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Comprehensive Assessment of Risk Assessment Tools and Academic Performance in Higher Education: A Meta-Analytic Perspective

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Abstract: Even though several researchers have used the Risk assessment theory to investigate the relationship between numerous factors and students at risk of failure, the consequences of previous studies determine different results. The current study is the first comprehensive indicator used to measure the relationships between particular forms of motivation and overall academic accomplishment using a meta-analysis and randomized, longitudinal research. 07 studies were examined in this review after scanning 918 studies extracted from search engines, i.e., Google Scholar. The extracted data was further examined by using PRISMA guidelines. A good association was found between different factors and their impact on students. The articles published from January 2015 to January 2022 were reviewed in this study. Overall, our outcomes highlight the exclusive significance of risk assessment tools for the upcoming academic achievement of higher education institutions. Moreover, the study also discusses the gaps in the previous research, thus introducing a new model to assess students at Risk of failure by assessing many factors and implementing new strategies to resolve the problems.

Keywords: Risk Assessment, At-Risk Students, Assessment Tools, Higher Education, Student Retention, Early Identification, Education Policy, Student Success, Academic Failure, Educational Interventions, Student Performance, Educational Practices, Motivation Factors, Student Engagement, Academic Counseling, Education Models

1. Introduction

Risk assessment is a sophisticated process, and when it is integrated into the operation of an educational organization, it necessitates an assessment of the duties and responsibilities of staff at all levels. Risk management is viewed as a process rather than a system. Specific, persistent promises should be formed when adopting strategic planning in an institution since this process is an inherent aspect of management choices and should not be isolated from them [1].

Even though this student engagement is an increasing issue in all academic institutions worldwide, several steps are taken to determine students who are in danger of dropping out of school

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[2] At-risk students exhibit characteristics such as poor grades or low academic involvement. Several experts claim that identifying at-risk students initially enables appropriate interventions to give required assistance and reduce the likelihood of students dropping out [33]. To reduce the gap between students' academic achievement and student retention rates at higher education institutions, several efforts and tactics have been employed to build the prototypes and increase by redesigning the approaches [4]. Despite this, students have been recognized with emotional and behavioral disorders, absenteeism, and lower grades, demonstrating disinterest in academics and expressing a disconnection from the learning environment due to a variety of factors such as economic hardship, lack of family support and instability, and assistance programs, both minority and privileged youth[5].

The management system of an educational institution to implement the risk assessment model follows the following steps (figure 1)[6].

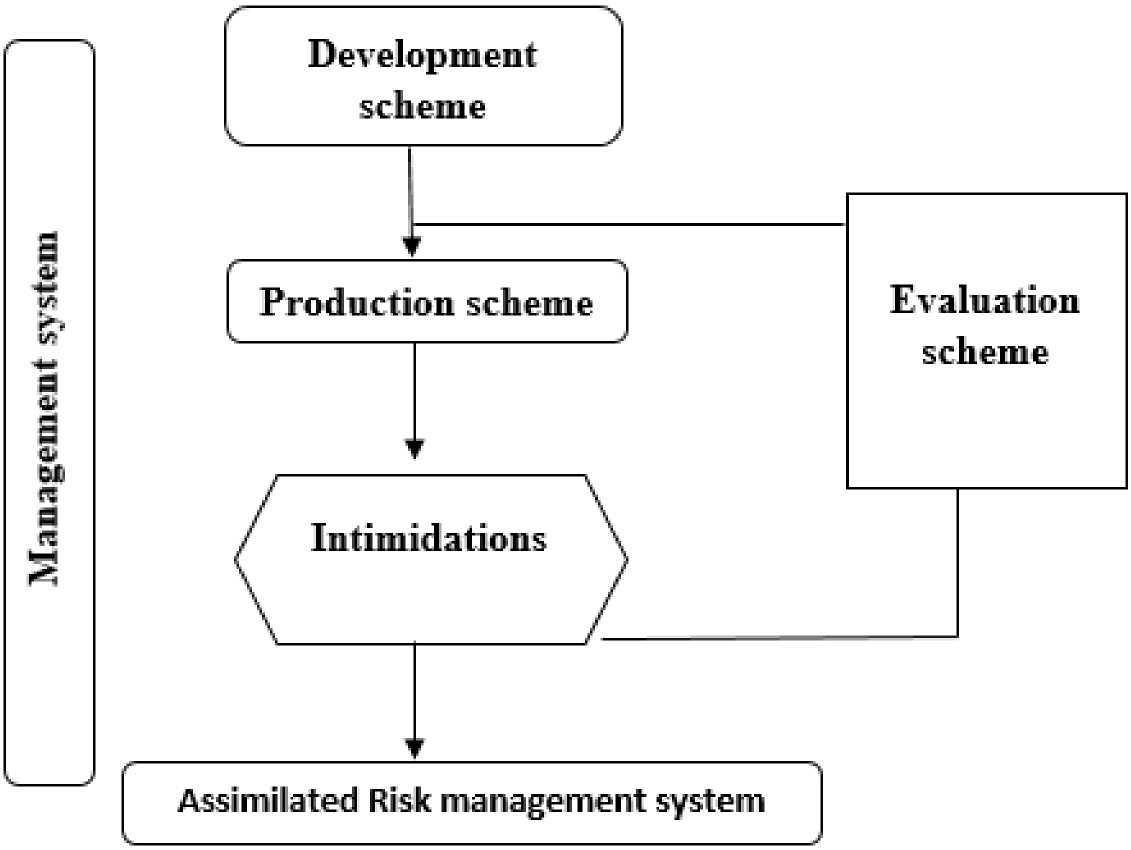

Fig. 1 - Management system of educational system

The flow diagram shows the development scheme, production scheme, and evaluation scheme of a risk management system. The development scheme is responsible for identifying the risks that the system faces. This can be done by conducting a risk assessment, which involves identifying the potential hazards, evaluating the likelihood of their occurrence, and assessing the severity of their consequences. The production scheme is responsible for implementing controls to mitigate the risks identified in the development scheme. These controls can be technical, procedural, or organizational. The evaluation scheme is responsible for monitoring the effectiveness of the controls and making necessary adjustments. This can be done by conducting periodic risk assessments or by responding to incidents as they occur. The main objective of implementing the risk assessment model in higher educational institutions is to certify the competence and efficacy of accomplishments and reduce the dropout ratio of students at Risk. Some objectives of the research are as follows:

- The procedure is conceded out continuously throughout the company, with exceptions made for certain operations.
- The aim is to realize threats related to purposes and protect predictable grades through the execution of the risk assessment model.
- The tactic twitches from the planned objectives rather than operational aims[6].

Risk assessment is a systematic, continuing procedure for determining and analyzing risks in students' academic performance and reporting on challenges and opportunities that may jeopardize the attainment of a student's goals.
The following are some of the advantages of applying the risk assessment model:

- Intellectual development in students[7].
- The risk assessment model helps the students make decisions[8].
- Students can have a greater focus on significant problems[9].
- The student can assess their academic performance, which might be helpful to overcome learning difficulties[10].
- The student can modify their strategic planning for self-evaluation[11].

Here are some factors on which the assessment of students related to their academic career are defined in figure 2[12].

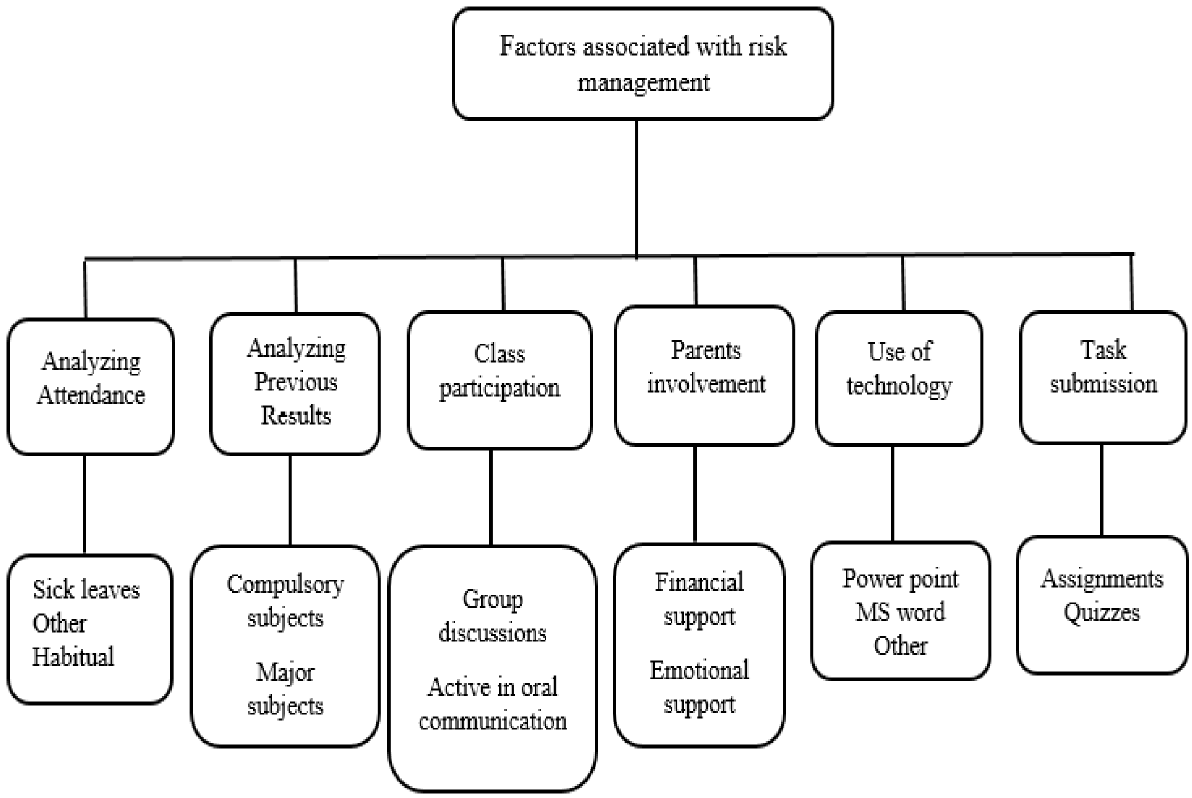

Fig. 2 - Factors associated with the assessment of students

Figure 2 shows the factors associated with the assessment of students related to their academic career. These factors can be divided into two main categories: student factors and assessment factors. Student factors include the following:

- Attendance: This refers to the student's regular attendance in class. Students who attend class regularly are more likely to learn the material and to perform well on assessments.
- Previous results: This refers to the student's past academic performance. Students who have a history of good academic performance are more likely to continue to perform well.
- Compulsory subjects: This refers to the subjects that are required for all students to take. Students who perform well in compulsory subjects are more likely to be successful in their academic career.
- Major subjects: This refers to the subjects that are relevant to the student's chosen major. Students who perform well in major subjects are more likely to succeed in their chosen field.
- Class participation: This refers to the student's active engagement in class discussions and activities. Students who participate actively in class are more likely to learn the material and to perform well on assessments.
- Group discussions: This refers to the student's ability to participate effectively in group discussions. Students who are able to participate effectively in group discussions are more likely to develop their critical thinking and communication skills.
- Active in oral communication: This refers to the student's ability to communicate effectively orally. Students who are able to communicate effectively orally are more likely to be successful in their academic career and in their future careers.
- Parents involvement: This refers to the level of involvement of the student's parents or guardians in their education. Students whose parents are involved in their education are more likely to succeed in school.
- Financial support: This refers to the financial resources available to the student to support their education. Students who have financial support are more likely to be able to afford the costs of education and to focus on their studies.
- Emotional support: This refers to the emotional support available to the student from their family, friends, and teachers. Students who have emotional support are more likely to be able to cope with the challenges of school and to succeed academically.
- Use of technology: This refers to the student's ability to use technology to support their learning. Students who are able to use technology effectively are more likely to be successful in their academic career.

Assessment factors include the following:

- Task submission: This refers to the student's timely submission of assignments and tasks. Students who submit their work on time are more likely to be successful in their academic career.
- Assignments: This refers to the student's performance on assignments and tasks. Students who perform well on assignments and tasks are more likely to be successful in their academic career.
- Quizzes: This refers to the student's performance on quizzes. Students who perform well on quizzes are more likely to be successful in their academic career.

2. Literature Review

Amy Gultice [13] researched developing tools to recognize learners at threat of failure in anatomy and physiology subjects. A substantial rate of failure in primary Colleges science classes, such as anatomy and physiology, is frequent throughout the nation, and pinpointing the particular elements that lead to this problem is complex. Therefore, an online pilot survey was provided to 200 science learners at our open-enrollment college to discover individuals at Risk of failing beginning physiological subjects. The poll's findings indicated various predicted indicators connected to the program of study, prompting a five-year review of the college transcripts of 2,000 biology students. To use this historical data, a model was constructed that was 91% able to predict student achievement in these subjects accurately. The findings of this study back up the use of assessments and other comparable representations to recognize at-risk learners and guide the creation of evidence-based counseling programs and approaches. This coordinated tactic might be a practical step toward enhancing student achievement in anatomy and physiology courses for students from various backgrounds[13].

James Li [14] researched using information from an assortment of tools for the initial identification of medical learners at threat of failure. Suffering medical students are a topic that has received little attention in medical education. Nevertheless, it is well understood that timely screening is helpful for a successful repair. The report's goal was to see if medical school admission methods could forecast whether or not a student would struggle academically.

A total of 700 learners from the University of New South Wales' undergraduate medical program were included in the study. The significant result of interest was whether these students battled during the 6-year program; they were classed as struggling if they failed any end-of-phase exams but still graduated. Discriminate Function Analysis (DFA) was used to see if their pre-admission academic performance, Undergraduate Medicine Admission Test (UMAT), and interview scores had any bearing on their chance to struggle. Lesser pre-admission formative assessment, as measured by the Australian Tertiary Admission Rank (ATAR) or Grade Point Average (GPA), was a significant predictor of whether or not a student will struggle. Lower UMAT and interview scores were found to have a substantially lesser predictive effect than higher UMAT and interview scores. Despite the widespread usage of medical entrance examinations, medical schools seldom use the data for teaching reasons. According to the findings of this study, entrance exam data can identify who among admitted students will struggle in the program. This knowledge is priceless in terms of education. These findings suggest that academic achievement before admission may predict which students will struggle in an Australian undergraduate medicine program. There is a need for more study into anticipating various categories of challenging pupils and remedial strategies [14].

Nick Z. Zacharis [15] researched “multivariate approach to predicting student outcomes in web-enabled blended learning courses.” The focus of this research was to create a viable model for predicting students who are at risk of failing blended learning courses. According to a previous study, evaluating the user data saved in the log files of current Learning Management Systems (LMSs) might help teachers generate timely, evidence-based interventions for at-risk or struggling learners. This study aimed to find a significant connection between multiple online activities and course grades by analyzing students' tracking data from a Moodle LMS-supported blended learning course. Only four factors – Reading and posting messages, Content production participation, Quiz attempts, and Number of documents seen – forecasted 52 percent of the variation in the final learner grade out of 29 LMS usage variables determined to be relevant [15].

Muluken Alemu Yehuala [16] researched the “Application of Data Mining Techniques for Student Success and Failure Prediction.” The possible use of data mining technology to forecast student success and failure cases using datasets from University students was studied in this study. The research will employ the CRISP-DM (Cross Industry Standard Process for Data Mining) data mining approach. Data mining functions such as classification and prediction are applied to uncover hidden patterns from students' data. These patterns may be found in connection to many factors in the records of the pupils. The classification rules were developed using Bayes's decision tree as a classification approach, and the results were reviewed and appraised. Information was retrieved from MS EXCEL files and preprocessed for model construction. A sample dataset of 11,873 regular undergraduate students was used to build and test models. WEKA 3.7 application software is used to do the analysis. The study's findings provide academic planners at higher education institutions with valuable and constructive advice for improving their decision-making processes. This will also assist in the structuring and customization of the curriculum in order to improve student academic performance. Furthermore, students can choose their study area before enrolling in a specific field of study based on experience and scientific reports. As a result of the research outcomes, student achievement will grow, and academic institutions will be able to avoid significant financial difficulties[16]

Evandro B.Costa [17] researched “Evaluating the effectiveness of educational data mining techniques for early prediction of students' academic failure in introductory programming courses.” Numerous educators have been alarmed by data concerning high student failure rates in introductory programming courses, which has raised several critical issues about prediction characteristics. This paper proposes comparative research on the use of educational data mining tools to predict students who are likely to fail basic programming courses.

Although other studies have looked at these approaches for identifying students' academic failures, ours differs from them in the following ways: (i) We examine the successfulness of such methods in identifying students who are likely to fail at a sooner enough phase to take initiatives to minimize the failure rate; (ii) We examine the impact of data preprocessing and algorithm fine-tuning tasks on the effectiveness of the techniques mentioned above. In this research, we compared the effectiveness of four prediction techniques on two different and independent data sources from two distinct and independent information sources on introductory programming courses offered by a Brazilian public university: one from distance education and the other from on-campus. The findings revealed that the techniques examined in this study are capable of identifying students who are likely to fail early on, that the effectiveness of some of these techniques is improved after data preparation or algorithm fine-tuning, and that the support vector machine method outperforms the others statistically significantly [17].

Samuel P. M. Choi [18] researched “At-risk student prediction with clicker data and systematic, proactive interventions.” While learning analytics (LA) approaches have been proved to be valuable and successful, most of them need a significant quantity of data and time. This paper presents a case study that illustrates the possibility of using LA to detect at-risk students in an undergraduate business quantitative techniques course at a reasonable cost to teachers. Instead of using tracking data from a learning management system as significant predictors, this study employed clicker replies as formative evaluations and student statistical characteristics and learning outcomes. This Los Angeles startup uses free cloud services, notably Online Surveys and Google Documents, to gather and analyze clicker data. Despite working with limited data, the LA application effectively determined at-risk students early. In addition, a systematic, proactive advising method is presented as an intervention option based on learners' at-risk likelihood predicted by a prediction model. The findings reveal that the success rate of interventions rises in proportion to the number of interventions and that intervention impacts on peer groups are significantly more effective than on individual students. Overall, the students' study pass percentage was 7% higher than the overall course pass rate [18].

Albreiki [19], in her study “Customized Rule-Based Model to Identify At-Risk Students and Propose Rational Remedial Actions,” Student acceptance rates, successful enrollment administration, alumni involvement, focused marketing enhancement, and organizational performance advancement all benefit from identifying at-risk students. Earlier detection and prioritizing of students in need of support is one of the successful determinants of educational institutions. The primary goal of this study is to identify at-risk pupils as early as feasible so that suitable corrective actions may be taken, taking into account the most essential and relevant characteristics of students' data. Using the Risk Flag, this article stresses using a customized rule-based system (RBS) to detect and visualize at-risk students early in the course delivery (RF). Furthermore, teachers can use it as a warning tool to identify students who may have difficulty grasping educational objectives. The teacher can use the module to create a dashboard that defines the frequency of the students' results in specific coursework elements. The student in danger will be identified (flagged), and corrective steps will be conveyed to the individual, teacher, and other stakeholders. The algorithm recommends corrective activities depending on the level of the situation and the duration of time the kid has been marked. It is projected to boost student accomplishment and accomplishment and have good consequences for underperforming individuals, instructors, and higher education institutions in general [19].

3. Methodology

In this research paper, we conducted a systematic review adhering to the PRISMA-P guidelines, as outlined by Page [20]. The utilization of these guidelines reflects our commitment to a rigorous and transparent methodology, ensuring the reliability and validity of our review process. Systematic reviews are a cornerstone of evidence-based research, aiming to comprehensively synthesize existing literature on a specific topic or research question. By adhering to established guidelines such as PRISMA-P (Preferred Reporting Items for Systematic review and Meta-Analysis Protocols), we enhance the rigor and transparency of our review, thereby strengthening the credibility of our findings, [21].

PRISMA-P, an extension of the PRISMA statement, offers a structured framework for protocol development in systematic reviews. It assists researchers in defining the research question, specifying inclusion and exclusion criteria, designing the search strategy, and planning data extraction and synthesis, [21]. Following these guidelines ensures that our review process is systematic, replicable, and minimizes bias. The decision to implement PRISMA-P in our systematic review signifies our methodological rigor [20].

We meticulously followed each step of the protocol, beginning with the formulation of our research question, followed by the development of a detailed review protocol that outlined our search strategy, eligibility criteria, and methods for data extraction and synthesis , [22].Adhering to PRISMA-P enables us to provide readers with a clear and comprehensive account of our research process, enhancing the transparency and reproducibility of our work , [22].Furthermore, the use of PRISMA-P demonstrates our commitment to adhering to best practices in systematic review methodology. By referencing the work of Page [20], we acknowledge the evolving nature of systematic review guidelines and the need to stay current with the latest methodological advancements in the field, [21]. In conclusion, the implementation of PRISMA-P guidelines in our systematic review underscores our dedication to a methodologically sound and transparent research process, [22]. This adherence ensures that our findings are robust, credible, and can inform evidence-based decision-making in our area of study.

3.1.Literature searching criteria

For a comprehensive systematic review and to sort the relevant data according to the area of research, search engines are used, such as (Google Scholar, and Research gate) with special filters that search articles from (2015 – to 2021). In addition, numerous keywords linked to the review were utilized, including (Assessment tools, At-risk students, Students failure ratio, and Variables that affect education).The keywords used in the study are shown below in Table 1.

Table 1 - Search Framework

Search framework	Keywords
Strategies	Risk scoring tools, techniques for earlier prediction, students at Risk.
Academic self-efficacy	Students' academic performance, self-esteem, academic stress.
Risk assessment	Analyzing attendance, analyzing previous results, class participation, use of technology, and task submission.

3.2.Exclusion and inclusion criteria

The bulk of current research articles on our subject were inclusive. To acquire high-quality research, journals with a high impact factor were selected. Publications were to be

(1) Written in the native language or English,

(2) On risk assessment,

(3) Published in peer-reviewed journals between January 2015 and January 2022,

(4) Have a prospective cohort design.

We looked at research that employed accurate and timely data. We only kept studies published in peer-reviewed journals, omitting conference papers and dissertations that used data from the same sample in several publications. Data on the year of publication, geography, and setting, characteristics of research participants, risk assessment, and academic effect were all collected using a standard form. Each experiment's papers were evaluated for consistency, and any discrepancies were resolved by discussion with other researchers.

Fig. 3 - Research design

4. Results

4.1.Study collection

Using several databases, 1158 studies were retrieved. First, the papers with duplicate data studies (n=240) were eliminated. Then, full articles were obtained and screened based on eligibility criteria after the abstracts and titles were examined to sort the relevant themes. Full articles were obtained and screened if the abstracts and titles offered adequate information based on eligibility criteria. In addition, owing to inaccessibility and eligibility rules, they were excluded and not recovered. As indicated in the flow diagram in Figure 4, several reviews (n=59) were successfully obtained, and a total of (n=07) articles were included as part of this review.

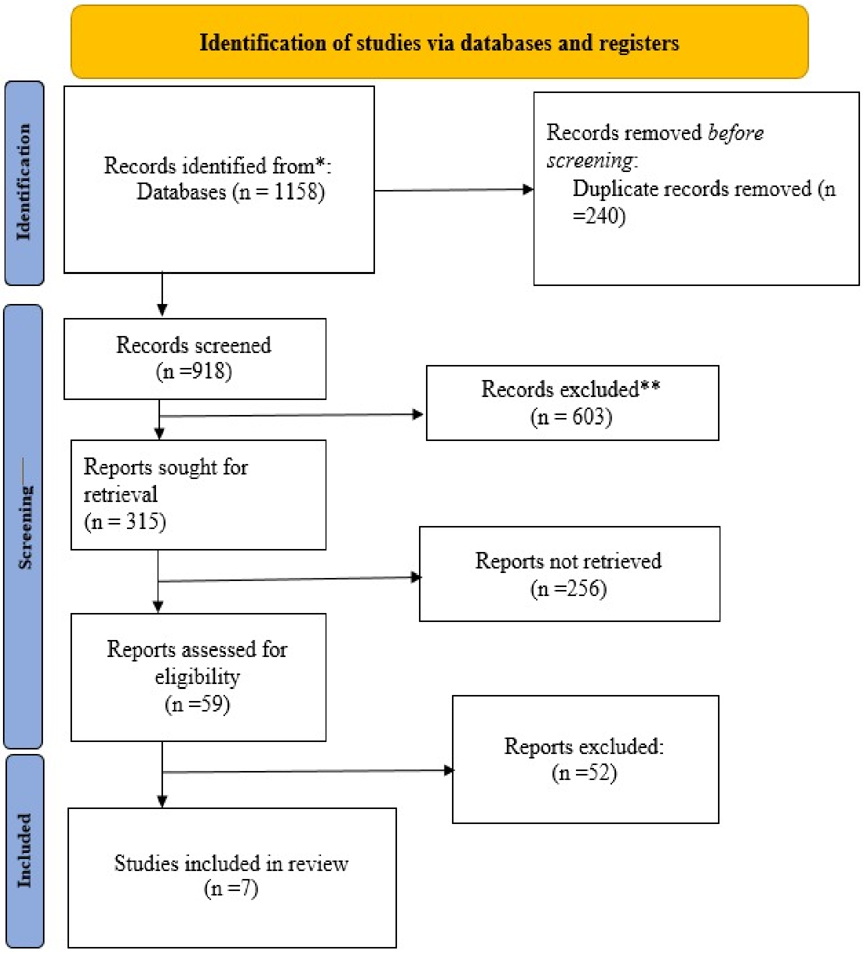

Fig. 4 – The PRISMA flow diagram

*4.2.*The study included in the review

After extensive analysis and discussion, 07 papers were chosen as the best candidates to examine academic assessment techniques and risk assessment. Between 2015 and 2022, the research was published. The papers examined throughout the research included not just those on evaluation tools but also those on other topics. In addition, every other study and review included in the analysis found a link between academic achievement and at-risk students.

5. Discussion

The overall purpose of this research was to uncover potential confounder's trends that correlate to student failure. Early detection of students at risk of academic failure is critical to increasing undergraduate retention and is a challenging assignment for any higher learning institution. Withdrawal by students is a multifaceted and complicated phenomenon that may be seen from various approaches and perspectives. Numerous factors determine the rate of failure at multiple phases, with the most important being student background characteristics, teaching and learning methodologies, and interrelationships. The Early Identification At-Risk Model helps identify students of an academic institution who have a high probability of dropping or getting academically dismissed due to the inability to maintain the minimum required GPA. This method revealed pupils at Risk; each group is distinguished by a unique set of variables and a varied propensity, as discussed in several studies in our review, yet found many advantages and disadvantages in the study Table 2.

Table 2 - Positive and Negative aspects of the previous studies

AUTHOR	TOPIC	POSITIVE ASPECTS	NEGATIVE ASPECTS
Gultice [13]	"Are your students ready for anatomy and physiology? Developing tools to identify students at Risk for failure"	The sample size for thestudy is appropriate.	• Cateredonlybiology students. • Fewer factors were involved (Age and GPA).
Thompson [14]	"Struggling with strugglers: using data from selection tools for early identification of medical students at risk of failure"	• GPA was one of the effective parameters. • Many tools are used in the study, yet finding the ATAR technique is more effective as compared to UMAT. • Categorize their study in 3 phases. • Study based on 3 phases which will be effective in-depth learning.	• Only struggling students were involved in the study that showed stereotype failing students. • Limited to Australian data, hence may not be applicable globally • Limited to the study of medical students.
Zacharis [15]	"A multivariate approach to predicting student outcomes in web-enabled blended learning courses"	• The study is applicable in a recent situation as it is based on a comparison of physical and online studies. • The socially constructive theory is effective to assess students at Risk. • Used LMS as a means of conducting lectures, providing notes and assignments.	• Catered only to programming students. • 134 universities are included in the research that making it a diverse study.
Yehuala [16]	"Application of data mining techniques for student success and failure prediction".	Work on 10 variables. WEKA software used.	Only 1 data mining software that gives a linear approach and doesn't define the reasons. Mainly focus on health and financial issues rather than academic issues.
Costa [17]	"Evaluating the effectiveness of educational data mining techniques for early prediction of students' academic failure in introductory programming courses".	• This approach is similar to the new model EIARM.	• Catered only programming course. • Limited only to Brazilian university.
Alberiki [19]	"Customized Rule-Based Model to Identify At-Risk Students and Propose Rational Remedial Actions. Big Data and Cognitive Computing"	• Evaluate social and economic factors. • This approach is similar to the new model EIARM.	• Computer-generated data that didn't evaluate the actual experiences of students.

6. Limitations

One of the limitations of the study was the sample size. Therefore, the data is insufficient to derivate the entire assessment tools regardless of multiple cohort studies. In addition, the study collected and reviewed in this systematic review were only in English due to the language barriers and open access to every audience. Nevertheless, the study can be assessed in the future with a diverse pool of data, and in-depth quantitative or mixed-method analysis can be carried out on different variables. In addition, there is a good possibility that data hidden in other languages possess information more innovative for this cohort study.

7. Research Gap

The survey's original purpose was to create a tool that could detect students who were in danger of failing early in the semester and help them. Moreover, we analyze some gaps that will be the potential cause for not relying on one study. Therefore, we proposed the EIARM model used to identify students at risk of failure early. This model assesses the students at various factors, especially the GPA of those students who are struggling in their academic careers, and provides the solutions and how to overcome the situation Table 3.

Table 3 - EIARM model

Primary Indicators: 60%	**Weightage**
Previous Semester GPA between 2.3-2.0	25%
Midterm failed	25%
Program duration: exceeded 5 years	25%
Dropped or withdrawn from a course	25%
Seconday Indicators: 40%	**Weightage**
Program Duration: Exceeded 4 years	30%
Current semester course absence reaches 15%	30%
Repeating a course	10%
Financial Aid Student	10%
Special needs Students	10%
Non- academic Issues reported	10%

This model uses two approaches, i.e., ERP & TAR. This model works in four stages. Stage 1 (watch list) is applicable when the score is greater than 50, stage 2 (Academic warning) when the semester GPA is less than 2.0 or cumulative GPA is greater than or equal to 2.0, stages 3 & 4 (Academic probation 1 & 2) works on cumulative GPA is less than 2.0 (Figure 5) and (Table 4).

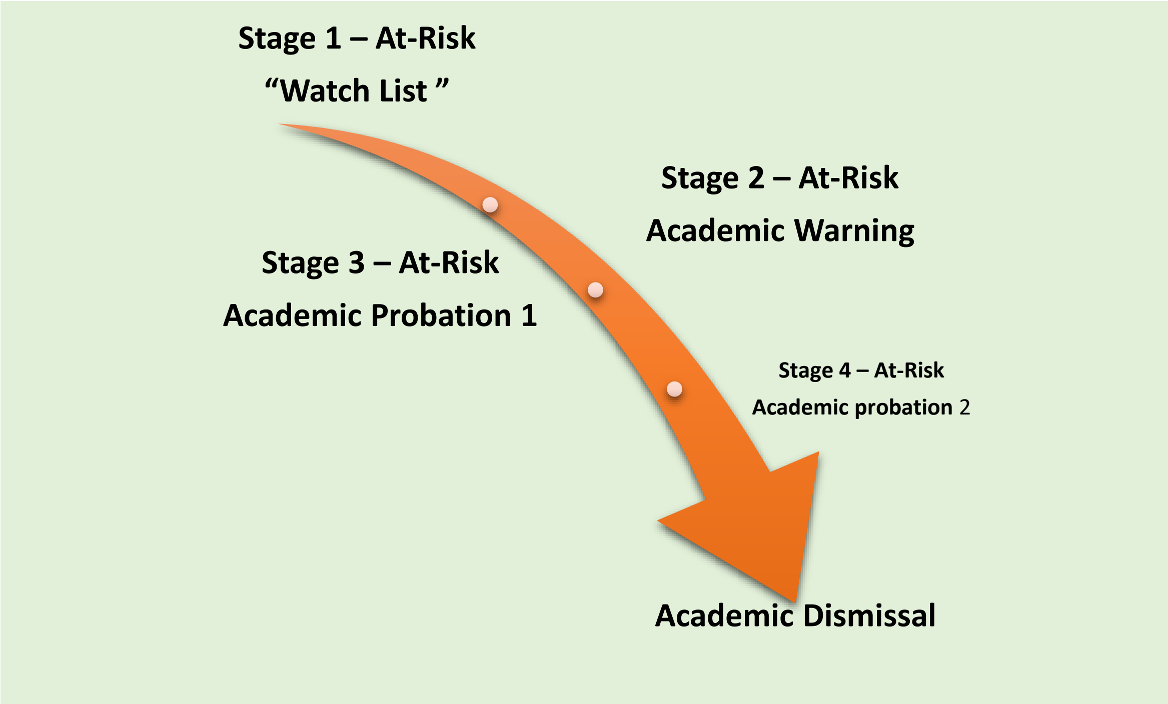

Fig. 5 - Stages of at-risk students

Table 5 - Criteria of student performance at each stage.

At-Risk Stages	Conditions	Academic Standing	Stakeholders
Stage 1	Level 1 parameters score greater than 50%	Watch List	Academic Advisor + Student Counselor + Course Faculty
Stage 2	Semester GPA less than 2.0 and Cumulative GPA greater than or equal to 2.0	Academic Warning	In addition to above Program chair
Stage 3	Cumulative GPA less than 2.0	Academic Probation 1	In addition to above Dean of Academics
Stage 4	Cumulative GPA less than 2.0	Academic Probation 2	In addition to above College Council

The model is proposed based on some research questions:
The research questions focus on measuring the accuracy and efficiency of the proposed EIARM

- How many of the projected students have been placed on probation or dismissed from school?
- Are there any students placed on probation or academic dismissal whom the model does not recognize?
- Has the individualized intervention plan for recognized at-risk students worked to enhance or stabilize their deteriorating grades?

Determinants of assessment tools were shown to have a positive relationship in the studied data. Other variables connected with the assessment tool and academics can be explored and worked on in the future to improve the protective strategies.

8. Conclusion

In conclusion, this research has undertaken a comprehensive examination of assessment tools and their critical role in the context of educational practices, policies, and existing literature. The primary objective of this study was to contribute to the enhancement of educational practices and policies by evaluating the effectiveness of assessment tools in identifying at-risk students and devising appropriate interventions. Through an exhaustive systematic review adhering to PRISMA-P guidelines, the study has achieved its intended goal and offers valuable insights into the multifaceted aspects of academic assessment and its impact on students' academic performance.

One of the key contributions of this research lies in its emphasis on early identification and support for at-risk students. By synthesizing a diverse range of studies from various educational contexts, this study underscores the significance of assessment tools in predicting and mitigating academic failure. The proposed Early Identification At-Risk Model (EIARM) presents a novel approach to addressing the challenges associated with student retention and performance. Moreover, this research provides an extensive literature review that highlights the ongoing efforts in the field of education to identify and support at-risk students. The discussions on various assessment techniques and predictive models, as evidenced in the literature, provide valuable reference points for educators, policymakers, and researchers alike. Furthermore, the limitations identified in this study open avenues for future research. The language and sample size constraints suggest the potential for expanding this research to encompass a more diverse set of data, including non-English sources, and larger cohorts. Future studies could explore additional variables and factors that contribute to student success or failure, thereby enriching the existing knowledge base in the field of education. In terms of practical implications, the EIARM model introduces a promising framework for educational institutions to proactively identify and support at-risk students. This model aligns with the broader objectives of enhancing student retention rates and academic achievement. Education administrators and policymakers may find the EIARM model valuable for formulating strategies aimed at improving student outcomes.

In conclusion, this research underscores the pivotal role of assessment tools in the realm of education, shedding light on their potential to aid in the early identification of at-risk students and the development of targeted interventions. By offering a systematic synthesis of existing literature and proposing a novel model, this study contributes to the ongoing discourse in education, fostering a more comprehensive understanding of how academic assessment can shape the academic journey of students. As education continues to evolve, future research endeavors may explore the intricacies of assessment tools further, broadening our understanding of their multifaceted impact on educational practices, policies, and student success.

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