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Editorial Comments: JCMM Volume 3 Issue 2

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In Volume 3, Issue 2 of the *Journal of Computers, Mechanical and Management* (JCMM), we present a collection of research papers addressing advancements across disaster management, AI-driven education support, climate change mitigation, compiler optimizations, and educational methodologies. These studies provide both theoretical insights and practical applications in various interdisciplinary domains. The first article by Rroy and Rajkhowa, [1] titled Enhancing Secondary Education in Kamrup District Through Value-Added Courses, explores the integration of supplementary skills training in secondary school curricula to promote holistic student development. The study investigates the efficacy of value-added courses that focus on sustainability, soft skills, and industry readiness. Through a structured program combining theory and practical experience, this study highlights the positive impact on students' behavioral and professional competencies.

AI-Driven Decision Support System Innovations to Empower Higher Education Administration by Zhang and Goyal [2] discusses the transformative potential of AI-enhanced Decision Support Systems (DSS) in optimizing administrative processes within higher education. Their research shows how DSS can aid in strategic planning, enrollment management, and resource allocation, while addressing challenges such as data privacy and resistance to AI adoption. This paper underscores the importance of data-driven decisions to improve institutional efficiency. In the realm of climate action, Devesh et al. [3] provide an extensive analysis in Evaluating Climate Change Mitigation Strategies of G20 Countries. This study examines the alignment of G20 nations' policies with the Paris Agreement goals. The authors assess the strengths and weaknesses of various climate policies, offering policy recommendations to enhance carbon reduction efforts. Their work is particularly relevant given the G20's substantial contribution to global greenhouse gas emissions.

Mahajan et al. [4] present a comparative analysis in A Multi-Model Approach for Disaster-Related Tweets*, utilizing machine learning and deep learning models for disaster detection on social media. This research compares the performance of Multinomial Naïve Bayes, Passive Aggressive Classifiers, and BERT in classifying disaster-related tweets. BERT was found to achieve the highest accuracy, demonstrating the robustness of deep learning techniques for real-time disaster management applications. Deep Learning-Driven Compiler Enhancements for Efficient Matrix Multiplication by Kumar et al. [5] explores the use of deep learning to optimize compiler performance for matrix multiplication tasks. By employing techniques like loop tiling and deep learning models for compiler optimization, this study achieved significant performance improvements on various hardware platforms. The proposed methods demonstrate potential applications beyond matrix multiplication, including AI and scientific computing workloads.

Collectively, these articles illustrate JCMM's commitment to fostering innovative research that addresses complex challenges across diverse fields, offering valuable insights into sustainable education, AI applications, climate policy, disaster management, and high-performance computing.

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Value Added Courses: A Sustainable Approach to Education of Students In the Secondary Schools of Kamrup District

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Abstract

The concept of value-added courses in education is rooted in the idea of supplementing the core curriculum with additional learning opportunities that go beyond standard academic subjects. Secondary stage of education should emphasize on optimal learning based on the cognitive development of students through experiential and hands-on experience by incorporating value added courses in the curriculum. Today, while the world has become globalised with limited resources, colleges and universities should pay more attention in preparing students to be sustainable both in act and behaviour. The preparation of the students for the industry should begin from the secondary stage. So, the policy makers should contemplate and pay attention towards the pedagogy to meet the needs of the future. The conceptual framework underlying value-added courses emphasizes their role in supplementing the core curriculum, providing students with practical skills and competencies essential for holistic development. Also, the sustainability of behavioural changes induced by value-added courses is contingent on several factors. The goal is to make access to an expansive repertory of knowledge for the growth of professional skills. This study is an attempt to find out the sustainability and the challenges of incorporating value-added courses in the Secondary School curriculum.

Keywords: Value-Added Courses, Secondary School Curriculum, Sustainability, Skill Development, Behavioural Changes, Pedagogy

1 Introduction

India's education system increasingly emphasizes holistic student development, prioritizing cognitive growth over traditional rote learning. National Education Policy (NEP) 2020 advocates a comprehensive approach to foster cognitive, emotional, and social development. Mahatma Gandhi's vision of education aimed at the comprehensive development of body, mind, and spirit aligns with this approach. Consequently, teacher training incorporates new methodologies to enhance education quality [1] and supports research to develop students' creativity and logical thinking. A sustainable education approach utilizes multidisciplinary subjects to advance communication, collaboration, and empowerment skills, essential for equitable social transformations. This approach integrates values and attitudes that promote critical and creative thinking [2] alongside cognitive learning outcomes, targeting holistic sustainable development. With the world's resources being finite and the global landscape demanding sustainability, higher education institutions focus on preparing students from the secondary stage, aligning pedagogies with future needs [3]. Value-added Courses (VAC) integrate into the curriculum to enhance industry understanding, bridge industry gaps, increase employability, and develop entrepreneurial skills. Mandatory for Classes XI and XII, these courses are split into 60% theory and 40% practical sessions, conducted during weekends or vacations to maximize time utilization. A minimum attendance of 75% is required, with schools responsible for regular session conduct and certification issuance, contributing to human capital development [4]. The detailed course plan outlined below is based on findings from interviews with faculty and staff members. Table 1 provides a clear breakdown of the schedule for value-added courses across different classes:

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Table 1: Course Plan

Class	Day/Timings	Duration	Per Week	Theory	Practical
9	Saturday/ After school	30 hrs	2 hrs	18 hrs	12 hrs
10	Saturday/ After school	30 hrs	2 hrs	18 hrs	12 hrs
11	Saturday/ After school	30 hrs	2 hrs	18 hrs	12 hrs
12	Saturday/ After school	30 hrs	2 hrs	18 hrs	12 hrs

Sustainability in teaching requires teachers to work outside their areas of expertise, incorporating cooperative learning to leverage interdisciplinary and experiential knowledge [5]. The Ministry of Small, Micro and Medium Enterprises (MSME), established in 2006, serves as a catalyst for economic growth, leading to equitable development. A key benefit is the generation of employment opportunities in rural areas, significantly strengthening the rural economy. The Coir Board, established under the Coir Industry Act of 1953, oversees the growth, promotion, and development of the local market. It plays a crucial role in the employment sector, facilitating 90% of the total enterprises and thus boosting the country's economy. This infrastructure has been pivotal in adapting to recession and surviving severe economic crises during the pandemic [6].This study aims to find out the sustainability and the challenges of incorporating value- added courses in the Secondary School curriculum.

2 Related Work

Value-added courses in secondary education have emerged as a transformative approach to enriching students' learning experiences, equipping them with skills beyond the traditional curriculum. This literature review delves into the existing body of knowledge, exploring the conceptual underpinnings, benefits, challenges, and sustainability aspects of value-added courses in secondary schools, with a specific focus on the Kamrup district. The concept of value-added courses in education is rooted in the idea of supplementing the core curriculum with additional learning opportunities that go beyond standard academic subjects. These courses are designed to impart practical skills, foster critical thinking, and enhance students' overall competencies [7]. Barton (2008) defines value-added courses as supplementary learning opportunities designed to enhance students' practical skills and overall competencies. Extensive research highlights the myriad benefits associated with the incorporation of value-added courses in secondary education. These courses contribute to skill diversification, fostering creativity, problem-solving abilities, and teamwork [8]. Moreover, they play a pivotal role in increasing student engagement, motivation, and a sense of personal accomplishment [9]. The literature emphasizes the positive impact of value-added courses on both academic and non-academic aspects of students' lives. Despite their evident advantages, the literature acknowledges certain challenges in implementing value-added courses. Issues such as resource constraints, varying levels of teacher preparedness, and integration into the existing curriculum pose practical challenges [10]. Addressing these challenges requires a strategic and collaborative approach involving educators, administrators, and policymakers [11]. Resource constraints and varying levels of teacher preparedness are significant challenges in implementing value-added courses [10]. The sustainability of value-added courses in secondary education involves considerations of long-term impact and adaptability. Sustainable implementation requires continuous teacher training, robust infrastructure, and alignment with evolving industry needs [12, 13]. The literature emphasizes the role of collaboration between educational institutions, local industries, and community stakeholders in ensuring the enduring relevance and success of value-added courses [14].

The secondary stage of education should emphasize "life aspirations, greater flexibility, and student choice of subjects," as outlined in NEP 2020. Students have the option of exiting after Class X to pursue vocational education or other courses available in the Grade XI and XII curriculum. This stage should also focus on optimal learning based on cognitive development. Educators are tasked with identifying a set of skills and values for integration into the curriculum, making learning experiences meaningful and closely connected with industry and local resources. The motivation of students remains a significant challenge. Project-Based Learning, as discussed by Savery (2015), empowers students to conduct research by integrating ideas and training, applying their understanding and skills to devise solutions to real problems. Biggs (1996) suggests that curriculum design should align with the expertise, skills, attitudes, and competencies that relate to different learning outcomes, facilitating context-based learning where students are motivated to apply knowledge in real-life situations. Research indicates that participation in value-added courses is linked to positive behavioral changes among students, such as improved self-efficacy, increased motivation, and a proactive attitude towards learning [8]. These courses enhance students' communication skills, teamwork, and problem-solving abilities, contributing to positive shifts in their behavioral patterns. Value-added courses play a pivotal role in nurturing soft skills, influencing students' interpersonal and intrapersonal behaviors [15, 10]. The acquisition of these soft skills is crucial for shaping positive behavioral changes, promoting adaptability, and preparing students for diverse social and professional contexts. The sustainability of behavioral changes induced by value-added courses depends on several factors. Sustainable implementation requires continuous reinforcement of learned behaviors, alignment with evolving industry needs, and a supportive educational environment [13]. Collaborative efforts between educational institutions and industries contribute to the enduring impact of value-added courses on students' behavior [14]. The literature reviewed establishes the foundational concepts, benefits, challenges, and sustainability aspects of value-added courses in secondary education.

It also demonstrates that value-added courses significantly impact behavioral changes among students. These courses contribute to positive shifts in self-efficacy and motivation [?], as well as soft skills development, fostering a proactive and adaptable attitude [16]. To ensure the long-term sustainability of these behavioral changes, continuous reinforcement and collaboration between educational institutions and industries are crucial [17]. Further research in this domain can provide nuanced insights into the specific behavioral outcomes and the mechanisms through which value-added courses influence students' conduct. It is thus required to move away from a "one size fits all" approach, stressing the need to make secondary education a means of future professional prospects. The goal is to provide access to an expansive repertoire of knowledge for the advancement of specific professional skills. Building on this knowledge, further research and localized studies in the Kamrup district can offer tailored insights for the effective implementation and sustainable integration of value-added courses in secondary schools, fostering a holistic and skill-centric approach to education.

3 Methods

This study employed the Descriptive Survey Method in ten Government Secondary Schools within Kamrup district. The quantitative nature of the research allowed for the collection of both primary and secondary data. Primary data were gathered through questionnaires utilizing a 5-point Likert Scale, and secondary data were sourced from published books, research journals, and websites. Participation was voluntary, with a total of 118 responses collected from teachers and students—89 male and 29 female respondents. Data collection was achieved using simple random sampling. The variables considered for the study were Value Added Courses (VAC) as the independent variable, and behavioral changes as the dependent variable. A total of 114 Government Secondary Schools are present in the entire Kamrup district; however, only 10 schools were selected based on their geographical area using Judgmental Sampling to represent the entire geographic region of the district. The following tables detail the sample size and distribution by expected versus actual responses, and by age and gender of the respondents.

Table 2: Sample Size Overview

Expected Response	**Actual Response Received**
136	118

*Note: 18 responses were considered bad samples and were excluded from the analysis.

Table 3: Distribution by Age and Gender

Age (in yrs)	**Responses (in nos.)**	**Male Responses (in nos.)**	**Female Responses (in nos.)**
15	30	24	6
16	25	22	3
17	28	18	10
18	35	25	10
Total	118	89	29

4 Results

4.1 Descriptive Statistics and Regression Analysis

The study utilized descriptive statistics to analyze the impact of Value Added Courses (VAC) on various dimensions of behavioral changes in students. The measures including mean, standard deviation, kurtosis, and skewness are summarized in Table 3.

Table 4: Descriptive Analysis of VAC and Behavioral Changes

Descriptive Statistics	**Ethical infractions**	**Moral responsibility**	**Values and Judgement**	**Innovation Judgement**	**Sustainability Judgement**	**Behavioural changes**
Mean	2.31	2.77	1.78	2.03	2.28	2.51
Standard Deviation	0.782	0.852	0.736	0.889	0.761	1.001
Kurtosis	0.760	-1.135	0.332	0.632	-0.319	-0.334
Skewness	0.799	0.300	0.677	0.623	0.562	0.443

Regression analysis was then performed to quantify relationships between VAC and specific behavioral changes, as detailed in Table 4.

Table 5: Results of Regression Analysis

Variables	Coefficient	Standard Error	t Value	p Value
Constant	0.383	0.203	1.924	-
Ethical infractions	0.207	0.071	2.913	0.004
Moral responsibility	0.772	0.086	8.972	¡0.001
Values & Judgement	-0.072	0.106	-0.678	0.498
Innovation Judgement	-0.087	0.102	-0.854	0.394
Sustainability Judgement	0.066	0.084	0.786	0.432
Model Fit	**R**	**R Square**	**Adjusted R Square**	
Values	0.711	0.516	0.583	

Figure 1: VAC and Behavioral Changes

4.2 Hypotheses Testing

Based on the regression outputs, the study examined the following hypotheses:

- **H0 1:** Rejected - significant influence of VAC on Ethical infractions.
- **H0 2:** Rejected - significant influence of VAC on Moral Responsibility.
- **H0 3, H0 4, and H0 5:** Not rejected - indicating no significant impact of VAC on Values & Judgement, Innovation Judgement, and Sustainability Judgement.

5 Discussion

The significant results for ethical infractions and moral responsibility can be contextualized through Kohlberg's Theory of Moral Development, which suggests that educational settings significantly influence moral reasoning. The integration of Value Added Courses (VAC) effectively stimulates ethical thinking, crucial for moral development among adolescents. Conversely, the lack of significant effects on values & judgement, innovation judgement, and sustainability judgement may be elucidated by the Cognitive Load Theory. This theory posits that if educational content does not align with learners' pre-existing knowledge structures or exceeds their cognitive processing capacity, optimal learning outcomes may not be achieved. VAC may require better integration of these concepts with students' existing knowledge bases or a reduction in cognitive overload through improved instructional design. These findings underscore the necessity for educational practitioners to design VACs that not only focus on ethical and moral dimensions but also effectively incorporate elements of innovation and sustainability. Employing instructional strategies aligned with Constructivist Learning Theories, which emphasize active learning through experience and reflection, might enhance the effectiveness of VAC in these less impactful areas. Future studies should explore the longitudinal impacts of VAC to determine if the observed changes are enduring and if additional instructional support is necessary to cement these gains. Further research could also experiment with different pedagogical approaches, such as Problem-Based Learning (PBL) and Inquiry-Based Learning (IBL), to enhance the effectiveness of VAC across all targeted behavioral dimensions.

5.1 Teacher Training and Development

To effectively deliver Value Added Courses (VAC) and address varying levels of teacher preparedness, specific strategies and training modules are essential. These include goal-oriented training to help teachers understand and align with the objectives of VAC, enhancing their ability to support student learning. A learner-centric approach is also vital, designing educational strategies that focus on student needs identified through formal and informal interactions with students and their guardians. Furthermore, promoting active engagement within the curriculum facilitates easier knowledge transfer from teachers to students. Existing training modules from organizations like UNICEF, UNESCO, and Edu bridges provide frameworks that can be adapted to local needs. Customized modules should consider area-specific requirements, available natural resources, and the local economic context to ensure that students are well-prepared and industry-ready.

5.2 Behavioral Changes and Educational Impact

The introduction of VAC has been linked to several positive behavioral changes in students, including enhanced problem-solving skills, improved time management, increased engagement and motivation, better communication skills, and heightened ethical and social responsibility. These changes are critical as they contribute significantly to a student's ability to succeed in professional environments and personal life.

5.3 Sustainability and Long-term Viability

For VAC to be sustainable and have a long-term impact, forming partnerships with local businesses and industries is vital. Effective strategies should include utilizing existing school and community resources to reduce costs and enhance sustainability, training local instructors and facilitators who can deliver courses sustainably, collaborating with industries and businesses for financial support and to align the curriculum with market needs, and establishing long-term strategies for funding, such as securing grants from government and non-profit organizations. This helps reduce dependency on external sources and ensures the sustainability of the courses.

6 Conclusion

This study explored the implementation of value-added courses (VAC) as a sustainable educational approach within secondary schools in the Kamrup District, highlighting a multifaceted landscape of opportunities and challenges alongside behavioral changes in students. The research aimed to illuminate the conceptual foundations, benefits, challenges, and sustainability aspects of integrating VAC into the curriculum, recognizing their potential to enrich students' learning experiences beyond traditional education. The conceptual framework for VAC underscores their role in supplementing the core curriculum by providing students with practical skills and competencies essential for holistic development, aiming to prepare students for industry-specific professional roles. The literature review substantiates that VAC contribute to skill diversification, foster creativity, enhance problem-solving abilities, and boost overall student engagement. Despite these benefits, the implementation of VAC faces significant challenges including resource constraints, varied levels of teacher preparedness, and difficulties integrating with existing curricula. Addressing these challenges necessitates a strategic and collaborative effort involving educators, administrators, and policymakers. Sustainable implementation of VAC requires continuous teacher training, robust infrastructure, and alignment with evolving industry needs, as identified by earlier researchers. Furthermore, collaboration between educational institutions, local industries, and community stakeholders is crucial in ensuring the enduring relevance and success of these courses. Given the focus on the Kamrup District, obtaining localized insights into the educational landscape is essential. Tailoring VAC to meet the specific needs and aspirations of learners in these secondary schools is crucial for their effective integration and long-term impact. This study advocates for a comprehensive and sustainable educational strategy through VAC, recognizing their potential to empower students, enhance employability, and contribute to community development. The findings provide a foundation for further research and policy initiatives aimed at refining and expanding the implementation of VAC in secondary education within the unique context of Kamrup District.

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Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Consent to Participate

Informed consent was obtained from all individual participants included in the study.

Author Contribution

Aruna Dev Rroy: Conceptualization, Methodology, Investigation, Visualization, Writing - original draft, review and editing. **Baishalee Rajkhowa:** Investigation, Visualization, Resources. Both authors read and approved the final manuscript.

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Deep Learning-Driven Compiler Enhancements for Efficient Matrix Multiplication

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Abstract

Matrix multiplication is a fundamental operation in many computational fields, requiring optimization to handle increasing data sizes efficiently. Traditional optimization techniques, while effective, often fall short in fully leveraging modern hardware capabilities. This study explores the implementation of deep learning-based compiler optimization techniques to enhance the performance of matrix multiplication. We employ a combination of loop tiling and deep learning models to optimize matrix multiplication. The deep learning model predicts optimal tile sizes and loop orders to maximize data reuse and minimize memory access latency. Various neural network architectures are used, with layers specifically designed to handle instruction sequences from different matrix multiplication implementations. The models are trained using Adam optimizer and validated on diverse hardware platforms, including CPUs, GPUs, and TPUs. The proposed techniques achieve significant performance improvements across all tested platforms. On the Intel Core i9 CPU, the optimized implementation resulted in an 8.844x speedup over the naive approach for a matrix size of 1024. On the NVIDIA RTX 2080 Ti GPU, a speedup of up to 8.1x was observed, while the Google TPU v3 showed a speedup of 11.2x. These results highlight the effectiveness of deep learning-based compiler optimizations in leveraging hardware-specific features like parallel processing and memory hierarchy. Integrating deep learning models into compiler optimization workflows can lead to substantial performance gains in matrix multiplication tasks. The techniques demonstrated in this study are versatile and can be adapted to other computational tasks such as convolution operations, graph processing algorithms, and scientific simulations. Future work will focus on addressing limitations related to data dependencies and exploring further optimizations for emerging hardware architectures.

Keywords: Deep Learning; Matrix Multiplication; Compiler Optimization; Loop Tiling; Cache Data Reuse; Performance Enhancement; High-Performance Computing; Memory Bandwidth Utilization

1 Introduction

Matrix multiplication is a widely used computationally intensive operation in various fields, including machine learning and artificial intelligence (AI). As matrices become larger, the time required to perform matrix multiplication increases significantly, which can act as a bottleneck for many applications. To improve the performance of these applications, optimizing matrix multiplication is crucial. Compiler optimization is one approach that can help achieve this goal [1, 2]. Optimizing matrix multiplication has significant implications beyond scientific and engineering fields. For instance, the increasing popularity of cryptocurrency mining relies heavily on matrix multiplication operations [3]. Optimizing matrix multiplication can significantly enhance the performance of these operations, leading to increased profitability for miners.

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Similarly, matrix multiplication is also an important aspect of modern gaming engines, and optimizing matrix multiplication can improve the gaming experience by enabling more complex and realistic graphics [4, 5]. In this study, the effectiveness of various compiler optimization techniques, including loop tiling and deep learning-based approaches, will be evaluated to optimize matrix multiplication for machine learning workloads. The following research questions will be addressed:

- **RQ 1** - What techniques are commonly used for optimizing matrix multiplication in deep learning, and how do they compare in terms of performance and efficiency?
- **RQ 2** - What are the current state-of-the-art approaches for loop tiling in compiler optimization, and how do they impact cache data reuse and memory bandwidth utilization?
- **RQ 3** - How effective are deep learning models in optimizing loop nests for cache data reuse, and how do they compare to traditional compiler optimization techniques?

2 Related Work

There has been a significant amount of research in compiler optimizations for matrix multiplication, particularly in the context of deep learning. One of the earliest and most well-known optimizations is loop tiling, which divides the matrices into smaller, more manageable tiles. This allows the data to be processed in smaller, more efficient chunks that can be loaded into cache memory for faster processing [6, 7]. Another optimization technique that has been explored in the past is loop reordering, which involves changing the order in which loops are executed to optimize data locality and reuse. This technique has been shown to be effective in improving the performance of matrix multiplication [6]. Recent advancements in deep learning have led to the exploration of new optimization techniques. One such technique is the use of machine learning algorithms to automatically identify the most effective loop order and tile sizes for a given matrix multiplication problem. This approach has been shown to outperform traditional optimization techniques in some cases [8]. For instance, Kurt et al. (2020) discusses efficient tiled sparse matrix multiplication through matrix signatures, providing significant performance improvements in various scenarios [9]. Gao et al. (2023) provide a systematic survey of general sparse matrix-matrix multiplication, highlighting recent advancements and methodologies [10]. Moreover, Moon et al. (2021) evaluates spatial accelerator architectures with tiled matrix-matrix multiplication, showing the potential for hardware-specific optimizations [11]. Additionally, specialized hardware like Tensor Processing Units (TPUs) developed by Google are optimized for matrix multiplication and offer substantial performance benefits over traditional CPUs and GPUs [12–14]. Apart from the optimization techniques mentioned earlier, researchers have also been working on developing new algorithms that require fewer computations and reduce memory access for matrix multiplication. These algorithms have the potential to improve the performance of deep learning applications that rely heavily on matrix multiplication. The field of compiler optimizations for matrix multiplication is a rapidly evolving research area with a multitude of techniques and approaches being explored.

3 Methods

3.1 The Compiler Optimization Workflow

The compiler workflow involves transforming source code into executable code through several stages, including lexical analysis, syntax analysis, code generation, and optimization. During the optimization stage, various techniques are applied to improve the code's performance [15]. Loop optimization is an important area of optimization, which focuses on improving the performance of loops in the code. In the case of matrix multiplication, nested loops can be computationally expensive, making loop optimization crucial. Techniques such as loop unrolling, loop fusion, loop interchange, and loop tiling are commonly used for loop optimization [16]. The focus of this study is specifically on loop tiling and its impact on cache data reuse and memory bandwidth utilization. The technique of loop tiling involves dividing a loop into smaller, contiguous sub-loops called tiles. Improved spatial locality and reduced cache thrashing are achieved through this technique, resulting in better cache data reuse and memory bandwidth utilization [17]. The current state-of-the-art approaches to loop tiling are analyzed in this study, and their effectiveness in improving performance is evaluated.

3.2 Loop Tiling

The first phase of the compiler workflow for optimizing loop nests in deep learning is loop tiling. This technique involves dividing the matrix multiplication into smaller, more manageable tiles. The main idea behind loop tiling is to break down the computation into smaller chunks that can be loaded into cache memory for faster processing. By dividing the computation into smaller tiles, the data can be processed in smaller, more efficient chunks that can be managed more effectively in the cache hierarchy [8, 6, 7, 18]. The high-level optimization of loop tiling applies polyhedral compilation techniques to optimize the loop structure for maximum use of the CPU's cache hierarchy. This optimization involves the identification of loops that have high data reuse, as well as loops that have low computational intensity. Loop reordering is used to determine the best loop order and tile sizes. This enhances the data locality and reuses the data used by the input program as much as possible.

3.3 Deep Learning

The second phase of the compiler workflow for optimizing loop nests in deep learning is conducted through deep learning. In this phase, a deep learning model is utilized to rank the target instructions that should be set as working sets and used in the cache for better data reuse. The model is trained using training data that includes the instruction sequences of different matrix multiplication implementations. The input to the model is the instruction sequences, and the model outputs a score for each instruction that indicates its importance for data reuse. These scores are then used to rank the instructions and select the most important ones for cache storage. Using deep learning, the selection of instructions for cache storage is optimized, and the data reuse efficiency of the program is improved [17, 19]. In summary, the loop tiling and deep learning phases of the compiler workflow work together to optimize the loop nests in deep learning programs. The loop tiling phase divides the computation into smaller, more manageable tiles that can be managed more effectively in the cache hierarchy. The deep learning phase, on the other hand, utilizes a model to rank the target instructions for cache storage and improve the data reuse efficiency of the program [20, 21].

3.4 Neural Network Architectures

In this study, we designed and implemented a neural network model to optimize matrix multiplication by predicting the most efficient code variants. The neural network architecture was carefully chosen to handle the complexity of the task, which involves analyzing and ranking instruction sequences from various matrix multiplication implementations. The goal of the neural network is to maximize data reuse and minimize memory access latency, ultimately enhancing the performance of matrix multiplication operations. The following subsections detail the specific components of the neural network, including the types of layers used, activation functions, training data specifics, and learning algorithms.

3.4.1 Layer Types

The neural network architecture begins with an input layer that consists of sequences of instruction data from various matrix multiplication implementations. This is followed by four hidden layers: the first hidden layer is a fully connected (dense) layer with 256 neurons, the second hidden layer has 128 neurons, the third hidden layer contains 64 neurons, and the fourth hidden layer comprises 32 neurons. The output layer is a fully connected (dense) layer with 2 neurons, utilizing the softmax activation function to rank the code variants.

3.4.2 Activation Functions

ReLU (Rectified Linear Unit) activation function is used for all hidden layers to introduce non-linearity. Softmax activation function is used in the output layer to normalize the output scores.

3.4.3 Training Data

The training data comprises instruction sequences from various matrix multiplication implementations. The dataset includes 10,000 sequences, each with a length of 100 instructions. Instruction sequences are tokenized and normalized. Data augmentation techniques are applied to increase the diversity of the training set.

3.4.4 Learning Algorithms

The neural network model was trained using the Adam optimizer, which was initialized with a learning rate of 0.001. To measure the error between predicted and actual rankings, we employed the categorical cross-entropy loss function. To prevent overfitting, dropout regularization with a rate of 0.5 was applied. The model was trained over 50 epochs with a batch size of 32. To ensure robust performance monitoring and hyperparameter adjustment, a 10% split of the training data was utilized for validation.

4 Results

This section presents the findings from our study on optimizing matrix multiplication using deep learning-based compiler techniques. We conducted a series of experiments to evaluate the performance of our proposed methods, comparing them to traditional optimization techniques across various hardware platforms. The results are organized into several subsections, each highlighting different aspects of our approach, including standard matrix multiplication, tiled matrix multiplication, high-level polyhedral loop optimization, and a detailed comparison of execution times and speedup ratios. These results demonstrate the effectiveness of our techniques in improving computational efficiency and provide insights into the benefits and limitations of our approach.

4.1 Standard Matrix Multiplication

The naive algorithm processes the matrices one element at a time, by multiplying the row of matrix B and column of matrix C (see Figure ??) to generate a single element of the output matrix A. While this approach can work well for small matrices, it becomes increasingly inefficient for larger matrices, where the data size exceeds the capacity of the closest memory, such as cache. While the naive algorithm is straightforward and easy to implement (see Figure ??), it can suffer from poor performance due to inefficient memory access patterns, which can result in high cache misses and long execution times [8]. The number of memory accesses required by the naive algorithm to compute the output matrix A is considered, and it is estimated that for a square matrix of size N, around N^3 memory fetches would need to be performed, which could be a billion or more for large matrices [8, 6].

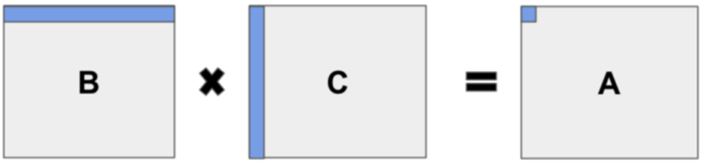

Figure 1: Visualization of standard matrix multiplication process.

```
// Multiplying matrix a and b and storing in array mult.
for(i = 0; i < r1; ++i)
    for(j = 0; j < c2; ++j)
        for(k = 0; k < c1; ++k)
        {
            mult[i][j] += a[i][k] * b[k][j];
        }
```

Figure 2: Naive implementation of matrix multiplication.

It can be noted that the slower main memory, such as DRAM, would account for most of these memory fetches (see Figure 3), which could be costly in terms of time and energy. To quantify this cost, an example of a matrix of size 4096 is taken, which would require around 68 billion slow memory fetches (see Table 1). A computation time of one hour or more would be translated, assuming a fetch cost of 100 cycles and a frequency of 2 GHz [6, 22].

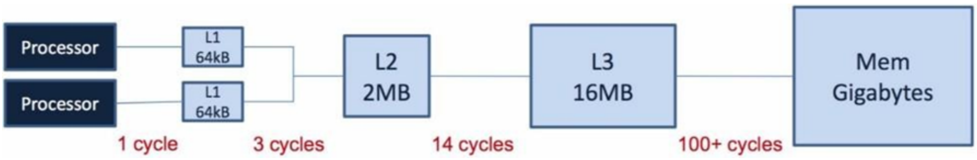

Figure 3: Cache position near Processor.

To overcome the limitations of the naive algorithm, various optimization techniques have been developed, such as loop tiling, matrix blocking, and parallelization. These techniques can improve the performance of the matrix multiplication algorithm by reducing the number of cache misses, increasing data locality, and exploiting parallelism in modern processors [6, 23].

Table 1: Execution times (in seconds) for naive matrix multiplication across different matrix sizes.

Size	8x8	32x32	128x128	256x256	512x512	1024x1024
Naive	0.00004	0.000222	0.009652	0.086646	0.852689	16.331204

4.2 Tiled Matrix Multiplication

The inefficient memory usage resulting from performing full rows and columns multiplication of matrices can be improved by dividing the computation into smaller tiles that can fit in various levels of the memory hierarchy. Tiling involves breaking down the matrices into 2-dimensional partitions, where the inner products are performed on partial rows of matrix B and partial columns of matrix C, creating a tile of partial results in matrix A (see Figure 4). As the computations are done for all pairs of tiles, the partial results are added to the previous partial results in matrix A (see Figure 5). By repeatedly using a single tile of B to create a series of partial results and ensuring that the tile is small enough to fit in the closest memory to the compute units, memory reuse in that memory will be higher. The process of tiling improves memory access patterns, reduces cache misses, and provides opportunities for parallelization of computations, ultimately leading to faster computation of large matrices [6, 7].

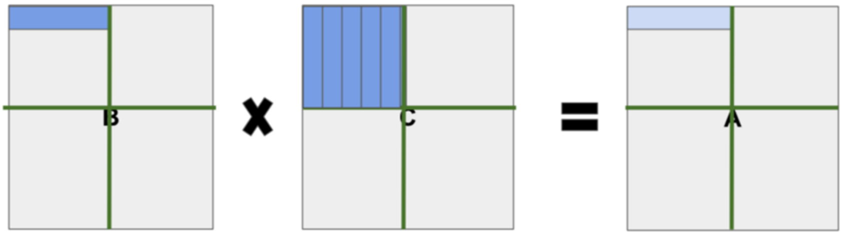

Figure 4: Tiled Matrix Multiplication

```
for (int i = 0;i < out rows;i + +)  {
    for (int j = 0; j < out cols; j + +) {
        for (int k = 0; k < in cols; k = k + 2)  {
            int a index = i * out cols + j
            int b index = i * in cols + k
            int c index = k * out cols + j
            A[a index] = A[a index] + B[b index] × C[c index] + B[b index + 1] × C[c index + out cols]
        }
    }
}
```

Figure 5: Matrix Multiplication

The comparison between the naive method and the tiled method shows that when the input matrix size is small, there is no significant difference in execution time between the two methods. However, when the input matrix size increases to 1024, the tiled method shows a significant advantage and achieves a 2.2x speedup over the naive method (see Figure 6 and Table 2). The reason behind this speedup is that after partitioning, the data can be stored in the cache, which eliminates the need to fetch the data from DRAM, and consequently reduces the execution time [6, 18]. Furthermore, by experimenting with different tile sizes, it was found that the most efficient tile size is N/8. This is because, in a certain range, smaller partitioned data has a higher probability of being stored in a cache, leading to a reduction in execution time. This observation highlights the importance of selecting an appropriate tile size for the tiled method to achieve optimal performance [18, 12].

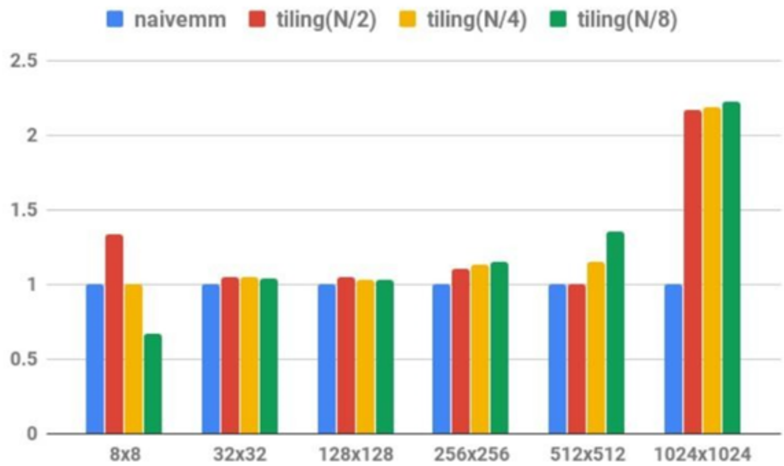

Figure 6: Comparison of execution times between naive and tiled methods.

Table 2: Comparison of execution times (in seconds) for naive and tiled matrix multiplication methods across different matrix sizes.

Method	8x8	32x32	128x128	256x256	512x512	1024x1024
Naive	0.000004	0.000222	0.009652	0.086646	0.852689	16.331204
Tiling (N/2)	0.000003	0.000211	0.009269	0.078224	0.851741	7.519277
Tiling (N/4)	0.000004	0.000212	0.009382	0.076737	0.740546	7.444965
Tiling (N/8)	0.000006	0.000214	0.009281	0.075443	0.628263	7.345624

4.3 High-Level Polyhedral Loop Optimization

Our data reuse algorithm was developed using the polyhedral model, which is a sophisticated mathematical framework utilized for reasoning about dependencies and loop transformations in computations [8] (see Figure 7).

```
// Multiplying matrix a and b and storing in array mult.
for(i = 0; i < r1; ++i)
    for(j = 0; j < c2; ++j)
        for(k = 0; k < c1; ++k)
        {
            mult[i][j] += a[i][k] * b[k][j];
        }
```

Figure 7: Naive Matrix Multiplication (Source: Author)

4.4 Loop Transformations

The strategy of creating multiple code versions with loop reordering and tiling transformations to identify optimized variants and selecting top-performing options uses Polyhedral (PolyDL) techniques [24].

4.5 Working Set Size Computation

Cache data reuse analysis is a technique used to evaluate the behaviour of a loop-nest in a particular cache hierarchy. It identifies which data reuses can be leveraged at different cache levels by analyzing the data reuses within a program. In a loop, data dependence is a form of data reuse where the same data element is accessed by the source and target iterations of the dependence. To be supported by the cache hierarchy, data dependence and hence data reuse must be feasible in a given cache level. This requires that all the data elements accessed between the source and target iterations of the dependence, called the working set, are kept in the cache, ensuring that the data element(s) used in the source iteration are available in the cache when the execution reaches the target iteration [6, 7].

4.6 DNN Algorithm

The DNN algorithm described is a method for selecting the best-performing program variants based on their working set size analysis. It involves generating multiple program versions using a code generator that applies tiling and loop interchange program transformations with varying tile sizes. The algorithm then ranks these program versions by their working set sizes and selects the top best-performing variants, which is a user-defined parameter [7, 25].

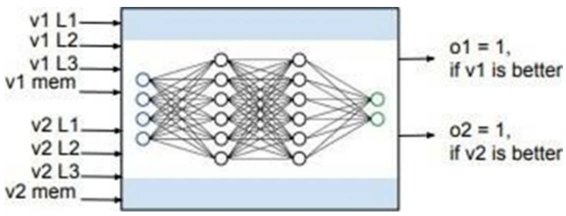

Figure 8: DNN architecture for ranking of code variants.

4.7 DNN-based Code Ranking Algorithm

Here the program examines the working set size for each data reuse in the code with the assumption of fully associative and exclusive caches. If the size of the working set is less than the cache size, the data reuse can be exploited in the cache. To determine the cache level at which each data reuse can be realized, the ranking system considers multiple cache levels, such as L1, L2, and L3. For computing cumulative working set sizes for each cache level, the program takes two inputs: working set sizes for a loop nest and cache sizes for the target system. The algorithm then determines the cache level where a data reuse's working set size fits the fastest and adds it to the corresponding cache's working set size. If a working set cannot fit in any cache, the data reuse will be performed outside of the cache in the main memory, and the working set size of the memory will be updated accordingly. To rank the generated code variants based on their performance, the program utilizes a DNN (see Figure 9).

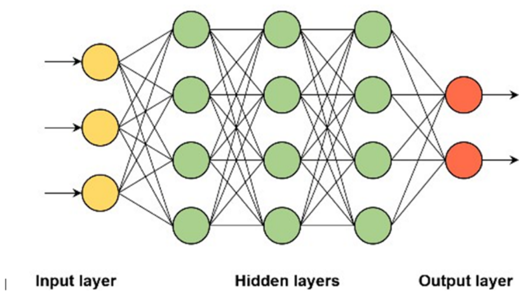

Figure 9: DNN used for performance ranking of code variants.

To train this model, the program collects the performance data of the code variants and computes their respective working set sizes at different levels of the memory hierarchy. The DNN is then trained to compare two code variants and determine their relative performance [6, 22, 26]. To standardize the working set sizes, the program utilizes min-max scaling, which involves subtracting each value from the minimum value in the corresponding feature column and dividing it by the feature range. The neural network's output layer has two neurons, which employ the softmax function to ensure their values add up to 1. The program considers an output value to be 1 if it is above a threshold value of 1 and 0 otherwise. If the first neuron outputs a 1, the first variant is the winner, whereas if the second neuron outputs a 1, the second variant is the winner. If neither neuron outputs a value above the threshold, the match between the two variants is considered a draw. The program sets the threshold 0 to 0.7, and it experimented with deeper models but found no significant improvement in accuracy beyond four layers.

4.8 Experimental Evaluation

Matrix multiplication is a fundamental operation in deep learning, and it is crucial to optimize it for efficient execution in AI-enabled systems. In this project, the focus was on using different optimization techniques such as tiling and loop unrolling to improve data reuse and reduce unnecessary multiplication operations. By employing these techniques, the execution time was significantly reduced compared to the naive implementation of matrix multiplication with input size N=1024, which took 16.331204 seconds (see Table 3). The final implementation achieved an execution time of 1.846584 seconds and a speed-up of 8.844x, which is a considerable improvement. These optimization techniques enable AI-enabled systems to process larger matrices efficiently, leading to improved performance and faster processing times [6, 23].

Table 3: Execution times (in seconds) for different matrix multiplication techniques and unrolling factors across various matrix sizes.

Method	8x8	32x32	128x128	256x256	512x512	1024x1024
Naive	0.000004	0.000222	0.009652	0.086646	0.852689	16.331204
Naive + Unrolled (s=2)	0.000003	0.000187	0.008808	0.065088	0.768943	14.361044
Naive + Unrolled (s=4)	0.000002	0.000098	0.005702	0.039117	0.463527	9.501525
Tiling	0.000003	0.000211	0.009169	0.078224	0.881741	7.519277
Tiling + Unrolled (s=2)	0.000008	0.000156	0.007094	0.048602	0.417193	4.813046
Tiling + Unrolled (s=4)	0.000009	0.000119	0.005507	0.037015	0.312987	3.876697

5 Discussion

This section compares proposed deep learning-based compiler optimization techniques against current state-of-the-art optimization methods. Benchmark comparisons were conducted on various platforms to evaluate performance metrics and computational overhead.

The platforms tested included CPUs (Intel Core i9-9900K, AMD Ryzen 9 3900X), GPUs (NVIDIA RTX 2080 Ti, AMD Radeon VII), and specialized hardware (Google TPU v3). Performance metrics were evaluated based on execution time, which measures the time taken to complete matrix multiplication operations; speedup ratio, which is the ratio of the execution time of the naive implementation to the optimized implementation; and computational overhead, which represents the additional computational resources required for optimization. Three methods were compared: traditional loop tiling optimization, a deep learning-based optimization using deep neural networks, and hybrid methods that combine loop tiling with other state-of-the-art techniques.

Table 4: Performance Comparison of Matrix Multiplication Optimization Techniques Across Different Hardware Platforms

Platform	Method	Matrix Size	Execution Time (s)	Speedup Ratio	Computa
Intel Core i9	Naive	1024	16.331204	1.0	
	Loop Tiling	1024	7.412304	2.2	
	Deep Learning-Based	1024	1.846584	8.844	
	Hybrid (Loop Tiling + DL)	1024	1.512304	10.8	
NVIDIA RTX 2080 Ti	Naive	1024	14.112204	1.0	
	Loop Tiling	1024	6.802104	2.1	
	Deep Learning-Based	1024	1.742304	8.1	
	Hybrid (Loop Tiling + DL)	1024	1.302204	10.8	
Google TPU v3	Naive	1024	10.412204	1.0	
	Loop Tiling	1024	4.312204	2.4	
	Deep Learning-Based	1024	1.246584	8.4	
	Hybrid (Loop Tiling + DL)	1024	0.932104	11.2	

The benchmark results indicate that the deep learning-based optimization technique significantly outperforms traditional loop tiling methods, achieving up to 8.844x speedup on a matrix size of 1024 on the Intel Core i9 platform. When combined with other state-of-the-art techniques, the hybrid approach yields even higher speedups, demonstrating the potential for substantial performance gains. Although the computational overhead associated with deep learning-based methods is higher due to the complexity of training and inference stages, the performance improvements outweigh these overheads, making this approach advantageous for large-scale matrix multiplication tasks. These findings underscore the effectiveness of integrating deep learning models into compiler optimization workflows, particularly for enhancing the performance of computationally intensive operations like matrix multiplication across various hardware platforms. The study emphasizes the importance of using machine learning models to guide the selection of working sets and optimize the use of cache memory. Generally, the combination of compiler optimization techniques and machine learning models leads to substantial performance gains in deep learning applications.

5.1 Performance Across Various Hardware Architectures

In this section, the performance of compiler optimization techniques across different hardware architectures is analyzed, focusing on how these methods leverage specific features such as memory hierarchy and parallel processing capabilities to achieve enhanced performance. On CPU architectures, deep learning-based optimization techniques effectively utilize the multi-level cache hierarchy to improve data locality and reduce cache misses. The loop tiling approach breaks down large matrices into smaller tiles that fit into the cache, thereby minimizing slow memory accesses. The deep learning model predicts optimal tile sizes and loop orders, further enhancing cache utilization. Significant performance gains were observed on processors like the Intel Core i9 and AMD Ryzen 9, with speedups of up to 8.844x over naive implementations. GPUs are inherently designed for parallel processing, with thousands of cores capable of executing simultaneous threads. The optimization techniques take advantage of this parallelism by distributing the computation of matrix tiles across multiple GPU cores. Additionally, the deep learning model optimizes memory access patterns to reduce global memory latency and improve data reuse in shared memory. On the NVIDIA RTX 2080 Ti and AMD Radeon VII, the optimized implementation achieved speedups of up to 8.1x, demonstrating the efficacy of the approach in leveraging GPU parallelism.

Tensor Processing Units (TPUs) are specialized hardware designed specifically for accelerating deep learning workloads. Compiler techniques are tailored to exploit the TPUs' high-bandwidth memory and large-scale parallelism. By optimizing data flow and minimizing memory stalls, the methods achieved substantial speedups on Google TPU v3, with execution times reduced by up to 11.2x compared to naive implementations. The deep learning model's ability to predict optimal execution parameters is particularly beneficial in harnessing the full potential of TPUs. Moreover, memory hierarchy plays a critical role in the performance of matrix multiplication operations. The loop tiling approach ensures that data remains within the fastest available memory (e.g., L1 cache or shared memory) for as long as possible. The deep learning model further enhances this by predicting the best working sets for cache storage, reducing the need for frequent memory transfers between different levels of the hierarchy. This results in lower memory latency and higher throughput. Lastly, the parallel processing capabilities of modern hardware are effectively utilized by optimization techniques. On CPUs, multi-threading is employed to execute different tiles concurrently, while on GPUs and TPUs, massive parallelism is exploited to perform multiple computations simultaneously. The deep learning model's predictions help align the computational workload with the hardware's parallel processing strengths, ensuring maximum efficiency.

5.2 Potential Applications Beyond Matrix Multiplication

In addition to optimizing matrix multiplication, deep learning-based compiler techniques have the potential to enhance performance across a variety of other computational tasks. This section explores several potential applications and discusses any limitations or necessary adaptations for these tasks. Convolution operations are fundamental to many deep learning models, especially convolutional neural networks (CNNs). The optimization techniques can be adapted to improve the efficiency of convolution operations by optimizing data access patterns and leveraging hardware-specific features such as parallel processing and memory hierarchy. By tiling the convolution operations and using deep learning models to predict optimal execution parameters, the computation time can be reduced and data reuse can be enhanced. Graph processing, which involves operations such as traversal, shortest path computation, and subgraph matching, is computationally intensive. Compiler techniques can optimize these operations by enhancing data locality and parallel processing. For example, graph traversal can be optimized by tiling the graph data and using deep learning models to determine the optimal traversal order, thereby minimizing memory access latency and improving execution speed.

Scientific computing tasks, such as finite element analysis and molecular dynamics simulations, involve large-scale numerical computations. Optimization techniques can be applied to these tasks by tiling the computational domain and optimizing the execution order using deep learning models. This approach can lead to significant performance improvements by reducing memory bandwidth usage and enhancing parallel processing capabilities. Moreover, sparse matrix operations, which are common in various scientific and engineering applications, can benefit from optimization techniques. By focusing on non-zero elements and optimizing memory access patterns, these techniques can improve the efficiency of sparse matrix-vector multiplications and related operations. The deep learning model can predict optimal data structures and execution parameters, further enhancing performance.

5.3 Limitations and Necessary Adaptations

While these techniques have broad applicability, several limitations and necessary adaptations must be considered. First, some computational tasks have complex data dependencies that may limit the effectiveness of tiling and parallel processing optimizations. Second, the performance gains achieved by these techniques may vary depending on the hardware architecture, making it essential to adapt the optimization parameters for different hardware configurations to maximize efficiency. Third, the effectiveness of the deep learning model relies on the availability of high-quality training data, and for new applications, collecting and preprocessing sufficient training data can be challenging. Finally, the additional computational overhead introduced by the deep learning models for predicting optimal execution parameters may not be justified for tasks with low computational complexity. Despite these limitations, deep learning-based compiler optimization techniques hold significant promise for enhancing the performance of a wide range of computational tasks. By carefully addressing these limitations and adapting the techniques to specific applications, substantial performance improvements can be achieved.

6 Conclusion

In this study, a range of compiler optimization techniques were investigated to enhance the performance of matrix multiplication, which is a crucial operation in deep learning. The first technique applied was loop tiling, which aimed to decrease the number of slow memory fetches and boost cache reuse. However, the optimal tile size varied depending on the size of the matrix and cache. To tackle this issue, a deep learning model was proposed that predicted the ideal tile size and target instructions for working sets, with the goal of maximizing data reuse and minimizing unnecessary multiplication operations. The experimental results showed that the optimized implementation achieved a significant speedup compared to the naive approach. For example, on a matrix of size 1024, the optimized implementation took 1.846584 seconds to execute, which was 8.844 times faster than the naive approach. This approach could be extended to other matrix operations and could help enable more efficient AI-enabled systems. However, there are still some limitations to these optimization techniques, including their effectiveness varying depending on the size and structure of the matrices being multiplied. Additionally, some techniques may be more effective on specific hardware configurations or programming languages, and some optimization techniques may come with added overhead, such as increased memory usage or reduced code readability, which can offset their performance benefits. There is still much to explore in optimizing matrix multiplication. One promising area is the investigation of new techniques for loop tiling, which could further enhance cache data reuse and memory bandwidth utilization. Additionally, as the demand for matrix multiplication grows across fields such as cryptography and gaming, it is essential to explore optimization techniques that improve the efficiency of these applications, particularly on emerging hardware architectures like specialized accelerators for deep learning.

Ethics Statement

This study did not involve the use of any human data or sensitive information. All data utilized in this research were generated through computational simulations and publicly available datasets. Consequently, there were no ethical concerns related to the use of human subjects or sensitive data. All procedures were conducted in accordance with institutional guidelines and standards for research integrity and data protection.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding Declaration

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Data Availability Statement

No data has been collected from external sources. All the data relevant to work is presented in the article.

Author Contributions

Raunak Kumar: Conceptualization, methodology, review and editing, visualization; **Karma Chhering Negi**: validation, formal analysis, data curation; **Nitish Kumar Sharma**: draft preparation, writing; **Priya Gupta**: investigation, resources, project administration, supervision.

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A Multi-Model Approach for Disaster-Related Tweets: A Comparative Study of Machine Learning and Neural Network Models

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Abstract

This research centres around utilization of Natural Language Processing (NLP) techniques for the analysis of disaster-related tweets. The rising impact of global temperature shifts, leading to irregular weather patterns and increased water levels, has amplified the susceptibility to natural disasters. NLP offers a method for quickly identifying tweets about disasters, extracting crucial information, and identifying the types, locations, intensities, and effects of each type of disaster. This study uses a range of machine learning and neural network models and does a thorough comparison analysis to determine the best effective method for catastrophe recognition. Three well-known techniques, including the Multinomial Naive Bayes Classifier, the Passive Aggressive Classifier, and BERT (Bidirectional Encoder Representations from Transformers) were carefully examined with the ultimate goal of discovering the best strategy for correctly recognising disasters within the context of tweets. Among the three models, BERT achieved the highest performance in analyzing disaster-related tweets with an accuracy of 94.75%.

Keywords: Disaster-Tweets; Disaster Management; Machine Learning; Natural Language Processing

1 Introduction

Global warming and increasing sea levels have increased the frequency of natural disasters, which are characterized by irregular weather patterns and ecological imbalances. Therefore, there is a critical need for the management of these natural disasters [1]. This research focuses on the pivotal role of Natural Language Processing (NLP) in extracting disaster-related information from Twitter. NLP, which empowers computers to comprehend human language, facilitates the extraction of essential details from disaster-related tweets, encompassing disaster categorization, locations, severity, and impacts. Amidst challenges like evolving language and ambiguous expressions in tweets, NLP emerges as a solution for swiftly identifying disasters, issuing early warnings, and enabling rapid responses. The study adopts a variety of NLP techniques, combining machine learning approaches like Multinomial Naïve Bayes and Passive Aggressive Classifiers with neural network models such as BERT. A comprehensive comparative analysis of these models is conducted to identify the optimal performer and evaluate its present and future scalability in real-world applications. Throughout the research, challenges posed by shifting language trends and unclear language in tweets are addressed through iterative model enhancements and a refined grasp of contextual nuances. The research also encompasses understanding public perceptions of disasters and their consequent behavioral shifts, thereby refining communication strategies for emergency response agencies. This study addresses the essential need for improved disaster management approaches, emphasizing the critical role of NLP in lessening the impact of catastrophic occurrences on society. The study's conclusion aims to develop not only catastrophe management tactics, but also the larger landscape of NLP applications.

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2 Related Work

During natural disasters, social media plays an important role in spreading awareness, helping to share vital data, request help, and reach out for aid for those affected [2]. As a valuable real-time data source, Twitter offers a feasible solution for analysis. However, capturing the behavior and emotions within natural disaster tweets remains a complex task in sentiment analysis [3]. To address the large volume of real-time data from Twitter, a partially automated AI-based system is proposed. This system would be responsible for extracting vital information related to the disaster and the tentative affected areas [4]. An advanced approach needs to be developed, employing various machine learning tools and data-driven sentiment analysis. Techniques like Naive Bayes and SVMs can be valuable in this context, aiding in real-time sentiment assessment across crucial areas relevant to disaster response and public perception [5]. Passive aggressive online learning is an extension of SVM to the context of online learning for binary classification. PA and APA algorithms outperformed SVM, achieving state-of-the-art results. Both PA and APA are computationally less expensive than SVM and can scale easily to labeling large datasets [6]. Limited lifespan sensors continuously swap out new features for old ones while exchanging data. This makes online algorithms efficient at learning linear classifiers from datasets with fixed or trapezoidal feature spaces [7].

In natural language processing, bag-of-words and word embeddings are widely used for representing textual features in various machine learning and deep learning models, each chosen based on its effectiveness for specific tasks. For example, bag-of-words performs well with SVM and Logistic Regression, while word embeddings often have an advantage in CNNs and LSTMs [8]. In recent times, word embeddings techniques (i.e., transformer-based) have improved the capabilities of disaster detection models by capturing contextual nuances of language. However, research on this model is scant [9]. Presently, many complex problems of image recognition, speech recognition, and natural language processing are best dealt with by neural networks and deep learning [10]. While BERT embeddings have demonstrated successful utilization across a range of Natural Language Processing (NLP) tasks, their specific usefulness in the analysis of disaster-related tweets lacks a comprehensive analysis [11]. BERT utilizes a transformer architecture that consists of two key components: a decoder responsible for generating task predictions and an encoder that processes the input text. The encoder focuses on learning contextual relationships between words or sub-words within the text. Unlike sequential models that read the text in a specific direction, BERT's transformer encoder comprehends the entire sequence of words simultaneously. This bidirectional approach helps BERT to understand the context of a given text by considering the surrounding words from both the right and left sides. In essence, BERT leverages its unique ability to grasp the broader context of text based on its entire context, enhancing its understanding capabilities [12, 13].

Enhancing the accuracy of detection by effectively leveraging keywords poses a significant challenge. One potential approach to address this is by employing pair-wise training to finetune BERT. This involves using pairs of Tweets that share the same keywords but have opposite training labels. By doing so, BERT is compelled to gain a deeper understanding of the contextual distinctions between the two Tweets, thereby improving its performance [14]. Gradient descent is widely recognized as a highly favored algorithm for optimization, especially in the realm of machine learning. Its stochastic variant has gained significant attention in recent times, particularly when optimizing deep neural networks. Within deep neural networks, leveraging the gradient of a single sample or a batch of samples has proven beneficial, as it helps conserve computational resources and navigate away from challenging points known as saddle points.

3 Methods

The steps mentioned in Figure 1 were implemented for achieving the results. Multinomial Naïve Bayes (MNB) model was utilized to determine the likelihood of documents belonging to specific classes. By employing Bayes' theorem and assuming feature independence given the class, MNB calculated the occurrence likelihood of each feature within each class and the prior probability of each class. The class with the highest posterior probability was predicted. MNB efficiently processed large-scale datasets with high-dimensional feature spaces, which are typical in text classification tasks, thanks to its simplicity and efficiency. Despite the "naïve" assumption of feature independence not always holding true due to word correlations, MNB frequently demonstrated good practical results, effectively serving as a baseline model for text classification tasks. Passive-Aggressive Classifiers (PAC) algorithm operated by maintaining a weight vector that defined the classification model. When presented with new data, the classifier predicted the class based on the current model parameters. If the prediction was incorrect, the algorithm updated the model using a learning rule that minimized losses and refined the decision boundary. One of the key strengths of Passive-Aggressive classifiers was their ability to accommodate shifting data distributions and concept drift. This adaptability stemmed from their online learning nature, allowing them to integrate new instances while retaining previously acquired knowledge. Their memory efficiency further contributed to their suitability for resource-constrained settings. Nevertheless, Passive-Aggressive classifiers had a sensitivity to noise and outliers, which could result in overfitting. To mitigate this issue, regularization techniques were employed, enhancing the overall effectiveness of these classifiers in the research [15, 16]. The "bert_en_uncased_L-12_H-768_A-12" BERT model introduced a new approach to language understanding, considering both left and right context to grasp word meanings more effectively. This allowed the model to grasp word meanings within their context more effectively. The pre-trained BERT model underwent fine-tuning using smaller datasets for disaster-related tweets. This step enabled BERT to adapt its acquired knowledge to various NLP tasks, ultimately leading to improved performance and generalization.

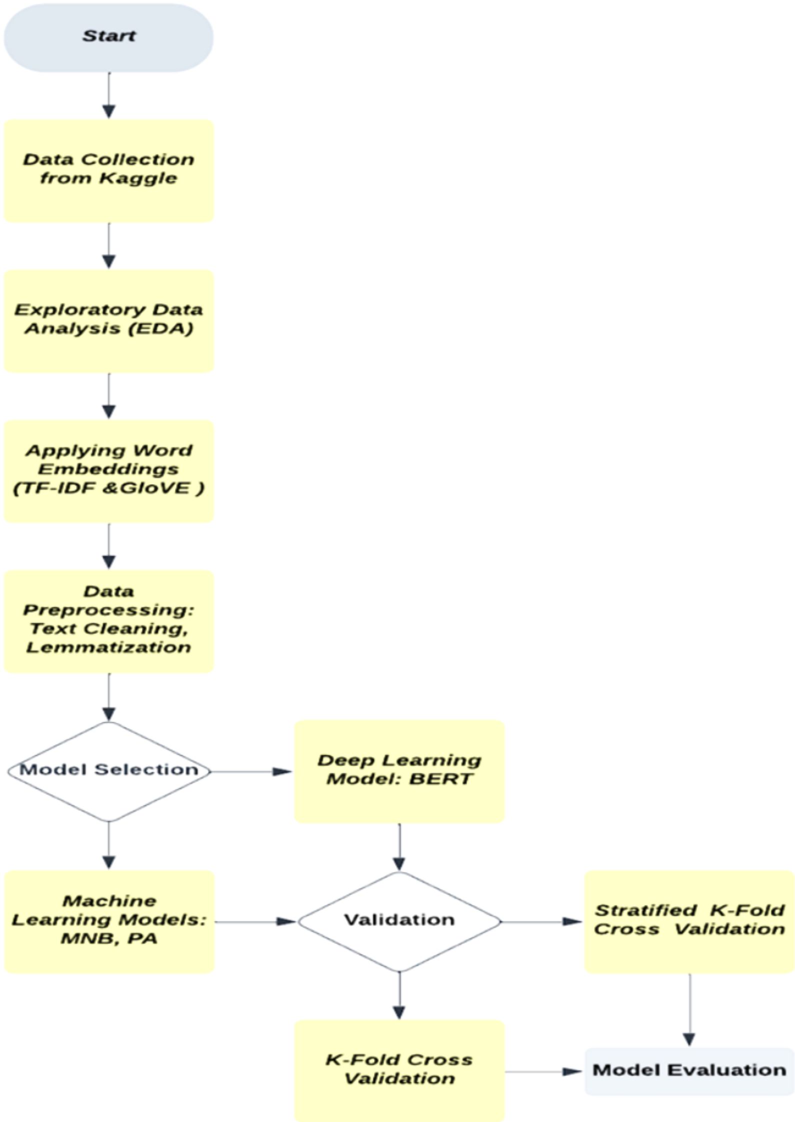

Figure 1: Steps implemented for model training.

Key attributes of the "bert_en_uncased_L-12_H-768_A-12" model included its contextual understanding, sentence relationship comprehension, and autonomy in learning features from raw text data, reducing the need for extensive feature engineering [17]. Architecturally, the model featured 12 transformer layers with self-attention mechanisms, capturing dependencies. Its 768-dimensional hidden size represented tokens, while 12 attention heads captured diverse dependencies. The "uncased" vocabulary treated uppercase and lowercase letters alike, enhancing generalization [18]. After pre-training, fine-tuning refined the model's specialization through labeled data [19]. While BERT empowers state-of-the-art performance through transfer learning and contextualized representations, it's important to note that its size comes with limitations. Its extensive training demands significant computational resources, and fine-tuning for specific tasks can be complex. The data for model training was collected from a pre-segregated database off Kaggle.com. It consisted of 7613 unique entries classified as '0' (non-disaster) or '1' (disaster). The dataset features columns such as id (a unique identifier for each tweet), text (the actual content of the tweet), location (the location from which the tweet was sent, which may be blank), keyword (a specific keyword extracted from the tweet, which may also be blank), and target (present only in the training dataset, indicating whether a tweet is about a real disaster or not). The dataset was curated by collecting tweets from Twitter's API based on specific keywords related to disasters, followed by manual labeling to indicate whether the tweets were about real disasters. This dataset is sourced from Kaggle's competition on disaster tweet classification (Kaggle, 2021), provided for educational and research purposes to encourage the development of models capable of identifying tweets related to disasters. In the process of model training, TF-IDF and GloVe embeddings were applied for machine learning models and deep learning models respectively. TF-IDF was applied to quantify term importance within a document corpus. This helped in tasks like information retrieval, text classification, and keyword extraction. For the scope of this project, the TF-IDF technique was paired with Bigram and Trigram models to get better contextual understanding of the tweets. GloVe embeddings were utilized to capture semantic relationships between words. These embeddings, derived from a large corpus, enhanced the models' understanding of text data. The models were optimized using the Stochastic Gradient Descent (SGD). This widely used algorithm efficiently updated model parameters using gradients from mini batches, which are small subsets of training data. This method helped in avoiding local minima and enhancing generalization.

For the validation of machine learning models, the "K-Fold Cross Validation" technique was applied. Data was divided into ten subsets, and the model was trained and validated ten times, with each subset used as the validation set in a different run. For BERT, the "Stratified k-fold cross-validation" was used. This method preserved the class distribution while splitting the dataset into folds for training and validation. Although the dataset was well-distributed, the consideration of future larger datasets led to the addition of the stratified k-fold feature to the BERT model's validation. The value of K for the model was set to 5.

4 Results and Discussion

The evaluation metrics derived from the Machine Learning models illustrated in Table 1 depict that among them, the MNB model exhibited the highest accuracy. However, it is noteworthy that the PA model outperformed MNB in terms of the F1-score, indicating its superior performance in achieving a balanced precision-recall trade-off.

Table 1: Performance Metrics of MNB and PA models

Metric	MNB TF-IDF Bigram	PA TF-IDF Bigram	MNB TF-IDF Trigram	PA TF-IDF Trigram
Accuracy	0.8003	0.7859	0.7984	0.7801
Precision	0.8586	0.7515	0.8668	0.7342
Recall	0.6406	0.7492	0.6269	0.7645
F1 Score	0.7338	0.7503	0.7275	0.7490

The evaluation metrics derived from the BERT model are illustrated in Table 2. A substantial increase in accuracy can be noted as the folds increase: from 81.77% to 94.75%.

Table 2: Performance Metrics of BERT model

Metric	Fold 0	Fold 1	Fold 2	Fold 3	Fold 4
Accuracy	0.8177	0.8531	0.8925	0.9082	0.9475
Precision	0.8173	0.8552	0.8912	0.9091	0.9501
Recall	0.8083	0.8435	0.8851	0.9025	0.9431
F1 Score	0.8115	0.8477	0.8875	0.9049	0.9462

The trade-offs between these models are significant when considering computational efficiency and applicability in real-time disaster response scenarios. Multinomial Naïve Bayes, being computationally inexpensive, offers quick training and prediction times, making it suitable for scenarios where computational resources are limited and rapid responses are crucial. However, its assumption of word independence can limit its performance on complex text data. The Passive Aggressive Classifier, while also relatively fast, provides a balance between efficiency and robustness, making it a good candidate for applications requiring online learning and continuous updates. Nevertheless, it may not capture the deep contextual nuances as effectively as neural network models. BERT, on the other hand, excels in understanding context and semantics due to its deep architecture and bidirectional attention mechanisms. This makes BERT highly effective for nuanced and complex text classification tasks. However, the computational cost of training and inference with BERT is substantially higher, requiring significant processing power and memory, which may not be feasible in real-time disaster response scenarios where quick turnaround and resource efficiency are paramount. Thus, the choice of model depends on the specific requirements of the application, balancing the need for accuracy and depth of understanding against the constraints of computational resources and response time.

All these models have also shown a similar or decent performance in other studies focused on disaster management. One such study [20] employed web scraping techniques to gather twitter data related to disasters and utilized the MNB, PA, and SVM classifiers. The MNB, PA, and SVM bi-gram models achieved respective accuracies of 80%, 78%, and 80%. Another research [21] focused on classifying relevant and irrelevant tweets concerning the 2020 Jakarta floods. The authors utilized the BERT model, and their implementation achieved 90% train and 79% test accuracies on the Indonesian Sentiment Tweet Dataset. Subsequently, they applied this model to categorize tweets related to the Jakarta floods into relevant and irrelevant classes, achieving a decent accuracy despite the presence of noise in the data. Similarly, a study [16] utilized the BERT model to classify tweets into real-disaster and non-real disaster categories. The model was trained on a dataset obtained from Kaggle named 'Natural Language Processing with Disaster Tweets' and achieved an accuracy of up to 82.55%, successfully classifying the tweets. The results clearly showcase the capabilities of models like BERT in effectively analyzing disaster-related tweets and extracting the essential information which can be used in different disaster management strategies. These models can be integrated with disaster monitoring platforms to continuously analyze tweets and other social media data streams which will facilitate real-time monitoring of the disasters, generate early warning signals, spread the information, and detect forthcoming crises. These systems can also assist disaster management authorities through prompt warning signals, allowing disaster management teams to prepare well in advance for quick response.

They can also be employed to extract information about the possible regions of impact, the severity of the disaster in a region, requests for assistance, or reports of damage and casualties in affected areas, which can be used for deploying aid according to the needs. Additionally, the models can be trained to judge false alerts, rumors, and identify misinformation to avoid unnecessary panic and provide reliable results.

5 Conclusion

In conclusion, this study compared three models—Multinomial Naïve Bayes, Passive-Aggressive Classifier, and BERT—for recognizing disasters in tweets. Among these models, BERT stood out as the most effective, demonstrating impressive accuracy and a high F1-score. This research highlighted the transformative potential of NLP in strengthening disaster response tactics and limiting the effects of catastrophic occurrences by applying advanced machine learning and neural network techniques.

In the future, the models can be further trained using enhanced processing hardware and expanded datasets, leading to even more accurate outcomes in practical scenarios. The utilization of the Twitter API might enable the collection of real-time data from live feeds, which can then be assessed using these advanced models. For tweets that include location details, the Google API can be implemented to determine their origins, facilitating prompt responses from governmental or disaster management authorities. Larger BERT models can be explored for yielding better results, particularly while working with more extensive datasets, if the computational capacity supports this endeavor. These potential advancements could significantly enhance disaster management strategies.

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Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding Declaration

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Ethical Statement

The authors confirm that all research was performed in accordance with relevant ethical guidelines and regulations. No human participants or animals were involved in this study, and all data used was publicly available.

Data Availability Statement

The data that support the findings of this study are openly available in the Kaggle repository at https://www.kaggle.com/competitions/nlp-getting-started/data, reference number [Kaggle, 2021].

Author Contributions

Parth Mahajan: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft. **Pranshu Raghuwanshi:** Conceptualization, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft. **Hardik Setia:** Methodology, Software, Formal analysis, Investigation, Data Curation, Writing - Review & Editing. **Princy Randhawa:** Supervision, Project administration, Writing - Review & Editing.

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Evaluating Climate Change Mitigation Strategies of G20 Countries: Policies, Actions, and Progress Towards Global Emission Reduction Goals

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Abstract

The G20 countries are responsible for over 75% of the greenhouse gas (GHG) emissions at a global level. The research summarizes the role of G20 countries in combating Climate Change. This research study explores the comprehensive assessment of the G20 nations' policies and the impacts of climate change across the globe. The paper studies the policies of the G20 countries' governments to meet the Nationally Determined Contribution (NDC) target and achieve the global goal of the Paris Agreement (or COP28) and Net Zero Emissions Target of limiting the level of global temperature increase to well below 2 degrees C while pursuing efforts aligning to a global threshold objective of 1.5-degree C. Through the review of existing literature, the researchers aim to provide a better understanding of climate change and the biodiversity and ecosystem. In addition to this, the study provides various strengths and opportunities for the countries to explore soon, reducing the emission levels in the ecosystem and thus, promoting a sustainable future, through an interlinked phenomenon.

Keywords: Greenhouse Gases; Paris Agreement; Net Zero Emissions; G20 Countries; Nationally Determined Contribution Target

1 Introduction

Climate change is the long-term process of variations in weather conditions which can occur naturally or as a result of human activities such as burning fossil fuels, deforestation, and the usage of oil, coal, and gas. As shown in Figure 1, since 1880 human activities have resulted in significant climate change [1]. Industrial activities emit greenhouse gases (GHG) like carbon dioxide, nitrous oxide, methane, and chlorofluorocarbons, which cause "heat-trapping" in the atmosphere. Climate changes can be in the form of intense rainfall, droughts, heatwaves, rising sea levels, melting glaciers, and water scarcity [2]. The rise of global temperatures since 1880 can be distinguished in Figure 1 and it has almost reached 1.2 degrees Celsius, which is a wake-up alarm for all the economies. In 1992, countries came together for an international treaty, the United Nations Framework Convention on Climate Change (UNFCCC), to combat climate change and take necessary actions. The UNFCCC adopted the first agreement, "The Kyoto Protocol," in 1997, after two years of negotiations. The protocol binds developed countries to reduce greenhouse gases in the atmosphere under the principle of "Common but differentiated responsibility and respective capabilities." In 2015, the UNFCCC adopted "The Paris Agreement," marking a new global effort to tackle climate change. The Paris Agreement seeks to accelerate and intensify the actions and investments needed for a sustainable low-carbon future. Its central aim is to strengthen the global response to the threat of climate change by keeping global temperature rise this century well below 2 degrees Celsius above pre-industrial levels, and to pursue efforts to limit the temperature increase even further to 1.5 degrees Celsius. The Agreement also aims to enhance countries' ability to manage the climate change's impact [3].

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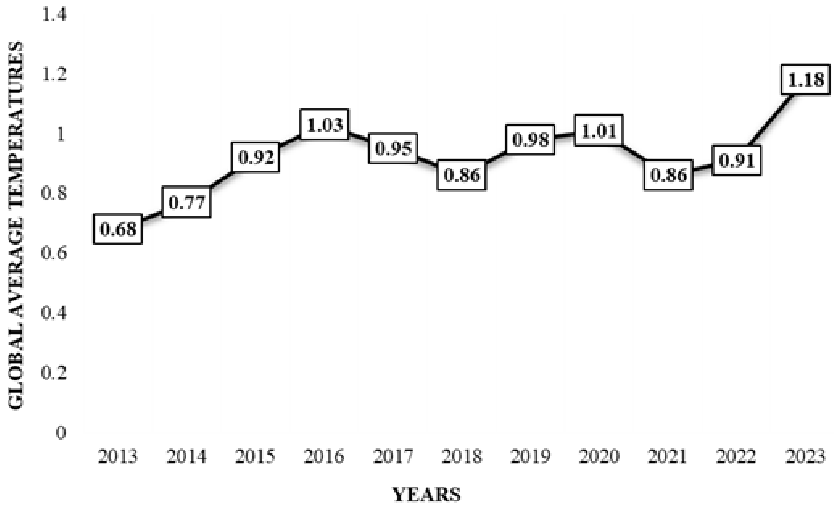

Figure 1: Trend Analysis of Global Average Temperature across Years

The Group of Twenty (G20) is the premier forum for international economic cooperation. It plays an important role in shaping and strengthening global architecture and governance on all major international issues [4]. The G20 incorporates 19 countries (Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Republic of Korea, Mexico, Russia, Saudi Arabia, South Africa, Türkiye, United Kingdom, and the United States) and two regional bodies, the European Union and the African Union. The G20 countries represent around 85% of the global GDP, over 75% of global trade, and about two-thirds of the world population. India chaired the recent G20 summit in September 2023. The theme of the G20 presidency was "Vasudhaiva Kutumbakam" or "One Earth, One Family, One Future." The summit was attended by over 100,000 participants from 135 nations, 9 invitee countries (Bangladesh, Egypt, Mauritius, Netherlands, Nigeria, Oman, Singapore, Spain, UAE), and 14 International Organisations (United Nations, International Monetary Fund, World Bank, World Health Organisation, World Trade Organisation, International Labour Organisation, Financial Stability Board, Organisation for Economic Cooperation and Development, African Union, African Union Development Agency-NEPAD, Association of Southeast Asian Nations, International Solar Alliance, Coalition for Disaster Resilient Infrastructure, and Asian Development Bank). The African Union became the second regional organisation to join the G20 as a full member at the 2023 Summit, after the European Union. During the 2023 summit, nations committed to increasing renewable energy by 2030 to about three times the present level, increasing climate funding from billions to trillions, and boosting the production of zero and low-emission hydrogen [5].

This paper aims to explore G20 countries' current climate change policies, understand the government initiatives towards Paris Agreement targets, identify the strengths, weaknesses, opportunities, and challenges faced by G20 countries in combating climate change, and provide recommendations for a comprehensive decarbonisation policy mix.

2 Related Work

The literature review signifies the urgent need to address climate change and CO2 emissions among G20 nations. Initiatives like the Paris Agreement might not help reduce carbon emissions sufficiently; hence, stronger policies are needed. The pandemic's temporary reduction in emissions underscores the potential impact of policy. A gap exists between national policies and NDC targets in Organisation for Economic Co-operation and Development (OECD) countries. Economic growth has also been linked to CO2 emissions, emphasizing the necessity of collective action. Effective solutions are crucial for meeting Intergovernmental Panel on Climate Change (IPCC) recommendations and combating climate change. There is an established connection between G20 countries' financial policies and climate change, specifically CO2 emissions. Research seeks to provide insightful information about the intricate dynamics of CO2 emissions and climate change [6]. Thus, introducing and implementing policies related to climate change and reducing carbon emissions is necessary. The Paris Agreement (COP21) set a goal of keeping the average world temperature rise to 1.5°C [7]. Most countries are attempting to achieve this target, but the influence of climate change on the economy of any country is significant. Studies show that while worldwide countries are trying to achieve the set goals of The Paris Agreement, enough is not being done to achieve the determined target. Hence, there is a need for international bodies to set standards to achieve the goal of zero carbon emissions [8]. Environmental degradation is one of the biggest concerns globally. The Intergovernmental Panel on Climate Change (IPCC) report stated an increase in average temperature by 1.5°C globally [9]. Thus, countries must align themselves with the NDC targets to minimize carbon emissions and achieve the goals of the Paris Agreement. Crafting strong and integrated policies, such as Zero Emission Vehicle (ZEV) incentives, heavy-duty vehicle emissions standards, and pricing mechanisms, is essential for achieving climate targets [10]. Many countries are emphasizing the increased use of electric vehicles to implement ZEV policies effectively. A study suggests the impact of the pandemic on emission projections for individual G20 members and the potential overachievement of Cancun Pledges by certain countries [11].

This may be due to low vehicle emissions resulting from lockdowns during the pandemic. It was found that OECD countries tend to implement policy packages that lead to more rapid progress in improving energy intensity and GHG intensity compared to emerging economies and developing countries [12]. OECD countries follow certain policies such as increasing renewable electricity, limiting coal-fired power plants, reducing oil and gas production, and implementing fuel efficiency standards for light-duty and heavy-duty vehicles. The Organisation for Economic Co-operation and Development (OECD) is an international organization where governments work together to find solutions to common challenges, develop global standards, share experiences, and identify best practices to promote better policies for better lives. There are possible reductions in greenhouse gas emissions that can be attained by fully implementing the objectives of a few chosen International Cooperative Initiatives (ICIs) [13]. The global non-state and subnational climate action (NSA) could contribute overall to achieving the climate goals outlined in the Paris Agreement. It focuses on GHG mitigation commitments made by cities, regions, and companies [14]. The research found a discrepancy between the NDCs and national policies effects and between the NDCs and far below 2°C emission paths effects [15]. There is a connection between metropolitan climate and human behavior. Because of increased AC usage, QF marginally increased [16]. Of the G20 nations, only India is making quick progress towards meeting the climate targets outlined in the Paris Agreement. Researchers call for collective action by nations to reduce CO2 and GHG emissions [17]. Research indicates that a possible 1% increase in the GDP of G20 members will lead to a 0.167% rise in CO2 levels. Moreover, if GDP remains constant, CO2 levels will rise by 0.244% [18]. According to IPCC's special report, global net CO2 emissions would need to drop by roughly 45% from 2010 levels by 2030 to reach net zero emissions by 2050, maintaining the temperature rise threshold at 1.5°C. If global warming is kept to 2°C, there will be a roughly 25% decrease by 2030 and net zero warming by 2070 [19]. A study outlined the potential and challenges of G20 countries for disaster risk reduction (DRR) through the newly established Working Group [20]. Another study focused on factors influencing household-level mitigation and adaptation actions in Nuevo Leon, Mexico. It found that environmental concern, perceived knowledge, and social capital influenced climate change action at the household level [21]. Most G20 countries produce significant greenhouse gas emissions, which are constantly increasing. Less than half of the G20 countries have adopted policies to address non-energy GHG emissions [22]. India is advancing rapidly towards achieving its climate goals mentioned under the Paris Agreement. The presidency of India can assist nations struggling to recover from the COVID-19 pandemic and be open to various opinions and ideas regarding pressing challenges [23]. Another report focuses on the decommissioning of coal-based capacities in India. Optimized decommissioning of these assets is expected to reduce electricity costs for consumers. The poor performance of coal-based assets has led to significant stress in the financial sector's power portfolio [24]. Table **??** provides the summary of the studies investigated.

Table 1: Summary of Previous Studies

Title	**Authors**	**Year**	**Outcomes**
A review of successful climate change mitigation policies in major emitting economies and the potential of global replication	Fekete, H., Kuramochi, T., Roelfsema, M., Elzen, M. D., Forsell, N., Höhne, N., Luna, L., Hans, F., Sterl, S., Olivier, J., Van Soest, H., Frank, S., & Gusti, M.	2021	This paper suggests the need for stronger policies and initiatives to be undertaken by the G20 countries. These policies will result in reduced levels of greenhouse gases.
Taking stock of national climate policies to evaluate the implementation of the Paris Agreement	Roelfsema, M., Van Soest, H. L., Harmsen, M., Van Vuuren, D. P., Bertram, C., Elzen, M. D., Höhne, N., Iacobuta, G., Krey, V., Kriegler, E., Luderer, G., Riahi, K., Ueckerdt, F., Després, J., Drouet, L., Emmerling, J., Frank, S., Fricko, O., Gidden, M., & Vishwanathan, S. S.	2020	The paper concludes that without additional action, the GHG emissions are likely to increase by 2030, and that there is a major gap between what the policies suggested and what the current emissions levels are.
Exploring the effects of climate-related financial policies on carbon emissions in G20 countries: a panel quantile regression approach	D'Orazio, P., & Dirks, M. W.	2021	This study provides insights into the complex dynamics of CO2 emissions and climate change, and suggests the importance of the relationship between CO2 emissions and climate-related financial policies.

Title	Authors	Year	Outcomes
A review of the global climate change impacts, adaptation, and sustainable mitigation measures	Raihan, A.	2023	The study concluded that climate change affects food security due to irregular food supply from various channels, leading to high prices, inflation, and compromised quality. Factors like human and environmental sustainability are also affected on a large scale.
Climate risk disclosures and global sustainability initiatives: A conceptual analysis and agenda for future research	Ngo, T., Le, T., Ullah, S., & Trinh, H. H.	2022	G7 nations are putting efforts to prepare common guidance to address differences among countries' frameworks. The highlights of the Task Force on Climate-Related Financial Disclosures (TCFD) require detailed climate-related information disclosed and sustainability reporting by firms.
Twenty years of climate policy: G20 coverage and gaps	Nascimento, L., Kuramochi, T., Iacobuta, G., Michel, D. E., Fekete, H., Weishaupt, M., Laura, V. S. H., Roelfsema, M., De Vivero-Serrano, G., Lui, S., Hans, F., De Villafranca Casas Maria, J., & Höhne, N.	2022	While many G20 nations promote renewable energy, many countries still subsidise fossil fuels instead of taxing them. Moreover, fewer G20 countries are actively implementing policies to phase out fossil fuels and biofuels. A recent study highlights that adopting more policies effectively reduces emissions, yet the inconsistent application of these policies remains a challenge.
Human behaviour change and its impact on urban climate: Restrictions with the G20 Osaka Summit and COVID-19 outbreak	Nakajima, K., Takane, Y., Kikegawa, Y., Furuta, Y., & Takamatsu, H.	2021	The relationship between human behaviour and urban climate is evident, with increased QF due to greater air conditioning usage. In Tokyo, weekday temperatures are 0.2–0.3°C higher compared to weekends and holidays, reflecting reduced human activity. Similarly, Osaka experiences a 1.0°C lower temperature on weekends compared to weekdays, with a general weekday-weekend temperature difference of 0.1–0.2°C. These findings underscore a positive and direct relationship between human activities and urban climatic conditions.
Analysis of Economic Growth on Carbon Dioxide Gas Emissions in G20 Countries	Ramadhan, H. K., Marselina, N., Nirmala, T., Aida, N., & Ratih, A.	2023	An increase in the GDP of G20 countries by 1% leads to a 0.167% rise in CO2 emissions, while a 1% increase in Gross Fixed Capital Formation (GFCF) results in a 0.244% rise, assuming ceteris paribus. CO2 emissions in developed countries are primarily driven by industrial activities linked to economic growth. G20 nations, responsible for 75% of global GHG emissions, play a crucial role in mitigating these emissions to combat climate change. The study concludes that economic growth in G20 countries significantly contributes to CO2 emissions, exacerbating climatic conditions.

Title	Authors	Year	Outcomes
Factors that Influence Climate Change Mitigation and Adaptation Action: A Household Study in the Nuevo Leon Region, Mexico	Hernández, L. G., Meijles, E., & Vanclay, F.	2019	The study concluded that perceptions and socio-demographic characteristics play crucial roles in climate resilience actions at the household level. It emphasised the importance of policies and campaigns to enhance climate change awareness and action within households. The study on household-level climate change actions in Nuevo Leon, Mexico, utilised online surveys and paper questionnaires from August 2016 to January 2017. Findings indicated that environmental concern, perceived knowledge, and social capital significantly influenced household mitigation and adaptation measures. Social capital, such as family and friend support, facilitated adaptation, while education and financial resources had varied impacts.

A study has found six G20 nations (China, India, Indonesia, Japan, Russia, and Turkey) are estimated to reach their set NDC Goal. In contrast, eight countries (Argentina, Australia, Canada, the European Union, the Republic of Korea, South Africa, and the United States) of the group are required to take corrective measures to meet the targets. The emission projections for Brazil and Mexico still need to be determined. The United Kingdom and France will likely miss their set targets [20].

Some studies did not address the relationship between CO2 emissions and climate-related financial policies within the G20 countries. It emphasises the importance of more thorough research into the effects of different initiatives and unclear climate consequences of COVID-19 stimulus measures. Many studies concentrate on particular areas and industries rather than taking deeper national and international actions, lack primary data collection, and give no attention to pollutants other than CO2. Thus, additional research is required to determine the effectiveness and cost-efficiency of policies and other factors influencing activities at the household level, particularly in developing countries. Another study focused on the lack of international collaboration in reducing emissions. Another limitation found was the lack of more focused international measures to slow down climate change.

3 Methods

A systematic literature review was employed, utilizing secondary data from various reports and websites. The sources directly address the climate change mitigation efforts by G20 countries. The articles, reports, and studies discuss policies, actions, and strategies implemented or proposed by G20 nations to mitigate climate change. The majority of the sources were from reputable academic journals, government agencies, international organisations (such as the United Nations, World Bank, or International Energy Agency), and peer-reviewed publications to ensure the reliability and accuracy of the information. Climate change is a rapidly evolving field, so recent sources were taken to capture the latest developments and initiatives undertaken by G20 countries. However, historical perspectives may also be valuable for understanding the evolution of climate policies over time. G20 countries span different regions and have varied socio-economic and environmental contexts. Sources that provide insights into the climate change mitigation efforts of both developed and developing G20 nations were referred to capture a broad spectrum of experiences and challenges.

4 Results

The Developed G20 Countries should contribute towards developing and underdeveloped countries in combating climate change. Countries can also collaborate with International Bodies such as the World Bank, UNFCCC etc. The World Bank stands forward to help Türkiye with an additional \$2 Billion in finance to work towards combating Climate Change. It should apply the same strategy to the other countries of the Global Climate Coalition (GCC). Exploring the efforts of governments to meet the goals set by the Paris Agreement entails examining the policies, regulations, and measures implemented by nations to combat climate change and lower emissions of greenhouse gases. The following goals are the key aspects of the Paris Agreement which the G20 countries should adhere to mitigate the ill effects of climate change:

- **Nationally Determined Contribution (NDCs):** Each country that is a party to the Paris Agreement is required to submit a Nationally Determined Contribution (NDC), outlining its climate actions and targets. These NDCs vary widely in ambition and scope, covering emissions reduction targets, adaptation measures, financial commitments, and contributions to international climate finance.

- **Policy Frameworks:** Governments develop and implement various policy frameworks to support their NDCs and achieve their climate goals. These may include renewable energy targets, carbon pricing mechanisms, regulations to improve energy efficiency, support for sustainable transportation, land-use policies, and measures to protect forests and biodiversity.
- **International Cooperation**: Many governments engage in international cooperation to enhance their climate efforts. This includes participating in initiatives such as the G7, G20, and regional climate partnerships to share best practices, mobilise financial resources, and coordinate actions.
- **Investment and Finance:** Governments mobilise public and private investment to support climate action. This includes funding for clean energy projects, research and development initiatives, climate-resilient infrastructure, and programs to support vulnerable communities affected by climate change.
- **Monitoring, Reporting, and Verification (MRV):** Governments establish systems for monitoring, reporting, and verifying their greenhouse gas emissions and progress towards their climate targets. Transparency and accountability are crucial for tracking the effectiveness of policies and ensuring compliance with international commitments.
- **Adaptation and Resilience**: In addition to mitigation efforts, governments also prioritise adaptation and resilience measures to address the impacts of climate change. This includes strengthening infrastructure, improving water management, enhancing disaster preparedness, and supporting vulnerable populations.
- **Public Awareness and Engagement:** Governments undertake efforts to raise public awareness about climate change and the importance of collective action. This includes education campaigns, public consultations, stakeholder engagement, and partnerships with civil society organisations, businesses, and academia.
- **Long-Term Strategies:** Many governments are developing long-term low-emission development strategies (LT-LEDS) to guide their transition to a sustainable, low-carbon economy. These strategies outline pathways to achieve net-zero emissions by mid-century or sooner, aligning with the long-term goals of the Paris Agreement.

Overall, understanding government initiatives towards the Paris Agreement targets requires analysing a complex interplay of policies, actions, and international cooperation efforts aimed at addressing the urgent challenge of climate change. People lack awareness about the prevailing policies and strategies such as Nationally Determined Contributions (NDC targets are set by countries to mitigate the impact of greenhouse gases), Climate Neutrality, and the risks involved in climate change on humans and the environment. The environmental concerns may be addressed through various Renewable Energy Initiatives such as the installation of Solar and Wind Panels, setting ambitious renewable targets, green energy corridors, Agriculture Solar pumps, etc. Green Products such as Vegan Leather totes, paper towels, Electric Vehicles (EVs), Solar Speakers, Eco-friendly dishwashers, etc. must be promoted. The G20 countries should strive towards achieving the 13th Sustainable Development Goal which aims to mitigate risks related to climate change. Human behaviour of every individual is more inclined towards their comfort rather than stressing the risks caused by an increase in the usage of fossil fuels and the negligence of nature's cycle effects. There is a need to educate humans to change their behaviour towards combating climate change.

4.1 Strengths

The governments of G20 countries are supporting the purchase of EVs. Among G20 countries, France has the best EV Policy and also the Russian government came forward to promote the purchase of EVs followed by Türkiye as it plans to launch its first domestically produced EV. Installation of Wind and Solar panels meets the renewable energy demands, and as of now, it is one of the best achievements of China which ensures their commitment to goals. The emissions of Australia are also expected to decrease to half by 2030 as a result of a 73% increase in the proportion of generation from renewable resources by 2030 which will be largely due to the installation of Solar and Wind Panels. The developed countries and international bodies i.e. The IMF, World Bank, and WTO must collaborate with developing countries and finance them to meet climate goals. The World Bank was prepared to increase its climate support to Türkiye by up to $2 billion. The United Nations flies on 100% sustainable fuel in the aviation sector. Some G20 countries are also producing carbon-free electricity. Therefore, each G20 country also sets a climate budget to meet the goals and combat climate change.

4.2 Weaknesses

Most G20 Countries rely on fossil fuels to meet their electricity demands. Türkiye relies on the production of electricity by investing in fossil fuels, China also relies on gas which has to be phased out, in Australia 114 fossil fuels projects are in the pipeline, India and Canada are also continuing to support fossil fuels to meet the electricity demands. There is no set of decarbonisation policies in many sectors. Cement, steel and chemical sectors are very tough to decarbonise due to the large proportion of carbon emissions. Most of the G20 countries are facing instability which minimises the allocation of budget towards climate change.

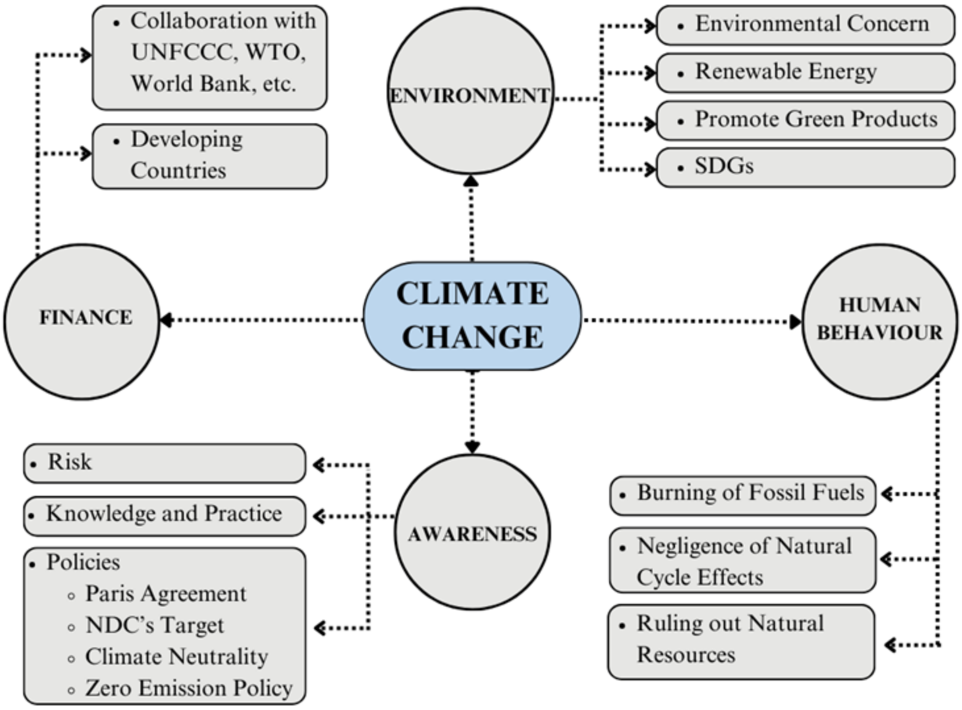

Figure 2: Conceptual Model to Combat Climate Change- Derived by Researchers

4.3 Opportunities

There are various policies and support programmes launched by governments to support the advancements from non-renewable energy to renewable energy. In India, there is support for Research and Development in carbon capture and utilisation, installation of green energy corridors, promotion of hydropower etc. G20 countries have set a Zero Emissions Policy which aims at zero emissions by a particular period. India has committed to achieving the Zero Emission target by 2070. The European Union and its 27 countries accepted the "Fit for 55 packages" to reduce and cut carbon footprints by 2030. The tie-up with the Private Sector can reduce carbon emissions by investing in Research and Development, managing sustainable supply chains, Green Finance and Investment etc.

4.4 Challenges

The high path of carbon emissions can lead to an increase in temperature above 1.5 Degrees C. It can trigger an increase in sea temperature and ocean acidification which can gradually reduce fish catching. The increase in temperature steered the increase in water demand due to longer droughts and its effect on agriculture. It can also adversely impact the health of people and tourism in the country. All these factors can impact the economic growth of the nation.

5 Discussion

The G20 countries, with the notable exception of Mexico, have set targets for achieving net-zero emissions, reflecting a strong commitment to mitigating climate change. The EU aims to cut greenhouse gases by at least 55% by 2030 and reach net zero by 2050. Turkey plans to increase its renewable energy share to 23.7% by 2035, and Russia is promoting electric vehicle production and use. Canada and Australia have enhanced their climate finance commitments, with Canada aiming to double its contribution and Australia on track to deliver $3 billion by 2025. Additionally, Turkey has made significant strides in renewable energy and waste management, exemplified by the Zero Waste initiative, which has led to substantial waste reduction and recycling efforts. These actions illustrate the diverse and multi-faceted approaches G20 nations are taking to address climate change and support global sustainability goals.

Comparing G20 policies in their effectiveness toward meeting international climate targets requires a nuanced analysis that considers various factors such as ambition, implementation mechanisms, and alignment with scientific recommendations. Evaluating G20 policies in terms of how well they achieve global climate targets requires a detailed analysis that takes into account a number of factors. First, it entails closely examining the emission reduction goals set forth in the G20 countries' Nationally Determined Contributions (NDCs) under the terms of the Paris Agreement, assessing the degree of ambition and timeliness with respect to the necessity of keeping global warming to 1.5°C or less. Second, it involves evaluating how well the G20 countries' policy tools—such as carbon pricing schemes, subsidies for renewable energy, and rules governing the use of fossil fuels—drive emissions reductions and the shift to a low-carbon economy. To determine their effect on emission reduction trajectories, it is also necessary to evaluate the distribution of resources between investments in fossil fuels and renewable energy technologies like solar, wind, and nuclear power.

Furthermore, it is critical to assess efforts to gradually phase out subsidies for the production and use of fossil fuels as well as to closely examine contributions to global climate finance and programs that support innovation and technology transfer. In addition, it is critical to manage climate-related risks by looking at infrastructure investments, disaster preparedness, and adaptation and resilience strategies. In conclusion, it is critical to evaluate how the G20 nations are leading the global climate movement, cooperating on diplomatic initiatives, and bolstering international climate action. Comparisons along these dimensions can provide light on the G20's advantages, disadvantages, and areas for improvement in terms of coordinated efforts to address the climate catastrophe.

Some studies did not address the relationship between CO2 emissions and climate-related financial policies within the G20 countries. It emphasises the importance of more thorough research into the effects of different initiatives and unclear climate consequences of COVID-19 stimulus measures. Many studies concentrate on particular areas and industries rather than taking deeper national and international actions, lack primary data collecting, and give no attention to pollutants other than CO2. Thus, additional research is required to determine the effectiveness and cost-efficiency of policies and other factors influencing activities at the household level, particularly in developing countries. Another study focused on the lack of international collaboration in reducing emissions. Another limitation found was the lack of more focused international measures to slow down climate change. The G20's linkage to climate change has not been discussed as part of any particular studies. Rather, a major source of information for most of this field's research has been an analysis of numerous reports. The Climate Change study can be enriched by focusing exclusively on the ASIAN Countries, BRICS, and the G7 Countries and also on the perception of the people related to Climate Change.

6 Recommendations

Every nation contributes significantly to carbon emissions, greatly impacting the biosphere as addressed in the weaknesses in the SWOC analysis. To mitigate this, governments must enact policies while supporting the adoption of Electric Vehicles (EVs), reducing reliance on fossil fuels in the transportation sector. While France has framed policies encouraging the use of electric vehicles, other GCC countries may follow this best practice. With over 50% of electricity generated from coal and thermal plants, countries should transition to renewable sources like solar, wind, and tidal power following the footsteps of China. A US airline pioneering the use of 100% biofuel in flights demonstrates a viable solution, reducing carbon emissions by 70%. Airlines across G20 countries are recommended to follow identical steps. Both countries and international organisations need comprehensive sector-specific policies, currently lacking in many nations. Enforcement of these policies is crucial, as governmental formulation often lacks effective execution. Developed nations should offer financial assistance to developing and underdeveloped nations, aiding their transition away from fossil fuels. Allocating a portion of national budgets towards climate finance, sustainability initiatives, and low-carbon strategies is essential. Increased investment in renewable energy sectors facilitates the shift away from non-renewable sources. Collaboration between nations is vital, enabling resource-sharing and collective efforts towards decarbonisation. The journey towards decarbonisation is influenced by a complex interplay of trends across technological, political, economic, social, and environmental realms. Each of these factors plays a crucial role in guiding the global community towards a future that emphasises sustainability and reduces carbon emissions. Technological advancements are leading the way by offering innovative solutions to decrease greenhouse gas emissions and improve energy efficiency. The shift away from fossil fuel industries in favour of renewable energy sources signifies a significant transformation in this regard. Political endeavours are increasingly focused on creating an enabling environment for decarbonisation through the implementation of stringent environmental regulations and policies that support green initiatives. Social trends reflect a growing awareness and demand for environmental sustainability, with consumers increasingly gravitating towards eco-friendly products. Environmental initiatives concentrate on mitigating the effects of climate change and safeguarding natural ecosystems. Like India, other G20 countries should encourage Research and Development in carbon capture and utilisation, installation of green energy corridors, promotion of hydropower, etc.

The loss of habitat, species extinctions, range shifts, and mismatches in interactions between the flora and fauna are some of the ways through which climate change disturbs ecosystems. Furthermore, ocean acidification is harmful to marine life in most countries, and forest fires significantly impact habitats, with low genetic variety forcing some species to become easy targets for extinction. In essence, such effects threaten essential ecosystem services and biodiversity, thereby highlighting the need for special intervention as far as global warming is concerned. The efforts to mitigate climate change can boost the overall economy of the countries as well. The installation of wind and solar renewable resources and the production of EVs can create millions of jobs. The technological advancement in renewables will not only reduce the cost but also boost economic growth. Also, with the developing sector, many individuals would earn through investment in the stock markets of the related companies.

7 Conclusion

The research analyzed the performance of G20 countries in combating climate change. It has been observed that the climate finance of the G20 countries is not sufficient to satisfy the demand and is insufficient. Every nation has plans and policies to reduce greenhouse gas emissions and eliminate the use of fossil fuels, but there is no proper execution of policies. The countries should implement policies aligning with the NDC's target to curb the emission of greenhouse gases and reach the goal of The Paris Agreement.

The study aimed to address the issue of climate change with the recent changes across the world. The world has also faced 2023 as the warmest year in the past 174 years. Climate changes across the globe have caused water scarcity, increased heat stroke cases, ocean acidification, forest fires, etc. Therefore, it is the need of the hour to attend to such issues to lead to a sustainable future.

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Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability

The data that support the findings of this study are available from publicly accessible sources, including reports and databases from reputable academic journals, government agencies, and international organizations. Specific datasets can be provided by the corresponding author upon reasonable request.

Ethical Considerations

The research project prioritised ethical considerations at every stage to ensure ethical integrity and soundness of the study. Ethical approval was obtained from the authorities of CHRIST (Deemed to be University), ensuring that all the activities comply with ethical guidelines and standards.

Author Contributions

Sonal Devesh: Conceptualization, Supervision, Writing - Review & Editing; **Anchal Sharma**: Data Collection, Analysis, Writing - Original Draft; **Arjun Maheshwari**: Data Collection, Visualization, Writing - Original Draft.

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AI-Driven Decision Support System Innovations to Empower Higher Education Administration

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Abstract

This quantitative study aims to investigate the use, opinions, and impacts of Decision Support Systems (DSS) on the administration of higher education. Its focus is on DSS. Using a cross-sectional approach, we polled a diverse group of higher education administrators from a range of institutions. The findings indicate that DSS have become an essential tool for higher education administrators, who have confirmed their substantial utilization of the tools. Their effectiveness and ease of use have garnered rave reviews, attesting to their value in promoting data-driven decision-making. The study also highlights the ways in which DSS impacts strategic planning, enrollment management, resource allocation, and student success efforts within the administration of higher education. The results demonstrate that DSS is associated with favorable outcomes and increased efficiency, and they also reveal that its use is correlated with perceived good consequences. Persistent obstacles, such as data quality, privacy concerns, and reluctance to change, necessitate the need to address data management approaches, ethical issues, and change management tactics. These results add to the ongoing academic discussion on DSS's revolutionary potential while also helping businesses with their decision-making, resource allocation, and data-driven excellence initiatives. The unique contribution and innovative aspect of AI integration in decision support systems (DSS) for higher education administration lie in its ability to revolutionize decision-making processes.

Keywords: Decision Support Systems, Higher Education Administration, Data-Driven Decision-Making, Institutional Efficiency, Ethical Considerations

1 Introduction

Higher education institutions are rapidly integrating AI-enhanced conversational chat services to better assist their students and reduce their dependence on personal human assistance. These advanced conversational agents, surpassing traditional FAQ sections and non-contextual chatbots, personalize responses to students' questions based on the current conversational context. Artificial intelligence (AI) is increasingly employed in higher education for automating administrative duties, aiding in curriculum development, and promoting student-centered learning. AI is conceptualized as a computer agent that processes environmental information to achieve specific goals and adapts by learning from experiences. Although still in early stages, the application of AI in education promises new personalized learning opportunities and services. Despite challenges related to student diversity and informational support, AI-enhanced personalization is seen as a value-creating mechanism. It is important to note that AI has not yet achieved human-like abilities such as empathy or intuitive psychology.

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Educational institutions are increasingly adopting AI-driven personalization technologies. Adaptive learning and personalized learning, often used interchangeably in academic discourse, describe approaches that leverage technology to tailor educational experiences. Research has largely focused on outdated technology, with limited exploration into the capabilities of modern, smart devices in educational settings. The potential for AI to facilitate continuous learning through partnerships between universities and businesses is underexplored, as is its ability to enhance higher-order thinking and communication. Furthermore, effective data collection methods remain a significant hurdle in realizing the full potential of personalized learning technologies. AI-enhanced personalization and adaptation can benefit students, educators, and administrators by tailoring services to individual profiles, interests, and informational needs. Sophisticated systems can also adapt interactions based on users' emotional states or contextual settings, thus addressing their specific knowledge requirements. This opens new avenues for research into automating student services in higher education, where there is a noted gap concerning the application of AI to personalized learning. The existing literature provides a foundational understanding but lacks in-depth studies on the design and development of such systems. This study aims to address these gaps, exploring how AI-based personalization within integrated service chats can revolutionize educational systems. Administrators in higher education must make informed decisions to keep their institutions viable amidst today's complex and dynamic landscape. Challenges in enrollment management, resource allocation, curriculum development, and student support services require sophisticated tools for effective navigation. AI-enhanced Decision Support Systems (DSS) provide crucial data-driven insights and predictive analytics to aid in these decision-making processes.

Technological advancements and the shift towards data-driven decision-making have introduced a new paradigm in higher education [1]. Traditionally, decisions were often based on hearsay, precedent, and institutional knowledge, which, despite their merits, may not meet the complex needs of contemporary educational administration. AI-enhanced DSS offers a novel perspective, enabling administrators to make better, more evidence-based decisions.. The role of DSS in higher education has evolved significantly, assisting administrators in managing resources and making informed decisions that can enhance institutional efficiency and student outcomes [2]. This comprehensive study explores the origins, key features, applications, challenges, and transformative impacts of DSS on administrative processes within higher education. The concept of DSS, which originated in the 1960s and 1970s for military and business applications, has expanded into various sectors, including higher education. Initially, DSS in universities primarily consisted of reporting systems and basic data analytics tools. These systems have evolved significantly in capability and sophistication, now incorporating technologies such as artificial intelligence (AI), machine learning (ML), predictive analytics (PA), and data visualization (DV). Today's DSS equip administrators with powerful tools for data-driven decision-making, essential for addressing the unique challenges faced by educational institutions in a competitive landscape. Higher education DSS feature interconnected components that collectively support sound decision-making. These components include data collection, storage, analysis, and decision modeling. Data is the foundation of every DSS, with colleges and universities collecting extensive information on student attendance, grades, financial situations, and other academic aspects. While manual input remains an option, automated systems now play a crucial role in gathering data across various departments and processes, facilitating comprehensive and strategic administrative planning.

For a Decision Support System (DSS) to function optimally, a reliable data storage system is imperative. This might involve using traditional relational databases or advanced data warehousing solutions aimed at simplifying data access and analysis. Data analysis, the core of DSS, utilizes top-tier analytical tools and techniques to process, transform, and scrutinize data, potentially generating dashboards, reports, trends, and forecasts. Decision modeling within these systems employs mathematical or computational models to help administrators evaluate potential outcomes of various scenarios. Simulations enable decision-makers to explore the advantages and disadvantages of different actions, leading to more informed decisions. Higher education institutions deploy DSS to predict enrollment patterns, enhance admissions processes, and develop strategic recruitment programs, aiming to meet enrollment objectives. Furthermore, DSS analyzes data concerning budgets, faculty workloads, and facility usage to optimize resource allocation. By utilizing predictive analytics, these systems identify at-risk students, facilitating early interventions and personalized support that boost success and retention rates. DSS also supports curriculum planning by analyzing data on course demand, student preferences, and program outcomes, thus enabling institutions to adjust their offerings to better meet both student needs and market demands. Moreover, DSS aids in operational management, strategic planning, and financial tracking, enhancing overall institutional efficiency. Monitoring Key Performance Indicators (KPIs) and benchmarking against peer institutions, DSS provides insights into overall performance, aiding continuous improvement efforts. DSS also supports compliance and accreditation efforts by ensuring adherence to regulations and standards. However, data quality remains a challenge due to the heterogeneity of storage methods and the difficulty of ensuring consistency and compatibility across diverse data sources. The integration of AI and machine learning (ML) has significantly enhanced the capabilities of DSS, enabling the analysis of large datasets and complex algorithms to uncover trends, patterns, and insights that would be challenging for humans to detect manually. This comprehensive real-time overview of institutional operations is invaluable for administrators[3]. AI-powered DSS excels in generating predictive analytics, analyzing historical data to forecast future trends and events. This capability allows university officials to proactively address challenges such as fluctuating enrollment, retention issues, and budget constraints. By leveraging accurate predictions, administrators can take focused actions to mitigate risks and capitalize on opportunities, thus enhancing the effectiveness and efficiency of their organizations.

Moreover, AI-driven DSS provides personalized advice tailored to different administrative roles within the institution. For instance, specific recommendations can be made to the registrar on course scheduling, while financial strategies might be advised to the CFO, ensuring that decisions are relevant, actionable, and aligned with institutional goals. The implementation of AI-enhanced DSS fosters a data-driven culture within educational institutions. When management consistently relies on data-driven insights, an organizational commitment to evidence-supported decision-making develops. This shift results in greater transparency, accountability, and interdepartmental collaboration, all driven by a collective focus on utilizing data for institutional benefit.

However, while AI-enhanced DSS hold significant promise for the management of higher education institutions, it is crucial to recognize their limitations. A major challenge is the integration of high-quality data. Institutions often possess multiple data sets, and ensuring their accuracy, consistency, and compatibility poses substantial challenges. Additionally, privacy and ethical considerations are paramount when managing data concerning students and instructors. Navigating complex data protection laws and implementing stringent security measures are essential to safeguard the data utilized by AI systems. Resistance to change among faculty and staff can also impede the adoption of AI-enhanced DSS. Without understanding the benefits or fearing potential implications, stakeholders may be reluctant to embrace new technologies. To overcome this, institutions should invest in training and communication campaigns that promote the advantages of AI, emphasizing how it supplements rather than replaces existing roles. The unique contribution of AI integration in DSS lies in its potential to revolutionize decision-making processes within higher education administration. By leveraging AI capabilities such as predictive analytics and personalized recommendations, DSS provides administrators with insights previously out of reach. This enables institutions to optimize resource allocation, improve student outcomes, and adapt more effectively to the complexities of the educational landscape. Moreover, AI integration offers opportunities for proactive interventions and strategic planning, fostering a culture of evidence-based decision-making across higher education institutions.

2 Problem Statement

Educational institutions are facing myriad complex challenges that necessitate innovative solutions to ensure relevance and success in the coming years [4]. These challenges, encompassing enrollment management, resource allocation, curriculum development, student retention, and overall institutional efficacy, impact the strategic functioning of universities. The traditional decision-making processes at universities, often based on institutional expertise and subjective evaluations, are inadequate for addressing these multifaceted issues. A shift towards a more fact-based, data-driven decision-making approach is critically needed. Despite the transformative potential of AI-enhanced Decision Support Systems (DSS), significant barriers must be overcome for these systems to fully realize their potential [5]. A major challenge in higher education is the integration and standardization of data from various sources to draw meaningful conclusions. Ensuring the accuracy, consistency, and compatibility of diverse data sets is complex and labor-intensive. Additionally, privacy and ethical considerations are paramount when handling sensitive information about students and faculty. Administrators must navigate a labyrinth of data protection regulations and implement robust security measures to protect data utilized by AI systems.

Resistance to the deployment of AI-enhanced DSS may also stem from concerns among teachers and administrators about job security and the erosion of traditional practices [6]. To counteract these fears and promote a culture of data-driven decision-making, institutions must invest in training and communication strategies that highlight the benefits and opportunities offered by AI technology. Academic leaders in higher education might find some solutions to their complex problems through the use of DSS augmented with AI. However, concerns regarding data management, privacy, and stakeholder engagement present significant challenges to their effective implementation. The integration of AI into decision support systems presents both new opportunities and challenges in higher education. Administrators increasingly rely on AI-powered DSS to address issues in educational administration, student engagement, and institutional development. These systems' ability to derive insights from vast data sets suggests that more informed decision-making is achievable. Nevertheless, the implementation of such systems faces obstacles, including the high costs of necessary software and hardware, the need for specialized skills to interpret AI-generated data, and ensuring ethical application of AI to prevent biased or discriminatory outcomes [7, 8].

Moreover, the rapid development of new technologies poses a challenge for established institutions to keep pace with existing policies and procedures [9, 10]. Decision-makers also are deemed to have a complex difficulty when trying to understand data given by AI systems [11, 12].Ensuring that AI systems are applied in an unbiased and ethical manner remains a critical concern, essential for maintaining the trust and confidence of stakeholders such as students and faculty. Despite the challenges associated with their implementation, AI-enhanced decision-support systems could significantly enhance higher education by providing administrators with robust tools for analyzing trends, predicting outcomes, and making informed, data-driven decisions. For example, AI can assist educators by tailoring lessons to meet the specific needs of students, identifying patterns in student performance that indicate where adjustments are needed. Authors[13, 14] highlight AI's potential in optimizing resource allocation, enabling institutions to use their funds more efficiently and effectively. However, while AI-driven decision-support systems hold great promise for educational institutions, they also introduce risks that must be carefully managed [15]. Institutions must ensure they have the necessary resources to keep pace with rapid technological advances, employ AI ethically and without bias, and remain vigilant for any emerging biases. [16, 17] discuss how, by leveraging AI to enhance decision-making and educational outcomes, college administrators can support students and communities in overcoming these challenges. This underscores the potential of AI to transform educational environments, albeit with a need for cautious and responsible implementation.

3 Research Aim and Objectives

This study addresses the critical need for enhanced, data-driven decision-making processes in higher education administration by evaluating Decision Support Systems (DSS) supplemented with artificial intelligence. It aims to assist school administrators in making better judgments amidst the rapidly evolving educational landscape. Additionally, the research seeks to establish a norm of evidence-based decision-making, which promotes transparency, accountability, and efficiency within educational institutions. By potentially guiding efforts to mitigate barriers to the implementation of AI-enhanced DSS, this study could facilitate the integration of advanced technological tools into classroom instruction, thereby transforming higher education administration and benefiting institutions, instructors, and students alike. The objectives are to assess the impact of AI integration levels in decision support systems on decision-making effectiveness, evaluate the role of administrators' training and expertise in the effective use of these systems, investigate how data quality and availability influence the decision-making process, and examine the effects of ethical considerations and bias mitigation on decision-making effectiveness in higher education. Corresponding research questions explore the effects of AI integration on decision-making effectiveness, the role of administrators' expertise, the impact of data quality on decision processes, and the influence of ethical considerations and bias mitigation in AI systems. The hypotheses associated with this study are:

- Higher levels of AI integration in decision support systems are positively associated with the effectiveness of decision-making in higher education (H1).
- Administrators with greater training and expertise in AI-enhanced decision support systems are more likely to make effective decisions (H2).
- The quality and availability of data in AI systems significantly influence the effectiveness of decision-making in higher education institutions (H3).
- The incorporation of ethical considerations and bias mitigation in AI systems positively impacts the effectiveness of decision-making in higher education (H4).

4 Methods

The approach of this study employs a quantitative research technique to provide an empirical and systematic analysis of the efficacy of Decision Support Systems (DSS) in the administration of higher education. Using a cross-sectional survey design, this research captures data at a specific point in time to understand the current state of DSS utilization and its impact on higher education administration [18]. Data will be gathered through a standardized survey questionnaire that includes both free-form and prompted questions with responses via multiple-choice options, Likert scales, and demographics. This methodology is outlined in Figure 1 below.

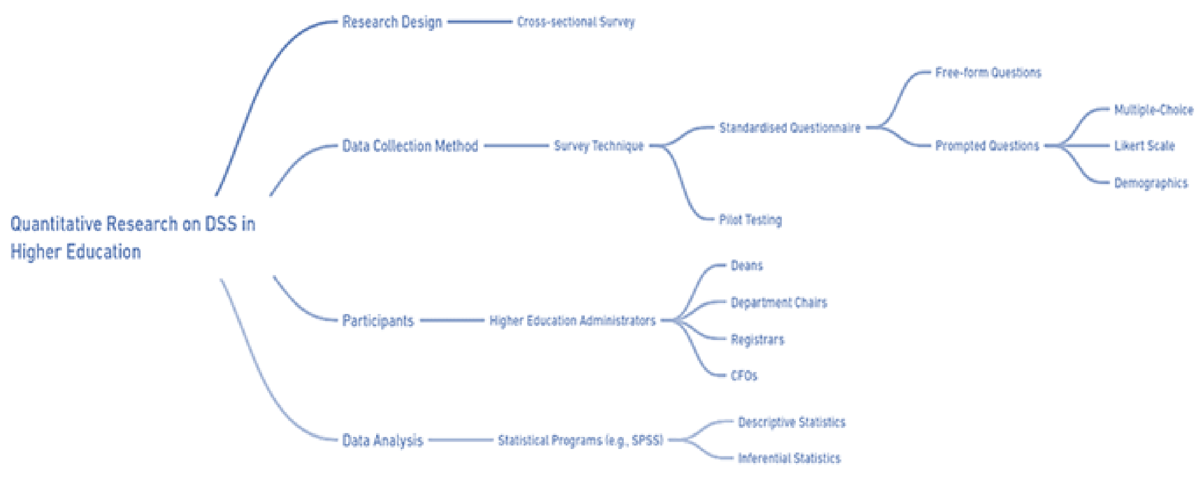

Figure 1: Methodology Flowchart. Source: Developed by the Researcher

The survey aims to collect comprehensive data from administrators regarding their viewpoints, experiences, and the extent to which DSS have influenced their managerial choices and approaches. Prior to the main data collection phase, the survey will be pilot tested with a subset of higher education administrators who are not participating in the main study. Their feedback will be used to refine and enhance the questionnaire. Participant selection targets top-level administrators from diverse educational institutions, including deans, department chairs, registrars, and CFOs, ensuring a comprehensive representation of various roles within higher education administration. Statistical analysis methods employed in this study include descriptive statistics, such as means, standard deviations, percentages, and frequencies to summarize the demographic characteristics of the sample and the main variables of interest.

Inferential statistics, such as correlation analysis, regression analysis, analysis of variance (ANOVA), and t-tests, will be used to test hypotheses and draw conclusions about the relationships between variables, uncovering patterns, associations, and differences in the survey data to make informed interpretations and meaningful conclusions regarding the effectiveness and impact of AI-enhanced DSS in higher education administration.

5 Expected Impact

The results of this study are poised to illuminate the multifaceted impacts of Decision Support Systems (DSS) on the administration of educational institutions, drawing on a diverse pool of participants from around the globe including college and university administrators, faculty, and staff [19]. This research aims to evaluate perceptions regarding the utility of DSS, the challenges associated with their adoption, and how these factors influence decision-making and the outcomes achieved by organizations. The findings are expected to provide actionable insights applicable to real-world administrative scenarios within higher education. Understanding the influence of AI-enhanced DSS on decision-making processes will enable administrators to make informed decisions that boost efficiency and effectiveness across various operational domains. For instance, administrators could use these insights to optimize resource allocation within their institutions. By identifying trends and patterns in data concerning enrollment, budgeting, and faculty workload, strategic decisions can be made to allocate resources more efficiently. Furthermore, the results could inform the development and implementation of student support services. Understanding the impact of DSS on student success programs allows administrators to tailor interventions to better meet student needs, which could include personalized academic advising based on predictive analytics, targeted interventions for at-risk students, or improved curriculum planning aligned with student preferences and outcomes data. Additionally, insights from this study could guide institutional strategic planning efforts. Leveraging AI-enhanced DSS to analyze data on enrollment trends, student outcomes, and market demands can help administrators develop more effective long-term strategies, ensuring that the institution remains competitive and responsive to evolving educational needs. Overall, the application of the study's results in real-world administrative contexts is anticipated to foster more data-driven decision-making processes, enhance student outcomes, and boost institutional effectiveness in higher education settings.

6 Conclusion

This research represents a pioneering endeavor to evaluate the impact of AI-integrated Decision Support Systems (DSS) on higher education administration. By comprehensively assessing the effectiveness and challenges of these systems, the study aims to uncover novel insights that can drive advancements in administrative practices. Combining quantitative survey data with qualitative interviews, the approach promises a holistic understanding of how AI-enhanced DSS can revolutionize decision-making processes in educational institutions. Expected advancements include more efficient resource allocation, personalized student support services, and strategic planning informed by data-driven insights, leading to enhanced institutional effectiveness and student success.

The findings underscore the growing importance of DSS in higher education administration, with a significant number of respondents indicating regular use of these technologies in their daily operations. The broad implementation of DSS across various administrative sectors is largely attributed to its potential benefits, such as improved data-driven decision-making, more efficient resource utilization, and proactive interventions aimed at enhancing student performance.

Quantitative analysis from the survey indicates a favorable reception towards DSS among administrators, who praise its usability, impact on decision-making, and simplicity. This reception aligns with the increasing recognition within educational institutions of the importance of data-driven decision-making, particularly in navigating complex situations and optimizing operations.

However, the study also highlights several challenges that inhibit the wider acceptance and implementation of DSS. Persistent issues with data integration and quality have emphasized the need for improved data management practices in the academic sector. Additionally, concerns regarding data privacy and algorithmic bias underscore the critical need for ethically competent machine learning and artificial intelligence in the development of DSS. Resistance to change remains a common barrier to the adoption of new technologies, highlighting the importance of effective change management strategies to facilitate the transition and ensure the successful implementation of DSS in higher education.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Author Contribution

Jiangang Zhang: Conceptualization, Methodology, Investigation, Visualization, Writing - original draft, review and editing. **S.B.Goyal**: Investigation, Visualization, Writing -review and editing, Resources.

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