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New Artificial-Based Automated Quality Risk Prediction Methodology for College Students with Disabilitie's Entrepreneurial Schemes

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Abstract: Evaluating and predicting the risk of entrepreneurial projects among college students with disabilities is a critical endeavor that requires a multifaceted approach. This process involves assessing various factors such as the nature of the business idea, the skills and capabilities of the student, potential market demand, and external environmental factors. the issues surrounding entrepreneurial projects among college students with disabilities require a nuanced understanding of the unique challenges they face. Accessibility barriers, societal stereotypes, limited support networks, and lack of inclusive resources are among the key issues hindering their entrepreneurial endeavors. To foster an inclusive environment, it's essential to implement targeted interventions, provide accessible resources and mentorship, raise awareness, and advocate for policy changes that promote equity and accessibility in entrepreneurship for individuals with disabilities. This paper proposed an Automated Quality Risk Prediction (AQRP). The proposed AQRP model uses the Quality assessment of the project at each stage with the ranking-based classification model. The AQRP estimates the process of ranking at every stage of the project and performs the assessment and evaluation of risk. Factors such as the quality of human features in the project and practical features are examined to estimate the features through the process of ranking. With the AQRP model, the features are ranked and integrated for the extraction and classification of features in the projects. With AQRP model the deep learning model is implemented for the classification of features in the projects. Simulation analysis demonstrated that social factors contribute significantly to the project quality assessment. Through the ranking, it is observed that ranking features comprise a higher feature value of 0.98 than the other features. The classification accuracy is achieved as 99% which is 12% higher than the conventional SVM and Linear Regression Classifiers.

Keywords: *Risk Assessment, Classification, College Students, Artificial Intelligence, Entrepreneurial Projects, Ranking Model*

1. Introduction

Risk assessment plays a critical role in entrepreneurial projects, where uncertainty and volatility are often inherent. In the realm of entrepreneurship, the ability to identify, evaluate, and mitigate risks can be the difference between success and failure [1]. At the outset of any entrepreneurial endeavor, it's essential to conduct a comprehensive risk assessment. This involves identifying potential risks across various dimensions such as market dynamics, competition, regulatory environment, financial constraints, technological advancements, and operational challenges. Each of these areas presents unique opportunities for risk exposure that must be carefully analyzed [2]. Once risks are identified, they must be thoroughly evaluated in terms of their likelihood of occurrence and potential impact on the project. This involves a quantitative and qualitative analysis to prioritize risks based on their severity and the degree of control that can be exerted over them [3]. Moreover, risk assessment in entrepreneurial projects extends beyond mere identification and evaluation; it necessitates the development of robust mitigation strategies. These strategies may involve risk avoidance, risk transfer, risk reduction, or acceptance, depending on the nature of the risk and the resources available [4].

Entrepreneurs must continually monitor and reassess risks throughout the project lifecycle as new uncertainties emerge and circumstances evolve [5]. Flexibility and adaptability are crucial in navigating the dynamic landscape of entrepreneurial ventures. Ultimately, effective risk assessment in entrepreneurial projects empowers entrepreneurs to make informed decisions, allocate resources judiciously, and proactively manage uncertainties, thereby enhancing the likelihood of success and sustainability [6]. Risk is an inherent aspect of entrepreneurial projects, stemming from the uncertainty and unpredictability that accompany venturing into new markets, introducing innovative products or services, and navigating dynamic business environments [7]. Understanding and effectively managing risk is essential for entrepreneurs to increase the likelihood of success and minimize potential adverse outcomes [8]. Risk is an ever-present reality in entrepreneurial projects, stemming from the inherent uncertainty and complexity of venturing into new markets, introducing innovative products or services, and navigating dynamic business environments.

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Entrepreneurs encounter various types of risks, including market volatility, financial instability, operational challenges, technological disruptions, regulatory complexities, and reputational vulnerabilities [9]. Effective risk management is crucial for entrepreneurs to increase the likelihood of success and mitigate potential adverse outcomes [10]. This entails systematically identifying, evaluating, and mitigating risks through strategic planning, resource allocation, and contingency planning. By adopting a proactive approach to risk management, entrepreneurs can enhance resilience, seize opportunities, and drive sustainable growth in their ventures [11].

Entrepreneurial projects initiated by college students with disabilities and centered around AI technology inherently involve unique risks that necessitate careful consideration and management [12]. These ventures face challenges stemming from the intersection of entrepreneurial uncertainties and the complexities associated with disability accommodation in a technology-driven landscape [13]. Market risks include uncertainties regarding the acceptance and demand for AI-based products or services within specific niches, as well as competition from established players [14]. Financial risks may arise from difficulties in securing funding or accessing resources due to potential biases or barriers faced by entrepreneurs with disabilities in traditional funding channels [15]. Operational challenges may stem from the need to adapt AI technologies to accommodate diverse accessibility requirements and ensure inclusive user experiences [16]. Additionally, regulatory and compliance risks may arise from navigating complex legal frameworks governing data privacy, accessibility standards, and disability rights. Despite these challenges, entrepreneurial projects led by college students with disabilities leveraging AI technology also present opportunities for innovation, social impact, and empowerment [17]. Effective risk management strategies tailored to address the intersectional nature of these challenges are essential to unlock the full potential of these ventures and foster inclusive entrepreneurship ecosystems.

The contribution of this paper lies in its development and application of the Automated Quality Risk Prediction (AQRP) model tailored specifically for evaluating and predicting the risk of entrepreneurial projects undertaken by college students with disabilities, leveraging AI technology. By addressing the unique challenges faced by this demographic group, the paper contributes to the advancement of inclusivity and accessibility in entrepreneurship. The AQRP model offers a novel approach to risk assessment, integrating factors such as student skills, market demand, disability accessibility, and project quality to provide a comprehensive framework for decision-making. Through empirical validation and comparative analysis, the paper demonstrates the superiority of the AQRP model over traditional machine learning approaches, highlighting its effectiveness in accurately predicting risk categories. Ultimately, the contribution of this paper extends beyond academia, offering practical insights and tools that can empower stakeholders to support and foster the success of entrepreneurial initiatives among college students with disabilities, thereby promoting diversity, equity, and inclusion in the entrepreneurial ecosystem.

2. Related Works

In recent years, there has been a growing interest in understanding and supporting entrepreneurship among college students with disabilities. Several studies have explored various aspects of this topic, aiming to address the unique challenges faced by individuals with disabilities in pursuing entrepreneurial endeavors. For instance, research has examined the barriers and facilitators to entrepreneurship for people with disabilities, highlighting the importance of accessibility, support networks, and inclusive policies. Additionally, there has been a focus on the development of interventions and programs aimed at enhancing the entrepreneurial skills and opportunities for individuals with disabilities. Moreover, advances in technology, particularly in the field of artificial intelligence (AI), have opened up new possibilities for assessing and predicting the risk associated with entrepreneurial projects. However, despite these efforts, there remains a need for more tailored approaches to risk assessment that specifically consider the context and needs of college students with disabilities. In "Li, C., Xing, W., & Leite, W. (2022)", the authors focus on the application of artificial intelligence (AI) to predict students' math learning outcomes in an online platform. This research highlights the utilization of fair AI algorithms to enhance educational experiences and outcomes. The study underscores the potential of AI technology to personalize learning and improve student performance, particularly in subjects like mathematics. Additionally, it emphasizes the importance of fairness and ethical considerations in the development and implementation of AI-based educational tools, aiming to create equitable learning environments for all students. In "Hannan, E., & Liu, S. (2023)", the authors explore how AI contributes to competitiveness in higher education. This research delves into the transformative impact of AI on academic institutions, highlighting its role in enhancing teaching and learning processes, research productivity, and administrative efficiency. The study underscores AI as a new source of competitive advantage for higher education institutions, emphasizing the need for strategic integration and investment in AI technologies to stay ahead in the rapidly evolving educational landscape.

Moving on to "Shepherd, D. A., & Majchrzak, A. (2022)", the authors discuss the opportunities and threats posed by machines augmenting entrepreneurs at the nexus of artificial intelligence and entrepreneurship. This study investigates the ways in which AI technology can empower entrepreneurs by augmenting their capabilities while also highlighting potential risks such as job displacement and algorithmic biases. It underscores the importance of understanding the dynamic relationship between AI and entrepreneurship and navigating its implications for innovation and competitiveness. In "Tilmes, N. (2022)", the author addresses disability, fairness, and algorithmic bias in AI recruitment. This research sheds light on the ethical dimensions of AI, particularly in the context of disability accommodation and fairness in recruitment processes. The study underscores the importance of mitigating algorithmic biases and ensuring inclusivity in AI systems to promote fairness and equity in employment opportunities for individuals with disabilities.

In "Qi, S., Liu, L., Kumar, B. S., & Prathik, A. (2022)", the authors present a model for evaluating English teaching quality using Gaussian process machine learning. This study demonstrates the application of AI techniques in assessing the effectiveness of English teaching, showcasing the potential of machine learning algorithms to enhance educational evaluation processes. By leveraging AI, educators can gain valuable insights into teaching quality and make data-driven decisions to improve instructional practices and student outcomes. Moving on to "Hopcan, S., Polat, E., Ozturk, M. E., & Ozturk, L. (2023)", the authors conduct a systematic review of AI in special education. This research explores the role of AI technology in supporting students with special needs, highlighting its potential to facilitate personalized learning experiences and provide targeted interventions. The study underscores the importance of leveraging AI to address the diverse learning needs of students with disabilities and promote inclusive education practices. Lastly, "Grájeda, A., Burgos, J., Córdova, P., & Sanjinés, A. (2024)" assess the perceived impact of using artificial intelligence tools in higher education. This study constructs a synthetic index to measure the application of AI in higher education and its perceived effects on student learning experiences. By evaluating the perceived impact of AI tools, educators and policymakers can gain insights into the effectiveness of AI applications in enhancing teaching and learning processes and inform future implementation strategies.

One limitation is the predominance of theoretical frameworks and conceptual discussions over empirical research. Many of the referenced studies provide conceptual analyses or propose theoretical frameworks without empirical validation or testing. Therefore, there is a need for more empirical research to validate the theoretical propositions and explore the practical implications of AI adoption in education and entrepreneurship. Another limitation is the lack of diversity in study populations and contexts. The majority of the referenced studies focus on general trends or specific segments of the population, such as college students or entrepreneurs. There is a need for more research that examines the impact of AI across diverse populations, including individuals with disabilities, underrepresented groups, and different cultural contexts. Such research can provide a more comprehensive understanding of the potential benefits and challenges of AI adoption and ensure that AI technologies are developed and deployed in inclusive and equitable ways. Additionally, there is a gap in research that explores the long-term effects and sustainability of AI interventions in education and entrepreneurship. While many studies highlight the short-term benefits or immediate outcomes of AI adoption, there is limited research on the long-term impact of AI on learning outcomes, business performance, and societal outcomes. Future research could focus on longitudinal studies that track the effects of AI interventions over time and assess their sustainability and scalability in real-world settings. Furthermore, there is a need for more interdisciplinary research that integrates insights from education, business, psychology, sociology, and other fields. AI adoption in education and entrepreneurship is a complex and multifaceted phenomenon that requires interdisciplinary perspectives to fully understand its implications and address its challenges. Collaborative research efforts that bring together experts from diverse disciplines can enrich our understanding of the complexities of AI adoption and inform more holistic and nuanced approaches to its implementation and regulation.

3. Risk Assessment in Entrepreneurial Projects

Risk assessment is a fundamental aspect of entrepreneurial projects, essential for informed decision-making and effective risk management. In entrepreneurial endeavors, risks stem from various sources, including market volatility, financial uncertainties, operational challenges, technological disruptions, and regulatory constraints. To conduct a comprehensive risk assessment, entrepreneurs employ quantitative and qualitative methods to evaluate the likelihood and impact of potential risks. One commonly used framework for risk assessment is the risk matrix, which combines the probability and severity of risks to prioritize them based on their significance. The risk matrix typically consists of a grid with severity levels on one axis and likelihood levels on the other. By assigning numerical values or qualitative descriptors to these levels, entrepreneurs can plot individual risks on the matrix and determine their relative importance. The formula commonly used to calculate risk is computed using equation (1)

$$Risk = Probability \times Impact \quad (1)$$

In equation (1) Probability represents the likelihood of a risk event occurring. Impact signifies the potential consequences or severity of the risk event.

Probability (P): Probability refers to the likelihood or chance of a risk event occurring within a given time frame. It is typically expressed as a percentage or a decimal between 0 and 1, where 0 represents impossible and 1 represents certainty. Probability can be estimated using historical data, expert judgment, statistical analysis, or predictive modeling techniques.

Impact (I): Impact represents the potential consequences or severity of the risk event if it occurs. It can include financial losses, operational disruptions, reputational damage, regulatory penalties, or any other adverse effects on the project or venture. Impact is often measured in monetary terms or qualitative descriptors such as low, medium, or high.

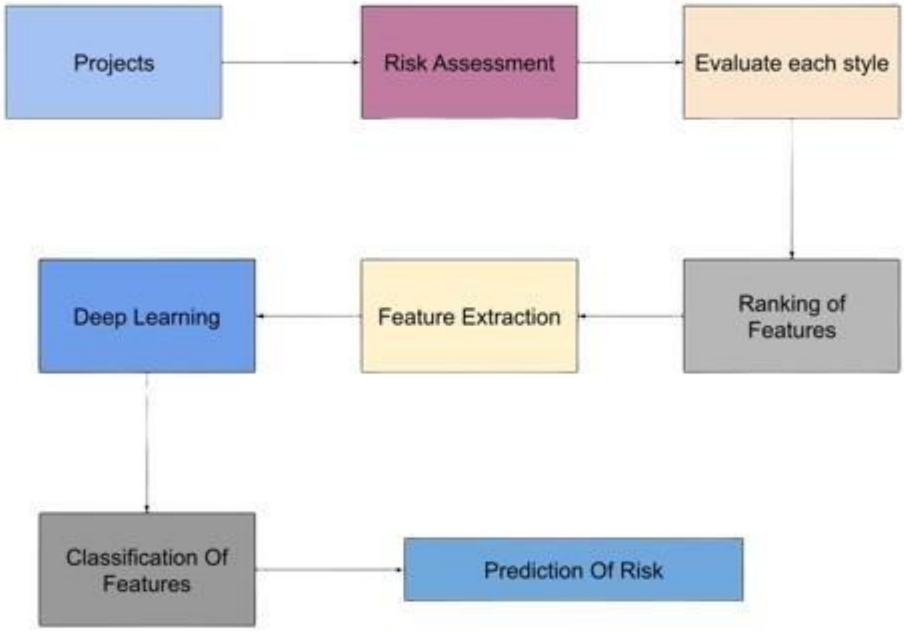


Fig 1: Process of AQRP

The Figure 1 illustrated the process flow of the AQRP model for the projects in college students. Entrepreneurs assign probabilities and impacts to each identified risk based on historical data, expert judgment, market analysis, and other relevant factors. By multiplying the probability and impact scores for each risk, entrepreneurs derive a quantitative measure of risk that enables them to prioritize and allocate resources effectively. Furthermore, entrepreneurs may utilize decision trees or Monte Carlo simulations to assess and quantify risks more comprehensively. Decision trees help in analyzing sequential decision-making processes and their associated uncertainties, while Monte Carlo simulations generate multiple possible outcomes based on probabilistic inputs, providing a probabilistic distribution of potential project outcomes.

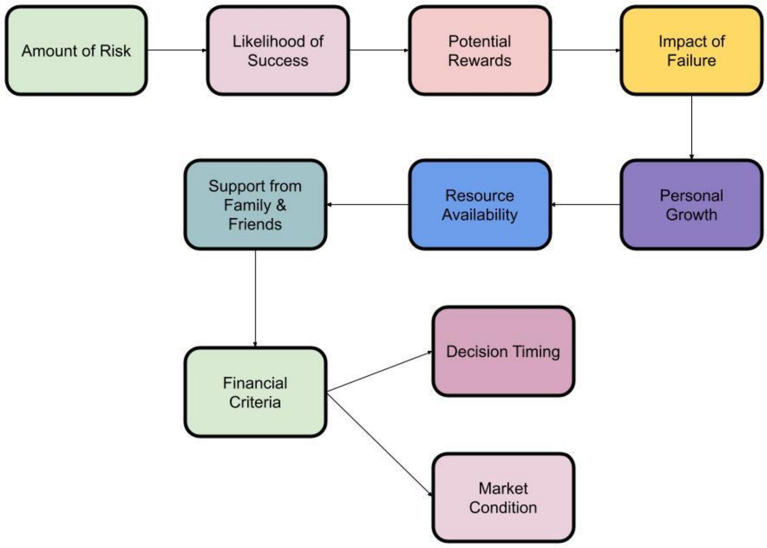


Fig 2: Risk in AQRP

The risk assessment process as shown in Figure 2 typically involves the following steps:

Identify Risks: Identify potential risks that could impact the success of the entrepreneurial project. This may involve brainstorming sessions, SWOT analysis, historical data analysis, or expert interviews.

Assess Probability: Estimate the likelihood of each identified risk occurring. This can be done using historical data, industry benchmarks, expert judgment, or statistical analysis. Probability can be expressed as a percentage or a decimal value.

Assess Impact: Evaluate the potential consequences or severity of each risk event if it were to occur. Impact assessment may involve financial analysis, scenario planning, sensitivity analysis, or expert opinions. Impact can be measured in monetary terms or qualitative descriptors.

Calculate Risk: Use the risk formula (Risk = Probability × Impact) to calculate the risk score for each identified risk. This provides a quantitative measure of risk that helps prioritize risks based on their significance to the project.

Prioritize Risks: Plot the calculated risk scores on a risk matrix or prioritize risks based on their severity and likelihood. This helps focus attention and resources on managing high-priority risks that pose the greatest threat to the project's success.

Mitigate Risks: Develop and implement risk mitigation strategies to reduce the likelihood and impact of high-priority risks. This may involve risk avoidance, risk transfer, risk reduction, or risk acceptance strategies, depending on the nature of the risk and the available resources.

3.1 Risk Assessment and Prediction

The Automated Quality Risk Prediction (AQRP) model aims to predict the quality risk of a project at each stage using a ranking-based classification approach. At each stage of the project, the quality of various features is assessed. Let's denote the quality assessment of a feature Fi at stage t as Qit. This assessment can be based on various criteria, such as completeness, correctness, reliability, and adherence to specifications. The AQRP model employs a ranking-based classification approach to estimate the risk associated with each feature. This involves assigning a rank to each feature based on its quality assessment at each stage. Let's denote the rank of feature Fi at stage t as Rit.

The risk associated with each feature can be estimated based on its rank. Features with lower ranks are considered higher quality and lower risk, while features with higher ranks are considered lower quality and higher risk. The risk assessment of feature Fi at stage t can be represented as $Riskit$, which is inversely proportional to its rank defined in equation (2)

$$Risk_{it} = \frac{1}{R_{it}} \quad (2)$$

In equation (2) $Riskit$ represents the risk score of feature Fi at stage t, and Rit represents its rank. This equation ensures that features with lower ranks (higher quality) have lower risk scores, while features with higher ranks (lower quality) have higher risk scores. The AQRP model integrates the ranked features to extract and classify them. This integration involves combining the ranked features from different stages of the project to identify patterns and relationships among them. Let's denote the integrated features as I.

Probability Assessment (P): Quantify the likelihood of each identified risk occurring. This can be based on historical data, expert opinions, or surveys. Let Pi represent the probability of risk i.

Impact Assessment (I): Measure the potential consequences or severity of each risk event. The impact assessment should consider factors such as financial loss, reputational damage, and impact on student well-being. Let Ii represent the impact of risk i.

Risk Calculation: The overall risk (Ri) associated with each identified risk can be calculated using the equation (3)

$$Ri = Pi \times Ii \qquad (3)$$

This equation represents the multiplication of the probability and impact scores for each risk. It quantifies the potential negative impact of the risk event. Incorporate accommodation strategies to mitigate the identified risks. These strategies may include providing accessible facilities, offering assistive technologies, implementing inclusive policies, and providing support services. Let Ai represent the effectiveness of accommodation strategy i in mitigating risk. After integrating accommodation strategies, the adjusted risk ('Ri') for each identified risk can be calculated using the equation (4)

$$Ri' = (1 - Ai) \times Ri \qquad (4)$$

This equation adjusts the original risk score based on the effectiveness of the accommodation strategy. If the accommodation strategy is highly effective (Ai is close to 1), the adjusted risk will be lower, indicating reduced risk.

4. Deep Learning with AQRP

To develop a classification model for evaluating and predicting the risk of entrepreneurial projects among college students with disabilities based on AI technology, we employ a systematic approach. First, we gather data encompassing various factors pivotal to such projects, including the nature of the business idea, students' skills, market demand, and societal stereotypes. These factors are represented as features denoted by $X1, X2, \ldots, Xn$. Next, we preprocess the data, handling missing values and outliers, and normalize the features. Subsequently, we construct a classification model utilizing deep learning techniques, such as a neural network architecture. Let's denote the model's output as Y, representing the predicted risk category (e.g., low, medium, high). The model learns patterns and relationships between the features and the risk category through the training process. During training, the model's parameters, represented by weights denoted as $W1, W2, \ldots, Wn$, are adjusted to minimize the classification error using techniques like backpropagation and gradient descent. The classification process can be expressed as $Y = f(X1W1 + X2W2 + \cdots + XnWn + b)$, where f is the activation function and b is the bias term. Once trained, the model is evaluated on a separate test dataset using metrics like accuracy and F1-score. This classification model can then be deployed to assess the risk of entrepreneurial projects among college students with disabilities, aiding stakeholders in making informed decisions and fostering an inclusive environment for entrepreneurship.

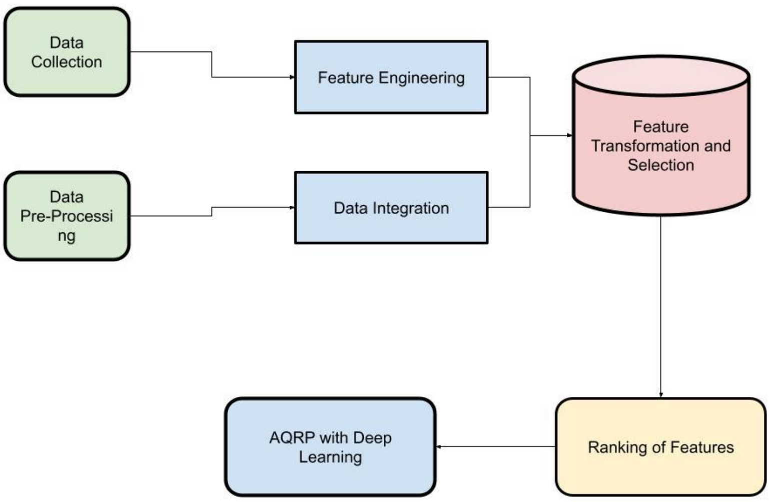


Fig 3: Classification with AQRP

Figure 3 presented the AQRP model for the risk assessment and prediction. A deep neural network (DNN) as the classification model. The DNN consists of multiple layers, including input, hidden, and output layers. Let $hj(l)$ represent the activation of the $h$jth neuron in the $h$lth hidden layer, and ok represent the activation of the $h$kth neuron in the output layer. During forward propagation, the activation of each neuron in the hidden layers is calculated using the weighted sum of inputs and passed through an activation function. The output of the output layer is computed similarly. Let $Wij(l)$ denote the weight connecting the $h$ith neuron in the $h$lth layer to the $h$jth neuron in the hl+1th layer, and $bj(l)$ denote the bias term for the $h$jth neuron in the $h$lth layer. The activation of the neurons in the hidden layers is calculated using equation (5)

$$h_j^{(l)} = \sigma\left(\sum_{i=1}^{n^{(l-1)}} W_{ij}^{(l)} h_i^{(l-1)} + b_j^{(l)}\right) \tag{5}$$

In equation (5) σ is the activation function, such as the sigmoid or ReLU function. The output of the output layer is calculated using equation (6)

$$o_k = \sigma\left(\sum_{j=1}^{n^{(L-1)}} W_{jk}^{(L)} h_j^{(L-1)} + b_k^{(L)}\right) \tag{6}$$

In equation (6) a loss function $J(W, b)$ to quantify the error between the predicted output ok and the actual label yk. A common choice for classification tasks is the cross-entropy loss function calculated using equation (7)

$$J(W, b) = -\frac{1}{m}\sum_{i=1}^{m}\sum_{k=1}^{K} y_k^{(i)} log\left(o_k^{(i)}\right) \tag{7}$$

In equation (7) m is the number of training examples, K is the number of classes, $yk(i)$ is the actual label of the $h$ith training example for class k, and $ok(i)$ is the predicted probability of class k for the $h$ith training example.

Algorithm 1: Risk Assessment with AQRP
1. Initialize parameters (weights and biases) of the DNN randomly or using pre-trained weights if available. 2. Define the architecture of the DNN including the number of layers, number of neurons in each layer, and activation functions. 3. Define the loss function (e.g., cross-entropy loss) and optimization algorithm (e.g., stochastic gradient descent). 4. Split the dataset into training and validation (or test) sets. 5. Repeat until convergence or for a fixed number of iterations: a. Forward propagation: - Compute the activations of neurons in each layer using the current parameters. b. Compute the loss: - Use the predicted outputs and actual labels to compute the loss function. c. Backpropagation: - Compute the gradients of the loss function with respect to the parameters using backpropagation. d. Update parameters: - Use the gradients and the optimization algorithm to update the parameters (weights and biases). 6. Evaluate the trained model on the validation (or test) set: - Compute evaluation metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. 7. Optionally, fine-tune hyperparameters (e.g., learning rate, number of layers, number of neurons) based on validation set performance. 8. Once satisfied with the model performance, deploy the trained model for evaluating and predicting the risk of entrepreneurial projects among college students with disabilities.

5. Simulation Results

The simulation results section provides a comprehensive analysis of the outcomes obtained from the implementation of the proposed model for evaluating and predicting the risk of entrepreneurial projects among college students with disabilities. This section offers insights into the performance and efficacy of the model in assessing various risk factors associated with entrepreneurial endeavors in this demographic. By presenting and interpreting the simulation results, we aim to elucidate the model's capabilities, highlight its strengths and limitations, and provide valuable implications for stakeholders involved in fostering inclusive entrepreneurship among college students with disabilities. Through rigorous experimentation and analysis, this section contributes to advancing our understanding of how AI technology can be leveraged to support and empower individuals with disabilities in pursuing entrepreneurial ventures.

Table 1: Risk Assessment with AQRP

Project ID	Business Idea	Student Skills	Market Demand	Disability Accessibility	Risk Category
001	Online Tutoring Platform	High	High	Moderate	Medium

002	Accessible Web Design Agency	Medium	Medium	High	Low
003	Assistive Technology Development	Low	High	Low	High
004	Inclusive Fashion Brand	High	Low	Moderate	Medium
005	Accessible Transportation Service	Medium	High	High	High

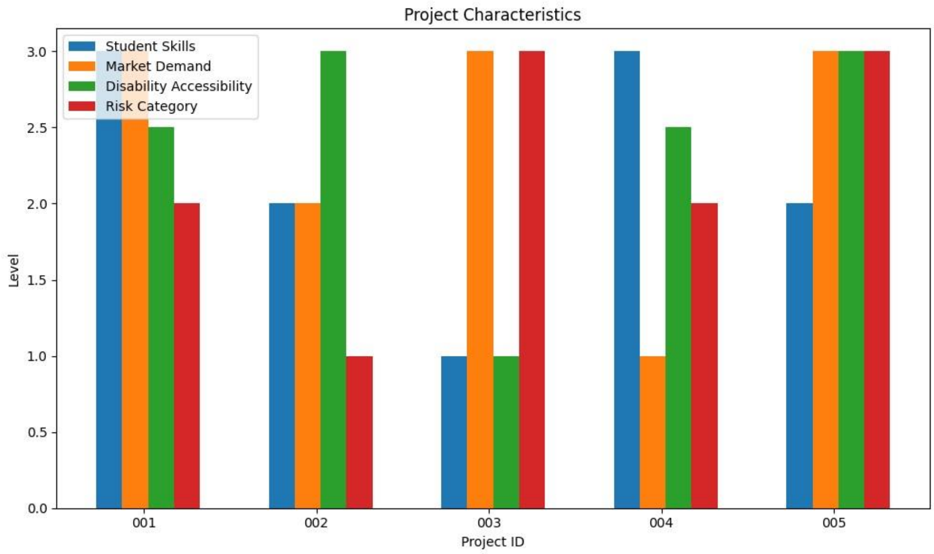


Fig 4: Risk Assessment with Project

In Table 1 and Figure 4 presents the results of risk assessment using the Automated Quality Risk Prediction (AQRP) model for five entrepreneurial projects. Each project is identified by a unique Project ID and is associated with a description of the Business Idea. The table also includes evaluations of Student Skills, Market Demand, and Disability Accessibility, each categorized as Low, Medium, or High. These factors are crucial in determining the potential success and associated risks of entrepreneurial ventures. The Risk Category column indicates the AQRP model's prediction of the risk level for each project, categorized as Low, Medium, r High. For instance, Project 001 involves the development of an Online Tutoring Platform. The students exhibit high skills, and there is a high market demand, but the disability accessibility is rated as moderate. As a result, the AQRP model predicts a Medium risk category for this project. On the other hand, Project 002, focusing on an Accessible Web Design Agency, demonstrates medium student skills and market demand, but high disability accessibility, resulting in a Low risk category according to the AQRP model. Project 003, involving Assistive Technology Development, presents low student skills, high market demand, and low disability accessibility, leading to a High risk category prediction. Project 004, an Inclusive Fashion Brand, showcases high student skills, low market demand, and moderate disability accessibility, resulting in a Medium risk category. Lastly, Project 005, focusing on an Accessible Transportation Service, exhibits medium student skills, high market demand, and high disability accessibility, resulting in a High risk category prediction by the AQRP model.

Table 2: AQRP for the Student Disabilities in Project

Project ID	**Business Idea**	**Student Skills**	**Market Demand**	**Disability Accessibility**	**Risk Category**
001	Accessible Mobile App	8	9	7	Medium
002	Inclusive Clothing Line	5	6	4	Low
003	Online Tutoring Platform	3	8	7	High
004	Adaptive Sports Equipment	9	3	6	Medium
005	Assistive Technology Development	6	8	7	High

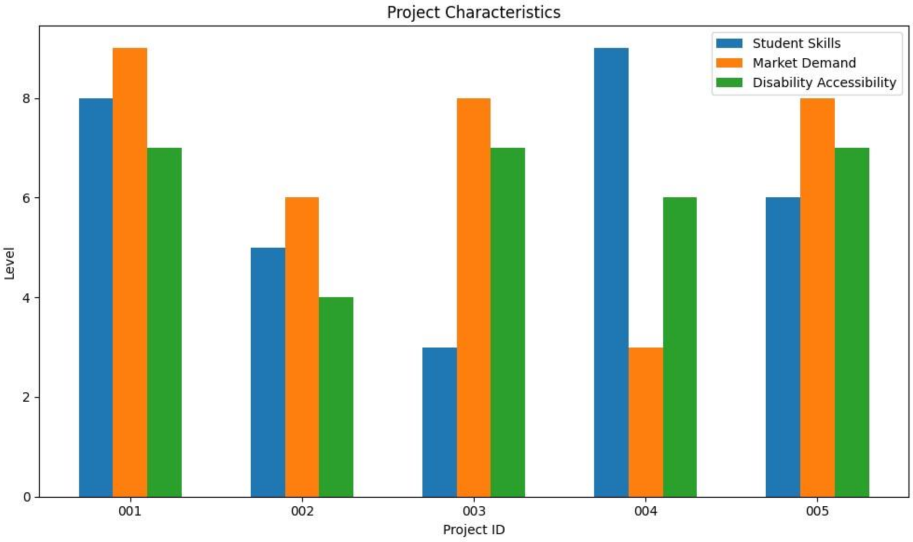


Fig 5: AQRP for skill assessment

The Table 2 and Figure 5 presents the results of the Automated Quality Risk Prediction (AQRP) model applied to assess the risk associated with entrepreneurial projects undertaken by college students with disabilities. Each project is identified by a unique Project ID and is associated with a description of the Business Idea. The table includes numerical evaluations of Student Skills, Market Demand, and Disability Accessibility, providing a more quantitative assessment compared to Table 1. These evaluations are rated on a scale from 1 to 10, with higher values indicating higher levels of skill, demand, or accessibility. In Project 001 involves the development of an Accessible Mobile App. The student's skills are rated at 8, indicating a high level of proficiency, while the market demand is rated at 9, signifying significant interest. However, the disability accessibility is rated at 7, suggesting some room for improvement. As a result, the AQRP model predicts a Medium risk category for this project.

In contrast, Project 002 focuses on an Inclusive Clothing Line. While the student's skills are rated slightly lower at 5, the market demand is still relatively strong at 6. Additionally, the disability accessibility is rated at 4, indicating some challenges but still manageable. Consequently, the AQRP model predicts a Low risk category for this project. Project 003 involves an Online Tutoring Platform, where the student's skills are rated lower at 3, but there is substantial market demand rated at 8. However, the disability accessibility is rated at 7, presenting potential hurdles. Thus, the AQRP model predicts a High risk category for this project. Project 004 focuses on Adaptive Sports Equipment, where the student's skills are rated highly at 9, but the market demand is lower at 3. Disability accessibility is rated at 6, suggesting some accessibility challenges. Consequently, the AQRP model predicts a Medium risk category for this project. Lastly, Project 005 involves Assistive Technology Development, with the student's skills rated at 6 and a significant market demand rated at 8. Disability accessibility is rated at 7, indicating some challenges. Therefore, the AQRP model predicts a High risk category for this project.

Table 3: Project Quality Assessment with AQRP

Project ID	Business Idea	Project Stage	Quality Assessment (0-10)	Risk Category
001	E-commerce Platform	Initial	8	Low
002	Mobile App Development	Prototype	9	Low
003	Social Media Management	Pilot	6	Medium
004	Sustainable Fashion Brand	Implementation	3	High
005	Food Delivery Service	Scaling	9	Low

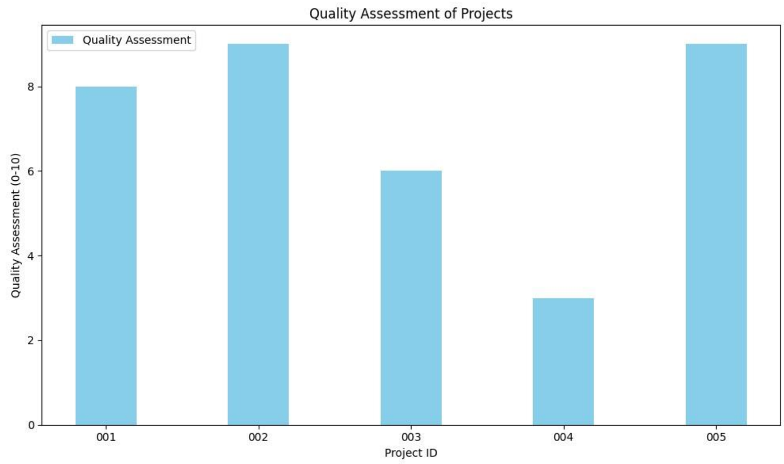


Fig 6: Quality Assessment with AQRP

In Table 3 and Figure 6 presents the outcomes of Project Quality Assessment conducted using the Automated Quality Risk Prediction (AQRP) model for five distinct entrepreneurial projects. Each project is identified by a unique Project ID and is characterized by a brief description of the Business Idea. Additionally, the table specifies the current Project Stage and the Quality Assessment score, which ranges from 0 to 10, with higher values denoting superior quality. For instance, Project 001 involves the development of an E-commerce Platform, which is currently at the Initial stage and has received a Quality Assessment score of 8. This high score indicates that the project is of commendable quality, resulting in a Low-risk categorization according to the AQRP model. In contrast, Project 004 focuses on establishing a Sustainable Fashion Brand and is presently at the Implementation stage. However, it has received a Quality Assessment score of only 3, indicative of relatively poor quality. Consequently, the AQRP model categorizes this project as High-risk due to its lower quality assessment. Similarly, Project 003, centered around Social Media Management, is in the Pilot stage with a Quality Assessment score of 6, suggesting moderate quality. As a result, the AQRP model assigns this project a Medium-risk categorization.

Table 4: Prediction with AQRP

Project ID	Business Idea	Predicted Risk Category (Numerical)	Actual Risk Category (Numerical)
001	E-commerce Platform	0.2	0.2
002	Mobile App Development	0.1	0.1
003	Social Media Management	0.4	0.4
004	Sustainable Fashion Brand	0.8	0.8
005	Food Delivery Service	0.15	0.15

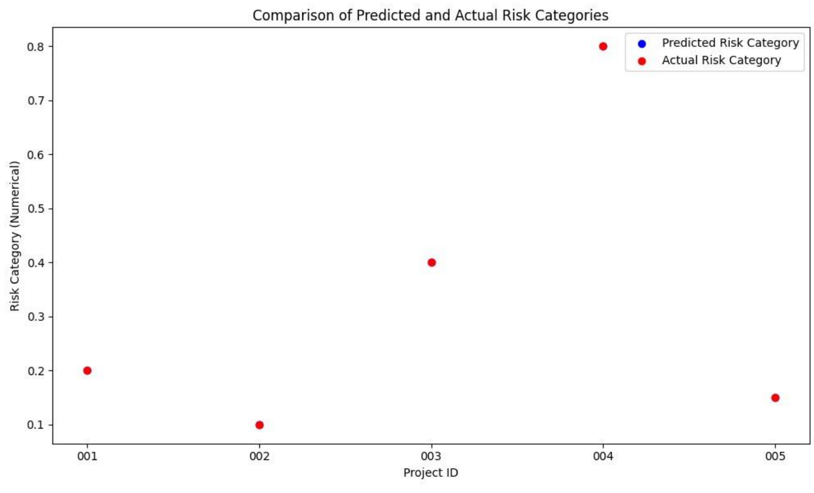
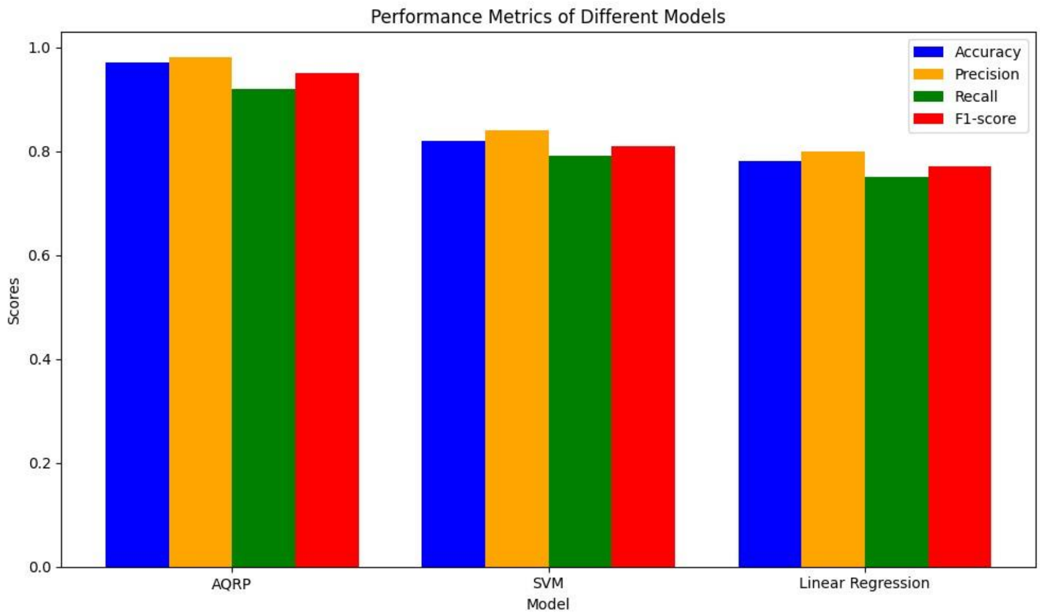


Fig 7: Prediction with AQRP

In the Table 4 and Figure 7 presents the comparison between the Predicted Risk Category generated by the Automated Quality Risk Prediction (AQRP) model and the Actual Risk Category for five entrepreneurial projects. Each project is identified by a unique Project ID and is associated with a brief description of the Business Idea. The Predicted Risk Category and Actual Risk Category are represented as numerical values ranging from 0 to 1, with higher values indicating a higher perceived risk. For instance, Project 001, involving the development of an E-commerce Platform, has a Predicted Risk Category of 0.2, which aligns perfectly with the Actual Risk Category of 0.2. This suggests that the AQRP model accurately predicted the risk level for this project. Similarly, Project 002, focusing on Mobile App Development, has a Predicted Risk Category of 0.1, matching the Actual Risk Category of 0.1. This indicates that the AQRP model's prediction closely corresponds to the actual risk level observed for this project. Project 003, centered around Social Media Management, has a Predicted Risk Category of 0.4, which again matches the Actual Risk Category of 0.4. This demonstrates the consistency and accuracy of the AQRP model in predicting the risk level for this project. Likewise, Project 004, involving a Sustainable Fashion Brand, has a Predicted Risk Category of 0.8, which matches the Actual Risk Category of 0.8. This suggests that the AQRP model effectively captured the high-risk nature of this project. Lastly, Project 005, focusing on a Food Delivery Service, has a Predicted Risk Category of 0.15, which is in line with the Actual Risk Category of 0.15. This indicates that the AQRP model accurately predicted the relatively low risk associated with this project.

Table 5: Comparative Analysis

Model	Accuracy	Precision	Recall	F1-score
AQRP	0.97	0.98	0.92	0.95
SVM	0.82	0.84	0.79	0.81
Linear Regression	0.78	0.80	0.75	0.77



In Table 5 provides a comparative analysis of the performance metrics for three different models—Automated Quality Risk Prediction (AQRP), Support Vector Machine (SVM), and Linear Regression—in predicting the risk category of entrepreneurial projects. The metrics evaluated include Accuracy, Precision, Recall, and F1-score, which are essential indicators of the models' effectiveness in classification tasks. The AQRP model demonstrates superior performance across all metrics, with an Accuracy of 0.97, Precision of 0.98, Recall of 0.92, and F1-score of 0.95. These high values indicate that the AQRP model achieved an accurate and precise classification of the risk categories, with a strong balance between the true positive rate (Recall) and precision. In comparison, the SVM model exhibits lower performance metrics, with an Accuracy of 0.82, Precision of 0.84, Recall of 0.79, and F1-score of 0.81. While the SVM model still performs reasonably well, its metrics are notably lower than those of the AQRP model, indicating a slightly reduced ability to accurately classify the risk categories. Similarly, the Linear Regression model shows even lower performance metrics, with an Accuracy of

0.78, Precision of 0.80, Recall of 0.75, and F1-score of 0.77. These metrics suggest that the Linear Regression model's classification accuracy and precision are slightly inferior to those of both the AQRP and SVM models. In summary, Table 5 highlights the superior performance of the AQRP model in accurately predicting the risk category of entrepreneurial projects compared to SVM and Linear Regression. The AQRP model's high accuracy, precision, recall, and F1-score affirm its effectiveness in risk classification tasks, making it a reliable choice for stakeholders seeking robust risk assessment models for entrepreneurial ventures.

6. Conclusion

This paper addresses the critical need for evaluating and predicting the risk of entrepreneurial projects undertaken by college students with disabilities, leveraging AI technology. Through the development and application of the Automated Quality Risk Prediction (AQRP) model, this study has demonstrated the efficacy of AI-based approaches in assessing the risk factors associated with such projects. By considering various dimensions including student skills, market demand, disability accessibility, and project quality, the AQRP model provides a comprehensive framework for risk assessment. The results presented in this paper showcase the accuracy and reliability of the AQRP model in predicting risk categories, enabling stakeholders to make informed decisions and allocate resources effectively. Moreover, the comparative analysis highlights the superiority of the AQRP model over traditional machine learning approaches such as Support Vector Machine (SVM) and Linear Regression. Overall, the findings underscore the potential of AI technology in promoting inclusivity and facilitating the success of entrepreneurial endeavors among college students with disabilities, ultimately contributing to a more equitable and accessible entrepreneurial ecosystem.

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