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Systematic review

Exploration and evaluation of the tools used to identify first year at-risk students in health science courses: A systematic review

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ABSTRACT

Objectives: High attrition rate in first year health science courses including allied health is a common problem in the higher education sector. This systematic review aims to explore the tools used by educators in identifying first year, at-risk students studying health science courses within higher education. The review identifies the tools and investigates their effectiveness in identifying at-risk students.

Methods: A mixed-methods systematic review of original research was undertaken exploring the tools used or developed for identification of the at-risk health science students in their first year of study. Following databases were searched: Academic OneFile, CINAHL PLUS, ERIC, ScienceDirect and Google Scholar.

Results: Collectively, the included studies (n = 13) revealed that a combination of both academic and non-academic factors are most effective in identifying at-risk students. All 13 identified studies developed tools based on one or more of the following three categories: those examining the personal background, academic preparedness and the student perceptions of their own abilities and readiness.

Conclusion: With students enrolling into health science courses coming from various diverse academic and personal backgrounds, the tools identified in this systematic review could enhance early identification of at-risk students, thereby enabling educational institutions to take timely educational interventions to support them.

What is already known about the topic?

- High attrition rate in first year health professional courses including allied health and Complementary Medicine is a common problem in the higher education sector.
- Previous research has identified various factors that influence student attrition and academic performance.
- Non-traditional students have increased risk for attrition. Non-traditional students are students who are older, students entering into college with varying degrees of academic aptitude, students who have multiple stressors, financial strain, employment constraints, and familial responsibilities [1].
- Early identification of at-risk students is essential to implement timely interventions to promote academic success.
- Development of tools for identification of first year at-risk students has been addressed by several studies.

What this paper adds

- Evaluation of all the tools found in the studies and used in educational institutions to identify first year at-risk students.
- Relevance of academic and non-academic factors to student success.
- Findings from qualitative and quantitative analysis of the included studies.
- Efficiency of the tools in identifying at-risk students and predicting student attrition.

1. Introduction

Student attrition has become one of the most challenging problems for higher education institutions [2]. This is highly pronounced within health science courses where high failure rates in introductory college science subjects, including anatomy and physiology, are a common occurrence [3]. On average, attrition rates have been reported to be 50% for students enrolled in

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baccalaureate nursing programs and 47% for students enrolled in associate degree nursing programs [1]. Similar findings are reported across other health degrees such as physiotherapy, medical education, and allied health courses [4–6]. Most studies have identified that student withdrawal and/or failure occurs during the first year of enrolment [6–8].

Also, there is growing awareness about Complementary Medicine (CM) in Australia with many students enrolling in CM degrees. CM along with other health science degrees require anatomy and physiology as well as other basic health sciences as their foundation subjects The students enrolling into these degree courses come from diverse backgrounds and have varying academic levels, but the entry into these degrees often does not require prerequisite college-level courses or entrance exams [3]. Many students would therefore begin their journey lacking the basic writing, math, science, and study skills. Additionally, non-traditional students have been enrolling into the health science courses and these students have been identified as having an increased risk for attrition [1].

Studies investigating the role of various factors influencing poor academic outcomes and student attrition have also highlighted the importance of preventing student attrition by early identification of at-risk students [3,9]. The significance of early identification motivated the development of effective tools or instruments to identify at-risk students at an early stage. The aim of this review is to identify these tools and explore their effectiveness, benefits and limitations in identifying first year students at-risk of failure. Furthermore, the review aims to provide a system for identifying students who are at risk of academic failure.

2. Methodology

The protocol for this systematic review was developed using preferred reporting items for systematic reviews and meta-analyses (PRISMA-P) statement [10].

2.1. Search strategies and inclusion criteria

Studies were identified using the following electronic databases: Academic OneFile, CINAHL PLUS, ERIC, ScienceDirect and Google Scholar. The following keywords were used in various combinations: at risk students, first year, retention, college freshmen, college students, higher education, retention and attrition. EndNote referencing software was used for data management.

This review included studies that reported on health science students in their first year of study, and the tools used to investigate their risk of attrition. Studies were also included from larger universities that reported on first year students' at-risk prediction. Only full text articles from peer reviewed journals were used for the purpose of this paper. Studies were excluded if they were not original research and if they did not address first year students.

2.2. Study selection and data extraction process

Both qualitative and quantitative studies were included in this review. The following items were included in the data extraction table: author name, tool used, course name, cohort size, efficiency identified, strategies identified, benefits/limitations, and reliability/validity values.

2.3. Data synthesis

As the review is a mixed-methods systematic review, the synthesis methods used in the review are mixed. The review includes studies with different research designs. A variety of tools have been identified in the review. Quantitative results provide information on the type of tool used and the variables included within each tool. Qualitative analysis of the findings were deductively categorized under the categories of 'personal background', 'academic preparedness' and 'student perceptions'. Thus, the qualitative findings contribute to the interpretation of quantitative results.

2.4. Critical appraisal

To facilitate the assessment of possible risk of bias for each study, information was collected using the 2011 Mixed Methods Appraisal Tool (MMAT) checklist [11]. This tool was selected as the systematic review included mixed study reviews and the MMAT tool allows appraisal for all study designs, including mixed methods research designs.

3. Results

Using the described methodology, the current review identified 13 relevant papers of which 5 were mixed methods studies and 8 were quantitative studies (see Fig. 1). The participants belonged to first year cohorts and the courses included nursing, health, science, biology, psychology, dentistry, medicine, and biomedical sciences.

Information on risk of bias was extracted for individual studies. The methodological quality criteria for quantitative non-randomized, quantitative descriptive and mixed methods study was applied based on the type of individual study. Articles were screened for information on relevance of the research design to the objective of the study, integration of qualitative and quantitative data relevant to the objective, limitations associated with this integration, process of randomization, participation selection process, and outcome data. Each component received a response of either 'yes', 'no' or 'can't tell' with appropriate rationale. Studies that received two or more 'no' responses were considered moderate risk. Studies that received two or more 'yes' responses were considered low risk. Appraisal with MMAT tool indicated low level of bias for 12 studies [12–23] and moderate level of bias for one study [24].

Considering the objectives of the review, the following outcomes have been identified:

3.1. Tool identification

Overall, most of the tools developed in the chosen studies were based on the following information: student perceptions [20], student entrance scores and readiness assessment score [14], attendance data [15], studying inventory information [21], data mining methods [16], college student expectations questionnaire [17], and historical data [18]. Two studies also utilised personal background preparation survey [19,22]. The 13 studies included in the review were subjected to a process of group analysis. All the variables were classified into groups containing either academic or non-academic factors with most of the tools using a combination of factors from both groups to identify at-risk students. These factors were encompassed within three broad categories: personal background, academic preparedness and student perceptions. 'Personal background' encompasses all information regarding personal aspects of the students that are known to influence academic performance. 'Academic preparedness' captures academic pre-entry information that could influence current performance. 'Student perceptions' gathers information on individual students' attitudes towards learning and achievement.

These three broad categories formed a theoretical framework for identifying students at risk. Therefore, all 13 identified studies

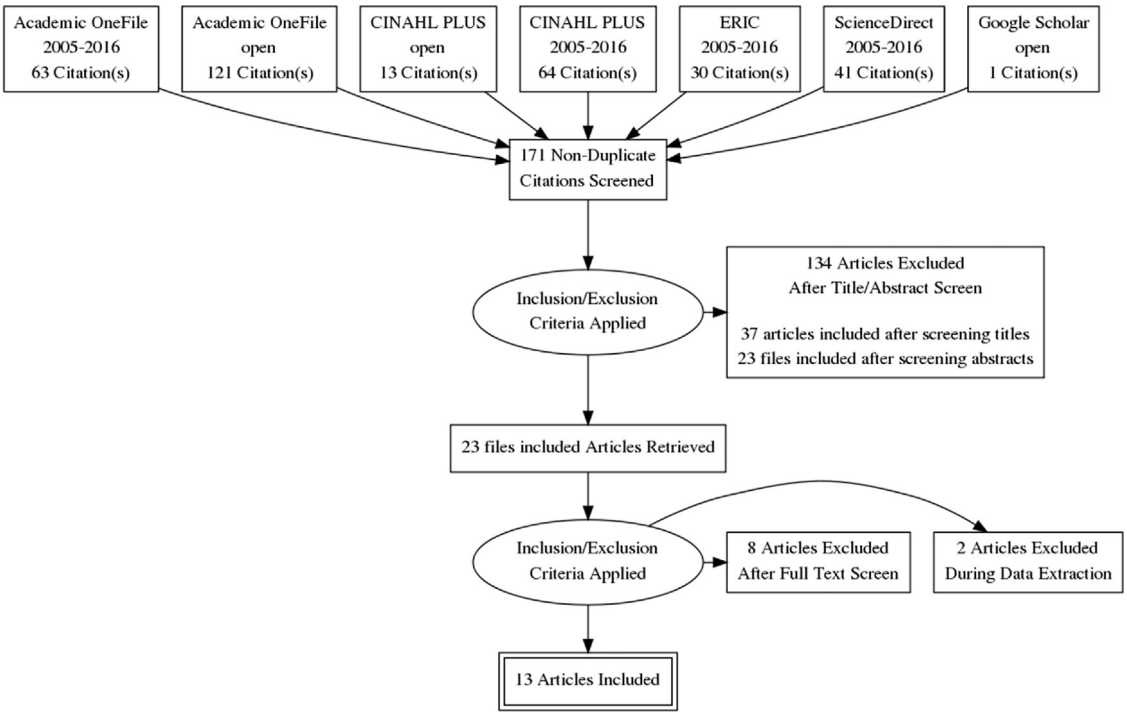

Fig. 1. PRISMA flowchart.

developed tools based on one or more of the following three categories: those examining the personal background, academic preparedness and the student perceptions of their own abilities and readiness. The descriptive items in the tools capture one or more of the above categories (see Table 1). Thus, the tools were developed not only from an educator and institutional perspective, but also from a student perspective. The quantitative findings revealed the strength of the evidence and the qualitative findings captured broad areas of risk category.

3.2. Evaluations of the tool effectiveness, benefit and limitations

The studies have clearly described the reliability and validity of the tools used (Table 2). Four studies showed Cronbach's α for the tools between 0.71 and 0.83 [12,19,21,23], while predictive validity of variables was identified to be ($p < 0.05$) for nine studies [12–15,19,20,22–24]. Therefore, the tools were effective in identifying students at-risk of failure, withdrawal or non-completion. Furthermore, the sample size for each study is significant enough to produce strong evidence.

In terms of benefits and limitations, the Johnson et al. study showed that the Personal Background Preparation Survey (PBPS) tool was useful in identifying cognitive and non-cognitive risks [19]. The authors believe that non-cognitive variables had a marked influence on non-traditional students' academic achievement and retention more than academic variables. PBPS tool produced an individualised report that presented the student's identified risks and prescribed intervention strategies to ameliorate the identified risks. Therefore, the tool served as a diagnostic and prescriptive instrument that facilitated early identification of nursing students at risk for adverse academic student outcomes. Besides this study, there was another study which, similar to PBPS tool, identified students at risk and at the same time prescribed individual advice on study strategies [21].

Some studies ($n = 6$) used institutional and/or historical data as a tool to identify students at-risk [13,14,16–18,23]. Such data was

Table 1
List of variables under each category.

Personal background	Academic preparedness	Student perceptions
• Student demographic data • Personal circumstances • Financial situation • Social support • Personal commitments • Work schedule • Time management skills • Attendance data • Study strategies	• Pre-entry scores • Pre-entry qualifications • Test scores • Reading comprehension scores • Anatomy and physiology grade • High school preparation for science details • Prior academic performance, Math performance • GPA score • Academic performance data • Standardized test scores • Course details • Readiness assessment	• Students' self-efficacy • Self-confidence • Motivation • Long range goals • Social identity • Personal feelings • Attitudes • Study strategies on deep approach, surface approach, strategic approach, apathetic approach and academic aptitude • Personal expectations • Professional identity
Nine studies [12,13,15,17,18,19,20,22,24] covered information on these variables	Eight studies [13,14,16,17,19,20,22,24] developed tools utilizing variables across this category.	Eight studies [12,13,19–24] covered information on these variables.

Table 2
Summary table of data extracted from the included studies.

Author (year)	Tool used	Course or degree	cohort size- at start	Efficiency identified/ measured	Strategy identified	Benefits and limitations	Reliability/Validity	Bias
Johnson et al. [19]	Personal Background Preparation Survey	Nursing students	187- 2004 cohort 188- 2005 cohort	Yes The diagnostic and prescriptive instrument facilitated early identification of nursing students at risk for AASE.	Academic and study skill, tutorial assistance, academic counselling and reassurance depending on the category identified.	Benefit: Identifies non-cognitive and cognitive risks.	$\alpha = 0.77$ for 2004 PBPS $\alpha = 0.71$ for 2005 PBPS Validity ($p < 0.05$)	Low
Walker et al. [20]	Nursing Student Survey I Nursing Student Survey II Student Perception Appraisal 1 Self-Efficacy Scale	Nursing program	898 students from across nine campuses in East Texas	Yes. The investigative study identified students on track, off track, or out of nursing program	Personal solutions modules, study aid modules, and course lifelines	Predictive variables helped in modifying at risk definitions	Lack of reading comprehension ($P < .0001$). Entrance examination composite scores ($P = .0271$). Anatomy and physiology grades ($P = .005$)	Low
Pearson and Naug [14]	Student OP score and readiness assessment (week one quiz). Readiness assessment was in the form of a quiz that was given in week one and consisted of 16 math questions at a Year 10-12 level on scientific notation, conversions, algebra, and quadratic equations	Health programs	941 students enrolled in at least one of the first semester courses at Griffith University	Of the students identified as at-risk, 25% based on OP, while 95% based on quiz score.	Essentials workshops ran from weeks 2 to 7 covering biology or math and academic skills	Benefits of identifying first year students as at-risk at a very early phase ie week 1	OP and quiz scores: $p = 2 \times 10^{-27}$ and quiz result: $p = 8 \times 10^{-20}$	Low
McCluckie [15]	Receiver Operating Characteristics (ROC) analysis of attendance data	First year undergraduate Science students	2007/2008 first year students. Total no not mentioned	Identify students at-risk by week seven.	Did mention advice and support being offered to students at-risk	ROC analysis uses discrimination threshold that is the point at which the test result goes from one outcome to the other (e.g. Negative to positive)	The Chi square statistical data shows: $P < 0.005$ for at-risk students were less likely to progress and $P < 0.005$ for at-risk students less likely to continue	Low
Tait and Entwistle [21]	Approaches to Studying Inventory	First year students from biology, psychology	640 students	Identified students with weak study strategies	Computer-based advice on study skills within HyperCard system	Allows identification of at-risk students through interactive ways on computer	α = between 0.77 and 0.83 indicates homogeneity of items- an internal reliability measure	Low
Delen, D. [16]	Data mining methods: Artificial neutral networks (ANN), decision trees, and logistic regression	Course/s not mentioned in the study	25, 224 students enrolled as freshmen from 1999 to 2006	Attrition Prediction rate: 80% accuracy	Authors suggest institutions choosing to enroll more academically successful students, monitoring academic experience of freshmen students in their first semester through looking at combination of GPA and the ratio of completed hours over enrolled hours	Because ANN and decision trees used in data mining methods are capable of modeling highly nonlinear relationships, they are more appropriate techniques to predict the complex nature of student attrition with a high level of accuracy Limitation: the tool aims to predict attrition (students at risk) using institutional data	10-fold cross validation process is used to minimize bias associated with random sampling of the training and testing data samples and determining predictive accuracy	Low Low

Table 2 (*Continued*)

Author (year)	Tool used	Course or degree	cohort size- at start	Efficiency identified/ measured	Strategy identified	Benefits and limitations	Reliability/Validity	Bias
Miller, T. E. [17]	College Student Expectations Questionnaire supplemented with demographic information, academic performance data, standardized test scores. Pre-matriculation characteristics of entering new students used	Course program not listed	3998 students (First time in College) who entered University of South Florida in fall 2006	The persistence rate of students in the study who were predicted by the model to be most likely to remain at USF was 87%	Week of Welcome program at start of academic year. Newsletter, social events. Mentoring program	Benefit of this tool is to identify individual students who are at risk based upon a variety of factors as opposed to single risk factor	Logistic regression analysis was used to determine which factors in the data set were of predictive value regarding risk of attrition of individual students	
Jia & Maloney [18]	Administrative data/historical data collected as part of enrollment process- Predictive Risk Models (PRM)	Bachelor degree programs	15,833 first-year students who enrolled in large public university in New Zealand for the first time during the 2009 through 2012 academic years	The tool effectively identified non-completion and non-retention students	Suggestion of special tutorials/ classes, student advising/ mentoring services is made	Benefits: low-cost tool and the information is routinely collected as part of enrolment process	PRM tool is at least 38.63% more target effective in identifying students vulnerable for course non-completions. ROC analysis was used to assess the predictive power of the PRM. Observations from validation samples in the top decile of risk scores account for nearly 28% of first-year course non-completions and 22% of second-year student non-retentions at this university	Low
Johnson et al. [22]	Personal background preparation survey (PBPS)	Dentistry, medicine, nursing, biomedical sciences	First year August 2004 = 441 students. First year August 2005 = 526 students	PBPS consistently significantly predicted 1st or 2nd year adverse academic status events (AASE)	Not discussed	Individualized PBPS reports not only quantify PBPS risks, but identify specific risks and corrective interventions for prevention of AASE	PBPS consistently demonstrated high reliability ($p < .05$) and significant ($p < .05$) predictive validity of the PBPS for AASE	Low
Singell & Waddell [13]	Retention model: personal attributes and information on performance, financial information and course-taking behavior acquired over the first year. Institutional data collected from National Student Clearinghouse (NSC)	Not specified	University of Oregon, first-time, fall-term freshmen from academic years 2001 through 2006	At-risk students can be identified at the time of student enrolment	Not suggested	The model enables early identification of at-risk students through student-level data available upon the arrival of students on campus	Not clear. P values ranging from $p < 0.01$ $P < 0.05$ and $P < 0.1$	Low
Dante et al. [24]	Nursing student profiles- nursing students' individual variables and Bachelor of Nursing Science (BNS) course level variables	Nursing students	378 students	A limited occurrence of early academic failure emerged, around 5.6%. Academic failure was high for some countries	Strategies aimed at harmonizing nursing education across Europe, at supporting nursing students' learning processes during first year are recommended	Although, the study aimed to compare the nursing student profiles and their academic outcomes at the end of the 1st year, these variables could be used as a tool to identify students at risk of failure	P value for each variable ranging from 0. 00 to 0.86	Minimum
Worthington et al. [12]	Macleod Clark Professional Identity Scale	Bachelor of Nursing course	n = 540 students comprised 51% of all first year	Results reveal students with high MCPIS-9 scores	Peer tutoring and mentoring, course content review	MCPIS-9 served as a significant predictor of	The scale revealed high reliability and validity values.	Low

Table 2 (*Continued*)

Author (year)	Tool used	Course or degree	cohort size- at start	Efficiency identified/ measured	Strategy identified	Benefits and limitations	Reliability/Validity	Bias
			students enrolled in the undergraduate nursing program in 2009	were 1.06 times more likely to have a probable retention in nursing studies at the 12-month follow up	sessions, personal and academic counselling and study skills workshops have been suggested	student retention. This instrument incorporated the concept of social identity theory	Reliability statistics using Cronbach's alpha of the MCPIS-9 was 0.83. Exploratory factor analysis of the MCPIS-9 yielded a one-component solution, accounting for 43.3% of the variance. All 9 items loaded highly on one component, ranging from 0.50 to 0.79. ($P < 0.001$)	
Campbell and Mislevy [23]	Beginning Student Survey (BSS) National Student Clearinghouse (NSC) is database of enrollment data	Degree-seeking undergraduate students	2084 respondents: first-time, full-time, degree seeking freshmen in Fall 2002 at the University of Maryland, in mid-Atlantic region	The study identified certain perceptions and demographics that were related to relative risk of enrollment pattern (stopping-out, dropping out, transferring out, and continuously enrolled)	Academic advisor, faculty, administrators asking students what is behind their attitude toward the university is suggested	This study uses tools that investigate students' perceptions.	$\alpha > 0.600$ for each factor suggest internal consistency. Bartlett's test of Sphericity revealed $P < 0.001$	Low

easily accessible making it convenient to analyse the data. However, Delen [16] highlights the limitation of tools that rely only on institutional data in predicting students at-risk and therefore suggests the need to include data from intentionally crafted survey-based data to capture information from multiple sources. Lastly, McCluckie [15] emphasises the importance of using attendance data to identify students at-risk especially in cases where students may be unable or unwilling to recognize that they have a problem posing risk. While most studies used existing data to identify at-risk students, Pearson and Naug [14] conducted an assessment quiz in week one that was able to gauge the ability of students entering health science courses. First year students at-risk were identified at very early phases such as week one [14] and week seven [15,22]. Early identification enabled implementing timely interventions to support at-risk students.

Researchers investigating variables that impact academic outcomes have additionally identified self-efficacy, long term goals, and study strategies as predictive variables towards student success [19,21–23]. The authors relate their findings to Bandura's theory of self-efficacy [25] according to which, self-efficacy strongly influences academic achievement. Tait and Entwistle [21] draw upon the role of intrinsic and extrinsic motivation on studying. Based on these factors students with weak study strategies were identified as at-risk. The tool developed in this project allows students to complete the inventory interactively on a computer and helps staff to collect data from a whole class and identify students who seem to need help with their study skills or strategies. Only one study [12] identified the professional identity variable as a predictive factor towards student retention. The authors describe professional identity as the attitudes, values and knowledge that are shared with others within the same profession and, according to them, this variable is a strong factor in predicting students at risk especially in health professions.

While not the focus of the current review, educational interventions to promote academic success and enhance student retention were also identified within some of the included studies. Interventions fell within the following categories: tutorials, academic counselling, study skill assistance, personal solutions, study aid modules, workshops covering biology or mathematics, welcome programs, social events, and mentoring program. Further research on the effect of each intervention in promoting academic success is suggested.

4. Discussion

The aim of this systematic review was to explore and evaluate the tools used by educators to identify first year students studying health science courses at risk of failure. In the context of this study, at-risk students include failures, those with low grades as well as drop-outs. The tools evaluated in the review identified first year at-risk students at a very early phase. As the goal of any educational institution is early identification of students at-risk in order to provide timely interventions that can promote academic success, the studies included in this review all emphasized this need and described tools for at-risk student identification at early phases of enrolment. Gultice et al. [3] argue that the traditional method of identifying at-risk students by their failure on the first exam means that struggling students began the term with grade deficits and weak mastery of the foundational knowledge for the course. They believe that at-risk students need to be identified either before registration for the course or early in the term, to receive assistance before the first exam. Therefore, most tools described used historical data already collected at the time of enrolment as the process of identifying students at-risk and predicting student attrition could occur at the very beginning of the course, prior to any indication of individual student's attrition.

The tools explored in the review captured various academic and non-academic factors. Non-academic factors include personal attributes as well as social risk factors. The review highlighted the significance of multiple factors in identifying at-risk students, including collecting information on personal characteristics, study strategies, social support, academic performance, GPA scores, and financial constraints. In particular, the open-enrolment educational institutions have students enrolling from diverse academic backgrounds and with varying study skills. Betts, Shirley and Kennedy [26] in their study investigating various academic and social risk factors that influence attrition, identified that non-academic risk factors seem to be a barrier to success in the health science program. The authors believe that academic testing for students at risk already exists in place. However, there is a need to determine non-academic factors that influence attrition. Therefore, the need to use tools that provide deeper understanding of personal and social factors is highlighted. This also means that the tools identify at-risk students on the basis of multiple factors as opposed to a single factor. Walker et al. [20] suggests that relying only on one single predictive variable yields false identification of students at-risk. Thus the review highlights the importance of both academic and non-academic factors as indicators of risk for attrition.

Further analysis of these factors grouped them into three main categories: personal background information, academic preparedness, and student perceptions of their abilities and attitudes. These factors provided information on personal, social, academic, institutional, and cognitive aspects of the student experience. As every student is unique and the challenges that surround them can be specific, knowing personal background information can serve as the starting point towards addressing attrition. Therefore, collecting information on personal background serves to identify at-risk students based on factors that look beyond the traditionally accepted factors. On the contrary, some educators emphasize the importance of academic preparedness. Academic preparedness and academic progression provides information on students' knowledge. This information can guide implementation of certain academic strategies to enhance student success. Scholtz and Allen-Ile [27] believe the level of academic preparedness for tertiary studies is related to how well students perform in their first year and subsequent years. Similarly, Lassibille and Gomez [28] in their study found that academic preparedness is one of the major influences on student completion. The third category, student perceptions, is also known to influence student success. An insight into these perceptions can help identify cognitive and non-cognitive risks thereby enabling educational institutions to take timely interventions. According to Elder et al. [9], students' intrinsic motivation and metacognitive abilities have profound impact on academic success. Therefore, student self-evaluation can serve as a personalised method for understanding areas of need. At the same time, with the advent of mature, diverse, and non-traditional students entering into professional degree programs, a need to understand student perceptions and psychological variables that influence academic achievement has surfaced. Numerous research studies highlight the importance of student perceptions in academic achievement [23,29,30]. Thus, the three main categories captured in the review provide a broader overview for identifying at-risk students. These three categories according to Madgett and Belanger [7] determine the persistence of students in universities, failure of which contributes to attrition in the first year. While previous studies have developed tools for identification of first year at-risk students, this review has explored and evaluated all those tools suggesting a framework of multiple factors (Table 2) that can be included in the identification process.

5. Conclusions

The issues facing at-risk students may be unique to the individual student and individual educational institution. The overall findings of the current review can provide a system for identifying students who are at risk of academic failure and highlight the potential of identifying at-risk students based on multiple factors as opposed to single predictive variable. The tools identified in this systematic review have not only improved our understanding of the factors that place students at-risk of adverse academic outcomes but can also be molded to the needs of specific educational institution and implemented for early identification of students at risk of failure.

6. Practice implications

The effectiveness of the tools identified in this systematic review will guide their implementation in institutions offering health science courses. The variables identified in the tools highlight the influence of multiple factors, academic and non-academic, in student success in the first year health science courses. Development of such tools enabling early identification of first year at-risk students will allow for timely interventions that could promote student success and retention at the college. This has implications for clinicians, health practitioners, administrators, educational institutions, as well as policy makers seeking to alleviate student attrition, thereby achieving long-term goals of improved learning outcomes. Educational institutions can play a vital role in providing equity of access to education to all students.

Conflictsof interest

None.

Contributions

TG and AB developed the conception of the review and designed the review protocol, conducted the review, extracted and synthesised data, and drafted the review article. Data extraction was completed by TG using data extraction table showing items that were approved by AB. Quality appraisal of the included studies was performed initially by TG and consensus was achieved after reviewing with AB. AB reviewed the process and contributed to revisions of the resulting review article. Both TG and AB have approved the final version of the manuscript.

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