MEASURING AI READINESS IN COMPUTER SCIENCE STUDENTS: DEVELOPMENT AND ANALYSIS OF AIRSUS

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Abstract. *This paper reports on the development of an AI readiness instrument for computing education through exploratory analysis of mixed-methods data. We administered the AI Readiness Assessment Questionnaire for University Students (AIRQUS) to 140 first-year undergraduate students (71 Software Technologies and Design, 69 Software Engineering) at the Faculty of Mathematics and Informatics of Paisii Hilendarski University of Plovdiv, Bulgaria. From AIRQUS, we extracted and analyzed a 15-item quantitative subset (AIRSUS v1.0) measuring six theoretical constructs: AI literacy and awareness, AI use for English language learning, AI applications in software engineering, non-academic AI use, ethical considerations and academic integrity, and attitudes toward future AI integration. Exploratory analysis revealed acceptable internal consistency (Cronbach's* $\alpha = .77$*, McDonald's* $\omega = .83$*) and a three-factor empirical structure accounting for 47.2% of variance. Bivariate analyses showed theoretically meaningful associations with prior AI exposure (*$\rho = .34$*, p ¡ .001) and programming experience (*$\rho = .27$*, p = .001 with code error identification;* $\rho = .24$*, p = .004 with total scores). Systematic qualitative analysis of open-ended responses (n = 140) identified key themes including AI conceptualization patterns (49.3% view AI as tool/utility), primary use cases (code generation, debugging, learning), accuracy concerns (25.4%), and adoption barriers (46.4% fear overdependence). Synthesizing quantitative findings with qualitative insights, we developed AIRSUS v2.0, a refined 38-item Likert scale with standardized response formats and improved construct coverage designed for future psychometric validation and cross-institutional comparison. This exploratory work addresses the need for validated instruments assessing AI readiness in computing education and provides a foundation for systematic measurement of this emerging competency domain.*

Key words: Artificial Intelligence, AI Readiness, AI Literacy, Instrument Development, Computing Education, Mixed Methods, Scale Development, University Students.

1. Introduction

Artificial intelligence (AI) is exerting a profound disruptive impact across society, particularly in higher education where STEM programs face rapid transformation. Many institutions are still developing policies on AI use in academic work to address generative AI's impact on learning and teaching.

This creates a pedagogical paradox: when AI generates course materials, students use AI to complete assignments, and instructors use AI for assessment, authentic learning becomes questionable. Educators face challenges determining genuine student work, while plagiarism detection has become a significant institutional burden.

Computing education faces particular challenges as some students develop overreliance on code completion tools, losing motivation when they cannot match AI-generated code quality. Understanding student AI readiness has therefore become a priority. Such assessment can build student profiles across classes and institutions, benefiting instructors, curriculum designers, and policymakers while promoting student self-reflection.

Defining AI readiness and AI literacy in educational contexts is challenging as these terms lack clear definitions and consensus in the literature. As Biagini [1] notes, "the diverse interpretations and evolving definitions of AI literacy reflect the dynamic nature of AI itself."

Based on [2, 3, 4], the following definition of AI literacy for higher education is adopted:

AI literacy is a set of socio-technical competencies that empower university students to evaluate AI technologies critically and to collaborate effectively, creatively, and ethically with AI for the fulfilment of meaningful academic and personal goals. Competencies should be assessed as objectively as context allows. AI literacy can be gauged before and after pedagogical interventions and can serve as a reference for job interviews or corporate AI upskilling programs.

For the purposes of this work, the following definition of AI readiness for higher education is introduced:

AI Readiness is self-reported AI literacy comprising self-awareness of one's competencies based on previous experience, knowledge, attitudes, and values, including perceptions, expectations, and concerns.

Note that this conceptualization differs from authors like Kotran [5], who attributes literacy to knowledge and readiness to competency application.

Literature reviews confirm the need for AI competency frameworks in higher education [6, 7], though psychometrically validated measures remain scarce [8]. Recent work emphasizes domain-specific assessment tools [9] and instruments balancing technical skills with ethical considerations [10].

This research surveyed first-year computing students to understand their AI-related experience, skills, attitudes, and concerns. The objectives were to: (1) differentiate and define AI literacy and AI readiness for computing education, (2) design, administer, and analyze a mixed-methods questionnaire (AIRQUS), and (3) develop an improved readiness instrument (AIRSUS v2.0) for future validation.

2. Related Work

We reviewed existing AI literacy instruments targeting higher education (Table 1). Most validated instruments (SNAIL, AILS, AILIT/AILIT-S, AILS-CCS, L2W-SAILS, RAIS) are self-report based, with few performance-based measures (AILIT, AILIT-S, GLAT).

Table 1. AI literacy scales relevant to higher education (short list)

Title (Items / N)	**Target Audience**
AILIT (28/1465) [11]	University students across disciplines
AILIT-S (10/1465) [12]	University students across disciplines
AILS (12/1849) [13]	General population; University students;
AILS-CCS (15/546) [12]	Chinese college/university students
AIRSUS v1.0 (15/140)	First-year undergraduate students in Computer Science and Software Engineering
ALTL [14]	Higher education students, faculty, and staff
GLAT (In progress) [15]	University students; Educators
L2W-SAILS (22/785) [16]	University students (second language writing context)
RAIS (?/63) [17]	Teachers (K-12 and higher education)
SNAIL (31/415) [6]	Non-experts; Higher education students

AIRSUS is among the few instruments specifically designed for computing students, incorporating domain-specific applications (software engineering, programming) alongside general AI literacy dimensions. While similar to AILIT in targeting university students, AIRSUS offers stronger domain-specificity for STEM education.

3. Methodology

We employed a mixed-methods exploratory design [18] combining quantitative (Likert-scale, multiple-choice) and open-ended questions. Open-ended items captured reasoning and insights beyond predefined categories, while quantitative items enabled comparison across groups and scalability.

AIRQUS comprised 32 items across six sections measuring: (A) AI literacy and awareness, (B) AI use for English learning, (C) AI applications in software engineering, (D) non-academic AI use, (E) ethical considerations, and (F) future AI integration attitudes. Question types included background items (2), open-ended (6), multiple-choice (11), and AIRSUS v1.0 Likert items (15). Administration time was approximately 20 minutes.

Participants (n = 140) were first-year undergraduates in Software Technologies and Design (n = 71) and Software Engineering (n = 69) at Paisii Hilendarski University of Plovdiv, Bulgaria, selected from a larger sample of 265 students.

Quantitative analysis included exploratory factor analysis (EFA), reliability analysis (Cronbach's α, McDonald's ω), and correlations. Qualitative analysis employed thematic analysis following Braun & Clarke (2006) [19].

AI assistance (Claude, Anthropic) was used for questionnaire development, data analysis, and manuscript editing.

4. Results

4.1. Quantitative Findings, AIRSUS

AIRSUS data departed from normality (Shapiro-Wilk $p < .001$ for all items), warranting Spearman correlations. Mean item scores ranged from 2.59 (AI for English learning) to 4.19 (distinguishing AI vs. human content), indicating a gap between high conceptual awareness and lower practical domain integration. The mean total score of 51.54 (SD = 7.49) out of 75 (68.7%) suggests moderate overall AI readiness.

Prior AI exposure emerged as the strongest predictor of AI academic readiness, showing 12 significant associations including correlations with personal AI use (ρ = .42), prompting confidence (ρ = .35), and total readiness (ρ = .34). CEFR level showed positive correlation with grammar evaluation (C2: ρ = .33) and negative correlation with AI usage frequency for English learning (C1: ρ = -.26), indicating higher-proficiency students report less frequent AI assistance for language tasks.

Programming experience showed domain-specific associations, correlating most strongly with software engineering items (D2 code error identification: ρ = .27, D3 verification: ρ = .23). More experienced programmers demonstrate stronger AI readiness in programming contexts but not necessarily in other domains, indicating the domain-specific nature of AI readiness in computing education.

Factor Structure: EFA results (Bartlett's $\chi^2 = 472.89$, $p < .001$; $KMO = .76$) confirmed suitability for factor analysis. A three-factor solution, supported by parallel analysis, explained 47.2% of variance:

Factor 1: AI Integration and Application (19.4% variance) encompasses practical usage patterns and future orientation (E1, E2, G1, G2, D1), reflecting students' active engagement with AI tools and confidence in their professional relevance.

Factor 2: Policy Awareness and Procedural Knowledge (11.2% variance) involves institutional awareness and compliance behaviors (F1, C1, F2), representing academic context knowledge essential for appropriate AI tool integration.

Factor 3: Critical Evaluation and Ethical Reasoning (16.6% variance) integrates assessment and judgment capabilities across domains (F3, C2, B2, B3, D3), reflecting metacognitive competencies for evaluating AI outputs critically.

This triad constitutes a more compact conceptual model of AI readiness than the original six sections and is more practical for curriculum design. Computing educators might organize instruction around these three dimensions: developing application skills, building policy awareness, and cultivating critical evaluation abilities.

Reliability: AIRSUS demonstrates adequate overall internal consistency (Cronbach's $\alpha = .77$, McDonald's $\omega = .83$), exceeding conventional thresholds for research instruments.

4.2. Quantitative Findings, AIRQUS

Key findings from multiple-choice items: Students reported using AI primarily for writing code and learning programming concepts (57.9% each), followed by debugging (54%). For English tasks, grammar checking (48.6%) and essay writing (37.9%) predominated. Most students used AI only for checking their own writing (30.7%) or as a starting point followed by revision (30%).

Regarding ethics, 37.9% found unacknowledged AI use never acceptable, while 33.6% considered it sometimes acceptable and 27.9% were uncertain. The primary barrier to effective AI use was fear of overdependence (46.4%), followed by academic integrity concerns (28.6%) and limited tool access (27.9%). Training needs focused on domain-specific AI applications for software engineering (25.7%), effective prompt writing (17.9%), while 19.3% felt adequately prepared.

4.3. Qualitative Findings, AIRQUS

Thematic analysis [19] of open-ended responses revealed several patterns. When defining AI, students viewed it as human-like intelligence (31.4%), gave positive characterizations (30.7%), or provided technical definitions (27.9%). For programming assistance, students primarily used AI for debugging (35.7%), code explanation (32.9%), and academic projects (28.6%).

Students reported using AI to explain complex concepts (31.4%), for research and information gathering (22.1%), and for personalized study support (19.3%). Regarding concerns, 51.4% reported no concerns or did not respond, while 29.3% worried about inaccurate information and 14.3% feared not truly learning when using AI. Students identified prompt engineering (27.9%) and critical thinking (23.6%) as key skills for responsible AI use. Overall, students view AI primarily as a productivity tool, use it mainly for debugging and understanding code, and recognize the need for critical evaluation skills.

5. Discussion

AIRQUS provides comprehensive coverage of technical, linguistic, ethical, and attitudinal dimensions through mixed response formats. Its synthesis of quantitative psychometrics with qualitative themes offers flexibility for various computing education contexts, though questions assume prior AI interaction that may not apply to all populations.

Limitations include the moderate sample size ($n = 140$), single-institution scope, and self-report format that may not reflect actual competencies. The 32-item length may discourage completion, and ethics items could benefit from scenario-based expansion.

AIRSUS v1.0 represents a first iteration in creating an effective instrument to measure AI readiness in computing education, positioning it among the few within the higher education STEM instrument landscape. As this is the first development phase, v1.0 has comparatively limited practical implications beyond awareness raising and reflection.

Future research will focus on validation study design, cross-institutional comparison, and longitudinal tracking. To this end, AIRSUS v2.0 has been developed as an improved 38-item 7-point Likert scale with enhanced construct coverage, improved item clarity based on v1.0 feedback, and design suited for cross-institutional validation. Rigorous psychometric validation will require a minimum sample of $N \geq 500$ participants across at least 5 universities to ensure adequate statistical power and generalizability. International validation would further require a minimum of 300 participants per country across 3–5 countries with English-medium CS/SE instruction to establish measurement invariance across diverse educational and cultural contexts.

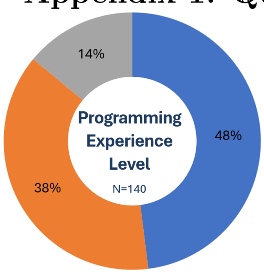
6. Conclusion

This study provides the first systematic assessment of AI readiness among Bulgarian computing students, establishing baseline data for the Eastern European technical education context. The proposed definitions of AI literacy and AI readiness contribute to understanding AI readiness diversity globally.

AIRSUS v1.0 is a 15-item exploratory instrument with acceptable psychometric properties ($\alpha = .77$, $\omega = .83$), while AIRSUS v2.0 is a 38-item refined version designed for rigorous validation. AIRSUS uniquely targets first-year CS/SE students, includes AI use for English language learning, and combines quantitative and qualitative development approaches. The self-assessment process promotes student reflection. Future developments include formal validation with larger, diverse samples and cross-institutional comparison; collaborative efforts are welcome.

Appendixes

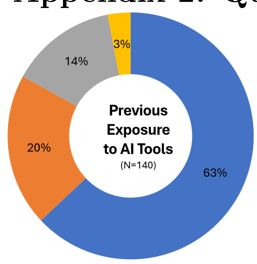
Appendix 1. Question A4



Beginner	67
Intermediate	53
Advanced	20

Figure 1. Programming Experience Level, $N = 140$

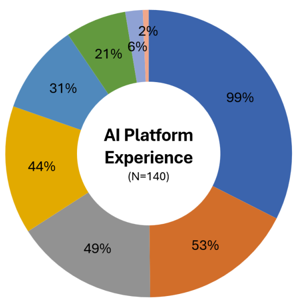
Appendix 2. Question A5



Moderate	88
Minimal	28
Extensive	20
None	4

Figure 2. Previous Exposure to AI Tools (before university), $N = 140$

Appendix 3. Question A6



AI Platform Experience	Count
ChatGPT	139
Google Bard/Gemini	74
Code completion tools, e.g. GitHub Copilot (47)	68
Microsoft Copilot	61
Writing assistants, e.g. Grammarly (25)	43
Claude	29
DeepSeek	8
Grok	3

Figure 3. Which AI tools have you used before? (Check all that apply) Other . . . ?, $N = 140$

Appendix 4. Factor loadings

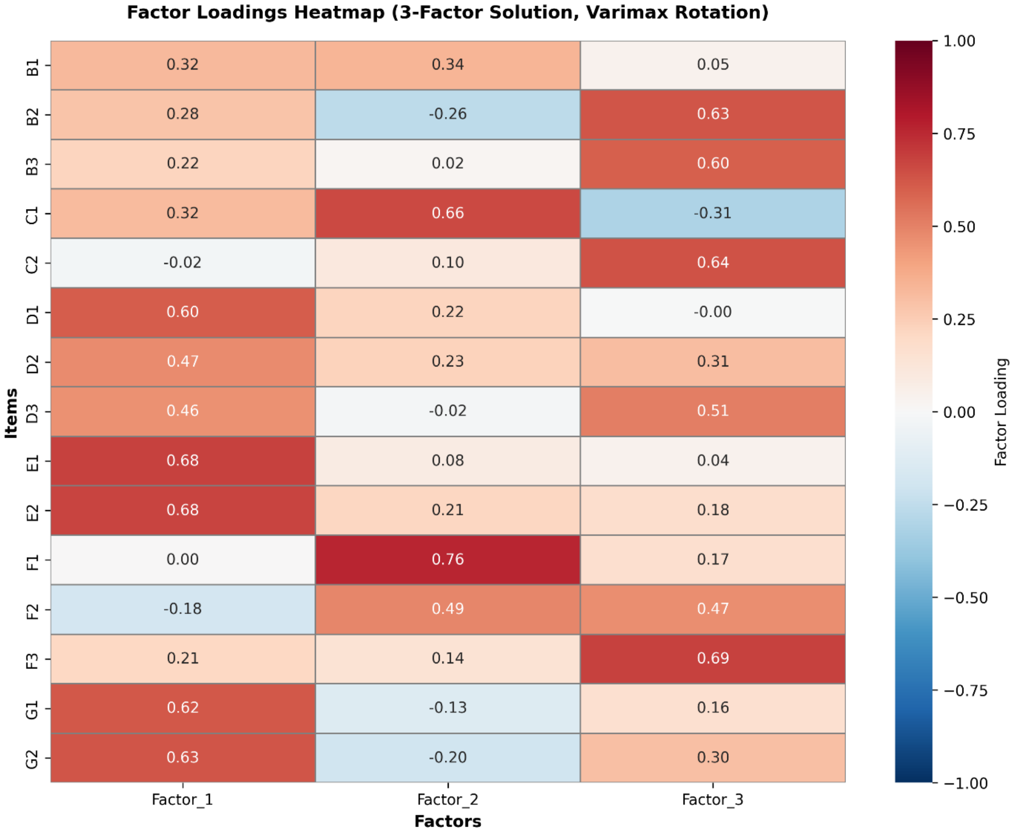


Figure 4. Factor loadings heatmap (3-Factor solution, Varimax rotation)

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