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Computer Science Student Selection — A Scoping Review and a National Entrance Examination Reform *

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ABSTRACT

Background
Higher education student selection has significant impact both on lives of young individuals but also on national economies. Current digital era calls for digital professionals. Countless applicants apply to study Computer Science (CS) and Information Technology (IT) each year worldwide. Thousands of them are left without the university place they aspire to. At the same time, these disciplines suffer from numerous dropouts.

Objective
Could performance and persistence in CS and IT higher education be fostered by more accurate acceptance criteria? Academic studies on skills assessed in entrance examinations along with their predictive power were systematically reviewed in this study to ultimately propose evidence based student selection criteria for the discipline.

Methods
Scoping review gathered peer-reviewed studies from four academic databases. Their findings on skills assessed in entrance examinations and their predictive value were extracted and synthesized. The results were evaluated in a national consultation round utilizing the Delphi method.

Findings
The review discovered seven skill categories assessed in CS and IT entrance examinations. However, the predictive values of these skills were contradictory. The Delphi process agreed on reasoning skills, verbal skills and mathematics as the most important skills to be assessed in the reformed national entrance examination.

Discussion
The skills studied were usually limited to mathematics and verbal skills. Reasoning and problem solving skills were seldom examined separately. Critical thinking skills were not mentioned in any of the articles reviewed. It seems that research is tethered with school subjects learned at secondary level and tested by the legacy methods.

CCS CONCEPTS

• Social and professional topics~Professional topics~Computing education

KEYWORDS

student selection, entrance examination, higher education, aptitude, academic performance, persistence, literature review

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1 Introduction

The wide-ranging spread of digital technologies is transforming economies, societies and daily lives of individuals. Estimates of the size of the digital economy run from 4.5 % to 15.5 % of world GDP, depending on the definition [37]. This digital era calls for digital professionals. Global employment in the ICT sector increased from 34 million in 2010 to 39 million employees in 2015 [37]. The ICT sector is struggling to find qualified professionals [25]. In the US, there were more than 500.000 open computing jobs available nationally in 2017, and fewer than 50.000 students graduated that same year from CS programs [35]. The labour market seems to absorb effectively all ICT graduates even through the economic and financial crisis [15].

The popularity of CS and IT studies has varied over decades [15, 24] and a lot could still be done to increase its attraction. The main problem of the field, however, seems to be student attrition. The average dropout rate of CS & IT students in Europe is around 19% [15]. There are several studies exploring the reasons for attrition and retention and the sources appear to be complex and cumulative. Studied factors vary from age and gender to effort, confronted difficulties and many aspects of motivation and social interaction [4, 20, 27]. A promising predictor for retention and academic success may be students' comfort level [20, 30, 38, 40]. What makes a student feel comfort? Teaching practices certainly have their impact but could comfort and self-efficacy rise from the balance between motivation, aptitude and requirements of the discipline? As dropout rates are highest in the first year of study [7], it evokes the question whether this balance could be foreseen prior to admission?

University admission in CS & IT fields is typically based on either high school grades, entrance examinations, or both [1]. Could the number of dropouts be reduced by more accurate acceptance criteria? Although determining the factors that best predict success in studies and career in these disciplines is widely debated, no Philosopher's Stone has yet been found. There seems to be a lack of evidence based selection criteria, and CS & IT institutes are facing the challenge of developing their own selection practices based on tradition and opinions only.

In the shadow of this knowledge gap this review addresses the lack of a well-grounded student selection criteria for undergraduate (Bachelor-level) CS & IT programmes. To that end, the following research questions were formulated:

1. **Which skills are assessed** in undergraduate CS & IT student selection?
2. **Which skills** assessed in undergraduate CS & IT student selection **correlate to academic performance and persistence**?
3. **Which instruments** are applied in the assessment of these skills in undergraduate CS & IT student selection?

This study is associated with the continuum of studies investigating predictors of academic performance and persistence in CS and IT tertiary degree programmes. Although mathematical skills are the most widely used factor in student selection in CS & IT, it has not proved to be as powerful a predictor of success as has been expected (e.g. [8, 10, 33]). Other skills investigated involve verbal skills in the language used in studies [28], previous programming experiences and sciences [3].

There are literature reviews on the topic from this century, but the majority of them concentrate on educational data mining and study mainly factors that accumulate during studies – or technologies used in learning analytics (e.g. [13, 26]). The existing reviews may also categorize predicting factors at such a coarse level that separate skill factors cannot be identified [12].

This study concentrates on factors involving cognitive skills that could be assessed prior to university admittance. Studies investigating personal dispositions and attitudes, social context or socio-economic status, fall out of the scope of this study.

2 Materials and Methods

Scoping review was chosen to synthesize research literature: to scope the research articles regardless of study design: to examine the extent, range and nature of research activity, to summarize and disseminate research findings, and to identify gaps in existing literature. It usually does not include quality assessment of selected studies as it focuses more on the breadth than the depth of the research activity. [2] Schryen et al. [31] categorize scoping review as a describing review on the grounds of its overarching research goals, Templier & Paré [36] classify it as a cumulative review.

This review follows the five stages defined by Arksey and O'Malley [2]: (1) Identifying the research questions, (2) Identifying the relevant studies, (3) Selecting the studies, (4) Charting the data and (5) Collating, summarizing and reporting the results. The process may not be linear but iterative to ensure comprehensive coverage. These steps were complemented by a consultation round [2] in which the findings were reported to and assessed and confirmed by CS & IT higher education executives utilizing the Delphi method.

2.1 Identifying and selecting the relevant studies

Having identified the research questions, four academic research databases were chosen as the source of articles: ACM (Association for Computing Machinery) and IEEE (Institute of Electrical and Electronics Engineers) as being the biggest CS and IT publishers, DPLP as a newcomer and Academic Search Elite (ASE) by EBSCO as a more general source of articles. Test searches were made to major science publishers' databases (Reed-Elsevier, Springer, Wiley-Blackwell), but Google Scholar, Scopus nor Web of Science gave promising results. The respective databases of these publishers were not employed. On the other hand, interesting articles were found from Taylor & Francis, but the project had no access to their full text articles and thus they had to be marked off this study.

The search terms are presented in Figure 1. Minor variations to the search syntax were inevitable in order to adapt to different search engines. Full-text search was applied when available to ensure sound coverage. Only peer-reviewed articles were approved to provide basic quality of the evidence. [23, 28] Articles written in English and published between 2000 and 2017 were accepted.

student **AND** (((admission OR entrance OR entry OR aptitude) **AND** (examination OR exam OR test OR criteria OR measures OR process OR qualification OR prerequisite OR skill OR ability OR competence)) **OR** ((success OR performance OR achievement OR retention OR attrition OR persistence OR drop-out OR dropout) **AND** (predict OR predictor OR correlate OR correlation)))

Figure 1: The Original Search Phrase in ACM Database

Inclusion criterion took in articles discussing skills predicting academic performance or persistence. Exclusion criteria cut out studies not covering entrance examination or focusing on levels under or above Bachelors and Masters levels (ISCED levels 6 and 7 [17]). The search result was not complemented with manual searches based on references. The searches were performed in Jan 2018. The process is documented in Table 1.

Table 1: The Retrieval and Selection Process

Number of articles at successive stages of the retrieval process		Number of articles from each database			
	Total	ACM	IEEE	DPLP	ASE
Articles identified in Database search	2062	816	1129	44	73
Articles after reviewing the Titles	70	36	28	3	3
Articles after duplicates removed	70	36	28	3	3
Articles after abstracts screened	35	22	9	2	2
Articles after full text examined	28	19	9	0	0
Articles after exclude criteria and included in analysis	10	3	7	0	0

2.2 Charting and summarizing the data

Literature review aims to aggregate the findings of empirical studies of different study design, in a consistent manner to provide objective summaries [6]. A common framework was applied to all selected articles and information was extracted accordingly [2]. Three tables were compiled to represent relevant data from the studies. The first one (available from author) includes basic information about the studies: authors, year of publication, study location, aims of the study, methodology and main results [2].

The second table (Table 2) contains data extracted from the studies covering the skill items assessed in CS and IT entrance examinations as original expressions used in the article, the instruments used in the assessment of these skills, the correlations found between the assessed skill item and performance and/or persistence, and article reference. Similar meanings from original expressions of skill items were classified into categories [39] using inductive content analysis [22]. The categorization was reviewed by a fellow researcher. Table 2 collates and summarizes the evidence answering the research questions.

The third table (available from author) presents the instruments used in assessing skills in CS & IT entrance examinations in a more detailed level, contributing to the third research question.

Table 2: Skills assessed in undergraduate CS & IT student selection and their correlation to academic performance and persistence

Category	Skills assessed in entrance examinations as original expressions	Instrument used in assessment *	Studies revealing use in selection process	Studies proposing correlation between skill and academic performance or persistence in CS & IT + = positive correlation o = no correlation				
				CS1 course	1^{st} year GPA	1^{st} two years GPA	degree program GPA (4 years)	Persistence
Mathematics	**Mathematics**	**SAT**	Alexander… 2003 Katz… 2006 Katz… 2003	+ Katz… 2003		+ Katz… 2006		+ Katz… 2006
		ACT	Alexander… 2003 Doyle… 2009	+ Doyle…. 2009				
		PAU	Alexander… 2003					
		AIEEE	Singh…2012		+ Singh… 2012			
		local test	Golding… 2005 Golding… 2006				o Golding… 2005 o Golding… 2006	
Communication skills	**Verbal test**	**SAT**	Alexander… 2003 Katz…2006 Katz… 2003	+ Katz… 2003		+ Katz… 2006		+ Katz… 2006
	English	local test	Golding… 2005 Golding… 2006				o Golding… 2005 o Golding… 2006	
		local test	Stanko…. 2017		+ Stanko… 2017			
	Foreign language	**PAU**	Alexander… 2003					
	Teamwork skills	local test	Stanko… 2017		o Stanko… 2017			
Reasoning skills	**Logic**	local test	Singh… 2012		+ Singh… 2012			
	IQ test	local test	Stanko… 2017		+ Stanko… 2017			
Computing skills	**Computer science**	**PAU**	Alexander… 2003					
	IT test	local test	Stanko… 2017		o Stanko… 2017			
	Programming	local test	Stanko…. 2017		o Stanko… 2017			
Sciences	**Physics**	**PAU**	Alexander… 2003					
		AIEEE	Singh… 2012		o Singh… 2012			
	Chemistry	**PAU**	Alexander… 2003					
		AIEEE	Singh… 2012		o Singh… 2012			
	Biology	**PAU**	Alexander… 2003					
Humanities	**History**	**PAU**	Alexander… 2003					
	Linguistics	**PAU**	Alexander… 2003					
Motivation	***Motivation***	*local system*	*Kori et al. 2015*					*+ Kori … 2015*

*) ACT American College Test; SAT Scholastic Aptitude Test; PAU Spanish University Access Test; AIEEE All India Engineering Entrance Examination

2.3 Consultation round with Delphi

The consultation round was conducted according to the Delphi method. Delphi process applies a series of questionnaires to a group of experts to gather opinions and ultimately formulate a group judgement [11]. Two successive rounds were deployed to assess the importance, unambiguity, assessability and coverage of the skill items presented in Table 2. A panel with 21 members representing the executives of CS & IT degree programmes at Universities of Applied Sciences in Finland was formed. The panelists were not aware of each other's identity nor answers. The first round included all the separate skill items represented in Table 2. The panelists were asked to evaluate the importance, unambiguity and assessability of each item in the student selection on a 0 to 1 scale. An open question was available for the panelists to suggest skills not covered in the questionnaire.

The second round consisted of only those skills achieving at least 67% consensus of importance. If the unambiguity of an item did not reach 67% consensus, it was reformulated before the second round. The assessability score had no effect to the skill items included in the second round. The open questions on the two rounds did not reveal any new skills to assess.

3 Results

This study focused on entrance examination and thus studies investigating correlations between performance in secondary and tertiary education were excluded. The national secondary level matriculation examinations were not regarded as entrance examination. The retrieval process found 28 studies investigating the skills predicting academic performance in CS and IT. In the context of entrance examination, the amount of studies was modest. In total, 10 studies met the criteria and qualified for the review. Review results are reported using tables and narratives.

3.1 Overview of studies

The following articles were analyzed: Alexander et al. (2003), Doyle et al. (2009), Golding & Donaldson (2006), Golding & McNamarah (2005), Iqbal et al. (2017), Katz et al. (2003) & (2006), Kori et al. (2015), Singh & Pundir (2012) and Stanko et al. (2017). All articles were peer reviewed. The studies were published between 2003 and 2017 and most of them (8) were presented in a conference run by ACM or IEEE. The studies originated from 12 countries: the US (4), Canada (1), Jamaica (2), United Kingdom (2), Ireland (1), Spain (1), Sweden (1), Estonia (1), Russia (1), India (1) and Pakistan (1), and covered 3 continents, Northern America, Europe and Asia.

Sample sizes varied from 38 to 783 students majoring in Computer Science, Information Systems, Information Technology or Software Engineering. Statistical analyses were used to find correlations between various factors and academic performance. Many of the articles included did not explicitly define academic performance. Success was understood as a good grade on the first programming course (CS1), passing the CS1 course, as a GPA of the first year of studies, or 1st two years of studies, or graduation from the programme. All these forms of academic performance were accepted in this review. Two articles accounted for persistence, too.

3.2 Skills assessed and their predictability

The review discovered 7 skill categories and 15 separate skill items assessed in CS and IT entrance examinations. They are presented in Table 2 associated with the method used to assess these skills. Mathematics was by far the most assessed skill. Verbal skills in language used in studies came second. Reasoning skills, computing skills and skills in sciences were mentioned in more than one study. Motivation and humanities were both found in one study. In Kori et al. (2015) motivation was tested in connection with the entrance examination but was not used as a selection criterion. After consideration, motivation was included in Table 2 even it is not a skill, due to its importance in successful studies.

The findings on the predictive value of these factors were contradictory: some studies showed positive correlation whereas others found none (Table 2). This is parallel to the larger body of literature that was studied prior to the exclude criterion. The aptitude for CS & IT domains, especially programming, is difficult to predict. Stanko et al. [34] performed an experimental study in entrance examination context on different plausible predictive factors suggested by literature, but found mainly weak or no correlations. Only reasoning skills scored solely positive results – but they were scoped separately only in two studies.

The exactitude of reporting varied. Iqbal et al. [16] stated that there was a strong correlation between entrance examination and academic performance but revealed nothing of the contents of the examination. Alexander et al. [1] described selection procedures from several countries, but calculated their correlations with first year academic performance as a whole and the role of separate skills could not be distinguished. At this general level the article claimed that they "found nothing in the entry qualifications to indicate success in the study of programming" [1]. These results could not be included in Table 2 due to insufficient exactitude.

Articles also examined skills assessed at secondary level, like GPA or individual grades in mathematics, sciences or verbal skills. These findings were not included in Table 2 either.

3.3 Instruments used in assessment

Methods used to assess skills in CS and IT entrance examination included standardized widely used tests, like ACT (American College Test), SAT (Scholastic Aptitude Test), PAU (Spanish University Access Test) and AIEEE (All India Engineering Entrance Examination), and locally conducted tests. ACT, SAT, AIEEE and some locally conducted tests used multiple-choice question format. As for ACT and SAT, there is no penalty for incorrect answers, but in AIEEE there is. For all the tests this information was not available. The descriptions of the local tests were often lean and information outside the articles, such as websites, could not be found. Test reliability or validity were not discussed in any of the selected studies. (A compilation of studied methods consisting of format, components, items, timing and scores is available from author.)

3.4 Consultation Round with Delphi

The skills assessed in CS & IT entrance examination presented in Table 2 were submitted to an expert panel consisting of 21 CS & IT degree programme executives, who agreed, in a two-round Delphi process, on the following items to be the most important selection criteria (Table 3):

Table 3: Results of the Delphi process on the most important selection criteria

Skills to assess in entrance examination	Importance	Unambiguity	Assessability
Reasoning skills			
• Logical reasoning	100%	90%	95%
• Problem solving	100%	80%	95%
Motivation			
• Motivation	95%	40%	55%
Communication skills			
• Verbal skills in language used in studies	90%	85%	95%
• Foreign language: English	80%	85%	95%
• Teamwork skills	80%	35%	45%
Mathematics			
• Basic Mathematics (ISCED level 2 [17])	75%	95%	95%

Reasoning and problem solving skills were found to be the most important skills required from the CS & IT students with 100% consensus. Motivation and verbal skills were regarded important almost as often (90-95% consensus). Skills in mathematics scored less, but significant support (75% consensus), which is somewhat surprising in regard to its wide use in admission practices. Motivation and teamwork skills – though found important (95% and 80% consensus respectively) – were diagnosed as ambiguous and problematic to assess. For these reasons, these skills were not included in the first version of the reformed national entrance examination that went into operation in October 2019.

4 Conclusions and Discussion

There is a multitude of research articles seeking predictors of performance and persistence in CS & IT domain. The question is important as the industry is demanding qualified professionals, but higher education institutes suffer from high attrition. Reasons for attrition and retention are multiple and cumulative [20].

This review provided the decision-makers a summary of the scientific evidence regarding cognitive skills found relevant in CS and IT disciplines [6, 36]. The project continued by constructing the new selection instrument. The new national entrance examination system was built and launched accordingly in 2019. A statistical follow-up study is under way.

However, the findings of the empirical studies are contradictory: Some find positive correlations whereas others find none. The studied skills are often limited to mathematics and verbal skills. A broader view could be fruitful. Logical reasoning and problem solving skills have seldom been examined separately from mathematics. Students identify these skills to be the most important ones in learning programming [32]. Critical thinking skills were not mentioned in any of the articles examined. It seems that in the quest of finding true predictors, research is tethered with school subjects learned at secondary level and tested by the legacy methods.

Problem solving, logical thinking and creativity are at the core of CS and IT. According to OECD Education Report 2017, problem solving, critical thinking, and creativity are seen critical for success in the labour market regardless of students' final occupation [25]. These same skills are placed as the top three skills one needs to thrive in the fourth industrial revolution by World Economic Forum (2020) [41]. Yet, they have no explicit role in CS & IT student selection.

5 Limitations

The first and foremost limitation of this study was discovered in 1739 and is known as the Hume's guillotine or the "no ought from is". It states that, strictly speaking, you cannot conclude how things should be, by looking at how things are – or – moral statements cannot be inferred from factual premises [14]. Thus, studying how entrance examinations have been compiled so far does not give you the knowledge as to how the examination should be assembled.

Secondly, and complementing the first limitation, the exclude criterion forced on this study (entrance examination context only) cut out studies investigating correlations between skills graded at secondary level and performance in CS and IT in higher education. This restriction made it difficult to answer the second research question as there were so few articles left.

Thirdly, there was a language barrier for a non-native speaker in selecting the appropriate search terms. This defect was tackled with recursive search of synonyms. Fourth came the pay wall; test searches found promising studies that were concealed behind the pay wall. The development project had access to many scientific resources but not all.

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