.274525	0.225065	0.218902	0.280736	0.194328	0.179952	0.037004

Table 8 presents the Total Relation Matrix (T), which is the culmination of the computations derived from the inverse of the matrix (I-Y) and its interactions. Each element in this matrix reflects the comprehensive relationship between pairs of alternatives, including both direct and indirect influences. The values in the matrix represent the total degree of influence that one alternative has over another, incorporating the self-relation and the interrelations that have been calculated in previous steps. For instance, the first row shows the total relation of the "ML" (Motivation to Learn) alternative with all other alternatives, where the value 0.03345 indicates the relationship between "ML" and itself. Similarly, the values across the rows for other alternatives (like "EDL," "AL," etc.) reflect how each alternative impacts the others. The diagonal elements in this matrix show the self-relation values, which help in understanding the internal influence or self-adjustment of each alternative. This matrix is crucial for assessing the overall relationships and dependencies within the decision system. It provides an essential foundation for further decision-making processes, as it accounts for both direct and indirect connections between the evaluated alternatives, enabling a deeper analysis of the system's structure and influence dynamics.

TABLE 9. Ri and Ci

	Ri	Ci
ML	**0.329836**	1.866071
EDL	**0.405909**	1.877501
AL	**0.618622**	1.252929
ETDL	**0.689337**	1.187542
SL	**0.986046**	1.082681
LE	**1.033055**	0.948711
TE	**1.656467**	0.576962
AUC	**1.782742**	0.457527
PA	**2.069419**	0.321509

Table 9 presents the Ri and Ci values, which are essential components of the decision-making process in this model. The Ri values represent the row sums of the Total Relation Matrix (T), capturing the total influence or strength of each alternative on all others. These values reflect the overall impact or contribution of each alternative in the system, with higher values indicating stronger influence. For example, "PA" has the highest Ri value of 2.069419, signifying that it has the most significant total impact on the other alternatives, whereas "ML" has a relatively lower Ri value of 0.329836, indicating a weaker influence in comparison. On the other hand, the Ci values represent the column sums of the Total Relation Matrix (T), indicating the total influence received by each alternative from all other alternatives. These values highlight the receptivity or sensitivity of each alternative to the influence exerted by others. For instance, "ML" has the highest Ci value of 1.866071, meaning it is the most influenced alternative, while "PA" has the lowest Ci value of 0.321509, indicating that it is less influenced by the other alternatives in the system. Together, these Ri and Ci values provide critical insights into the relative importance and influence dynamics of each alternative within the decision model, helping to evaluate the overall performance and interactions of the system.

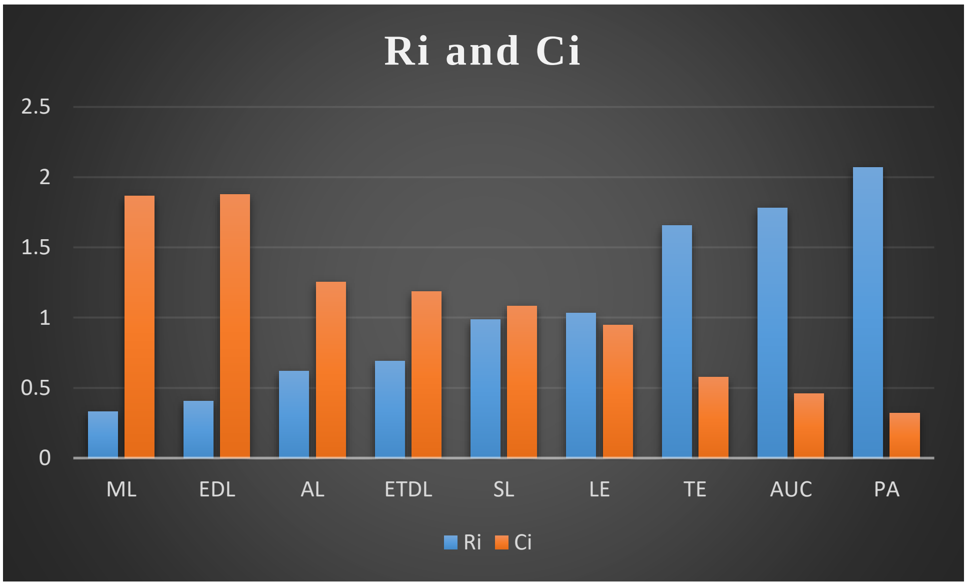


FIGURE 1. Ri and Ci

Figure 1 presents the values of Ri (representing the influence exerted by a factor) and Ci (representing the influence received by a factor), offering insights into the interdependencies among various elements in distance learning. *Participation (PA)* exhibits the highest influence with an Ri value of 2.069419 while being the least influenced factor with a Ci value of 0.321509, suggesting its crucial role in shaping other factors. Conversely, *Motivation to Learn (ML)* has the lowest influence, with an Ri of 0.329836, but is significantly influenced by other factors, as indicated by its high Ci value of 1.866071. *Ability to Understand Curriculum (AUC)* also holds considerable influence with an Ri of 1.782742 and a lower Ci of 0.457527, highlighting its importance in the learning process. Similarly, *Teaching Environment (TE)* has an Ri of 1.656467 and a Ci of 0.576962, indicating its notable impact. On the other hand, *Effectiveness of Distance Learning (EDL)* is highly influenced by other factors with a Ci of 1.877501 while exerting a moderate influence of Ri 0.405909. Factors such as *Learning Environment (LE)* and *Enjoyment in Teaching Distance Learning (ETDL)* exhibit balanced interactions, with Ri values of 1.033055 and 0.689337, and Ci values of 0.948711 and 1.187542, respectively. These findings underscore the intricate relationships among these factors and their varying degrees of influence in distance learning environments.

TABLE 10. Ri+Ci, Ri-Ci and Identity

	Ri+Ci	**Ri-Ci**	**Identity**
ML	2.195907	-1.53624	cause
EDL	2.28341	-1.47159	cause
AL	1.871551	-0.63431	effect
ETDL	1.87688	-0.49821	effect
SL	2.068726	-0.09664	cause
LE	1.981766	0.084344	effect
TE	2.233429	1.079505	effect
AUC	2.240269	1.325215	effect
PA	2.390928	1.74791	cause

Table 10 illustrates the values of Ri+Ci, Ri-Ci, and the corresponding identity classification for each alternative. The sum of Ri and Ci (Ri+Ci) indicates the combined influence and receptivity of an alternative within the system, with higher values reflecting a more balanced interaction. For example, "PA" has the highest Ri+Ci value of 2.390928, signifying a strong overall interaction with other alternatives. Conversely, "ML" has a lower value of 2.195907, indicating a more limited influence. The difference between Ri and Ci (Ri-Ci) reveals the disparity between an alternative's influence and the influence it receives. Positive values suggest that the alternative has a greater influence on others than it is influenced by them, while negative values indicate the opposite. For instance, "PA" has the highest Ri-Ci value of 1.74791, indicating that it exerts more influence than it receives, whereas "ML" has a negative value of -1.53624, suggesting it is more influenced by others than it influences them. The final column classifies each alternative as either a "cause" or "effect" based on the relationship dynamics. Alternatives like "ML," "EDL," "SL," and "PA" are classified as causes, meaning they primarily exert influence on others, while alternatives like "AL," "ETDL," "LE," "TE," and "AUC" are classified as effects, meaning they are more influenced by the other alternatives. This classification helps to understand the directionality of influence within the system and the roles of each alternative in the overall process.

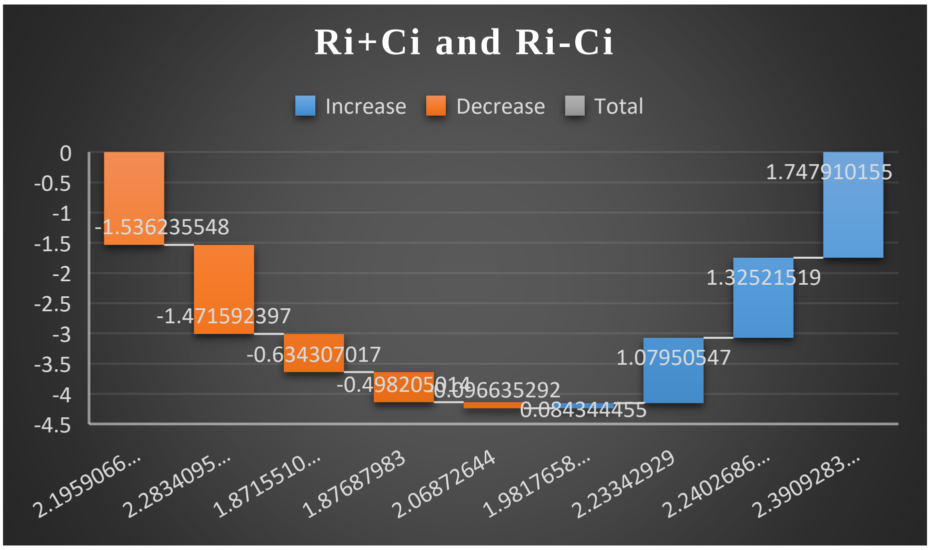


FIGURE 2. Ri+Ci, and Ri-Ci

Figure 2 provides the calculated values of Ri+Ci and Ri−Ci, which represent the overall significance and net influence of factors in the distance learning context. The factor *Participation (PA)* holds the highest total influence with an Ri+Ci value of 2.3909, and a positive net influence of 1.7479, indicating that it acts predominantly as a cause rather than an effect. Similarly, *Ability to Understand Curriculum (AUC)* and *Teaching Environment (TE)* demonstrate strong influence with Ri+Ci values of 2.2403 and 2.2334, respectively, and positive Ri−Ci values of 1.3252 and 1.0795, categorizing them as causal factors. On the other hand, *Motivation to Learn (ML)* and *Effectiveness of Distance Learning (EDL)* have relatively high total influence scores of 2.1959 and 2.2834, respectively; however, their negative net influence values of -1.5362 and -1.4716 suggest that they are significantly influenced by other factors, making them effects rather than causes. Factors such as *Satisfaction*

Level (SL) and *Learning Environment (LE)* exhibit moderate total influence values of 2.0687 and 1.9818, respectively, with slightly negative and positive net influence values of -0.0966 and 0.0843, indicating a balanced interplay between cause and effect roles. Meanwhile, *Enjoyment in Teaching Distance Learning (ETDL)* and *Anxiety Level (AL)* show relatively lower total influence values of 1.8769 and 1.8716, with net influence values of -0.4982 and -0.6343, suggesting that they function primarily as effects within the system. These findings highlight the critical role of participation and teaching environment as primary drivers in enhancing distance learning effectiveness.

TABLE 11. Rank

	Rank
Motivation to learn	5
Efectiveness of DL	2
Anxiety level	9
Enjoyment in teaching DL	8
Satisfaction level	6
Learning environment	7
Teaching environment	4
Ability to understand curriculum	3
Participation	1

Table 11 presents the ranks assigned to various factors influencing the learning process. The "Participation" factor is ranked the highest with a rank of 1, indicating it is considered the most important or influential aspect in the context. Following closely is the "Effectiveness of DL" (Distance Learning), ranked 2, which emphasizes the significance of how well the delivery method contributes to learning outcomes. The "Ability to understand curriculum" holds the third position, suggesting that comprehension of the content is a key factor for effective learning. On the other hand, the "Motivation to learn" is ranked 5, showing it is crucial but slightly less influential compared to the top-ranked factors. The "Teaching environment" follows in the fourth position, pointing to the importance of the surroundings in which teaching occurs. "Satisfaction level," ranked 6, and "Learning environment," ranked 7, are both factors that also contribute to the overall experience but have a relatively lesser impact in this ranking system. Finally, the "Enjoyment in teaching DL" is ranked 8, and "Anxiety level" is ranked 9, both indicating that while they are important, they are considered less influential in comparison to the other factors when evaluating the learning process.

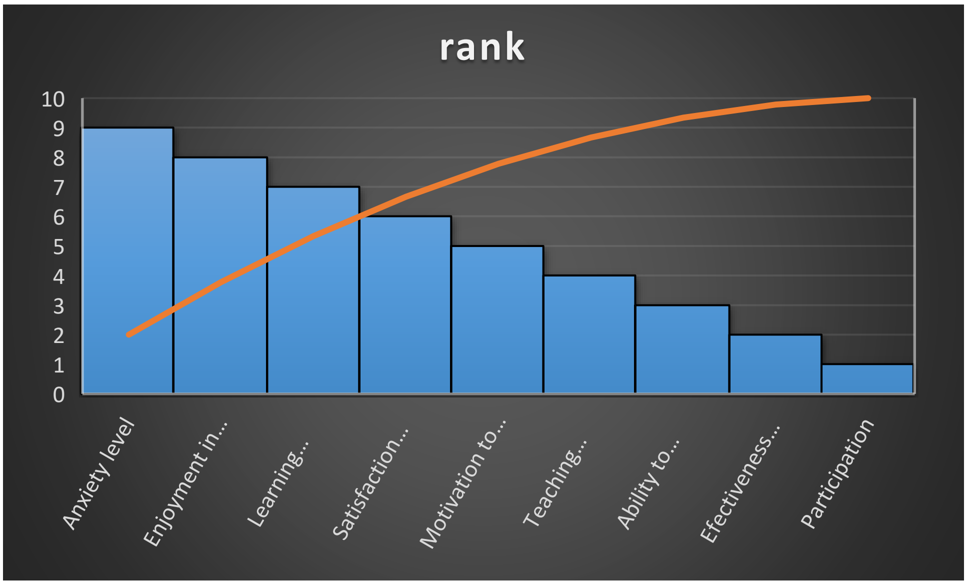


FIGURE 3. Ri+Ci, and Ri-Ciu

Figure 3 presents the ranking of various factors influencing distance learning effectiveness based on their overall significance. *Participation (PA)* emerges as the most critical factor, securing the highest rank (1), indicating its paramount importance in ensuring successful engagement and learning outcomes. *Effectiveness of Distance Learning (EDL)* follows closely in the second position, underscoring its crucial role in determining the overall success and efficiency of the learning process. *Ability to Understand Curriculum (AUC)* holds the third rank, reflecting its significant impact on student comprehension and academic performance. *Teaching Environment (TE)* is ranked fourth, emphasizing the importance of a conducive instructional setting in facilitating effective knowledge transfer. *Motivation to Learn (ML)* is positioned at rank five, highlighting the role of intrinsic and extrinsic motivation in sustaining student interest and performance. *Satisfaction Level (SL)* and *Learning Environment (LE)* are ranked sixth and seventh, respectively, indicating their moderate influence on the overall learning experience. Lower-ranked factors include *Enjoyment in Teaching Distance Learning (ETDL)* at eighth place and *Anxiety Level (AL)* at ninth place, suggesting that while these factors contribute to the learning experience, they may not be as influential as the others in determining success. The rankings provide valuable insights for educators and policymakers to prioritize strategies that enhance participation, effectiveness, and comprehension to improve distance learning outcomes.

4. CONCLUSION

In conclusion, the analysis of various factors impacting the learning process reveals a complex interplay between multiple elements that contribute to the effectiveness of education, particularly in distance learning (DL) environments. The highest-ranked factor, "Participation," underscores the critical role active engagement plays in enhancing the learning experience. Active participation not only facilitates better understanding of the content but also fosters a deeper connection between the learner and the subject matter, highlighting its centrality in successful learning outcomes. Closely following in importance is the "Effectiveness of DL," which emphasizes the significance of the delivery method in ensuring that students can absorb and apply the material. This factor highlights that the tools and techniques employed in delivering education remotely are pivotal to its success, making it an essential consideration for educators and policymakers. The "Ability to understand curriculum" is also a key factor, emphasizing the necessity for clear, structured, and accessible educational materials. A well-designed curriculum that is easy to understand and aligns with the learning objectives enables students to engage with the content more effectively. Meanwhile, "Motivation to learn," ranked 5, reflects the internal drive that propels students to pursue their studies and overcome challenges. It is clear that while motivation is crucial, it is not as impactful as the structural factors influencing learning. The "Teaching environment," ranked 4, further reinforces the importance of creating a supportive atmosphere conducive to learning, whether in physical or virtual spaces. While "Satisfaction level," "Learning environment," "Enjoyment in teaching DL," and "Anxiety level" are important, they are relatively less influential in this context. These factors, though contributing to the overall experience, do not overshadow the primary elements of active participation, the effectiveness of DL, and the clarity of the curriculum. This ranking reveals that the foundation of successful learning lies in engagement, effective delivery, and understanding, while secondary aspects like enjoyment and anxiety, though significant, are secondary in driving outcomes.

REFERENCES

[1]. Alshamsi, Aysha Meshaal, Hadeel El-Kassabi, Mohamed Adel Serhani, and Chafik Bouhaddioui. "A multi-criterion decision-making (MCDM) approach for data-driven distance learning recommendations." *Education and Information Technologies* 28, no. 8 (2023): 10421-10458.

[2]. Gao, Peng, Jingyi Li, and Shuai Liu. "An introduction to key technology in artificial intelligence and big data driven e-learning and e-education." *Mobile Networks and Applications* 26, no. 5 (2021): 2123-2126.

[3]. Botvin, Maya, Arnon Hershkovitz, and Alona Forkosh-Baruch. "Data-driven decision-making in emergency remote teaching." *Education and Information Technologies* 28, no. 1 (2023): 489-506.

[4]. Boulton, Alex. "Data-driven learning: on paper, in practice." *Corpus Linguistics in Language Teaching.* (2009): 17-52.

[5]. Kurilovas, Eugenijus. "On data-driven decision-making for quality education." *Computers in Human Behavior* 107 (2020): 105774.

[6]. Ruipérez-Valiente, José A., Srecko Joksimović, Vitomir Kovanović, Dragan Gašević, Pedro J. Muñoz-Merino, and Carlos Delgado Kloos. "A data-driven method for the detection of close submitters in online learning environments." In *Proceedings of the 26th international conference on world wide web companion*, pp. 361-368. 2017.

[7]. Balcan, Maria-Florina, Travis Dick, and Ellen Vitercik. "Dispersion for data-driven algorithm design, online learning, and private optimization." In *2018 IEEE 59th Annual Symposium on Foundations of Computer Science (FOCS)*, pp. 603-614. IEEE, 2018.

[8]. Liu, Peng, Lizhe Wang, Rajiv Ranjan, Guojin He, and Lei Zhao. "A survey on active deep learning: from model driven to data driven." *ACM Computing Surveys (CSUR)* 54, no. 10s (2022): 1-34.

[9]. Zeide, Elana. "The structural consequences of big data-driven education." *Big Data* 5, no. 2 (2017): 164-172.

[10]. Qiao, Lishan, Limei Zhang, Songcan Chen, and Dinggang Shen. "Data-driven graph construction and graph learning: A review." *Neurocomputing* 312 (2018): 336-351.

[11]. Msekelwa, Patrick Zingisa. "DATA DRIVEN PEDAGOGY: LEVERAGING ANALYTICS FOR EFFECTIVE E-LEARNING STRATEGIES." *Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online)* 1, no. 1 (2023): 55-68.

[12]. Inventado, Paul Salvador, and Peter Scupelli. "Data-driven design pattern production: a case study on the ASSISTments online learning system." In *Proceedings of the 20th European conference on pattern languages of programs*, pp. 1-13. 2015.

[13]. Conte, C., G. Rufino, G. De Alteriis, V. Bottino, and D. Accardo. "A data-driven learning method for online prediction of drone battery discharge." *Aerospace Science and Technology* 130 (2022): 107921.

[14]. Gilquin, Gaëtanelle, and Sylviane Granger. "How can data-driven learning be used in language teaching?." In *The Routledge handbook of corpus linguistics*, pp. 359-370. Routledge, 2010.

[15]. Ma, Kai-Chieh, Lantao Liu, Hordur K. Heidarsson, and Gaurav S. Sukhatme. "Data-driven learning and planning for environmental sampling." *Journal of Field Robotics* 35, no. 5 (2018): 643-661.

[16]. Azkune, Gorka, Aitor Almeida, Diego López-de-Ipiña, and Liming Chen. "Extending knowledge-driven activity models through data-driven learning techniques." *Expert Systems with Applications* 42, no. 6 (2015): 3115-3128.

[17]. Wu, Wei-Wen. "Choosing knowledge management strategies by using a combined ANP and DEMATEL approach." *Expert systems with applications* 35, no. 3 (2008): 828-835.

[18]. Lee, Hsuan-Shih, Gwo-Hshiung Tzeng, Weichung Yeih, Yu-Jie Wang, and Shing-Chih Yang. "Revised DEMATEL: resolving the infeasibility of DEMATEL." *Applied Mathematical Modelling* 37, no. 10-11 (2013): 6746-6757.

[19]. Du, Yuan-Wei, and Xiao-Xue Li. "Hierarchical DEMATEL method for complex systems." *Expert Systems with Applications* 167 (2021): 113871.

[20]. Chinnasamy, Sathiyaraj, Manjula Selvem, M. Ramachandran, and Chandrasekar Raja. "Evaluation of Forensic Medical Examination using the DEMATEL Method."

[21]. Yazdi, Mohammad, Faisal Khan, Rouzbeh Abbassi, and Risza Rusli. "Improved DEMATEL methodology for effective safety management decision-making." *Safety science* 127 (2020): 104705.

[22]. Lin, Chia-Li, and Gwo-Hshiung Tzeng. "A value-created system of science (technology) park by using DEMATEL." *Expert systems with applications* 36, no. 6 (2009): 9683-9697.

[23]. Gölcük, İlker, and Adil Baykasoğlu. "An analysis of DEMATEL approaches for criteria interaction handling within ANP." *Expert Systems with Applications* 46 (2016): 346-366.

[24]. Wang, Wei-Chih, Yueh-Hua Lin, Chia-Li Lin, Chu-Hsuan Chung, and Ming-Tsung Lee. "DEMATEL-based model to improve the performance in a matrix organization." *Expert Systems with Applications* 39, no. 5 (2012): 4978-4986.

[25]. Braga, Irina FB, Fernando AF Ferreira, João JM Ferreira, Ricardo JC Correia, Leandro F. Pereira, and Pedro F. Falcão. "A DEMATEL analysis of smart city determinants." *Technology in Society* 66 (2021): 101687.

[26]. Shieh, Jiunn-I., and Hsin-Hung Wu. "Measures of consistency for DEMATEL method." *Communications in Statistics-Simulation and Computation* 45, no. 3 (2016): 781-790.

[27]. Si, Sheng-Li, Xiao-Yue You, Hu-Chen Liu, and Ping Zhang. "DEMATEL technique: a systematic review of the state-of-the-art literature on methodologies and applications." *Mathematical problems in Engineering* 2018, no. 1 (2018): 3696457.

[28]. Zhang, Weiquan, and Yong Deng. "Combining conflicting evidence using the DEMATEL method." *Soft computing* 23 (2019): 8207-8216.

[29]. Koca, Gözde, and Seda Yıldırım. "Bibliometric analysis of DEMATEL method." *Decision Making: Applications in Management and Engineering* 4, no. 1 (2021): 85-103.

