Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Generative AI in Technical Support Systems: Enhancing Problem Resolution Efficiency Through AIDriven Learning and Adaptation Models

Sathya Kannan[1], Kanthety Sundeep Saradhi[2]

[1]*AI Engineer, sathyakannan.vsl@gmail.com*
[2]*Assistant Professor, BVRIT Hyderabad College of Women, sundeepsaradhi.k@bvrithyderabad.edu.in*

This work explores how technologically supported technical support systems can be enhanced through the integration of generative AI models. These models can learn and adapt according to the various equilibrations in the resolution of a technical issue. To present the scope of the essay, recent advances in existing commercial AI drivers for user dialogues and IT processes working in sync are overviewed.

This work aims to propose a learning and adaptation technical support AI model that could enhance the efficiency in the overall resolution of problems. The research utilizes two different approaches. First, the state of the art of existing AI-driven technical support systems is analyzed. Second, we propose a possible methodology used in the development of an AI learning and recommendation proposal in a technical support system. Finally, the potential impact of generative AI on user experience and IT operational efficiency will be discussed. The most efficient AI-driven conversational agents leverage large amounts of implicitly and/or explicitly labeled dialogues and IT processes acting in symbiosis to optimize a specific outcome. However, every system that works with a fixed dialogue model, where every tracer is thought to generate a limited predefined number of moves, can lead to a plateau in operation. We need a system that continuously adapts and learns from best practices. This knowledge will be used in the generation of a more adequate answer through the interface.

Keywords: Generative AI, Technical Support Systems, AI-Driven Models, User Dialogue Optimization, IT Processes, Problem Resolution, AI Learning Models, Adaptation Mechanisms, Conversational Agents, Operational Efficiency, User Experience, AI Recommendations, Implicitly Labeled Data, Explicitly Labeled Data, Symbiotic Systems, Methodology Development, AI Optimization, Fixed Dialogue Models, Adaptive Systems, Best Practices.

1. Introduction

Support systems have become more and more complex, thus requiring more time and effort to resolve the customer problems they are targeted for. As a result, delivering a support automation system that assists in creating an accurate and adequate response through AI technology is a hot topic today. In this regard, problem resolution efficiency relying on a given context can directly benefit customer satisfaction. Also, the support systems in industries and companies such as banking, telecoms, or IT service providers are required to deliver high-quality services, including fast and efficient customer support, which should be both convenient for the customer and not add significant running costs for service providers. Consequently, companies provide one or more ways to connect with a helpdesk for customers to report a problem and get useful advice or solutions to solve it. Moreover, in the current situation where self-service solutions are increasing at a fast pace, some industries provide online solutions like a FAQ page, active forums, spaces for questions and answers about new products, or a virtual assistant based on conversational AI. These technical support systems rely on AI and aim to improve the quality of FAQ pages. However, in the introduction, we lastly evaluate the advantages and disadvantages pointing to the future trends of research to conclude. From the remainder of this introduction, we discuss the nature of customer support systems provided to understand their diverse reasons against this evolution.

Fig 1 : Generative AI for Technical Support

1.1. Background and Significance

Technical support systems have progressed from traditional call centers and help desks to be web-enabled, and more recently to those capable of a range of new functions such as network management, customer relationship management, e-commerce, and CRM. Also, the volume of requests continues to be high, and the expectations of today's consumers and business customers are increasing. In a business environment increasingly reliant upon technological innovation and integrated information systems, technical support is being placed center stage to keep business-critical systems running and to care for the customer who consistently wants faster and better resolutions to their support demands. For a multitude of reasons, AI, or intelligent support systems, are becoming part of the infrastructures of support operations. Enhancements in automating problem resolution facilities and migrating to self-service on a desired basis are seen as an essential array of offerings for commercial support organizations to help control their costs, increase their service portfolios, and maintain their edge in the market. Furthermore, by moving to AI, providers of support hope to eliminate the repetitiveness and error introduced into systems by time-pressured human operators when turning to new support paradigms. The potential is identified in their more flexible and intelligent applicative nature. Initially, research was aimed at developing expert systems, then knowledge-based AI, adaptive-intelligent support systems, and more recently generative AI. Most contemporary research in support systems has focused on the development of generative

AI. These systems can port end-users away from unfulfilling, finite decision tree logic systems or non-introducible text-based analytic solutions. Such systems help introduce the new paradigm of personalized support.

Equation 1 : Problem Resolution Efficiency Model Using AI:

P_{res} is the problem resolution efficiency.

D represents the diagnostic data from the system.

K is the knowledge base (e.g., historical solutions, FAQs).

L is user feedback and interaction data.

T stands for technical interventions, including AI algorithms.

$$P_{res} = f(D, K, L, T)$$

1.2. Research Objectives

The primary focus of this research is to examine the role of generative AI in improving the efficiency of problem resolution in the field of technical support systems. The main objective of this research is to identify the key benefits of using an AI model in the system of technical support and then check the usability of AI-driven support to solve problems. The key aim of this theoretical research is to elaborate on and propose a conceptual framework for investigating the potential integrated approach for technical support systems, as well as formulating the executive summary of required domain knowledge, research methodology, empirical study, and assessments from the resultant knowledge. Objectives of this Research: 1. To identify the key benefits of utilizing AI-driven models, including machine and deep learning models, as a part of a technical support system or service. Analysis of the potential outcome measures used will also be carried out. 2. Examination of these performance metrics and a thorough review of generative AI approval models in leading systems or online technical support to form the supportive background for the use cases and facilitate our study. 3. Propose our conceptual approach based on the analysis of related work wherein a learner-learning framework uses three views in one adaptive model for embedding specifically a learner's knowledge for conceptual feedback and adaptability. A well-defined procedure to evaluate mostly related technical guidance and support systems necessarily needs to accommodate diverse users' needs.

2. Fundamentals of Generative AI

Generative AI is an emerging field of study within AI research that focuses on data generation. In particular, generative AIs can be used to create content that is of human-level quality, such as text, images, music, and speech segments. Generative AI differs from traditional machine learning paradigms, especially discriminative models, in the sense that instead of learning a boundary that separates classes in the data manifold, the AI tries to map from a latent space to the data space to generate new data from randomness. The state-of-the-art generative AI systems are based on neural networks that can approximate complicated distributions via data generation.

All current deep learning models can be considered as a three-step process: data input, data processing, and data output. Concerning deep learning, image recognition of faces and texts belongs to the domain of neural networks. Data generation techniques are used to create new training data. Adversarial models, VAEs, and GANs are sophisticated neural generative models for creating real-looking data through latent space manipulation. Deep learning models can be used to approximate functions via massive training data and adjustable parameters to tune behaviors. Neural networks can process input data for image, text, and audio processing and generate a value at the output layer. Generative AI learning techniques can generate new data that has not been seen before by the model.

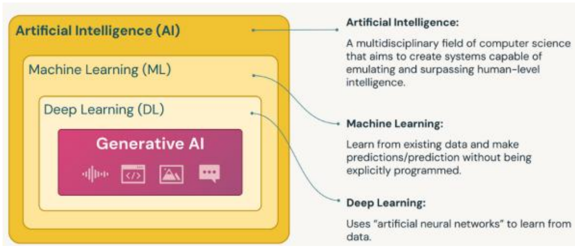

Fig 2 : Generative AI Fundamental

Current deep learning models, such as convolutional networks and recurrent networks, can be combined with basic generative models to build generative models that understand content, process data with natural language processing, or generate new data. Generative AI technology has been advancing with deep neural networks and has started to show capabilities that are close to human creativity for developing new information for text, voice, and images. Generative AI has been widely adopted in various domains that have multidimensional data for content generation. AI researchers and deep learning specialists develop generative models that can understand services and employers.

2.1. Definition and Overview

Generative AI is an area of artificial intelligence that is used to develop new, synthetic data. This data can take many different forms, such as programming code, natural language text, and image data. At a high level, generative AI seeks to simulate life to provide support in creative tasks or assist in human activities that are based on complex situational interactions with the real world. As such, generative AI is often classified under weak AI or narrow AI, which is domain-specific and typically exemplified in the use of a restricted problem-solving area. Beyond tools, for instance, in the potential applications in professional training videos, books, animations, and even acting, generative AI may also be used in more sophisticated systems such as intelligent help systems, and even to generate synthetic data to augment small sample sizes in deep learning algorithms. A key feature of generative AI is its unsupervised operations, requiring only a large dataset and a powerful GPU or TPU to run a model using either a complex learning or optimization algorithm. Generative AI models leverage a large amount of data to generate new samples. This is a significant difference from other learning algorithms that require large volumes of user-generated and evaluated feedback data. In sum, generative AI breaks barriers with the advancement of knowledge about creating agents that can inspect data, learn new concepts of the real world, and then generate new data. This is akin to intuition, a form of human understanding that is difficult to put into words, making generative AI very exciting in its current applications. Generative AI models are often tasked with solving some type of modeling problem that might include predicting possible outcomes of future events, generating new problem scenarios, or creating new synthetic content. This technique aims to leverage the power of AI to automate certain tasks or enhance others. It has significant potential to enhance the capability of systems to learn more complex situations using an adaptable or reactive generative AI model.

2.2. Key Concepts and Techniques

Generative AI refers to a broad pool of techniques applied to AI models to enable creative processes and to allow AI to craft new data using existing information. Generative methods leverage both supervised and unsupervised learning to teach an AI system to understand patterns in sets of data and to apply existing knowledge to the learning and creation of new content. Generative algorithms have already found use in natural language processing, facilitating tasks such as language translation, chatbot sentiment ratings, and question-answering mechanisms. More recently, synthesis systems have grown more sophisticated and have been employed to artificially generate digital images and videos, in some cases sufficiently convincingly to be indistinguishable by the human eye from original content. Generative techniques have also provided much-debated applications, including synthesized depictions of human beings and non-human primates.

A subfield of generative AI focuses squarely on the generation of content, building on existing data. Computational models based on statistical learning are capable of capturing very high-dimensional structures in complex data points, particularly when implemented with techniques such as neural network structures. These are the frameworks that enable a multitude of generative functionalities and themselves are a focus of much excitement, caution, and debate. When these algorithms are applied to natural language, they are termed generative language models, settings in which they may learn to auto-complete text, mimic and construct after the writing style of existing texts when drafting new material, and in controlled settings to synthesize program source code. Reaching generative potential in support systems is desirable, as captured knowledge generated by models is useful for attracting new support staff to the IT workforce and can be sufficiently generic to be transferred among large sets of providers at a time.

3. Technical Support Systems in Industry

Technical support systems play a pivotal role across different industries to ensure rapid problem resolution and maintain high customer satisfaction throughout the lifespan of the product. Modern technical support systems are equipped with well-designed structures and dedicated personnel, including human agents and system administrators, responsible for communication and automated resolution. The flexible interplay between human agents and useful automated systems ensures the seamless operation of knowledge management and knowledge discovery phases. It not only fosters the enhancement of the organizational knowledge base but also establishes Automated Multi-Resolution, which can upscale customer support.

Technical support is provided using standalone customized platforms, widely available CRM platforms, web-based platforms, social media, or recently growing rich collaboration tools. Both human agents and customers have the flexibility to cope with existing and emerging media-level innovations while solving and reporting problems. Traditionally, human agents are responsible for documenting resolutions and sharing information with system administrators, QA teams, and other stakeholders. Today, helpful automated systems enable easy and flexible knowledge documentation and sharing, which is instrumental in increasing value in the competitive market. However, a majority of standalone and widely used systems offer mostly rule-based syntax, and vocabulary-prescribed resolutions, and do not support changing customer segments or non-native speakers, thereby resulting in inaccurate, irrelevant, and unhelpful recommendations and resolution generation that misleads well-intentioned systems. As a remedy, human and automated authority systems were introduced to deal with simple problem descriptions, comprehension, and resolution generation in a community-approved and friendly manner. Given the widespread limitations, support system owners encounter the aforementioned challenges, including high operational and maintenance costs, inconsistency in service quality, and unresolved problem resolution with delayed response times. In conclusion, the lack of user-friendliness, outdated support services, information duplication, and erroneous resolutions require innovation applicable to one or more phases for increased performance. Generative AI and transforming learning systems are a viable solution, especially for self-service and chat support during well-designed learning phases from scratch, adaptation phase, and transition. The narrative-based problem description has four advantages, including training data preparation benefits, adaptive and accurate intent detection, and learning of contextualized segment-specific knowledge generation.

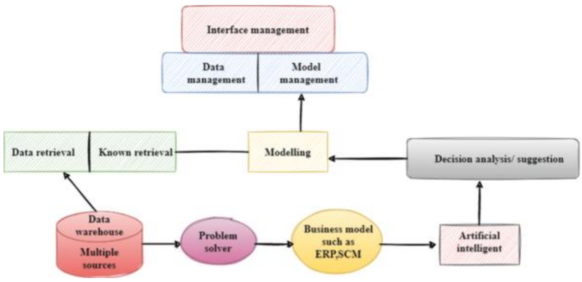

Fig 3 : Support Systems Framework with Artificial Intelligence

3.1. Overview of Technical Support Systems

Technical support systems range from small cohesive groups focused on a single product or service line to large organizations that provide technical support as part of a broader IT service. Many support systems break down into different categories based on the function they provide or the product to which they are attached. A common bifurcation is offering a foundation of base-level services in a self-help manner, and if more assistance is needed, directing the issue to a higher level of support, typical of a tiered support model. For the self-help aspect of these systems, some organizations may opt for ticketing systems that allow them to prioritize which issues are solved first, while others may look to learning services that can allow the AI to guide the user based on their issue history. The most end-user visible aspect of these do-it-yourself (DIY) support systems is a knowledge base of troubleshooting tips, which can be either a side note or center stage.

Whether or not the organization uses a common data structure to handle each step of analyzing and solving the user's inquiry, there are metadata aspects for the learning algorithm approach, knowledge update aspect, and user feedback input. Historically, these systems have faced several challenges, regardless of how information is delivered to users. Foremost is the challenge of attrition: there is no way to ensure that the knowledge is kept up to date. One of these documents might be someone's last-ditch attempt at sharing accrued wisdom. Otherwise, user inquiries start calling the accuracy and clarity of the solution material into question, as well as the author's fundamental expertise in whatever the situation is. Any tip that becomes less effective with time reduces the trust of the user in the troubleshooting tips in general. Large or enterprise-level support is typically handled by a call center. Call centers for help with hardware, such as consumer electronics and internet installations, can be handled by the household or business and provide a variety of methods to reach the operator, anything from a direct call to a pager system to request an immediate ring back. Conversely, software is often supported by the charge for the total number of calls or lines rather than for the number of seats or people with access to the software. These situations, sometimes third-party, still face the same knowledge update challenges. Of course, the user in these larger scenarios is even more likely to be knowledgeable and to seek clarification when a tip seems senseless. A variety of industries now offer lower-level technical support, such as software developers and game manufacturers. As computing technology becomes more and more involved in niche markets, such categories can be expected to increase.

3.2. Challenges and Limitations

Technical support systems, when managed manually or without supporting technology solutions, generally face numerous challenges in handling technical issues quickly and efficiently. As customer growth continues to increase, a significant challenge faced by real-time support systems is scalability. Even though multiple conversational agents are purchased to handle user tickets, the system can drastically lag in responding to customer demands. Furthermore, generating accurate responses for a large number of support tickets in real time becomes practically implausible. Commonly, rapidly solving complex issues through hand-crafted textual responses becomes infeasible for real-time support systems. Addressing problems using support tools or a conversational human agent is generally the only practical way to resolve these concerns immediately. However, many automated support systems rely on human agents for problem resolution and hand-labeled data for creating data-driven resolution models.

Finally, service data contains user context, entity relationships, application behavior, indications of operation faults, and ongoing unestablished communication between business applications. The current support system becomes inefficient when it operates over application data and user queries, with the lack of data interaction from human operators leading to communication breakdowns and other inefficiencies in resolving user issues. Moreover, support conversations that end with users switching to other means of support, or not achieving the solution they need, introduce an element of inefficient service quality. Due to these limitations, there is a need to develop adaptive conversation learning models and actionable fault severity classification for online business support. However, due to the nature of demands on real-time support, these learning models should strive to increase online efficiency and customer satisfaction.

Equation 2 : Generative AI Model for Adaptive Learning in Technical Support:

$$R_{learn} = G(A, S, U, N)$$

R_{learn} is the rate of learning in the system.

G is the generative AI model.

A represents the available data for problem-solving.

S is the support team interventions and solutions.

U is user interaction history.

N represents neural network parameters that adapt over time.

4. Integration of Generative AI in Technical Support Systems

Technical support is a rapidly evolving field, benefiting from a range of emerging technologies. Front and center in the spotlight of recent developments is AI or machine learning, with some remarkable advancements in computer vision and natural language processing. The goal of this report is to examine the potential benefits of integrating generative AI within technical support frameworks and automating responses to improve ticket resolution rates or response times. Recognizing patterns in vast amounts of data to autonomously generate output, analysis, or solutions can have several benefits, which are covered in more depth later in this report.

Recent work within several industries on generative AI has shown promising results in automating many complex tasks across multiple industries. In practice, the use of AI in front-end interfaces can help simplify and streamline operations by automating low-level tasks that can impact a human's time. Using AI, systems can take long written prose, emails, or verbal communications and quickly create a written text that can be analyzed or actioned. This can drastically reduce the time a human spends reading said communication to respond. In a technical support system, this could be advantageous while searching for potential solutions or creating a draft response for a human to check for validity. Furthermore, an integrated AI model has the potential to assist in automating personalized products. Using other factors such as geographical location and the time of year can heighten the user experience by providing quicker and tailored assistance. The AI could use big data and user trends to automatically offer personalized products based on just a few customer details and reduce user wait times as a result. It could attempt to predict and recommend core issues that users in a geographical area might experience based on historical data.

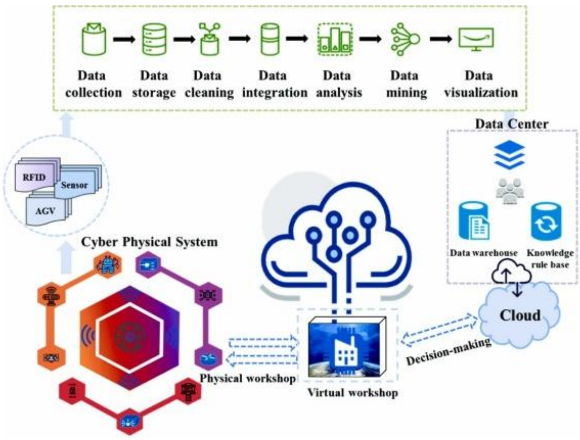

Fig 4 : AI-Based Decision Support Systems

There are, however, challenges to be overcome to integrate successfully with such systems. It might not be immediately feasible to integrate this kind of technology. A mix of user resistance and an increase in job roles required to build, maintain, and use such a complex support system may be off-putting to companies at first. Meanwhile, staff would require training in how to use and interpret the data generated, posing an additional obstacle. Given the accessibility of AI components and frameworks, it is likely that we might see the introduction of some kind of AI interface replacement, or that the implementation might be part of a longer multistage process. In the future, it will be interesting to see how this would develop. It would be fascinating to see what avenues companies might take to streamline their support and deployment systems. Cross-border collaboration could take AI support systems down a whole new lane that currently would be unlikely without this type of AI. It will be important, for all the nuts and bolts involved in integrating AI with a technical support framework, to keep the user and system integration always in the light to get the best out of the advancement.

4.1. Benefits and Applications

Generative AI will significantly change the operational efficiency of the support function. Automation leads to immediate costs as well as supreme scalability since operational costs are more constant once the technology has been bought and implemented. Moreover, generative AI's insights into multiple business problem domains such as anomaly detection, pattern mining, and customer segmentation help avoid problems occurring in the first instance as they provide clarity for improvements. The superior service level of technical support will have a very positive impact on customer satisfaction, which ranks high on any company's KPI list. Generative AI-powered technical support agents are not only personalized but also extremely efficient in problem resolution. In essence, such a bot can be used in chat environments where a high speed of response and accuracy are equally important and can handle end-to-end tasks from ticket acquisition to problem resolution. It can handle this instantly for up to several minutes and can draw from the wealth of historical problem resolution documented in tickets and emails.

Rapid ticket resolution can be substituted with troubleshooting on arrival, and the benefits extend to both convenience and cost. Administrators can benefit from better tools to manage their operations, such as work/inbox prioritization and automation that fully exploit prior experiences. Having the system use predefined responses and adapt those to a specific support context would not only reduce the number of response errors but also add meaning to the support data in a way that is more valuable than using uncontrolled text entry fields. Using this support intelligence, organizations can become truly agile problem solvers, directly translating this into even higher service levels, which is valuable to many businesses. To an organization, a learning support system would mean precision-based knowledge management, a means to spot structural inadequacies, cost savings through automation, and a more streamlined operation. It would be a welcome assistant to operations administrators in tailoring their inputs to optimize their site performance, alongside the knowledge gleaned through the lived experience of practical tips. It would add accuracy to incident management tools by adding valuable context to the incident record such that a generic response currently not possible with existing incident technology is born. In the end, the accrued practical knowledge and expertise represented in the learning cycles can be the fundamental bedrock of true procedural discipline in an organization. The age-old problem of data management and unnecessary IT costs in archiving all the information would disappear as the first level of excitement is the start of utilizing all that knowledge effectively and adapting an organization to become a dynamic, learning actor in the world of IT or any vocation for that matter.

4.2. Case Studies

MCI is a global player in virtual meetings and events with more than 30 years of experience. The implementation of generative AI technology was triggered by its quality assurance team. The AI-driven model became MCI's actual training environment, while experienced agents could evaluate the model's performance in real time as MCI scaled its capabilities. Possible lessons learned from our implementation: their support is more in line with the e-commerce/retail sector and is famous for having a money-back policy. The system's AI integration has increased FCR rates and CSAT scores. The number of agent escalations and refunds has dropped significantly. The AI training on increasing customer satisfaction and first contact resolution makes it possible for us to recoup these losses.

Global money transfer, foreign exchange, and business payments company. The company's technical issue resolution was once significantly slower than its SLA. Different people were using different networks and having different experiences – there was no established way of providing the best possible support. The support team members were also drawn from varying backgrounds and were not necessarily familiar with the company's products. This presented a problem when the support team had less than ten minutes to log in, get on the same page as a customer, and then aim to resolve an issue. The introduction of generative AI has allowed the company to cut SLA breaches in half in just three months, with a third technology. ADIs are the overarching concept of how to utilize AI to learn and adapt, with specific AI approaches to help reach such a solution. These AI approaches have been combined thanks to the introduction of models that can handle varying narrative inputs and provide fixes. They believe AI and technology now have a multiplier effect, with the support team working harder, smarter, and faster than non-integrated AI solutions in a similar role. In the process, such a solution has also "freed up our human counterparts to be more human" and "show care, empathy, and compassion".

5. AI-Driven Learning and Adaptation Models

AI-driven learning models and adaptation models can significantly enhance technical support systems. By learning from past interactions, these systems can become more adept at resolving problems. Not only can they recognize problem descriptions, but they can also learn from the actions taken by technical support analysts. By respecting adaptation over time, these systems avoid stagnation and remain permanently useful. In any AI-driven service quality improvement system, continuous improvement should be based on real-time feedback loops. They collect information representing how relevant the provided results cover the problem and its solution and feed this information back into the AI-driven adaptation and learning model.

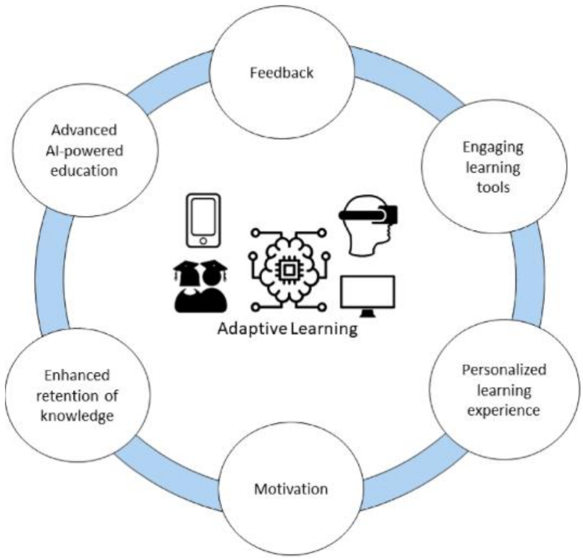

Fig 5 : AI-driven Adaptive Learning

For technical support environments, three methodologies of learning and adaptation can be applied: (1) Supervised learning can adapt support articles and troubleshooters to user problem descriptions. It can use this information to adapt problems and change classifiers, thus optimizing support delivery to user needs. (2) Unsupervised learning can self-organize knowledge and thus cluster problems into problem groups or problem troubles into similarities, thus allowing information browsing in a natural problem-relationship structure. (3) Reinforcement learning can be used to optimize the exploration and exploitation of knowledge. If exploration algorithms are good, then new problem knowledge can be obtained faster. If exploitation algorithms are good, then support can be directly tailored to user requirements.

To optimize the performance of the learning and adaptation models, it is important to initially train such models with as much behavioral information as possible, and then periodically refine them. The behavioral information helps power the models that are based on prior real interactions. Mathematically, such models could be trained via supervised learning, value iterative or reinforcement-based learning, based on a combination of agent behavior and signaled state values, i.e., different supervised learning sets. Systematic exploration of reinforcement learning is important to prevent overtraining on featured cases. Consequently, a richness and a diversity of behavioral states will lead to the most optimal adaptation. Given such behavioral data, it is possible to optimally adapt virtual agents to the largest number of offline user interactions available. The inputs to train systems for problem definitions or symptom analysis can also be gathered from any form of information resource.

5.1. Types of Learning Models

AI and machine learning employ several learning models with different mechanisms and characteristics. These learning models are classifications or categorizations of different learning techniques that can be utilized in AI-driven technical support systems for enhancing problem resolution efficiently. The learning models driven by AI include supervised, unsupervised, and reinforcement learning. Supervised learning refers to utilizing labeled data that consists of input and output data. The training models have supervised abilities to understand patterns and learn from input data to predict final output results. Supervised learning is a powerful training model that can be used in different scenarios. This model requires a large amount of input data to be trained for the AI system. Unsupervised learning refers to the training models that are used for classifying or categorizing data without utilizing labeled data. These models discover patterns and structures of the given data. These learned patterns can be further utilized for defining values and behaviors for any system or application. Reinforcement learning is a learning model that learns decision logic and AI in bounding conditions, and performs certain tasks based on prior learned experiences. In reinforcement learning, the information received from the outputs or actions of training data has feedback from the environment as a final result. This learning model is widely used in the development of gaming or robotics applications, in which actions and patterns are learned by trial and error. This is a powerful learning model that can be used in establishing the training model for every action. The collection of learned patterns can be determined from different AI learning models and aid in the design and evolution of systems. It provides the functional idea behind the workings of adaptive AI systems for technical support applications.

5.2. Adaptation Techniques

Regular adaptations of support systems play a critical role in a satisfying, personalized interaction with users. Next to adapting generation processes, recent technical support systems also offer user-centered adaptation techniques that customize their customer interactions. Adaptation of interfaces during the selection of fabric designs and different fits was realized for conversational AI shops. A support service for the resolution of production problems for high-precision devices is adjusted based on the dynamic processing learning of individual users. A different approach is presented, identifying shifts in user-generated topics to adapt the classification capabilities of the system in a compliant way. Connecting support queries with a user-generated model of a system was chosen, who identify falsely classified records in the neighborhood of a user's support case in a user-verified adaptation approach. Automatic content production was adapted to align the information needs of support staff with different competencies in the domain of auditory processes. A case study of context-sensitive adjustments in a conversational tutoring system to broaden students' engagement and understanding is presented.

System-centric adaptation mechanisms in conversational supports include active correction of user errors, user feedback as input for evaluation processes (evaluation-only; evaluation-and-adaptation), and dynamic learning models. Offers chatbots with additional learning capabilities. An initially provided learning model is adjusted to user feedback during daily operation. Query allocations based on user feedback were adjusted through new categorization prototypes. The combining of content-based database retrieval with user ratings for result relevance is presented. They integrate user ratings in a query expansion scenario. The user feedback, in this case, serves as the requirement for query expansion and triggers model updates for the underlying vector space model. A chatbot runtime framework features dynamic learning during conversations. The dialogue management model predicts the next action based on user feedback as the utterance, solving several issues. Another AI conversational support tool uses real-time operational data to monitor users, suggesting combinations of additional configurations based on user behaviors. Publishes real-time complaints about help page contents based on user feedback.

Figures offer practical examples of a more adaptable human-centered support system. Dynamic learning is adjusted based on underlying behavior only. The relevance rating prediction model is adjusted based on the active correction of user errors. Correction supervision means that the bot explicitly corrects a severe error of the user. The user feedback corresponds to the controllability of the help section “Content Features.” The numbers on the y-axis represent the closing changing ratio, for how many users the problem could be solved with our support system. There is no issue-closing ratio because some issues are not closed at all due to various reasons. The adaptive approach for operational dialogue systems opts for a natural combination of several adaptation mechanisms by combining system-centric evaluation and dynamic learning based on user feedback. To be effective in the long run, such chatbots should learn continually during production operations and adjust to users’ changing behavior to proactively reflect their needs.

6. Enhancing Problem Resolution Efficiency

One of the most important objectives and challenges in technical support is enhancing the efficiency of the problem-resolution process. Automated methods and tools offer several advantages in this respect. Automation provides the potential to respond to user needs in near real-time, which is a requirement for web-based applications and interfaces. Automation can guide users to troubleshoot key parts of the system and possibly achieve the system's goals, leading to faster execution times. Moreover, automation is indispensable for anticipating and preempting user needs and problem occurrences.

Data-driven automated systems in general possess several features that contribute to improving problem resolution efficiency. They characterize user behavior to anticipate the problems that the user is likely to face. They provide optimization strategies that can predict the success of the solution offered. They offer solutions that are based on past data to ensure good solution quality. They provide varied solutions that cater to users' expectations and offer a diverse and rich set of features and services. They ground their offer on studying user behavior from recorded use-case scenarios. Support systems should take a data-informed, AI-driven approach that capitalizes on call center conversations to learn from user-agent interactions and personalize a new response based on updated knowledge. AI systems distinguish users' moods, browsing profile history, and products and services preferred by the user. AI systems draw on the success and failure of knowledge articles to identify the most effective response. AI-hosted agents operate in direct response to questions from users. The ability of AI to disambiguate more complex inquiries and feed agents better information could improve their service levels. A strategy that ensures coherence and coordination among human steps and the automated digital self in solving the user's problem is indispensable. AI-driven data modeling can offer insights into which content and tools work best together for a given class of issues. AI provides insights into the most appropriate course agents should take when a problem is elevated to a higher-tech agent. This feature is also likely to be developed once enough evolution and resolution steps have been observed by data to offer meaningful alerts to human agents.

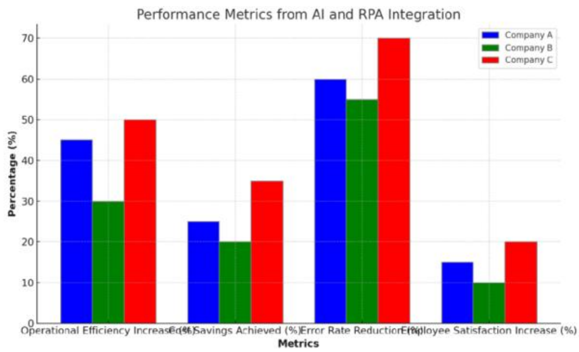

Fig 6 : Bar chart representing the performance metrics from the integration

6.1. Automated Troubleshooting Processes

Automated troubleshooting processes are designed to quickly and accurately diagnose issues in enterprise applications to enhance the overall efficiency of a support system—a priority for any customer and solutions strategy. Many technical support systems use a combination of troubleshooting frameworks and algorithms that lead them automatically to the root cause of a problem. Quite a few models exist that can be used to implement such a system in an existing product. These systems require zero to minimal human intervention and resolve the problem within a predefined resolution time. A seamless experience between the two approaches is crucial for user acceptance and long-term satisfaction when handling different problems. Automation can provide efficient problem resolution and reduce human intervention. Faster resolution times increase customer satisfaction and can reduce operational costs.

The support system operates in an automated mode by scanning through the range of products for a given problem and selecting the most relevant ones without any human intervention. Automating part of the process increases user acceptance, as only products handling the same problems are presented, instead of all products available through the phone and chat support channels. Some administrative overhead can be reduced, such as the number of hand tools necessary for a support agent to handle different products successfully. The benefits of the system are:

1. The system results in consistent and valid outcomes across the board, leading to better customer satisfaction. For example, for a given problem, if a solution is known, it gets recommended by the system regardless of the end-to-end user need and product combination.

2. Increases customer satisfaction. The reduced user wait time and elimination of all human judgment increase overall customer satisfaction in getting their problem addressed. Shortly, once the training has been done accurately, there is an overall increase in customer satisfaction.

3. The artificial intelligence-driven model gets continually improved over time based on the case resolutions available in problem escalation systems, leading to the proactive creation of new rules by learning from previous cases and solutions to enable correct end-to-end problem resolution. However, initially, the ruleset that the intelligent system produces can have gaps in it, i.e., the system has learned only from some of the problem management solutions but not from all other possibly different solutions.

Equation 3 : Optimization of Problem-Solving Models Using Neural Networks:

$$O = \mathrm{NN}(P, F, H, R)$$

Where:

- O is the optimized solution recommendation.
- P represents problem data and issue severity.
- F is feedback from previous resolutions.
- H is historical problem resolution patterns.
- R is resource data (e.g., time, tools, personnel).

6.2. Personalized Support Experiences

Today's fast-paced world is driven by technological advancements, and customers expect simple, time-saving support solutions. Support solutions today aim to simplify support processes, taking into account the user's context, which is referred to as a "personalized experience." One of the ways a personalized experience can be achieved to increase user satisfaction using context is by rendering all possible support solutions in terms of examples and solutions that are in the user's context. Personal preference can also be used to recommend support solutions for problems that are not directly solvable from the user's context.

Recommending the best possible solution will directly increase user satisfaction at problem resolution. The long-term impact of this service can lead to customer loyalty and trust with the personalized support approach, which is a long-term benefit for the overall organization. This approach can be achieved through AI-driven user modeling, using conversational data from the past, including chat logs, email, voice data, search data, and user feedback. Several organizations are already incorporating aspects of personalized support within their systems, which include the most popular domain of customer service chatbots. The recommendation model becomes stronger if user feedback is recorded and looped back into the learning and adaptation model to provide a highly popular, recommended solution.

Although some levels of personalization for an individual user are achieved using intelligent learning and data-driven recommendation models, a balance between automation and human touch is necessary for business scenarios to provide a personalized solution. It is also paramount that AI solutions continuously evolve using feedback loops. AI can learn the most suitable user interface, data view, or natural language to provide the support that is most accessible to the user. Furthermore, information about a user's technical background can be learned and adapted over time.

References

[1] Laxminarayana Korada. (2023). Role of 5G & Edge Computing in Industry 4.0 Story. International Journal of Communication Networks and Information Security (IJCNIS), 15(3), 366–377. Retrieved from https://www.ijcnis.org/index.php/ijcnis/article/view/7751

[2] Eswar Prasad G, Hemanth Kumar G, Venkata Nagesh B, Manikanth S, Kiran P, et al. (2023) Enhancing Performance of Financial Fraud Detection Through Machine Learning Model. J Contemp Edu Theo Artific Intel: JCETAI-101.

[3] Siddharth K, Gagan Kumar P, Chandrababu K, Janardhana Rao S, Sanjay Ramdas B, et al. (2023) A Comparative Analysis of Network Intrusion Detection Using Different Machine Learning Techniques. J Contemp Edu Theo Artific Intel: JCETAI-102.

[4] Vankayalapati, R. K., Sondinti, L. R., Kalisetty, S., & Valiki, S. (2023). Unifying Edge and Cloud Computing: A Framework for Distributed AI and Real-Time Processing. In Journal for ReAttach Therapy and Developmental Diversities. Green Publication. https://doi.org/10.53555/jrtdd.v6i9s(2).3348

[5] Reddy, R. (2023). Predictive Health Insights: Ai And Ml's Frontier In Disease Prevention And Patient Management. Available at SSRN 5038240.

[6] Nampalli, R. C. R. (2023). Moderlizing AI Applications In Ticketing And Reservation Systems: Revolutionizing Passenger Transport Services. In Journal for ReAttach Therapy and Developmental Diversities. Green Publication. https://doi.org/10.53555/jrtdd.v6i10s(2).3280

[7] Syed, S. (2023). Shaping The Future Of Large-Scale Vehicle Manufacturing: Planet 2050 Initiatives And The Role Of Predictive Analytics. Nanotechnology Perceptions, 19(3), 103-116.

[8] Korada, L. (2022). Using Digital Twins of a Smart City for Disaster Management. Journal of Computational Analysis and Applications, 30(1).

[9] Janardhana Rao Sunkara, Sanjay Ramdas Bauskar, Chandrakanth Rao Madhavaram, Eswar Prasad Galla, Hemanth Kumar Gollangi, et al. (2023) An Evaluation of Medical Image Analysis Using Image Segmentation and Deep Learning Techniques. Journal of Artificial Intelligence & Cloud Computing. SRC/JAICC-407.DOI: doi.org/10.47363/JAICC/2023(2)388

[10] Kalisetty, S., Pandugula, C., & Mallesham, G. (2023). Leveraging Artificial Intelligence to Enhance Supply Chain Resilience: A Study of Predictive Analytics and Risk Mitigation Strategies. Journal of Artificial Intelligence and Big Data, 3(1), 29–45. Retrieved from https://www.scipublications.com/journal/index.php/jaibd/article/view/1202

[11] Danda, R. R. Digital Transformation In Agriculture: The Role Of Precision Farming Technologies.

[12] Syed, S. Big Data Analytics In Heavy Vehicle Manufacturing: Advancing Planet 2050 Goals For A Sustainable Automotive Industry.

[13] Gagan Kumar Patra, Chandrababu Kuraku, Siddharth Konkimalla, Venkata Nagesh Boddapati, Manikanth Sarisa, et al. (2023) Sentiment Analysis of Customer Product Review Based on Machine Learning Techniques in E-Commerce. Journal of Artificial Intelligence & Cloud Computing. SRC/JAICC-408.DOI: doi.org/10.47363/JAICC/2023(2)38

[14] Sondinti, L. R. K., Kalisetty, S., Polineni, T. N. S., & abhireddy, N. (2023). Towards Quantum-Enhanced Cloud Platforms: Bridging Classical and Quantum Computing for Future Workloads. In Journal for ReAttach Therapy and Developmental Diversities. Green Publication. https://doi.org/10.53555/jrtdd.v6i10s(2).3347

[15] Ramanakar Reddy Danda, Z. Y. (2023). Impact of AI-Powered Health Insurance Discounts and Wellness Programs on Member Engagement and Retention. Letters in High Energy Physics.

[16] Syed, S. (2023). Zero Carbon Manufacturing in the Automotive Industry: Integrating Predictive Analytics to Achieve Sustainable Production. Journal of Artificial Intelligence and Big Data, 3, 17-28.

[17] Nagesh Boddapati, V. (2023). AI-Powered Insights: Leveraging Machine Learning And Big Data For Advanced Genomic Research In Healthcare. In Educational Administration: Theory

and Practice (pp. 2849–2857). Green Publication. https://doi.org/10.53555/kuey.v29i4.7531
[18] Polineni, T. N. S., abhireddy, N., & Yasmeen, Z. (2023). AI-Powered Predictive Systems for Managing Epidemic Spread in High-Density Populations. In Journal for ReAttach Therapy and Developmental Diversities. Green Publication. https://doi.org/10.53555/jrtdd.v6i10s(2).3374
[19] Danda, R. R. (2023). AI-Driven Incentives in Insurance Plans: Transforming Member Health Behavior through Personalized Preventive Care. Letters in High Energy Physics.
[20] Nampalli, R. C. R. (2022). Neural Networks for Enhancing Rail Safety and Security: Real-Time Monitoring and Incident Prediction. In Journal of Artificial Intelligence and Big Data (Vol. 2, Issue 1, pp. 49–63). Science Publications (SCIPUB). https://doi.org/10.31586/jaibd.2022.1155
[21] Syed, S. (2023). Advanced Manufacturing Analytics: Optimizing Engine Performance through Real-Time Data and Predictive Maintenance. Letters in High Energy Physics, 2023, 184-195.
[22] Patra, G. K., Kuraku, C., Konkimalla, S., Boddapati, V. N., & Sarisa, M. (2023). Voice classification in AI: Harnessing machine learning for enhanced speech recognition. Global Research and Development Journals, 8(12), 19–26. https://doi.org/10.70179/grdjev09i110003
[23] Danda, R. R. (2023). Neural Network-Based Models For Predicting Healthcare Needs In International Travel Coverage Plans.
[24] Subhash Polineni, T. N., Pandugula, C., & Azith Teja Ganti, V. K. (2022). AI-Driven Automation in Monitoring Post-Operative Complications Across Health Systems. Global Journal of Medical Case Reports, 2(1), 1225. Retrieved from https://www.scipublications.com/journal/index.php/gjmcr/article/view/1225
[25] Nampalli, R. C. R. (2022). Machine Learning Applications in Fleet Electrification: Optimizing Vehicle Maintenance and Energy Consumption. In Educational Administration: Theory and Practice. Green Publication. https://doi.org/10.53555/kuey.v28i4.8258
[26] Syed, S. (2022). Towards Autonomous Analytics: The Evolution of Self-Service BI Platforms with Machine Learning Integration. In Journal of Artificial Intelligence and Big Data (Vol. 2, Issue 1, pp. 84–96). Science Publications (SCIPUB).https://doi.org/10.31586/jaibd.2022.1157
[27] Sunkara, J. R., Bauskar, S. R., Madhavaram, C. R., Galla, E. P., & Gollangi, H. K. (2023). Optimizing Cloud Computing Performance with Advanced DBMS Techniques: A Comparative Study. In Journal for ReAttach Therapy and Developmental Diversities. Green Publication. https://doi.org/10.53555/jrtdd.v6i10s(2).3206
[28] Mandala, G., Danda, R. R., Nishanth, A., Yasmeen, Z., & Maguluri, K. K. AI AND ML IN HEALTHCARE: REDEFINING DIAGNOSTICS, TREATMENT, AND PERSONALIZED MEDICINE.
[29] Kothapalli Sondinti, L. R., & Yasmeen, Z. (2022). Analyzing Behavioral Trends in Credit Card Fraud Patterns: Leveraging Federated Learning and Privacy-Preserving Artificial Intelligence Frameworks. Universal Journal of Business and Management, 2(1), 1224. Retrieved from https://www.scipublications.com/journal/index.php/ujbm/article/view/1224
[30] Rama Chandra Rao Nampalli. (2022). Deep Learning-Based Predictive Models For Rail Signaling And Control Systems: Improving Operational Efficiency And Safety. Migration Letters, 19(6), 1065–1077. Retrieved from https://migrationletters.com/index.php/ml/article/view/11335
[31] Syed, S. (2022). Integrating Predictive Analytics Into Manufacturing Finance: A Case Study On Cost Control And Zero-Carbon Goals In Automotive Production. Migration Letters, 19(6), 1078-1090.
[32] Rajaram, S. K., Konkimalla, S., Sarisa, M., Gollangi, H. K., Madhavaram, C. R., Reddy, M. S., (2023). AI/ML-Powered Phishing Detection: Building an Impenetrable Email Security System. ISAR Journal of Science and Technology, 1(2), 10-19.
[33] Danda, R. R., Maguluri, K. K., Yasmeen, Z., Mandala, G., & Dileep, V. (2023). Intelligent Healthcare Systems: Harnessing Ai and Ml To Revolutionize Patient Care And Clinical Decision-Making.

[34] Kothapalli Sondinti, L. R., & Syed, S. (2021). The Impact of Instant Credit Card Issuance and Personalized Financial Solutions on Enhancing Customer Experience in the Digital Banking Era. Universal Journal of Finance and Economics, 1(1), 1223. Retrieved from https://www.scipublications.com/journal/index.php/ujfe/article/view/1223
[35] Nampalli, R. C. R. (2021). Leveraging AI in Urban Traffic Management: Addressing Congestion and Traffic Flow with Intelligent Systems. In Journal of Artificial Intelligence and Big Data (Vol. 1, Issue 1, pp. 86–99). Science Publications (SCIPUB). https://doi.org/10.31586/jaibd.2021.1151
[36] Syed, S. (2021). Financial Implications of Predictive Analytics in Vehicle Manufacturing: Insights for Budget Optimization and Resource Allocation. Journal of Artificial Intelligence and Big Data, 1(1), 111–125. Retrieved from https://www.scipublications.com/journal/index.php/jaibd/article/view/1154
[37] Patra, G. K., Rajaram, S. K., Boddapati, V. N., Kuraku, C., & Gollangi, H. K. (2022). Advancing Digital Payment Systems: Combining AI, Big Data, and Biometric Authentication for Enhanced Security. International Journal of Engineering and Computer Science, 11(08), 25618–25631. https://doi.org/10.18535/ijecs/v11i08.4698
[38] Danda, R. R. Decision-Making in Medicare Prescription Drug Plans: A Generative AI Approach to Consumer Behavior Analysis.
[39] Vankayalapati, R. K., Edward, A., & Yasmeen, Z. (2022). Composable Infrastructure: Towards Dynamic Resource Allocation in Multi-Cloud Environments. Universal Journal of Computer Sciences and Communications, 1(1), 1222. Retrieved from https://www.scipublications.com/journal/index.php/ujcsc/article/view/1222
[40] Syed, S., & Nampalli, R. C. R. (2021). Empowering Users: The Role Of AI In Enhancing Self-Service BI For Data-Driven Decision Making. In Educational Administration: Theory and Practice. Green Publication. https://doi.org/10.53555/kuey.v27i4.8105
[41] Sarisa, M., Boddapati, V. N., Kumar Patra, G., Kuraku, C., & Konkimalla, S. (2022). Deep Learning Approaches To Image Classification: Exploring The Future Of Visual Data Analysis. In Educational Administration: Theory and Practice. Green Publication. https://doi.org/10.53555/kuey.v28i4.7863
[42] Danda, R. R. (2022). Application of Neural Networks in Optimizing Health Outcomes in Medicare Advantage and Supplement Plans. Journal of Artificial Intelligence and Big Data, 2(1), 97–111. Retrieved from https://www.scipublications.com/journal/index.php/jaibd/article/view/1178
[43] Syed, S., & Nampalli, R. C. R. (2020). Data Lineage Strategies – A Modernized View. In Educational Administration: Theory and Practice. Green Publication. https://doi.org/10.53555/kuey.v26i4.8104
[44] Sondinti, L. R. K., & Yasmeen, Z. (2022). Analyzing Behavioral Trends in Credit Card Fraud Patterns: Leveraging Federated Learning and Privacy-Preserving Artificial Intelligence Frameworks.
[45] Syed, S. (2019). Roadmap for Enterprise Information Management: Strategies and Approaches in 2019. International Journal of Engineering and Computer Science, 8(12), 24907–24917. https://doi.org/10.18535/ijecs/v8i12.4415
[46] Bauskar, S. R., Madhavaram, C. R., Galla, E. P., Sunkara, J. R., & Gollangi, H. K. (2022). PREDICTING DISEASE OUTBREAKS USING AI AND BIG DATA: A NEW FRONTIER IN HEALTHCARE ANALYTICS. In European Chemical Bulletin. Green Publication. https://doi.org/10.53555/ecb.v11:i12.17745
[47] Danda, R. R. (2022). Deep Learning Approaches For Cost-Benefit Analysis Of Vision And Dental Coverage In Comprehensive Health Plans. Migration Letters, 19(6), 1103-1118.
[48] Maguluri, K. K., Yasmeen, Z., & Nampalli, R. C. R. (2022). Big Data Solutions For Mapping Genetic Markers Associated With Lifestyle Diseases. Migration Letters, 19(6), 1188-1204.

[49] Eswar Prasad Galla.et.al. (2021). Big Data And AI Innovations In Biometric Authentication For Secure Digital Transactions Educational Administration: Theory and Practice, 27(4), 1228 – 1236Doi: 10.53555/kuey.v27i4.7592
[50] Ramanakar Reddy Danda. (2022). Telehealth In Medicare Plans: Leveraging AI For Improved Accessibility And Senior Care Quality. Migration Letters, 19(6), 1133–1143. Retrieved from https://migrationletters.com/index.php/ml/article/view/11446
[51] Vankayalapati, R. K., & Syed, S. (2020). Green Cloud Computing: Strategies for Building Sustainable Data Center Ecosystems. Online Journal of Engineering Sciences, 1(1), 1229. Retrieved from https://www.scipublications.com/journal/index.php/ojes/article/view/1229
[52] Venkata Nagesh Boddapati, Eswar Prasad Galla, Janardhana Rao Sunkara, Sanjay Ramdas Bauskar, Gagan Kumar Patra, Chandrababu Kuraku, Chandrakanth Rao Madhavaram, 2021. "Harnessing the Power of Big Data: The Evolution of AI and Machine Learning in Modern Times", ESP Journal of Engineering & Technology Advancements, 1(2): 134-146.
[53] Danda, R. R. (2020). Predictive Modeling with AI and ML for Small Business Health Plans: Improving Employee Health Outcomes and Reducing Costs. In International Journal of Engineering and Computer Science (Vol. 9, Issue 12, pp. 25275–25288). Valley International. https://doi.org/10.18535/ijecs/v9i12.4572
[54] Vankayalapati, R. K., & Rao Nampalli, R. C. (2019). Explainable Analytics in Multi-Cloud Environments: A Framework for Transparent Decision-Making. Journal of Artificial Intelligence and Big Data, 1(1), 1228. Retrieved from https://www.scipublications.com/journal/index.php/jaibd/article/view/1228
[55] Mohit Surender Reddy, Manikanth Sarisa, Siddharth Konkimalla, Sanjay Ramdas Bauskar, Hemanth Kumar Gollangi, Eswar Prasad Galla, Shravan Kumar Rajaram, 2021. "Predicting tomorrow’s Ailments: How AI/ML Is Transforming Disease Forecasting", ESP Journal of Engineering & Technology Advancements, 1(2): 188-200.
[56] Ganti, V. K. A. T., & Pandugula, C. Tulasi Naga Subhash Polineni, Goli Mallesham (2023) Exploring the Intersection of Bioethics and AI-Driven Clinical Decision-Making: Navigating the Ethical Challenges of Deep Learning Applications in Personalized Medicine and Experimental Treatments. Journal of Material Sciences & Manufacturing Research. SRC/JMSMR-230. DOI: doi. org/10.47363/JMSMR/2023 (4), 192, 1-10.
[57] Chandrakanth R. M., Eswar P. G., Mohit S. R., Manikanth S., Venkata N. B., & Siddharth K. (2021). Predicting Diabetes Mellitus in Healthcare: A Comparative Analysis of Machine Learning Algorithms on Big Dataset. In Global Journal of Research in Engineering & Computer Sciences (Vol. 1, Number 1, pp. 1–11). https://doi.org/10.5281/zenodo.14010835
[58] Sondinti, L. R. K., & Syed, S. (2022). The Impact of Instant Credit Card Issuance and Personalized Financial Solutions on Enhancing Customer Experience in the Digital Banking Era. Finance and Economics, 1(1), 1223.
[59] Vaka, D. K. (2023). Achieving Digital Excellence In Supply Chain Through Advanced Technologies. Educational Administration: Theory and Practice, 29(4), 680-688.
[60] Sarisa, M., Boddapati, V. N., Patra, G. K., Kuraku, C., Konkimalla, S., & Rajaram, S. K. (2020). An Effective Predicting E-Commerce Sales & Management System Based on Machine Learning Methods. Journal of Artificial Intelligence and Big Data, 1(1), 75–85. Retrieved from https://www.scipublications.com/journal/index.php/jaibd/article/view/1110
[61] Vaka, D. K. Empowering Food and Beverage Businesses with S/4HANA: Addressing Challenges Effectively. J Artif Intell Mach Learn & Data Sci 2023, 1(2), 376-381.
[62] Gollangi, H. K., Bauskar, S. R., Madhavaram, C. R., Galla, E. P., Sunkara, J. R., & Reddy, M. S. (2020). Exploring AI Algorithms for Cancer Classification and Prediction Using Electronic Health Records. Journal of Artificial Intelligence and Big Data, 1(1), 65–74. Retrieved from https://www.scipublications.com/journal/index.php/jaibd/article/view/1109
[63] Vaka, D. K. “Artificial intelligence enabled Demand Sensing: Enhancing Supply Chain

Responsiveness.

[64] Manikanth Sarisa, Venkata Nagesh Boddapati, Gagan Kumar Patra, Chandrababu Kuraku, Siddharth Konkimalla, Shravan Kumar Rajaram.Navigating the Complexities of Cyber Threats, Sentiment, and Health with AI/ML. (2020). JOURNAL OF RECENT TRENDS IN COMPUTER SCIENCE AND ENGINEERING (JRTCSE), 8(2), 22-40. https://doi.org/10.70589/JRTCSE.2020.2.3

[65] Vaka, D. K. (2020). Navigating Uncertainty: The Power of 'Just in Time SAP for Supply Chain Dynamics. Journal of Technological Innovations, 1(2).

[66] Gollangi, H. K., Bauskar, S. R., Madhavaram, C. R., Galla, E. P., Sunkara, J. R., & Reddy, M. S. (2020).Unveiling the Hidden Patterns: AI-Driven Innovations in Image Processing and Acoustic Signal Detection. (2020). JOURNAL OF RECENT TRENDS IN COMPUTER SCIENCE AND ENGINEERING (JRTCSE), 8(1), 25-45. https://doi.org/10.70589/JRTCSE.2020.1.3.

[67] Dilip Kumar Vaka. (2019). Cloud-Driven Excellence: A Comprehensive Evaluation of SAP S/4HANA ERP. Journal of Scientific and Engineering Research. https://doi.org/10.5281/ZENODO.11219959

[68] Hemanth Kumar Gollangi, Sanjay Ramdas Bauskar, Chandrakanth Rao Madhavaram, Eswar Prasad Galla, Janardhana Rao Sunkara and Mohit Surender Reddy.(2020). "Echoes in Pixels: The intersection of Image Processing and Sound detection through the lens of AI and Ml", International Journal of Development Research. 10,(08),39735-39743. https://doi.org/10.37118/ijdr.28839.28.2020.

[69] Manikanth Sarisa, Venkata Nagesh Boddapati, Gagan Kumar Patra, Chandrababu Kuraku, Siddharth Konkimalla and Shravan Kumar Rajaram. "The power of sentiment: big data analytics meets machine learning for emotional insights", International Journal of Development Research, 10, (10), 41565-41573.