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Developing a Personality-Aware Agentic AI Framework for Academic and Career Recommendation in Higher Education: A Systematic Literature Review

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Abstract

Artificial intelligence-based academic advising systems are increasingly used in higher education to support course selection, academic planning, and career guidance. However, existing recommender systems often prioritize academic records, course histories, and behavioural data, while students' psychological characteristics, particularly personality traits, remain insufficiently integrated into recommendation logic. This study aims to examine how personality traits can support personalized academic and career guidance and to propose a personality-aware agentic AI framework for higher education. Using a systematic literature review guided by PRISMA 2020, this study searched Scopus-indexed publications related to personality traits, artificial intelligence, recommender systems, academic advising, and career guidance. From 199 initial records, 45 studies were screened, 27 reports were assessed for eligibility, and 21 studies were included in the qualitative synthesis. Data were analysed through thematic synthesis and organized into five evidence clusters: personality and career development, AI-based academic advising, agentic AI architecture, cross-domain personality-aware recommender systems, and ethics and explainability. The findings reveal three major gaps: personality traits are mostly used as explanatory rather than operational variables; AI-based advising systems remain dominated by performance-driven data; and integrated frameworks combining psychological modelling, agentic reasoning, and recommendation delivery are still limited. In response, this study proposes a conceptual personality-aware agentic AI framework consisting of personality modelling, psychological profiling, agentic AI processing, intelligent recommendation generation, and decision-support interfaces. Although the framework has not yet been empirically validated, it offers a structured foundation for future prototype development, ethical implementation, and human-centred academic advising in higher education.

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Introduction

Artificial intelligence (AI) technologies are increasingly used in higher education to support academic planning, course selection, student success analytics, and career guidance (da Silva et al., 2023; Kamal et al., 2024; Maphosa & Maphosa, 2023; Chiu et al., 2023; Long et al., 2026; S. Wang et al., 2024). AI-based advising systems can improve scalability and timeliness by using academic performance data, course histories, and interaction logs to produce personalized recommendations. However, many systems still privilege observable academic and behavioural data over psychological characteristics that influence how students make decisions, respond to uncertainty, persist through academic difficulty, and imagine future careers (Herzog et al., 2026).

Personality is one psychological construct with strong relevance to academic and career decision-making. The Big Five model openness, conscientiousness, extraversion, agreeableness, and neuroticism or negative emotionality has been widely used to explain individual differences in learning behavior, achievement, employability, and career adaptability (Hassan & Hassan, 2024a; Herzog et al., 2026; L. Wang et al., 2024). Meta-analytic evidence indicates that traits such as conscientiousness and openness are associated with academic outcomes, while career research connects personality-related adaptivity with exploration, decision confidence, and long-term vocational development. Yet, in most AI-based advising systems, personality remains a supplementary explanatory variable rather than an operational feature embedded in recommendation logic (Jiang et al., 2024).

A clearer distinction is needed between conventional recommender systems, adaptive AI systems, and agentic AI. Conventional recommender systems typically map user and item features to suggested options, such as courses, majors, or career pathways, using collaborative filtering, content-based filtering, machine learning, or hybrid methods. Adaptive AI systems update recommendations as user data, performance indicators, or preferences change. Agentic AI goes further by organizing one or more intelligent agents that can reason over goals, plan multi-step actions, use external tools or knowledge sources, interact with users, and revise decisions through feedback (Jiang et al., 2024; S. Wang et al., 2024). In this paper, the proposed framework should therefore be understood as a conceptual agentic architecture rather than an implemented autonomous system (Jones, 2019; L. Wang et al., 2024).

Current literature remains fragmented. One stream examines personality traits, vocational identity, career adaptability, and academic success, but often without computational implementation. Another stream develops educational recommender systems and predictive analytics but often uses limited psychological inputs. A third emerging stream examines LLM-based and multi-agent learning environments but rarely connects agentic reasoning with validated personality profiles for academic and career recommendation. The reviewed evidence therefore supports a more cautious claim: within the selected literature corpus, systematic integration of personality modelling, agentic AI, and academic-career recommender systems remains limited.

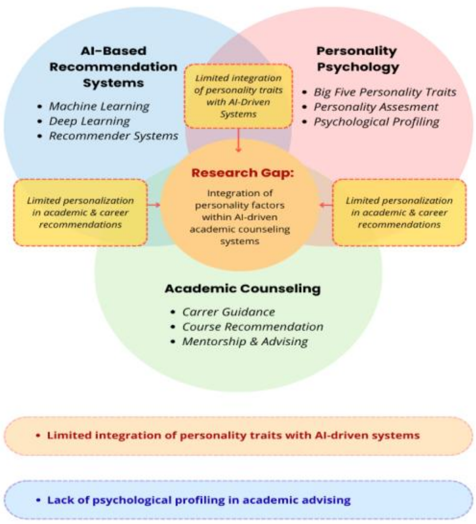

Figure 1. Research Gap Map of Personality-Aware AI for Academic Guidance

This study addresses the gap through a systematic literature review and conceptual modelling. The objectives are to examine how personality traits have been used in academic and career guidance, identify AI and recommender techniques applied in higher education, and propose a personality-aware agentic AI framework that can guide future prototype development and empirical evaluation.

A. RQ1: How can personality traits, particularly those based on the Big Five model, support personalized academic and career guidance for students?
B. RQ2: How can an agentic AI architecture integrate personality traits, academic performance, and student interests in academic guidance systems?
C. RQ3: What conceptual framework can enable personality-aware recommendation mechanisms for academic and career decision support?

Method

Research Design

This study adopts a literature-based conceptual research design. The review component follows PRISMA 2020 reporting principles (Page, McKenzie, et al., 2021; Page, Moher, et al., 2021), while the modelling component synthesizes the reviewed evidence into a layered architecture for personality-aware academic and career recommendation. The conceptual framework is intended as a design proposal and does not claim empirical validation or operational deployment.

Review Scope and PICO Framework

To define the scope of the systematic literature review, this study adopts an adapted PICO (Population, Intervention, Comparison, Outcome) framework, as presented in Table 1. The Population focuses on students in higher education, while the Intervention refers to AI-based academic advising and recommendation systems incorporating personality traits. The Comparison includes traditional advising approaches or AI-based systems that do not integrate personality characteristics. The Outcome relates to improved personalization, recommendation relevance, and decision support quality.

Table 1. PICO Framework for Literature Review Scope

Component	Description
Population (P)	Students in higher education environments
Intervention (I)	AI-based academic advising, career guidance, and recommendation systems incorporating personality or psychological profiles
Comparison (C)	Traditional advising systems or AI-based approaches without explicit personality integration
Outcome (O)	Improved personalization, recommendation relevance, decision support quality, transparency, and alignment with students' individual characteristics

The PICO framework serves as a guiding structure for developing the search strategy, refining the analysis selection process, and maintaining consistency between the research objectives and the included literature.

Search Strategy

The literature search was conducted using Scopus. Scopus was selected because it provides broad interdisciplinary coverage across education, psychology, computer science, engineering, and social sciences, which matches the interdisciplinary nature of personality-aware AI advising. The use of Scopus alone was intended to ensure a replicable and quality-controlled search process; however, this is also acknowledged as a limitation because relevant publications indexed only in Web of Science, IEEE Xplore, ACM Digital Library, ERIC, or ScienceDirect may have been excluded. Future reviews should triangulate these databases to improve coverage.

TITLE-ABS-KEY(("personality traits" OR "Big Five" OR "five-factor model" OR personality OR psychometric OR "career personality") AND ("academic advising" OR "academic guidance" OR "career guidance" OR "career counseling" OR "course recommendation" OR "major recommendation" OR "academic choice") AND ("recommender system" OR "recommendation system" OR "decision support system" OR "machine learning" OR "artificial intelligence" OR "agentic AI" OR "agent-based AI" OR "multi-agent system" OR "LLM agent" OR "intelligent agent") AND (student OR "higher education" OR universit*))*

The expanded query directly incorporated reviewer-suggested terms such as recommender system, agent-based AI, multi-agent system, LLM agent, and intelligent agent. The initial broad Scopus search yielded 199 records. After duplicate removal and refined search alignment with the AI/recommender/agentic-AI focus, 45 records were retained for title and abstract screening.

Inclusion and Exclusion Criteria

To ensure the relevance of the literature, several inclusion and exclusion criteria were applied during the screening process. These criteria were designed to select studies that discuss personality traits, artificial intelligence methods, and academic or career guidance systems in higher education.

Table 2. Inclusion and Exclusion Criteria

Criteria	Description
Language	English
Publication Stage	Final publication or peer-reviewed conference proceeding; preprints used only for emerging agentic-AI context
Year Range	2022-2026 for primary synthesis, with seminal works included for theory and measurement
Topical Scope	Personality traits, psychometrics, academic advising, career guidance, AI-based decision support, recommender systems, agentic AI, or multi-agent learning
Population/context	Higher education, university students, or vocational/transition-to-career settings
Exclusion	Studies unrelated to education/career decision support; studies using personality only in unrelated consumer domains unless explicitly treated as design analogues

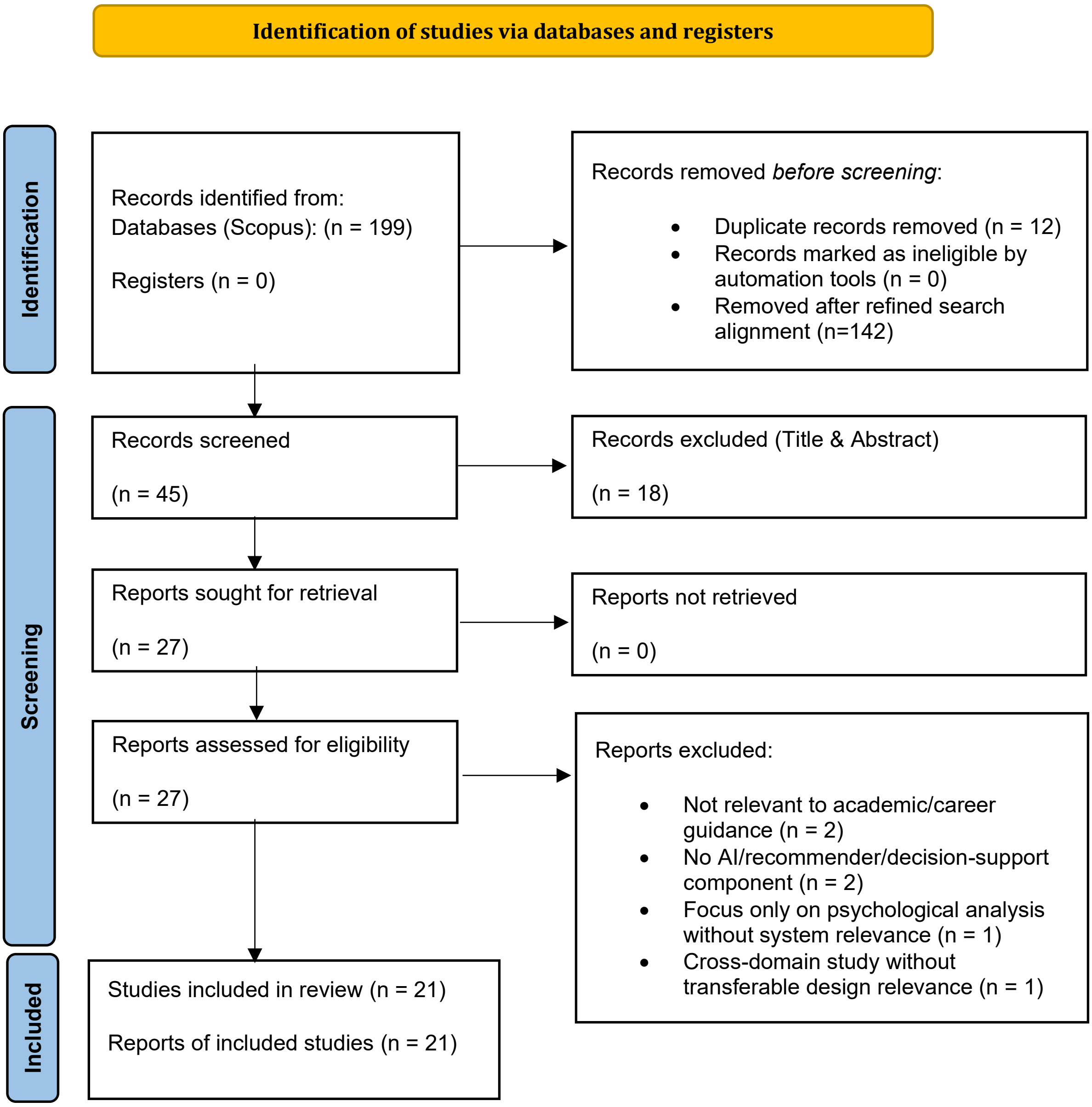

Figure 2. PRISMA 2020 flow diagram of study selection (Page, McKenzie, et al., 2021)

As shown in Figure 2, the initial broad Scopus search identified 199 records. Following the removal of 12 duplicate records, a refined search alignment was applied to ensure that the retrieved studies were closely related to the core focus of the review, namely personality traits, AI-based recommendation or decision-support systems, and agentic AI in academic or career guidance. This refinement removed 142 records and resulted in 45 records for title and abstract screening. Of these, 18 records were excluded during title and abstract screening, leaving 27 reports for retrieval and eligibility assessment. All 27 reports were retrieved and assessed. Six reports were excluded after full-text assessment because they were not relevant to academic or career guidance, lacked an AI/recommender or decision-support component, focused only on psychological analysis without system relevance, or represented cross-domain applications without transferable design relevance. The final synthesis included 21 studies.

Data Extraction and Synthesis

The qualitative synthesis focused only on the 21 studies that met the full eligibility criteria. Additional references were used only to strengthen theoretical, methodological, architectural, and ethical discussion. To systematically analyze the selected studies, a structured data extraction and synthesis process was conducted. Each included study was coded according to several variables, including personality or psychological construct, AI method, application domain, type of recommendation or decision support, evaluation method, and relevance to the proposed framework. These extraction variables are summarized in Table 3. The selected studies were then synthesized into five evidence clusters: direct higher-education recommender or advising evidence, personality and career-development evidence, agentic or LLM-based architecture evidence, cross-domain personality-aware recommender evidence, and ethics or explainability evidence. Cross-domain recommender studies were not treated as direct evidence for academic advising; rather, they were retained only when they offered transferable design insights, such as personality-aware personalization, dynamic adaptation, or explainable recommendation delivery.

Table 3. Data Extraction Variables

Variable	Description
Study ID	Identifier assigned to each selected study
Personality Model	Personality framework used in the study (e.g., Big Five, character strengths, MBTI)
AI Method	Computational approach used (e.g., machine learning, deep learning, hybrid recommender systems)
Application Domain	Context of the system (e.g., academic advising, course recommendation, career guidance)
Recommendation Type	Type of recommendation generated by the system
Evaluation	Validation method or performance metrics used in the study

The extracted data were organized into a literature matrix to facilitate comparison between studies and identify patterns in current research.

Result and Discussion

Result

This section presents the findings of the systematic literature review based on the selected studies and supporting literature. To address the reviewer's concern regarding domain relevance, the studies were not synthesized as a single homogeneous group. Instead, they were organized into evidence clusters according to their methodological and conceptual contribution to the proposed framework. Direct higher-education recommender and advising studies were treated as primary evidence, while cross-domain recommender studies were used only as supporting evidence when they provided transferable design insights, such as personality-aware personalization, adaptive recommendation logic, explainable recommendation delivery, or dynamic user profiling.

The synthesis resulted in five evidence clusters: (1) personality and career-development evidence, (2) AI-based academic advising and recommendation evidence, (3) agentic AI or LLM-based architecture evidence, (4) cross-domain personality-aware recommender systems, and (5) ethics and explainability evidence. This clustering approach allowed the review to distinguish between evidence that directly supports academic advising in higher education and evidence that indirectly informs the design of the proposed personality-aware agentic AI framework.

Role of Personality Traits in Academic and Career Guidance

The analysis indicates that personality traits are consistently recognized as significant predictors of academic performance, career decision-making, and student development. Across the reviewed studies, the Big Five personality model emerged as the most frequently used framework in personality-based analyses. A closer examination shows that personality traits were mainly used in three ways: (1) to explain academic performance and learning behaviour, (2) to predict career preferences and adaptability, and (3) to support personal development and career decision-making processes. However, despite their strong theoretical relevance, personality traits were generally used as descriptive or explanatory variables rather than as operational inputs in recommendation systems. Most studies focused on identifying relationships between personality traits and academic or career outcomes, while only a limited number translated these insights into computational mechanisms for personalized academic or career guidance. This finding indicates a clear gap between personality theory and intelligent system implementation. Personality traits remain underutilized as core input variables in AI-based academic advising and recommendation systems. This gap supports the need for a personality-aware recommendation framework in which psychological characteristics are not only analyzed but also integrated into the logic of academic and career decision support.

Table 4. Evidence Clusters Informing the Proposed Personality-Aware Agentic AI Framework

Evidence cluster	Evidence Status	Focus	Representative Studies	Contribution to the proposed Framework
Personality and academic/career development	Primary conceptual evidence	Big Five traits, psychometric measurement, career adaptability, vocational identity, academic success, and student development	(Di Fabio et al., 2022; Fu et al., 2024; Goldberg, 1992; Hassan & Hassan, 2024a; Herzog et al., 2026; Judge et al., 1999; Mendoza et al., 2025; Rudolph et al., 2017; Villacís et al., 2023)	Supports the use of personality traits as psychologically meaningful variables for understanding academic performance, career adaptability, and decision-making.
AI-based academic advising and course/career recommendation	Primary system evidence	Academic advising, course recommendation, degree/major recommendation, student counselling, academic planning, and performance prediction	(Akib et al., 2024; Algarni & Sheldon, 2023; da Silva et al., 2023; Delahoz-Domínguez & Hijón-Neira, 2024; Hassan et al., 2024, 2025; Kamal et al., 2024; Kord et al., 2025; Lekan & Pardos, 2025; Maphosa & Maphosa, 2023; Salazar et al., 2021; Wagner et al., 2024)	Supports the recommendation and decision-support components of the framework in higher education and vocational education contexts.
Agentic AI, LLM, and adaptive AI architecture	Architectural supporting evidence	LLM-based agents, autonomous reasoning, multi-source information processing, personalization, user control, and	(Chiu et al., 2023; Jiang et al., 2024; Klostermann et al., 2026; Long et al., 2026; S. Wang et al., 2024; Zhou & Khatibi, 2025)	Supports the agentic AI layer, especially adaptive reasoning, dynamic personalization, feedback monitoring, and multi-source data integration.

		adaptive system design		
Cross-domain personality-aware recommender systems	Supporting design evidence only	Affective recommendation, personality-aware personalization, cognitive/context-aware recommendation, job recommendation, and non-educational recommender design	(Han et al., 2024; Ismail et al., 2026; Salazar et al., 2021; Sarsenbay et al., 2025)	Not treated as direct evidence for academic advising. Retained only for transferable design insights such as personality-aware personalization, dynamic adaptation, and explainable recommendation delivery.
Ethics, explainability, and responsible AI	Safeguard and implementation evidence	Explainable AI, bias mitigation, privacy, consent, responsible use of psychological data	(Ali et al., 2023; Färber et al., 2023; Hofeditz et al., 2022; Jones, 2019; Lekan & Pardos, 2025; Mauro et al., 2023; Shneiderman, 2020)	Supports ethical safeguards, transparency, bias awareness, and responsible handling of student personality data.

As shown in Table 4, the reviewed literature was not treated as a homogeneous body of evidence. Studies directly related to academic advising, course recommendation, career guidance, or higher education decision support were treated as primary evidence. In contrast, cross-domain recommender studies were retained only as supporting design evidence because they offer transferable insights into personality-aware personalization, adaptive recommendation logic, and explainable recommendation delivery. This distinction ensures that the proposed framework remains grounded in higher education while still drawing useful design principles from broader recommender-system research.

AI Techniques for Personality-Aware Recommendation Systems

The review shows that AI techniques have been widely applied to support personalized recommendation and decision-support systems. The identified approaches can be grouped into three categories: traditional machine learning models, deep learning approaches, and hybrid or advanced AI methods, including LLM-based and RAG-supported systems. In higher education contexts, traditional machine learning models remain common because they are relatively interpretable and computationally efficient. However, recent studies indicate a growing interest in advanced AI architectures that support adaptive reasoning, multi-source data integration, and more personalized recommendation delivery. Despite these developments, most AI-based academic advising and recommendation systems still rely heavily on academic and behavioural data, such as grades, course histories, interaction logs, and performance indicators. Psychological variables, including personality traits, are often treated as secondary features or are not incorporated into the recommendation logic. This indicates a critical limitation: AI techniques are becoming increasingly sophisticated, but the input features used in academic recommendation systems remain relatively narrow. As a result, the recommendations may be technically accurate but insufficiently aligned with students' psychological characteristics, motivations, and long-term career orientations.

Integration Gap Between Personality Modelling and AI Systems

One of the main findings of this review is the limited integration between personality modelling and AI-based academic recommendation systems. The reviewed literature can be grouped into two dominant research streams. The first stream consists of psychological and career-development studies that examine the influence of personality traits on academic performance, career adaptability, vocational identity, and decision-making, but do not translate these findings into computational recommendation mechanisms. The second stream consists of AI-driven studies that develop academic advising, course recommendation, or decision-support systems, but primarily rely on academic and behavioural data rather than personality traits as core input variables. A small number of studies attempt to connect psychological profiling with recommendation systems, but this integration is often partial or developed outside the academic advising context. Therefore, cross-domain recommender studies should not be interpreted as direct evidence for higher education advising. Instead, they are useful only as design references for transferable mechanisms such as personality-aware personalization, dynamic user profiling, adaptive recommendation logic, and explainable recommendation delivery. This distinction strengthens the methodological relevance of the review and clarifies the role of supporting evidence in developing the proposed framework. Overall, the absence of a unified framework that combines personality traits, AI-based recommendation techniques, and adaptive reasoning mechanisms highlights a critical research gap. This gap motivates the development of a personality-aware agentic AI framework for academic and career guidance in higher education.

Table 5. Synthesis of Research Gaps Across Evidence Clusters

Evidence cluster	*Main finding*	*Identified gap*	*Implication for proposed framework*
Personality and academic/career development	Personality traits influence academic performance, career adaptability, and decision-making.	Personality is mostly used as an explanatory variable, not as an operational input in recommendation systems.	Personality traits should be integrated as core input variables in academic and career recommendation logic.
AI-based academic advising and recommendation	AI models can support course recommendation, academic guidance, and career decision support.	Most systems rely on grades, course history, and behavioural data, with limited psychological integration.	Academic advising systems need to combine academic indicators with psychological profiling.
Agentic AI and adaptive architecture	Agentic and LLM-based systems enable adaptive reasoning and multi-source data integration.	Agentic AI is rarely applied specifically to personality-aware academic advising.	The framework should include an agentic reasoning layer for contextual and adaptive decision support.
Cross-domain personality-aware recommender systems	Personality-aware recommendation has been explored in non-educational domains.	These studies are not direct evidence for academic advising and require careful positioning.	Cross-domain studies can provide transferable design insights only, not direct empirical support.

Ethics and explainability	Responsible AI literature highlights privacy, bias, consent, and transparency concerns.	Existing academic recommender frameworks often under-discuss ethical risks of using psychological data.	The framework should include ethical safeguards, explainability, and student consent mechanisms.

Synthesis of Findings

Based on the cross-cluster synthesis, three key findings can be identified. First, personality traits are theoretically well established in explaining academic performance, career adaptability, and student decision-making, but they remain underutilized in system-level recommendation design. Second, AI-based recommendation techniques are increasingly advanced, yet many academic advising systems continue to rely on limited academic and behavioural input features. Third, there is a lack of integrated frameworks that combine psychological modelling, AI-based recommendation mechanisms, agentic reasoning, and ethical safeguards within a unified academic advising architecture. These findings justify the development of a personality-aware agentic AI framework for academic and career guidance. The proposed framework is therefore grounded in systematic evidence while also drawing on supporting literature related to agentic AI, explainability, privacy, and responsible use of psychological data.

Proposed Conceptual Framework

Based on the synthesis of the reviewed studies, this study proposes a conceptual personality-aware agentic AI framework for academic and career guidance in higher education. The framework consists of five interconnected components: personality data layer, psychological profiling layer, agentic AI layer, intelligent recommendation engine, and decision-support interface.

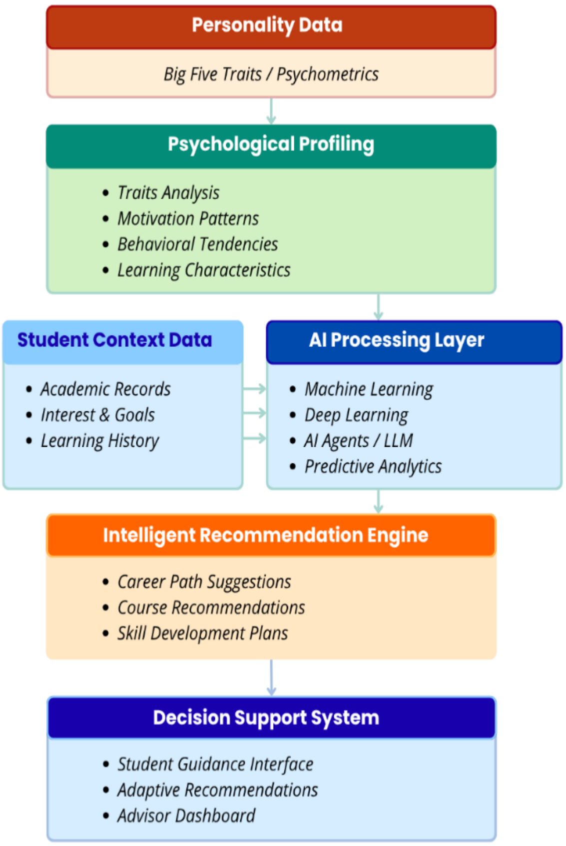

Figure 3. Conceptual Framework of the AI-Assisted Career Guidance Model

First, the personality data layer is designed to collect validated personality information from students. This layer should preferably rely on established instruments such as BFI-2 or IPIP-derived Big Five measures rather than opaque personality inference from indirect digital traces (Goldberg, 1992; Hassan & Hassan, 2024a). Second, the psychological profiling layer translates raw trait scores into interpretable academic and career-relevant profiles, including learning preferences, decision-making risks, motivation indicators, and career adaptability patterns (Fu et al., 2024; Hassan et al., 2025; Hassan & Hassan, 2024b; Rudolph et al., 2017).

Third, the agentic AI layer is conceptualized as a reasoning layer that coordinates multiple functional agents, including student profile interpretation, course or career knowledge retrieval, constraint checking, recommendation generation, and feedback monitoring (Jiang et al., 2024; Long et al., 2026; Zhou & Khatibi, 2025). Fourth, the intelligent recommendation engine generates academic and career suggestions by combining personality profiles with academic performance, student interests, curriculum constraints, and individual goals (Akib et al., 2024; Algarni & Sheldon, 2023; da Silva et al., 2023; Kamal et al., 2024; Kord et al., 2025; Wagner et al., 2024). Fifth, the decision-support interface presents recommendations with explanations, uncertainty indicators, and options for student and advisor feedback (Ali et al., 2023; Mauro et al., 2023; Shneiderman, 2020).

This framework should be understood as a conceptual model rather than an empirically validated system. Its purpose is to provide a structured foundation for future prototype development and empirical evaluation of personality-aware agentic AI in higher education advising.

Table 6. Mapping of Framework Layers and Operational Components

Framework Layer	Operational Components	Function
Personality Modelling Layer	Personality Data Layer, Psychological Profiling	Collect and interpret student personality traits
Agentic AI Layer	AI Processing Layer	Analyse personality and academic data using intelligent agents
Recommendation Layer	Recommendation Engine, Decision Support Interface	Generate and deliver personalized academic and career guidance

Table 6 showed, the Agentic AI Layer represents the core of the AI Processing Layer, where machine learning models and autonomous intelligent agents work together to process, interpret, and integrate multiple types of student data. In this layer, students' personality profiles are analysed alongside academic performance records, learning preferences, interests, and potential career orientations. The use of agentic AI enables the system not only to classify or predict student tendencies but also to reason across different data dimensions, identify meaningful patterns, and adapt its responses to each learner's unique profile. As a result, this layer functions as the analytical foundation of the system, transforming raw student information into interpretable insights that can support more accurate academic and career decision-making.

The Recommendation Layer is operationalized through the Intelligent Recommendation Engine and the Decision Support Interface. The Intelligent Recommendation Engine generates personalized academic and career recommendations based on the analytical outputs produced by the Agentic AI Layer, including suitable courses, learning pathways, skill-development priorities, and potential career directions. Meanwhile, the Decision Support Interface presents these recommendations in a clear, accessible, and actionable format for students, lecturers, academic advisors, or institutional decision-makers. Through this layer, the system moves beyond data analysis and becomes a practical guidance tool that helps students make more informed, personalized, and future-oriented decisions regarding their academic development and career planning.

Proposed Architecture

To operationalize the conceptual model, a system architecture is proposed to represent how the identified components can be implemented in an intelligent system.

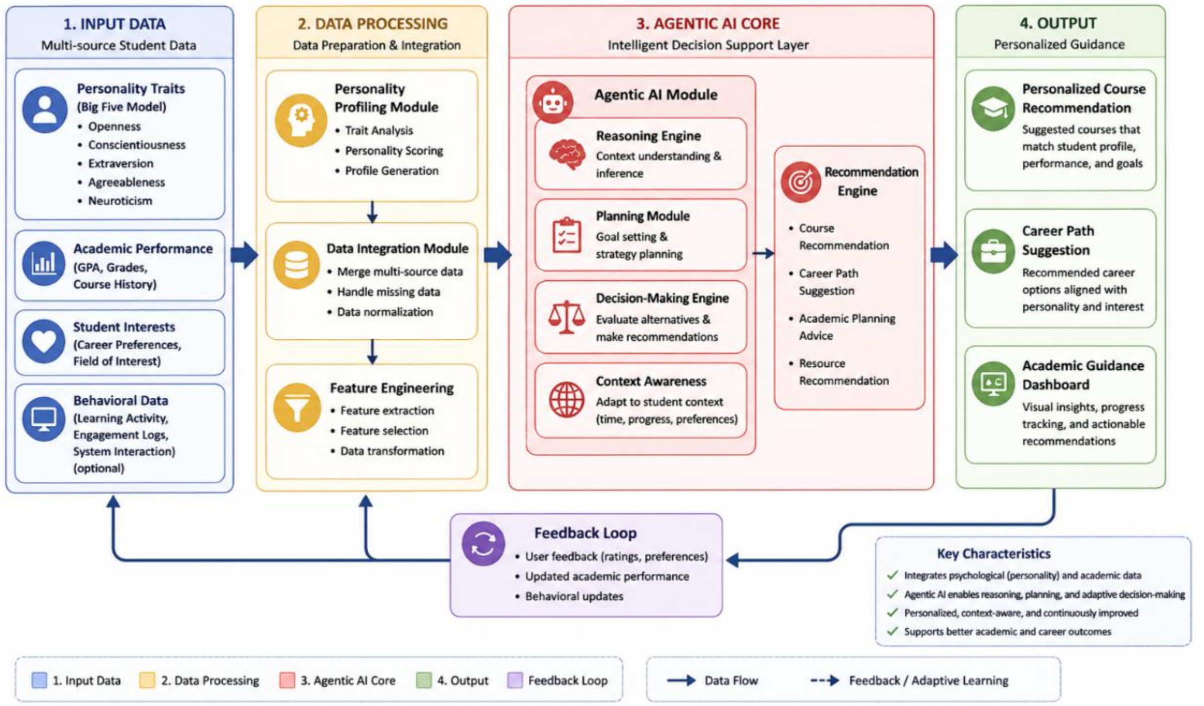

Figure 4. Proposed Personality-Aware Agentic AI Architecture for Academic & Career Guidance

This figure presents the proposed conceptual architecture that operationalizes the conceptual model into an implementable framework. The architecture consists of four main layers: input data, data processing, agentic AI core, and output. Multi-source student data, including personality traits, academic performance, and interests, are processed through profiling and integration modules before being analysed by the agentic AI component. In a future implementation scenario, the framework could generate personalized academic and career recommendations. The architecture is presented as a conceptual design rather than an implemented software system. Its components represent functional layers that should be empirically tested in future prototype development.

Illustrative Implementation Scenario

To clarify how the proposed conceptual architecture could be operationalized, this section presents an illustrative implementation scenario. This scenario is hypothetical and does not represent an empirically tested deployment. Rather, it is intended to demonstrate the possible workflow of a personality-aware agentic AI system if implemented in a higher education academic advising context.

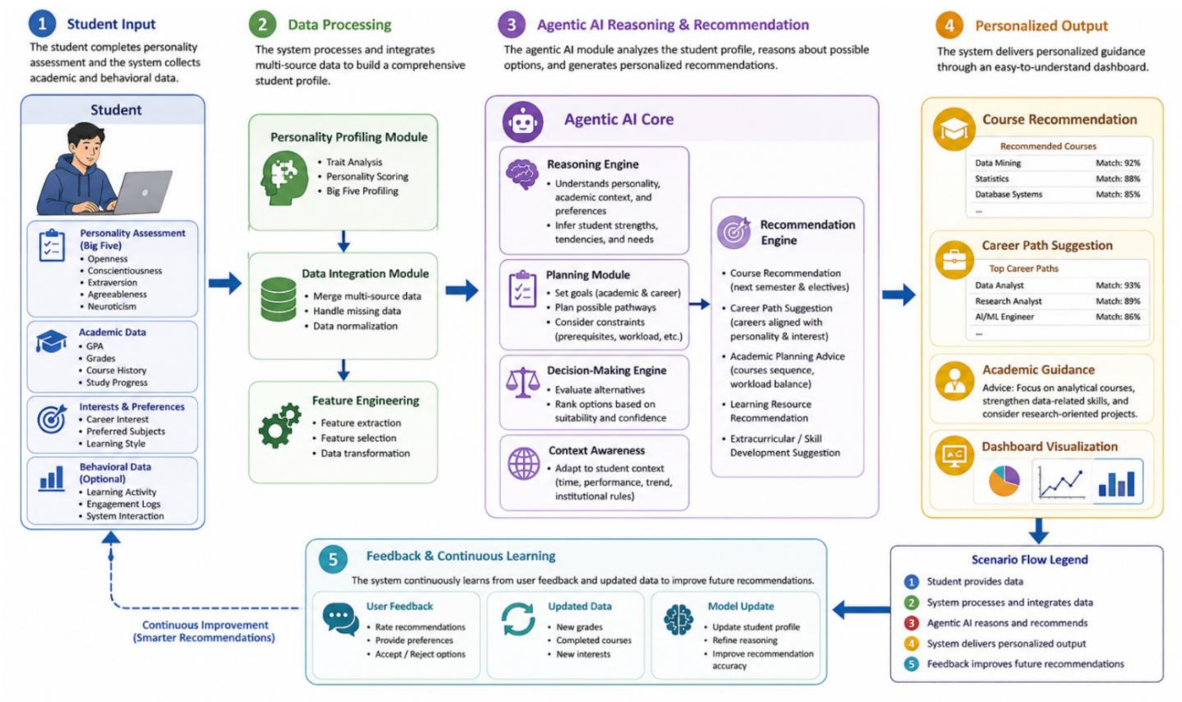

Figure 5. Scenario: How the Personality-Aware Agentic AI System Works

Figure 5 illustrates a hypothetical workflow of the proposed framework. In this scenario, student data, including personality traits, academic performance, interests, and feedback, could be collected and processed through the personality profiling and data integration layers. The agentic AI module would then analyse these inputs to generate personalized academic and career recommendations, such as course selection, academic pathways, or career development suggestions. The feedback mechanism is conceptualized as a means for future systems to update recommendations over time based on student interaction, advisor input, and changes in academic records. As such, the scenario should be understood as a design illustration rather than evidence of system implementation or empirical validation.

Discussion

This study provides a structured synthesis of existing research on personality traits, artificial intelligence, and academic advising systems. More importantly, the findings address the research questions by clarifying how personality traits, AI techniques, and integrated frameworks can support intelligent academic and career guidance systems.

In relation to RQ1, this study finds that personality traits influence academic performance and career decision-making. This review reveals a critical limitation: personality is predominantly treated as an explanatory variable rather than an operational component in intelligent systems. In most existing research, personality traits are used to interpret student behavior or predict outcomes, but they are rarely embedded into computational models that actively generate recommendations. This creates a disconnect between psychological theory and system implementation. From a system design perspective, this finding suggests that personality traits should not be positioned merely as supplementary features, but rather as core input variables that shape recommendation logic. Integrating personality into AI-based systems requires a shift from static profiling toward dynamic and context-aware modelling, where personality traits influence not only what recommendations are generated, but also how they are presented and adapted over time.

Addressing RQ2, the findings indicate that existing AI-based academic advising systems are still dominated by performance-driven and behavior-based data inputs, such as grades, course histories, and learning interaction records. Although these inputs are useful for predictive modelling, they often fail to capture the psychological characteristics that influence students' academic and career decisions. As a result, current recommendation systems may produce technically accurate suggestions but remain insufficiently aligned with students' motivations, preferences, and long-term aspirations. Agentic AI offers a potential direction to address this limitation because it enables autonomous reasoning, contextual adaptation, and multi-source data integration. In the proposed framework, the agentic AI layer is conceptualized as a reasoning component that connects personality profiles, academic performance, student interests, and feedback data. This allows the recommendation process to move beyond static matching toward more adaptive and context-aware decision support. For example, rather than recommending courses only based on grades or curriculum requirements, an agentic system could consider whether the recommendation aligns with the student's personality profile, learning preferences, academic goals, and career orientation. However, this study does not claim that such an agentic AI system has already been implemented or empirically validated. The proposed architecture should be understood as a conceptual design that requires future prototype development, user testing, and validation in real higher education settings. Therefore, the contribution of this study lies in outlining how agentic AI could be structured to support personality-aware academic and career guidance, rather than demonstrating the performance of a deployed system.

In response to RQ3, this study proposes a personality-aware agentic AI framework that integrates psychological modelling, AI-based reasoning, and recommendation mechanisms into a unified conceptual architecture. The need for this framework is supported by the finding that current research remains fragmented. Personality-related studies often explain academic and career outcomes without translating these insights into computational systems, while AI-based recommendation studies often focus on prediction accuracy without incorporating psychological variables as core inputs. The proposed framework addresses this fragmentation by positioning personality traits as operational input variables within an AI-driven recommendation process. It consists of three main layers: personality modelling, agentic AI processing, and recommendation delivery. The personality modelling layer captures and interprets students' psychological characteristics. The Agentic AI layer analyzes personality profiles together with academic performance, interests, and feedback. The recommendation layer then provides personalized academic and career guidance in a form that can support student decision-making and academic advising. This integrated structure distinguishes the proposed framework from previous approaches that treat personality modelling and AI-based recommendation as separate domains. However, the framework remains conceptual and should be further tested through prototype development and empirical evaluation.

The use of personality data in academic advising requires stronger ethical safeguards than systems that rely only on grades or course histories. Personality profiles can be sensitive because they may influence how students are perceived, categorized, and guided. Therefore, the proposed system should require informed consent, clear explanation of how personality data are collected and used, the ability to opt out, data minimization, secure storage, and governance procedures for auditing data access and model behavior (Hofeditz et al., 2022; Jones, 2019; Lekan & Pardos, 2025).

Psychometric validity is also central. Personality scores should not be inferred casually from social media, images, or digital traces without validation, fairness testing, and student consent. Whenever possible, the system should use validated instruments and report reliability, construct validity, cultural adaptation, and measurement limitations. Because personality instruments may carry cultural, linguistic, or demographic biases, model outputs should be tested across student groups before being used in high-impact academic or career decisions. Recommendation outputs should not be deterministic. A personality-aware AI system should not tell a student that a trait profile makes them suited or unsuited for a specific major or career. Instead, recommendations should be framed as decision-support options with explanations, confidence levels, alternative pathways, and opportunities for human advisor review. Recommendation outputs should be explainable and reviewable by students and academic advisors (Ali et al., 2023; Mauro et al., 2023). This human-in-the-loop approach reduces the risk of self-fulfilling labels, preserves student autonomy, and aligns the system with responsible and human-centred AI principles.

This study offers both theoretical and practical implications. Theoretically, it contributes to the literature by integrating personality psychology, AI-based recommendation systems, and agentic AI into a unified conceptual framework. While previous studies have often examined personality traits, academic advising systems, and AI-based recommendations separately, this study positions these elements as interconnected components of a personality-aware academic and career guidance model. The framework also extends prior research by treating personality traits as operational input variables rather than merely explanatory factors. This shift provides a basis for future studies that aim to design psychologically informed, adaptive, and human-centred recommendation systems in higher education. Practically, the proposed framework can guide universities, academic advisors, and system developers in designing more personalized academic and career advising tools. By integrating personality profiles with academic performance, interests, and feedback data, future systems may provide recommendations that are not only data-driven but also more aligned with students' psychological characteristics and career aspirations. For academic advisors, such systems may function as decision-support tools that enrich, rather than replace, human advising. For system developers, the proposed layered architecture offers a foundation for future prototype development, including personality modelling, agentic AI-based reasoning, and recommendation delivery. However, implementation should be accompanied by explainability, informed consent, data protection, bias monitoring, and human oversight to ensure responsible use in higher education settings.

This study has four main limitations. First, the review relies on a Scopus-based search strategy, which may exclude relevant studies indexed in other databases. Second, the synthesis is qualitative and does not include quantitative meta-analysis. Third, some agentic-AI literature is emerging and may include preprints or rapidly evolving technical work. Fourth, the proposed framework is conceptual and has not yet been implemented, tested, or evaluated with real students, academic advisors, or institutional data.

Future research should rerun the search across multiple databases, develop a working prototype, evaluate recommendation accuracy and user trust, test fairness across student groups, and conduct longitudinal studies on whether personality-aware recommendations improve academic fit, career confidence, and student autonomy. Although the refined search improved topical relevance, it may also have excluded broader studies on academic advising, personality, or AI that used different terminology.

Conclusion

This study revises the contribution of the manuscript by positioning the proposed personality-aware agentic AI framework as a conceptual model grounded in systematic literature synthesis rather than as a validated system. The reviewed literature indicates that personality traits, particularly those captured by the Big Five model, are strongly relevant to academic achievement, career adaptability, and decision-making. However, they are still rarely operationalized as core inputs in AI-based academic advising systems. At the same time, educational recommender systems and AI advising tools increasingly support course, major, and career-related decisions, but they often rely on performance-driven data and do not sufficiently integrate psychological modelling.

The proposed framework addresses this gap by integrating personality modelling, psychological profiling, agentic reasoning, intelligent recommendation generation, and decision-support interfaces. Its main contribution is to provide a structured foundation for future personality-aware, adaptive, and human-centred advising systems in higher education. Nevertheless, the framework remains conceptual. Its validity depends on future prototype development, empirical testing, transparent evaluation, psychometric validation, data governance, bias mitigation, and human advisor oversight. These limitations should be clearly stated so that the manuscript presents a balanced and academically rigorous contribution.

References

Algarni, S., & Sheldon, F. (2023). Systematic review of recommendation systems for course selection. *Machine Learning and Knowledge Extraction, 5*(2), 560–596. https://doi.org/10.3390/make5020033

Ali, S., Abuhmed, T., El-Sappagh, S., Muhammad, K., Alonso-Moral, J. M., Confalonieri, R., Guidotti, R., Del Ser, J., Díaz-Rodríguez, N., & Herrera, F. (2023). Explainable artificial intelligence (XAI): What we know and what is left to attain trustworthy artificial intelligence. *Information Fusion, 99*, Article 101805. https://doi.org/10.1016/j.inffus.2023.101805

Chiu, T. K. F., Xia, Q., Zhou, X., Chai, C. S., & Cheng, M. (2023). Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. *Computers and Education: Artificial Intelligence, 4*, Article 100118. https://doi.org/10.1016/j.caeai.2022.100118

da Silva, F. L., Slodkowski, B. K., da Silva, K. K. A., & Cazella, S. C. (2023). A systematic literature review on educational recommender systems for teaching and learning: Research trends, limitations and opportunities. *Education and Information Technologies, 28*(3), 3289–3328. https://doi.org/10.1007/s10639-022-11341-9

Delahoz-Domínguez, E. J., & Hijón-Neira, R. (2024). Recommender system for university degree selection: A socioeconomic and standardised test data approach. *Applied Sciences, 14*(18), Article 8311. https://doi.org/10.3390/app14188311

Di Fabio, A., Svicher, A., Palazzeschi, L., & Gori, A. (2022). Revitalising career counseling for sustainable decent work and decent lives: From personality traits to life project reflexivity for well-being. *Cypriot Journal of Educational Sciences, 17*(5), 1468–1476. https://doi.org/10.18844/cjes.v17iSI.1.6675

Färber, M., Coutinho, M., & Yuan, S. (2023). Biases in scholarly recommender systems: Impact, prevalence, and mitigation. *Scientometrics, 128*(5), 2703–2736. https://doi.org/10.1007/s11192-023-04636-2

Fu, M., Bo, W. V., Lin, X., & Zhang, J. (2024). Beyond person-environment congruence: Career adaptability, career personality styles, and thinking styles. *Acta Psychologica, 247*, Article 104308. https://doi.org/10.1016/j.actpsy.2024.104308

Goldberg, L. R. (1992). The development of markers for the Big-Five factor structure. *Psychological Assessment, 4*(1), 26–42. https://doi.org/10.1037/1040-3590.4.1.26

Han, J., Li, W., Li, Y., & Cai, Z. (2024). Quantum cognition-inspired EEG-based recommendation via graph neural networks. In *Proceedings of the 33rd ACM International Conference on Information and Knowledge*

Management (pp. 778–788). Association for Computing Machinery. https://doi.org/10.1145/3627673.3679564

Hassan, R. H., & Hassan, M. T. (2024a). A meta-analysis of correlation between Big Five personality traits and TVET skills acquisition. *Journal of Xi'an Shiyou University, Natural Science Edition, 20*(7), 168–174.

Hassan, R. H., & Hassan, M. T. (2024b). Unlocking potential: Personality-aware TVET course recommendations revolutionize skill development. *International Journal of Innovations in Science and Technology, 6*(3), 1228–1248. https://doi.org/10.33411/ijist/20246312281248

Hassan, R. H., Hassan, M. T., & Rana, A. H. (2025). Linking personality traits to vocational proficiency: A study of TVET learners using advanced feature engineering. *VFAST Transactions on Software Engineering, 13*(3), 1–15. https://doi.org/10.21015/vtse.v13i3.2187

Hassan, R. H., Hassan, M. T., Sameem, M. S. I., & Rafique, M. A. (2024). Personality-aware course recommender system using deep learning for technical and vocational education and training. *Information, 15*(12), Article 803. https://doi.org/10.3390/info15120803

Herzog, N. J., Bin Sulaiman, R., Herzog, D. J., & Fong, R. (2026). AI-driven personalized learning: Predicting academic performance through leadership personality traits. *Journal of Business and Digital Innovation, 1*(1), 1–16. https://doi.org/10.19164/jbdi.v1i1.1741

Hofeditz, L., Clausen, S., Rieß, A., Mirbabaie, M., & Stieglitz, S. (2022). Applying XAI to an AI-based system for candidate management to mitigate bias and discrimination in hiring. *Electronic Markets, 32*(4), 2207–2233. https://doi.org/10.1007/s12525-022-00600-9

Ismail, H., Alhefeiti, M., & Khalil, A. (2026). Image and metadata-driven personality inference for career recommendation: A social media-based AI framework for adolescents. *Discover Artificial Intelligence, 6*(1). https://doi.org/10.1007/s44163-026-00981-2

Jiang, H., Zhang, X., Cao, X., Breazeal, C., Roy, D., & Kabbara, J. (2024). PersonaLLM: Investigating the ability of large language models to express personality traits. In *Findings of the Association for Computational Linguistics: NAACL 2024* (pp. 3605–3627). Association for Computational Linguistics. https://doi.org/10.18653/v1/2024.findings-naacl.229

Jones, K. M. L. (2019). Learning analytics and higher education: A proposed model for establishing informed consent mechanisms to promote student privacy and autonomy. *International Journal of Educational Technology in Higher Education, 16*(1), Article 24. https://doi.org/10.1186/s41239-019-0155-0

Judge, T. A., Higgins, C. A., Thoresen, C. J., & Barrick, M. R. (1999). The Big Five personality traits, general mental ability, and career success across the life span. *Personnel Psychology, 52*(3), 621–652. https://doi.org/10.1111/j.1744-6570.1999.tb00174.x

Kamal, N., Sarker, F., Rahman, A., Hossain, S., & Mamun, K. A. (2024). Recommender system in academic choices of higher education: A systematic review. *IEEE Access, 12*, 35475–35501. https://doi.org/10.1109/ACCESS.2024.3368058

Khan, M. A. Z., & Polyzou, A. (2024). Session-based methods for course recommendation. *Journal of Educational Data Mining, 16*(1), 164–196. https://doi.org/10.5281/zenodo.11384740

Klostermann, M., Brenzke, M., Dietz, A., Kluge, A., & Radüntz, T. (2026). The power of choice: Understanding the role of control in learning recommender systems for workplace learning. *International Journal of Human–Computer Interaction*, 1–28. https://doi.org/10.1080/10447318.2026.2617137

Kord, A., Aboelfetouh, A., & Shohieb, S. M. (2025). Academic course planning recommendation and students' performance prediction multi-modal based on educational data mining techniques. *Journal of Computing in Higher Education*. https://doi.org/10.1007/s12528-024-09426-0

Lekan, K., & Pardos, Z. A. (2025). AI-augmented advising: A comparative study of GPT-4 and advisor-based major recommendations. *Journal of Learning Analytics, 12*(1), 110–128. https://doi.org/10.18608/jla.2025.8593

Long, D. Y., Wang, S., Md Rashid, S., & Lu, X. T. (2026). Artificial intelligence in higher education: A systematic review of its impact on student engagement and the mediating role of teaching methods. *Frontiers in Education, 10*, Article 1648661. https://doi.org/10.3389/feduc.2025.1648661

Maphosa, V., & Maphosa, M. (2023). Fifteen years of recommender systems research in higher education: Current trends and future direction. *Applied Artificial Intelligence, 37*(1), Article 2175106. https://doi.org/10.1080/08839514.2023.2175106

Mauro, N., Hu, Z. F., & Ardissono, L. (2023). Justification of recommender systems results: A service-based approach. *User Modeling and User-Adapted Interaction, 33*(3), 643–685. https://doi.org/10.1007/s11257-022-09345-8

Mendoza, G. A. G., Figeroa, R. B., & Thian, T. H. (2025). Exploring success in higher education in Japan: Students' perceptions of successful peers and the meaning of success. *Journal of Pedagogical Sociology and Psychology, 7*(4), 209–226. https://doi.org/10.33902/jpsp.202535864

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, Article n71. https://doi.org/10.1136/bmj.n71

Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … McKenzie, J. E. (2021). PRISMA 2020 explanation and elaboration: Updated guidance and exemplars for reporting systematic reviews. *BMJ, 372*, Article n160. https://doi.org/10.1136/bmj.n160

Rudolph, C. W., Lavigne, K. N., & Zacher, H. (2017). Career adaptability: A meta-analysis of relationships with measures of adaptivity, adapting responses, and adaptation results. *Journal of Vocational Behavior, 98*, 17–34. https://doi.org/10.1016/j.jvb.2016.09.002

Salazar, C., Aguilar, J., Monsalve-Pulido, J., & Montoya, E. (2021). Affective recommender systems in the educational field: A systematic literature review. *Computer Science Review, 40*, Article 100377. https://doi.org/10.1016/j.cosrev.2021.100377

Sarsenbay, S., Kabdiyev, A., Varlamis, I., Sardianos, C., Turan, C., Razhametov, B., & Kazym, Y. (2025). Generating job recommendations based on user personality and Gallup tests. *Algorithms, 18*(5), Article 275. https://doi.org/10.3390/a18050275

Shneiderman, B. (2020). Human-centered artificial intelligence: Three fresh ideas. *AIS Transactions on Human-Computer Interaction, 12*(3), 109–124. https://doi.org/10.17705/1thci.00131

Villacís, J. L., Naval, C., & De la Fuente, J. (2023). Character strengths, moral motivation and vocational identity in adolescents and young adults: A scoping review. *Current Psychology, 42*(27), 23448–23463. https://doi.org/10.1007/s12144-022-03427-x

Wagner, K., Merceron, A., Sauer, P., & Pinkwart, N. (2024). A course recommender system built on success to support students at risk in higher education. *Journal of Educational Data Mining, 16*(1), 330–364. https://doi.org/10.5281/zenodo.11384083

Wang, L., Ma, C., Feng, X., Zhang, Z., Yang, H., Zhang, J., Chen, Z., Tang, J., Chen, X., Lin, Y., Zhao, W. X., Wei, Z., & Wen, J. (2024). A survey on large language model based autonomous agents. *Frontiers of Computer Science, 18*(6), Article 186345. https://doi.org/10.1007/s11704-024-40231-1

Wang, S., Wang, F., Zhu, Z., Wang, J., Tran, T., & Du, Z. (2024). Artificial intelligence in education: A systematic literature review. *Expert Systems with Applications, 252*, Article 124167. https://doi.org/10.1016/j.eswa.2024.124167

Zhou, Y., & Khatibi, S. (2025). Exploring artificial personality grouping through decision making in feature spaces. *AI, 6*(8), Article 184. https://doi.org/10.3390/ai6080184