BEYOND A SINGLE SCORE: A SUB-DIMENSIONAL ANALYSIS OF CAREER READINESS AMONG AI-ADOPTING UNIVERSITY STUDENTS

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***Abstract**. Purpose – University career-readiness research typically treats the construct as a single holistic score, obscuring which specific competencies AI-adopting students report most and least strongly. This paper disaggregates career readiness into its five conceptual sub-dimensions to identify differential patterns and to lay the groundwork for future inferential testing.*

Design/methodology/approach – Secondary descriptive analysis of item-level statistics (n = 331) from a dual-mediation study of AI adoption, academic success, and career readiness among Uzbekistani university students (Tukhtaeva & Mirza, 2026). The 15-item career readiness scale was disaggregated into its five underlying dimensions — professional orientation, knowledge application and problem-solving, communication and interpersonal skills, learning orientation and adaptability, and professional self-awareness — following the original study's own operationalisation (adapted from NACE, 2024; Portocarrero Ramos et al., 2025).

Findings – Communication and interpersonal skills and professional orientation scored highest among the five dimensions; professional self-awareness scored lowest. This lowest-scoring dimension is measured by a single item, and its low mean echoes a parallel gap identified in the same sample's critical-thinking construct, where the lowest-scoring item also concerned reflective self-evaluation.

Originality/value – To the authors' knowledge, this is the first sub-dimensional analysis of this dataset. It proposes a disaggregated structural model — explicitly anticipated as future work in the original study — as the next empirical step, contingent on access to respondent-level data.

***Keywords:** career readiness, employability, AI adoption, higher education, sub-dimension analysis*

1. Introduction

As artificial intelligence (AI) technologies increasingly shape graduate labour markets (World Economic Forum, 2023), career readiness has become a central outcome variable in higher education research. Most studies — including the dual-mediation study this paper builds on — model career readiness as a single, holistic higher-order construct (Tukhtaeva & Mirza, 2026), following the conceptual precedent set by NACE (2024) and Portocarrero Ramos et al. (2025).

This treatment is defensible for parsimony and is consistent with how the construct was originally validated, but it obscures a practically important question: which specific employability competencies are strongest, and which need institutional attention?

The original study, having tested career readiness as a unitary 15-item construct (Cronbach's $\alpha = 0.91$; CR = 0.93) spanning five conceptual dimensions, explicitly identifies this as a limitation: "Future research may examine whether sub-dimensions exhibit differential associations with AI adoption" (Tukhtaeva & Mirza, 2026). This paper takes up that call. Using the item-level descriptive statistics already collected in the original n = 331 survey of university students in Uzbekistan, it disaggregates career readiness into its five constituent dimensions and compares them descriptively, as a first step toward the fully disaggregated structural model the original study anticipates.

2. Career Readiness as a Multidimensional Construct

NACE (2024) defines career readiness through a set of discrete competencies — including professional behaviour, communication, critical thinking, and career and self-development — that graduates are expected to demonstrate to prospective employers. Portocarrero Ramos et al. (2025) provide empirical support for treating structured AI engagement as differentially related to these competencies, finding that unstructured AI exposure yields limited employability benefit compared with deliberate, skill-building engagement. Taken together, this literature suggests that career readiness is not a monolithic outcome: different sub-competencies may plausibly respond differently to the same antecedent (AI adoption, AI literacy, critical thinking), even where the aggregate construct shows a uniform positive relationship, as the original study found for AI adoption ($\beta = 0.198$, $p < .001$; Tukhtaeva & Mirza, 2026).

3. Data and Method

This paper conducts a secondary descriptive analysis of previously reported item-level statistics from Tukhtaeva and Mirza (2026), a cross-sectional survey of n = 331 university students in Uzbekistan. Career readiness was measured with 15 items adapted from NACE (2024) and Portocarrero Ramos et al. (2025), grouped a priori — per the original study's own operationalisation — into five dimensions: professional orientation (CRS5–CRS8), knowledge application and problem-solving (CRS9–CRS12), communication and interpersonal skills (CRS13–CRS15), learning orientation and adaptability (CRS1, CRS3–CRS4), and professional self-awareness (CRS2).

For each dimension, a descriptive score was computed as the unweighted mean of its constituent item means, and measurement quality was summarised using the mean of the standardised confirmatory factor analysis (CFA) loadings reported for those items in the original study.

This analysis is explicitly descriptive rather than inferential: it compares published aggregate statistics across dimensions and does not re-estimate structural paths. Testing whether AI adoption, AI literacy, or critical thinking differentially predict each sub-dimension requires respondent-level data and bootstrapped path estimation in SmartPLS, which was not available for this analysis and is proposed as the direct next step (see Section 6).

4. Results

Table 1 presents the five career-readiness dimensions ranked by descriptive mean score. Communication and interpersonal skills ($M = 3.80$) and professional orientation ($M = 3.79$) scored highest, followed by knowledge application and problem-solving ($M = 3.74$) and learning orientation and adaptability ($M = 3.72$).

Professional self-awareness scored lowest by a visible margin ($M = 3.49$) and is measured by a single item (CRS2: "I see feedback from instructors or peers as an opportunity to improve myself"), which also carries the lowest standardised loading of the five dimensions ($\lambda = 0.68$).

Dimension	Items (n)	Mean of Item Means	Mean Std. Loading
Communication & interpersonal skills	CRS13–CRS15 (3)	3.80	0.72
Professional orientation	CRS5–CRS8 (4)	3.79	0.74
Knowledge application & problem-solving	CRS9–CRS12 (4)	3.74	0.75
Learning orientation & adaptability	CRS1, CRS3–CRS4 (3)	3.72	0.74
Professional self-awareness	CRS2 (1)	3.49	0.68

Table 1. Career readiness sub-dimensions ranked by descriptive mean score (n = 331). Source: item-level statistics reported in Tukhtaeva & Mirza (2026).

This pattern is notable alongside a parallel finding in the same dataset's critical-thinking construct: CTS10 (“Before using AI-generated information, I consider its possible implications or limitations”) was the single lowest-scoring item across the entire 44-item survey (M = 3.32), and, like CRS2, it concerns reflective self-evaluation rather than task execution. The co-occurrence of the lowest scores in both constructs on self-reflective, evaluative items — as opposed to applied or interpersonal ones — suggests a possible common gap that a single-construct view of either variable would not reveal.

5. Discussion

The comparatively strong scores for communication and interpersonal skills and professional orientation suggest that these dimensions may draw more on general social and professional development than on AI engagement specifically, whereas knowledge application and problem-solving — conceptually closer to the critical evaluation of AI outputs — may be more sensitive to AI literacy and critical thinking in a future disaggregated model. This is offered as a hypothesis for subsequent testing, not a finding from the present descriptive analysis.

The low, single-item score for professional self-awareness is best read as a measurement gap alongside a possible substantive one: with only one item, the construct cannot be assessed for internal reliability, and its lower mean could partly reflect item-specific wording rather than a genuinely weaker competency. Future survey revisions should expand this dimension to two or three items before it is entered into a disaggregated structural model. Practically, however, the convergence of the lowest scores in both career readiness (CRS2) and critical thinking (CTS10) around reflective self-evaluation is consistent with the original study's recommendation that institutions build structured reflection into AI-integrated coursework (Tukhtaeva & Mirza, 2026) — this analysis suggests that recommendation may apply as much to career self-assessment as to AI-specific critical evaluation.

6. Limitations and Future Research

This analysis is descriptive and secondary: it compares published aggregate statistics and does not establish whether AI adoption, AI literacy, or critical thinking predict the five career-readiness dimensions differently. The direct next step is a disaggregated structural model, re-estimated in SmartPLS using respondent-level data, with each of the five dimensions (or four, if professional self-awareness is merged with professional orientation pending item expansion) entered as a separate endogenous variable alongside AI adoption, AI literacy, and critical thinking as predictors. Bootstrapped path coefficients and confidence intervals for each dimension-specific path would indicate whether the uniform positive effect observed for the aggregate career-readiness construct (H2, H6, H8; Tukhtaeva & Mirza, 2026) holds equally across dimensions, or concentrates in specific competencies as hypothesised in Section 5.

7. Conclusion

Treating career readiness as a single score is a defensible modelling choice but hides variation that matters for practice. This descriptive disaggregation of an existing dataset shows that AI-adopting students in this sample report stronger communication and professional-orientation competencies than self-awareness, and identifies a possible shared gap in reflective self-evaluation that cuts across both the career readiness and critical thinking constructs. These patterns motivate — but do not yet test — a disaggregated structural model, which remains the necessary next step once respondent-level data are available.

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