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Generative artificial intelligence in ERP education: The role of personality traits and GAI perceptions in academic performance

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Abstract

The increasing use of generative artificial intelligence (GenAI) in higher education has raised important questions about its role in student learning and academic performance. While prior research suggests that GenAI tools can enhance learning outcomes, their effectiveness may depend on how students use them and on individual learner characteristics. This study examines the relationship between GenAI usage, personality traits, and academic performance in an enterprise resource planning (ERP) course. Using data from undergraduate students, GenAI usage was measured through survey-based perceptions and reduced into four dimensions using exploratory factor analysis, while personality traits were assessed using the Big Five framework. Student performance was evaluated across conceptual understanding, system operation performance, and overall course learning outcomes. The results suggest that GenAI usage alone does not consistently predict improved academic performance, particularly in highly specialized, complex subject areas such as ERP. In contrast, personality traits show more consistent relationships with performance, and interaction effects indicate that the effectiveness of GenAI depends on its alignment with individual learner characteristics. Overall, the findings highlight that generative AI functions as a context-dependent learning tool whose impact varies across students and learning environments.

Keywords: generative artificial intelligence, ERP, personality traits, academic performance, exploratory factor analysis

Introduction

The increasing use of digital technologies in higher education has changed how students learn and interact with course material. In particular, generative artificial intelligence (GenAI) tools such as ChatGPT are increasingly used by students for tasks such as problem-solving, concept explanation, and assignment completion. While these tools have the potential to improve learning efficiency and engagement, their actual impact on academic performance remains unclear and may depend on how students use them.

At the same time, prior research shows that individual differences among students play an important role in learning outcomes (Mammadov, 2022; Komarraju et al., 2011). Personality traits, commonly studied through the Big Five framework, influence how students approach learning, adopt new tools, and perform academically. For example, more conscientious students tend to be organized and disciplined, while students high in openness are more likely to explore new learning approaches. These differences may also shape how students use generative AI in their studies.

This interaction becomes particularly important in complex learning environments such as enterprise resource planning (ERP) education. ERP courses require both conceptual understanding and hands-on system skills, making them more demanding than traditional lecture-based courses. In such settings, learning outcomes depend not only on access to tools like generative AI but also on how effectively students engage with them.

Although research on generative AI in education is growing, most studies focus on general learning contexts and do not consider system-intensive courses like ERP. Similarly, limited research has examined how personality traits interact with generative AI usage to influence academic performance. This creates a gap in understanding whether generative AI supports learning in such environments and for which types of students.

To address this gap, this study examines the relationship between generative artificial intelligence (GenAI) usage and academic performance in an ERP course, while considering personality traits as a moderating factor. Specifically, student performance is evaluated across three dimensions: conceptual understanding, operational (computer-based) performance, and overall course outcomes. By integrating perspectives from technology use and individual differences within a system-intensive learning environment, this study provides a more nuanced understanding of when and for whom generative AI supports learning in higher education.

Literature Review

Prior research relevant to this study can be organized into four key areas: ERP learning as a distinct educational context, generative artificial intelligence (GenAI) and student learning outcomes, personality traits and academic performance, and personality in technology and GenAI use. Together, these streams provide the foundation for understanding how the effects of GenAI in ERP education may vary across students rather than remain uniform (Deng, et al. 2025; Mammadov, 2022). In particular, this structure highlights that learning outcomes in system-intensive environments are shaped not only by the availability of AI tools but also by how these tools interact with individual learner characteristics.

ERP Learning as a Distinct Educational Context

Enterprise Resource Planning (ERP) education differs from traditional lecture-based instruction, emphasizing process-oriented, experiential learning over memorization. By requiring students to navigate integrated business functions through system-based tasks, ERP courses often utilize simulation games to foster deeper learning outcomes, such as applied problem-solving and process mastery (Seethamraju, 2006).

Success in these environments is driven by both technological and psychological factors. Research indicates that student outcomes are shaped by cognitive and affective responses, where perceived enjoyment and behavioral intention significantly influence learning effectiveness (Chen et al., 2025). Furthermore, individual differences play a critical role; varying personality profiles, prior knowledge, and learning orientations suggest that engagement with complex ERP systems is not uniform across the student body (Lea et al., 2020; Lea et al., 2024).

Generative Artificial Intelligence and Student Learning Outcomes

The rapid emergence of generative artificial intelligence (GenAI) has transformed the educational landscape, sparking significant interest in its role in student learning. While tools like ChatGPT can enhance academic performance, efficiency, and engagement, meta-analytic evidence suggests these positive outcomes are largely contingent on appropriate usage (Deng et al., 2025; Wang & Fan, 2025).

Several studies published in 2025 indicate that GenAI effectiveness is highly sensitive to the nature of the academic task. Specifically, these tools appear more proficient at supporting lower-order cognitive tasks such as conceptual understanding than higher-order outcomes like evaluation and original knowledge creation (Qu et al., 2025). Furthermore, GenAI tends to be more effective in declarative knowledge domains than in procedural ones (Liu et al., 2025). This distinction is particularly critical in complex environments like Enterprise Resource Planning (ERP) education, which requires specialized, system-based procedural skills.

The educational impact of GenAI is further mediated by how students choose to engage with the technology. Research distinguishes between constructive, mastery-oriented use, where students actively interrogate AI-generated content, and shortcut-based use, where the technology is used to bypass deep cognitive processing (Pallant et al., 2025). While the former supports robust knowledge development, the latter may inhibit higher-order thinking and lead to an overreliance that undermines critical problem-solving skills (Zafar et al., 2024).

Behavioral frameworks, such as the Theory of Planned Behavior and Task-Technology Fit, suggest that these varying outcomes are driven by students' attitudes and the alignment between AI capabilities and specific learning tasks (Al-Emran et al., 2025; Abu-Taieh et al., 2025). TPB proposes that behavior is influenced by attitudes, social norms, and perceived behavioral control, while TTF suggests that technology is more effective when its capabilities align with the requirements of the task being performed. While GenAI can indirectly benefit students through increased personalization and immediate feedback (Kamau, 2025), researchers caution that heightened motivation and engagement do not always translate into improved performance (Qu et al., 2025). The literature suggests that GenAI is not a uniformly beneficial tool but a context-dependent technology whose value is shaped by task type, cognitive demands, and individual patterns of use.

Personality Traits and Academic Performance

Researchers have reported that personality traits are key predictors of academic performance, particularly within the Big Five Personality traits framework. Conscientiousness is reported as a strong predictor of achievement, reflecting the self-discipline and persistence necessary for structured study habits (Mammadov, 2022; Chen et al., 2025). Openness to experience supports deep learning and reflective thinking through intellectual curiosity and receptiveness to complex educational environments (Komarraju et al., 2011).

Researchers further reported that personality traits are especially critical in Enterprise Resource Planning (ERP) education, which differs from traditional lecture-based learning by requiring students to integrate conceptual knowledge with procedural system operations. Because ERP systems are process-oriented and highly interdependent, students must simultaneously develop technical skills, business process knowledge, and analytical reasoning (Lea, et al., 2022; Kang & Santhanam, 2003). This "steep learning curve" demands higher-order learning and the ability to understand complex task interdependencies across organizational functions (Lea, et al., 2025; Lea, et al., 2022; Seethamraju, 2006; Cronan, 2012).

Prior studies suggest that ERP learning success depends heavily on behavioral tendencies rather than technical ability alone (Lea, et al., 2025; Lea, et al., 2022). In these cognitively complex settings, Openness facilitates engagement with novel, abstract systems, while Conscientiousness supports the effort required to navigate challenging procedural tasks (Paunonen & Ashton, 2001; Lea, et al., 2025). Collectively, these findings indicate that personality traits are important factors on how students interact with educational technologies. Consequently, the educational value of Generative AI likely varies across learners, as its effectiveness is mediated by individual personality differences in discipline, curiosity, and self-regulation within these demanding environments.

Personality as a Predictor of Technology and Generative AI Use

Beyond academic performance, personality traits also play an important role in shaping how students interact with technology. Research on information and communication technology use shows that personality traits systematically influence technology adoption and engagement. In particular, openness to experience and conscientiousness are generally associated with higher levels of technology use, while neuroticism may reduce confidence in adopting new systems (Joshi, Das, & Sekar, 2023).

Research on ChatGPT usage suggests that students' adoption of GenAI tools is influenced not only by perceived usefulness but also by psychological factors such as novelty, perceived humanness, and individual personality traits (Pal & Ninrutsirikun, 2023). This indicates that GenAI usage is not purely functional but also shaped by how students experience and interpret the technology. Empirical evidence in higher education further shows that personality traits directly predict educational use of generative AI. Traits such as openness, conscientiousness, and extraversion are generally associated with greater adoption of GenAI for learning purposes, while neuroticism tends to have a negative relationship (Arpaci, et al., 2025). However, some studies find that higher academic use of GenAI may be associated with lower self-efficacy and performance, particularly when usage reflects dependence rather than meaningful engagement (Azeem & Abbas, 2025).

Personality also influences how students experience interaction with AI systems. Research on human–AI collaboration shows that personality traits influence enjoyment, trust, and willingness to engage with AI tools, with trust acting as an important link between positive experience and continued use (Kovbasiuk, et al., 2026). These psychological responses can affect whether AI is used as a supportive learning tool or as a shortcut.

Similar results are reported in ERP-specific technology contexts, and personality traits also influence technology acceptance and system engagement, reinforcing the idea that individual differences matter in system-intensive learning environments (Brajektarovic, et al, 2025).

Research suggests that personality traits not only determine whether students use generative AI, but also how they use it, how they perceive it, and how beneficial that usage becomes. These differences imply that the educational effects of GenAI are likely to vary across students, depending on their underlying behavioral tendencies and interaction patterns with technology.

Conceptual Integration and Research Gap

The literature reviewed highlights four key insights relevant to this study. First, ERP education represents a distinct learning context that requires both conceptual understanding and procedural system skills, making it more complex than traditional learning environments (Seethamraju, 2006; Chen, et al., 2015). Second, while generative artificial intelligence has been shown to improve learning outcomes on average, its effectiveness varies depending on task type, cognitive level, and patterns of use (Deng, et al., 2025; Liu, et al., 2025; Pallant et al., 2025).

Third, personality traits consistently influence academic performance by shaping learning behaviors, motivation, and engagement (Mammadov, 2022; Komarraju, et al., 2011). Fourth, personality also plays an important role in determining how students adopt and interact with technologies, including generative AI, affecting perceptions, trust, and patterns of use (Joshi, et al., 2023; Arpaci, et al., 2025; Azeem & Abbas, 2025).

Despite these insights, limited research has examined how generative AI usage and personality traits jointly influence academic performance within system-intensive learning environments such as ERP education. In particular, prior studies rarely distinguish between different dimensions of performance, such as conceptual

understanding and operational system skills, which may respond differently to AI-supported learning. Building on these gaps, this study develops a framework that integrates generative AI usage and personality traits to examine their direct and interactive effects on multiple dimensions of student performance in ERP courses.

Research Model and Hypothesis

Based on the literature reviewed, this study examines how generative artificial intelligence (GenAI) usage and personality traits jointly influence student performance in an ERP learning environment. The conceptual framework is built on the premise that learning outcomes in system-intensive contexts are shaped by both technological engagement and individual characteristics.

GenAI usage is conceptualized as a multidimensional construct reflecting students' perceptions and engagement with AI-supported learning, including attitudes and perceived usefulness, curiosity and exploration, hands-on learning preference, and engagement. These dimensions capture how students interact with generative AI tools within the course.

Student performance is measured across three dimensions: conceptual ERP performance, operational (computer-based) ERP performance, and overall course performance. This distinction is important because ERP learning requires both theoretical understanding and practical system execution, and the influence of GenAI usage may differ across these outcomes.

Personality traits, based on the Big Five framework, are incorporated as individual-level characteristics that influence learning behavior and technology use. In addition to their direct effects on performance, personality traits are expected to shape how students engage with and benefit from generative AI. Accordingly, personality is examined both as an independent predictor and as a moderating factor.

Overall, the framework proposes that student performance is influenced by both GenAI usage and personality traits, and that the effectiveness of AI-supported learning depends on the alignment between technology use and individual characteristics.

Direct Effects of Generative AI Usage on Performance

Generative AI tools can support learning by providing explanations, assisting with problem-solving, and improving efficiency. However, prior research suggests that their impact on academic performance is context-dependent and influenced by how students use these tools. In system-oriented learning environments such as ERP courses, reliance on AI tools may not always lead to improved performance, particularly when usage replaces deeper engagement with underlying concepts and processes. Therefore, the first hypothesis examines whether students' orientations toward generative AI usage are associated with their academic performance across different learning dimensions.

H1: Generative AI usage is associated with student performance in ERP courses (conceptual, operational, and overall).

Direct Effects of Personality Traits on Performance

Personality traits influence academic performance by influence motivation, learning strategies, and behavioral engagement. Traits such as conscientiousness and openness are generally associated with stronger learning outcomes, while traits such as neuroticism may negatively affect performance. In ERP learning environments that require sustained effort and structured problem-solving, these individual differences are expected to play an important role. Therefore, the second hypothesis examines whether

personality traits are expected to have direct effects on student performance across different dimensions of learning outcomes.

H2: Personality traits are associated with student performance in ERP courses (conceptual, operational, and overall).

Moderating Role of Personality Traits

Personality traits may also influence how students use and benefit from generative AI tools. Prior research suggests that students differ in their approach to technology use depending on characteristics such as openness, conscientiousness, and emotional stability. As a result, the same level of AI usage may lead to different learning outcomes for individuals.

In ERP education, where both conceptual understanding and system-based skills are required, the effectiveness of generative AI likely depends on whether students engage with these tools in a structured and meaningful way. Personality traits may therefore strengthen or weaken the relationship between AI usage and performance. Therefore, the third hypothesis examines whether personality traits moderate the relationship between generative AI usage and student performance across different learning dimensions.

H3: Personality traits moderate the relationship between generative AI usage and student performance in ERP courses.

Methodology

The data for this study were collected from undergraduate students enrolled in an introductory enterprise resource planning (ERP) course in a research 1 university in the United States. The course emphasized both conceptual understanding and hands-on interaction with ERP systems, providing an appropriate context for examining technology-supported learning behaviors.

Two sources of data were used. First, a survey was administered to collect students' perceptions and experiences related to generative artificial intelligence (GenAI) usage in the course. The personality data were collected using Mini-IPIP, a validated 20-item instrument covering the Big Five Personality Traits: Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness (Donnellan, et al., 2006). After screening for completeness, the final sample consisted of 63 students

Student performance was measured using three indicators derived from course grading data. Conceptual ERP performance reflects students' understanding of theoretical concepts and course material, while operational ERP performance captures students' ability to perform system-based tasks and exercises. Overall course performance represents the aggregate performance across all graded components of the course.

Factor Analysis

To examine the underlying structure of the generative AI perception items, exploratory factor analysis (EFA) was conducted on the 29 survey items described in the previous section. The purpose of this analysis was to identify a smaller set of meaningful latent constructs representing students' orientations toward GenAI usage in the ERP learning context. EFA is commonly used in survey-based research to uncover latent dimensions and establish construct validity when the underlying structure is not predetermined (Marengo et al., 2025; Nemt-allah et al., 2024). In this study, EFA was used as a dimension-reduction technique to group related items into interpretable factors for subsequent analysis.

Data suitability for exploratory factor analysis was confirmed by an overall Kaiser's Measure of Sampling Adequacy (KMO) of 0.788, exceeding the recommended 0.70 threshold. While one item fell below the individual 0.50 cutoff (0.39), it was retained due to its conceptual relevance and the strength of the overall model. Supplemented by moderate inter-item correlations, these metrics collectively justify that the dataset shares sufficient common variance for robust factor extraction.

To identify the latent dimensions of Generative AI perception, an exploratory factor analysis was conducted using the principal factor method to isolate underlying constructs rather than merely reducing variables. Both Kaiser's criterion and scree plot inspection supported a four-factor solution, as the first four factors yielded eigenvalues above 1.00 (ranging from 5.91 to 1.15) and preceded a clear "elbow" in the variance curve. These four factors accounted for a substantial proportion of the shared variance and were retained for subsequent rotation and interpretation.

A Promax rotation, an oblique rotation method, was conducted for the four factors because the dimensions of student perceptions were expected to be correlated rather than completely independent. The inter-factor correlation matrix showed moderate correlations (e.g., $r = 0.351$ between Factors 1 and 2). Using a factor loading cutoff of 0.40, the analyses result in four interpretable factors:

- Factor 1 **GenAI Attitudes & Usefulness** represents institutional encouragement, perceived usefulness, and positive attitudes toward using generative AI tools
- Factor 2 **GenAI Curiosity & Exploration** captures intrinsic interest and experimentation with generative AI tools
- Factor 3 **Hands-On Learning Preference** represents enjoyment of hands-on activities and the perceived importance of practical engagement using GenAI for understanding
- Factor 4 **Engagement and Perceived Learning Improvement** measures perceived educational gains.

Overall, the rotated solution demonstrated a clear and interpretable four-factor structure with meaningful conceptual groupings (Table 1). These factors were retained for subsequent analysis and potential creation of composite or factor scores.

Table 1. Promax-Rotated Factor Loadings for GenAI Perception Items (Loadings ≥ 0.40 , N = 63)

Factors	Survey Item Description	Factor 1	Factor 2	Factor 3	Factor 4
GenAI Attitudes & Usefulness	GenAI should be demonstrated in learning contexts	0.891			
	I actively use GenAI tools	0.892			
	GenAI is useful for learning	0.848			
	Instructors should encourage GenAI use	0.718			
	GenAI is an effective way to complete tasks	0.622			
	GenAI helps create novel contributions	0.614			
	GenAI can be used in many different ways	0.697			
GenAI Curiosity & Exploration	I am open to learning new ways to use GenAI		0.797		
	I have an open mindset toward AI use		0.849		
	I like investing time to explore GenAI		0.782		
	I am curious about different GenAI applications		0.875		
	I enjoy figuring out different uses of GenAI		0.868		
Hands-On Learning Preference	I enjoy hands-on learning activities			0.877	
	Hands-on work improves my understanding			0.735	
	Tutorials help me complete tasks effectively			0.716	
Engagement & Perceived Learning Improvement	GenAI increases my engagement in the course				0.692
	GenAI Improves my learning outcomes				0.733

Note. Values represent standardized regression coefficients from the Promax-rotated factor pattern matrix. Only primary loadings ≥ 0.40 are displayed. Promax rotation was used due to observed correlations among factors.

Internal consistency for the four constructs was assessed using Cronbach's alpha (α) based on standardized items. As shown in Table 2, both GenAI Attitudes and Usefulness ($\alpha = 0.891$) and Curiosity and Exploration ($\alpha = 0.916$) demonstrated excellent reliability, while Hands-On Learning Preference ($\alpha = 0.820$) showed good consistency. Although Engagement and Learning Improvement yielded a slightly lower alpha (α) of 0.699, this remains acceptable for exploratory research, particularly for a two-item scale where lower variability is expected. Overall, these results confirm that all factors possess sufficient reliability for subsequent analysis.

Table 2. Internal Consistency Reliability for Extracted GenAI Constructs (N = 63)

Construct	Number of Items	Cronbach's Alpha
GenAI Attitudes & Usefulness	7	0.891
GenAI Curiosity & Exploration	5	0.916
Hands-On Learning Preference	3	0.820
Engagement & Perceived Learning Improvement	2	0.699

Note: Cronbach's alpha coefficients are based on standardized items retained from the final Promax-rotated solution. All values indicate acceptable to excellent internal consistency.

The exploratory factor analysis identified a clear and interpretable four-factor structure representing distinct dimensions of students' perceptions of generative AI. The results show adequate sampling adequacy, meaningful eigenvalues, and strong rotated factor loadings. Subsequent reliability analysis confirmed acceptable to excellent internal consistency across all constructs.

Reliability Assessment of Personality Scales

To examine the role of individual differences, personality traits were measured using the Mini-IPIP, a validated 20-item instrument covering the Big Five Personality Traits: Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness (Donnellan, et al., 2006). Psychometric studies of the IPIP and the Mini-IPIP have confirmed the reliability and validity of both instruments. Students responded to each item in the 20-item questionnaire on a 5-point Likert scale from 1 (Very Inaccurate) to 5 (Very Accurate). Internal consistency of each personality scale was evaluated using Cronbach's alpha using the full available sample to ensure measurement stability.

The scales demonstrated acceptable reliability for a short-form instrument: Extraversion ($\alpha = 0.77$), Openness ($\alpha = 0.70$), Neuroticism ($\alpha = 0.64$), and Agreeableness ($\alpha = 0.59$). For Conscientiousness, one item was removed to improve the scale's internal consistency, resulting in a final alpha of approximately 0.63. While some values are moderate, they align with prior research using brief measures. These constructs were retained for the final matched analysis, which explored the relationships among personality, GenAI usage, and academic performance. Table 3 summarizes the reliability results for all five personality traits. Composite scores for the five personality traits were calculated by averaging item responses, maintaining the original response metric for better interpretability.

Table 3. Reliability of Personality Scales

Personality Trait	Number of Items Used	Cronbach's Alpha
Extraversion	4	0.77
Agreeableness	4	0.59
Conscientiousness	3	0.63
Neuroticism	4	0.64
Openness	4	0.70

Empirical Analysis and Results

Descriptive Statistics and Correlation Analysis

Table 4 presents descriptive statistics for the study variables, including four GenAI usage dimensions, the Big Five personality traits, and three indicators of academic performance in the introductory ERP course. The final sample consisted of 63 undergraduate students, although one observation contained missing personality data, resulting in slightly fewer valid responses for the personality constructs.

The GenAI usage dimensions were derived through exploratory factor analysis and subsequently standardized. As expected, the mean values for these variables are approximately zero, with standard deviations ranging from 0.843 to 0.966, indicating adequate variability in students' orientations toward generative AI use in learning. The observed ranges of these standardized scores (e.g., -3.434 to 1.238 for hands-on learning preference and -1.771 to 2.554 for perceived usefulness) suggest meaningful differences in how students perceive and engage with AI-supported learning tools.

Descriptive statistics for personality traits indicate moderate levels across the sample. Agreeableness exhibited the highest mean ($M = 3.653$, $SD = 0.697$), followed by openness ($M = 3.560$, $SD = 0.804$) and conscientiousness ($M = 3.495$, $SD = 0.842$). In contrast, extraversion ($M = 2.907$, $SD = 1.007$) and neuroticism ($M = 2.556$, $SD = 0.785$) were comparatively lower. The variability observed across personality dimensions suggests sufficient dispersion to examine their potential influence on academic performance and interactions with GenAI learning orientations.

Student performance outcomes also showed meaningful variation. Conceptual ERP performance averaged 0.790 ($SD = 0.111$), operational ERP performance averaged 0.862 ($SD = 0.157$), and overall course performance averaged 0.846 ($SD = 0.079$). Although students generally performed well, the spread in scores indicates adequate variability for subsequent regression analyses.

Table 4. Descriptive Statistics of Study Variables

Variable	N	Mean	Std. Dev.	Min	Max
GenAI Attitudes & Usefulness	63	0	0.966	-1.771	2.554
GenAI Curiosity & Exploration	63	0	0.966	-3.179	1.552
Hands-On Learning Preference	63	0	0.926	-3.434	1.238
Engagement & Learning Improvement	63	0	0.843	-1.615	2.218
Extraversion	63	2.907	1.007	1.000	5.000
Agreeableness	62	3.653	0.697	1.750	5.000
Conscientiousness	62	3.495	0.842	1.333	5.000
Neuroticism	62	2.556	0.785	1.000	4.500
Openness	62	3.560	0.804	1.500	5.000
Conceptual ERP Performance	63	0.790	0.111	0.592	0.974
Operational ERP Performance	63	0.862	0.157	0.313	1.084
Overall Course Performance	63	0.846	0.079	0.693	1.044

Pearson correlation coefficients among the study variables are reported in Table 5. Among the GenAI dimensions, perceived usefulness and curiosity toward exploration were moderately positively associated ($r = .36$, $p < .01$), suggesting that students who perceived AI tools as useful were also more likely to exhibit exploratory learning behavior. Hands-on learning preference showed a positive relationship with conscientiousness ($r = .31$, $p < .05$), indicating that students who favored practical learning approaches tended to display stronger task-focused personality characteristics.

Several notable relationships emerged between personality traits and ERP performance outcomes. Extraversion demonstrated significant negative correlations with conceptual ERP performance ($r = -.34$, $p < .01$) and operational ERP performance ($r = -.27$, $p < .05$), suggesting that relatively less extraverted students achieved higher performance in both theoretical and system-based ERP tasks. Additionally, curiosity toward AI tools was negatively associated with operational performance ($r = -.27$, $p < .05$), and perceived usefulness of AI showed a marginal negative relationship with the same outcome ($r = -.25$, $p < .05$). These preliminary findings suggest that the relationship between generative AI usage and performance may vary across different types of ERP learning outcomes, particularly in operationally intensive tasks.

Strong positive correlations were observed among the three performance indicators. Conceptual performance was significantly related to operational performance ($r = .49$, $p < .001$) and overall course performance ($r = .45$, $p < .001$), while operational performance demonstrated the strongest association with overall course performance ($r = .58$, $p < .001$). These results indicate that both conceptual understanding and operational proficiency contribute meaningfully to overall academic success in the ERP course.

Importantly, none of the correlations among independent variables exceeded commonly accepted thresholds for multicollinearity concerns. This suggests that the GenAI usage dimensions and personality traits capture related yet distinct constructs, supporting their inclusion in the hierarchical regression models presented in the following section.

Table 5. Pearson Correlation Matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12
1. GenAI -Usefulness	1											
2. GenAI -Curiosity	.36**	1										
3. GenAI -Hands-on	-.14	-.09	1									
4. GenAI -Engagement	.22	.13	-.06	1								
5. Extraversion	.25*	.09	.03	-.16	1							
6. Agreeableness	.28*	.02	.00	-.06	.47***	1						
7. Conscientiousness	.07	.10	.31*	.04	.06	.17	1					
8. Neuroticism	.35**	.19	-.23	.04	-.20	-.01	.05	1				
9. Openness	.12	.25	-.01	-.17	.35**	.28*	.03	.17	1			
10. Concept Performance	-.24	-.22	.05	.09	-.34**	.11	-.08	-.04	.01	1		
11. Computer Performance	-.25*	-.27*	.18	-.11	-.27*	.03	.03	-.12	-.19	.49***	1	
12. Course Performance	-.23	-.20	.17	.00	-.11	.10	.10	-.00	-.17	.45***	.58***	1

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

Correlations involving personality variables are based on $N = 62$; all other correlations are based on $N = 63$.

Regression Results

To examine the relationships among Generative AI (GenAI) learning orientations, personality traits, and student performance in an introductory ERP course, hierarchical regression analyses were conducted. Three dependent variables were evaluated across four models: overall course performance, conceptual performance, and operational performance. Model 1 examined GenAI usage dimensions alone; Model 2 isolated personality traits; Model 3 combined both sets of predictors; and Model 4 introduced interaction terms. variance inflation factor (VIF) diagnostics fell well within acceptable thresholds across all models, confirming that multicollinearity does not compromise the stability or interpretation of these results.

Across all performance indicators, Model 1 demonstrates limited explanatory power, indicating that GenAI usage orientations alone do not substantially predict ERP learning outcomes. Although most GenAI dimensions are non-significant, the coefficients trend negatively. For example, GenAI curiosity displays negative associations across all outcomes, becoming strongly negative for conceptual performance in the full interaction model ($\beta = -0.170$, $p < .001$). These findings suggest that an exploratory orientation toward

AI does not automatically translate into improved performance in operationally intensive learning environments.

As shown in Table 6, when personality traits are introduced in Model 2, the explanatory power of the models improves notably, particularly for conceptual ERP performance ($R^2 = 0.262$, $F = 3.980$, $p < .001$). Agreeableness emerges as a consistent positive predictor across outcomes, showing significant effects on overall course performance ($\beta = 0.034$, $p < .05$) and conceptual performance ($\beta = 0.058$, $p < .001$). In contrast, Extraversion demonstrates a stable negative relationship with ERP performance measures, including conceptual performance ($\beta = -0.066$, $p < .001$) and operational performance ($\beta = -0.062$, $p < .001$). These results suggest that personality characteristics may play a more consistent role in explaining ERP learning outcomes than direct measures of AI use.

The combined models (Model 3) further increase explanatory power across outcomes, indicating that both personality traits and AI learning orientations jointly contribute to performance variation. However, personality effects are more consistent and stronger in magnitude than direct GenAI effects. For example, Agreeableness continues to positively predict overall course performance ($\beta = 0.039$, $p < .01$), while Extraversion maintains negative associations with both conceptual and operational performance. These findings further suggest the importance of individual learner characteristics in shaping performance in structured and procedural-oriented ERP learning environments.

Model 4 introduces interaction terms and shows the strongest overall explanatory power, particularly for course performance ($R^2 = 0.355$) and conceptual performance ($R^2 = 0.426$). For overall course performance, GenAI engagement shows a positive direct effect ($\beta = 0.065$, $p < .01$), but its interaction with extraversion is significantly negative ($\beta = -0.025$, $p < .01$), suggesting extraverted students experienced fewer performance benefits from AI engagement. Similarly, the interaction between perceived AI usefulness and neuroticism is negative ($\beta = -0.032$, $p < .01$), indicating that highly anxious students experience diminished gains when relying on AI.

For ERP conceptual performance, the interaction between AI curiosity and openness is positive and highly significant ($\beta = 0.045$, $p < .001$). This result indicates that exploratory use of AI tools may enhance conceptual understanding primarily among students who are naturally receptive to new experiences. In contrast, the main effect of AI curiosity remains negative in the same model, reinforcing the idea that exploratory AI usage may not universally support deep conceptual learning without alignment with appropriate learner characteristics.

For ERP operational performance, the interaction between hands-on AI learning preference and conscientiousness is positive and significant ($\beta = 0.049$, $p < .01$). This suggests that students who are disciplined and task-oriented benefit more from experiential engagement with AI-supported learning activities. The finding highlights the importance of structured learning behavior in translating AI engagement into improved system execution skills.

Results from the regression suggest that personality traits play a more robust role in predicting ERP success than direct GenAI usage. While AI learning orientations alone exhibit limited explanatory power, their interactions with personality traits reveal that the educational impact of GenAI is context-dependent. The efficacy of AI-supported learning relies heavily on the alignment between technology use and the individual learner's behavioral tendencies.

Table 6. Regression Results for Overall Course Performance, Concept Performance, and Computer Operation Performance

Factors	Models	Regression Results for Overall Course Performance				Regression Results for Concept Performance				Regression Results for Computer Operation Performance			
		Model 1 (GenAI)	Model 2 (Personality)	Model 3 (Combined)	Model 4 (Interaction)	Model 1 (GenAI)	Model 2 (Personality)	Model 3 (Combined)	Model 4 (Interaction)	Model 1 (GenAI)	Model 2 (Personality)	Model 3 (Combined)	Model 4 (Interaction)
GenAI Usefulness		-0.014 (0.01)	-0.024 * (0.01)	0.067 * (0.04)	0.024 (0.05)	-0.025 (0.02)	-0.017 (0.02)	-0.017 (0.02)	0.024 (0.05)	-0.025 (0.02)	-0.016 (0.03)	-0.016 (0.03)	0.009 (0.08)
GenAI Curiosity		-0.011 (0.01)	-0.006 (0.01)	-0.070 * (0.04)	-0.170 *** (0.06)	-0.019 (0.02)	-0.017 (0.02)	-0.017 (0.02)	-0.170 *** (0.06)	-0.031 (0.02)	-0.023 (0.02)	-0.023 (0.02)	-0.124 (0.09)
GenAI Hands-on		0.012 (0.01)	0.013 (0.01)	-0.035 (0.04)	0.052 (0.05)	0.002 (0.02)	0.006 (0.02)	0.006 (0.02)	0.052 (0.05)	0.023 (0.02)	0.023 (0.02)	0.023 (0.02)	-0.119 (0.07)
GenAI Engagement		0.006 (0.01)	0.004 (0.01)	0.065 ** (0.03)	0.035 (0.04)	0.022 (0.02)	0.017 (0.02)	0.017 (0.02)	0.035 (0.04)	-0.008 (0.02)	-0.022 (0.02)	-0.022 (0.02)	0.014 (0.06)
Extraversion		-0.015 (0.01)	-0.007 (0.01)	-0.009 (0.01)	-0.067 *** (0.02)	-0.066 *** (0.02)	-0.056 *** (0.02)	-0.056 *** (0.02)	-0.067 *** (0.02)	-0.062 *** (0.02)	-0.057 *** (0.02)	-0.057 *** (0.02)	-0.058 ** (0.03)
Agreeableness		0.034 ** (0.02)	0.039 ** (0.02)	0.033 ** (0.02)	0.069 *** (0.02)	0.058 *** (0.02)	0.059 *** (0.02)	0.059 *** (0.02)	0.069 *** (0.02)	0.054 * (0.03)	0.056 * (0.03)	0.056 * (0.03)	0.047 (0.03)
Conscientiousness		0.007 (0.01)	0.004 (0.01)	0.007 (0.01)	-0.016 (0.02)	-0.015 (0.02)	-0.015 (0.02)	-0.015 (0.02)	-0.016 (0.02)	0.002 (0.02)	-0.001 (0.03)	-0.001 (0.03)	-0.008 (0.03)
Neuroticism		-0.001 (0.01)	0.017 (0.02)	0.023 (0.01)	-0.009 (0.02)	-0.027 (0.02)	-0.013 (0.02)	-0.013 (0.02)	-0.009 (0.02)	-0.034 (0.03)	-0.016 (0.03)	-0.016 (0.03)	-0.018 (0.03)
Openness		-0.018 (0.01)	-0.02 (0.01)	-0.013 (0.01)	0.036 * (0.02)	0.02 (0.02)	0.025 (0.02)	0.025 (0.02)	0.036 * (0.02)	-0.017 (0.03)	-0.018 (0.03)	-0.018 (0.03)	-0.018 (0.03)
Hands-on x Conscientiousness			0.018 (0.01)	0.018 (0.01)	-0.014 (0.02)				-0.014 (0.02)				0.049 ** (0.02)
Curiosity x Openness			0.017 (0.01)	0.017 (0.01)	0.045 *** (0.02)				0.045 *** (0.02)				0.028 (0.03)
Engagement x Extraversion			-0.025 ** (0.01)	-0.025 ** (0.01)	-0.006 (0.01)				-0.006 (0.01)				-0.015 (0.02)
Usefulness x Neuroticism			-0.032 ** (0.02)	-0.032 ** (0.02)	-0.016 (0.02)				-0.016 (0.02)				-0.005 (0.03)
R ²		0.09	0.108	0.21	0.355	0.104	0.262	0.315	0.426	0.119	0.154	0.234	0.311
Adj R ²		0.027	0.028	0.073	0.181	0.042	0.196	0.197	0.271	0.058	0.079	0.101	0.124
F Statistic		1.44	1.35	1.54	2.040 **	1.68	3.980 ***	2.660 **	2.740 ***	1.95	2.040 *	1.760 *	1.660 *

Note: *p<.05, **p<.01, ***p<.001

Discussion of Findings

The findings of this study provide important insights into the role of generative artificial intelligence (GenAI) and personality characteristics in shaping student performance within an operationally oriented ERP learning environment. Overall, the results suggest that personality traits play a more consistent and meaningful role in predicting academic outcomes than direct measures of AI learning orientations. While GenAI usage factors alone exhibit limited explanatory power, their interaction with individual learner characteristics reveals nuanced patterns of influence.

One key observation is the generally weak or negative relationship between certain GenAI learning orientations and ERP performance outcomes. Specifically, exploratory curiosity toward AI tools shows a consistent negative association with conceptual ERP performance. These findings suggest that the relationship between AI-supported learning and performance is not uniform. Unlike theoretical subjects, ERP learning requires structured problem solving, process understanding, and system-based execution. As a result, unstructured or exploratory AI engagement may not align well with these operational demands.

Furthermore, the results highlight the importance of personality traits in influencing learning outcomes. Agreeableness is a positive predictor of performance, particularly in conceptual learning, suggesting that cooperative tendencies may facilitate persistence on complex, system-oriented tasks. In contrast, extraversion demonstrates a consistent negative relationship with both conceptual and operational ERP performance. This pattern may reflect differences in learning preferences, with introverted students performing better in the focused, independent interaction required by enterprise systems.

Interaction effects reveal how GenAI usage influences performance alongside individual traits. For example, a positive interaction between AI curiosity and openness indicates that exploratory AI engagement enhances conceptual understanding primarily for students receptive to new experiences. Similarly, a positive interaction between hands-on AI preference and conscientiousness suggests disciplined, task-oriented students better translate AI activities into operational performance. Conversely, negative interactions with extraversion and neuroticism imply AI benefits are reduced for socially oriented or emotionally unstable learners.

This study indicates that generative AI's effectiveness is contingent upon alignment with individual learner characteristics rather than being universally beneficial. Consequently, educators must look beyond tool availability. Designing structured activities that encourage disciplined, conceptually grounded AI use can maximize educational benefits while minimizing drawbacks like overreliance or shallow learning.

Research Implications, Limitations, and Future Research Directions

This study contributes to the literature on generative artificial intelligence (GenAI) in education by demonstrating that its impact on academic performance is context-dependent. While prior research often reports positive effects of AI-supported learning, these findings suggest that such effects vary in system-intensive environments like ERP education, where performance depends on both conceptual understanding and procedural skills.

A key contribution of this study is the integration of personality traits into the analysis of AI-supported learning. The results indicate that personality characteristics not only influence academic performance directly but also shape how students engage with and benefit from generative AI tools. This highlights the importance of individual-level differences when evaluating the effectiveness of emerging educational

technologies, moving toward a more nuanced perspective where success depends on the alignment between technology use, learner characteristics, and environmental demands.

The findings offer several insights for instructors integrating generative AI tools into ERP and similar system-oriented courses. First, simply providing access to AI tools is insufficient to improve student performance. Instead, the structured, guided use of generative AI should be emphasized to encourage students to engage more deeply with the material rather than relying on AI for quick solutions. Second, the results highlight the importance of considering individual differences in instructional design. For example, highly conscientious students benefit from hands-on and structured AI-supported activities, while students high in openness benefit from exploratory AI use for conceptual understanding. Recognizing these differences can help instructors design learning activities that better align with diverse student profiles. Finally, students should be guided toward meaningful and structured use of generative AI tools. This includes providing clear guidelines on using AI tools for learning rather than substitution, integrating AI into assignments in a controlled manner, and explicitly emphasizing critical thinking and problem-solving skills alongside AI use.

This study demonstrates that GenAI usage alone does not consistently predict academic success, particularly in operationally intensive ERP environments that require structured problem-solving. Instead, personality traits play a far more robust role in explaining student outcomes, both directly and through interaction effects. Ultimately, successful GenAI integration depends less on tool availability and more on how it is incorporated into the learning process. By actively aligning AI use with course objectives and individual student characteristics, educators can maximize its pedagogical potential while minimizing the risks of overreliance and shallow learning.

This study has several limitations that should be considered when interpreting the results. First, the samples are collected from an introductory ERP course and sample size is relative small, so additional data from different classes can improve the generalizability of the findings. Second, the study focuses on self-reported perceptions of GenAI usage that may be subject to response bias rather than capturing objective behavior. Additionally, although the Mini-IPIP is a widely used short-form personality instrument, some personality dimensions demonstrated lower internal consistency than the conventional reliability threshold, particularly Agreeableness ($\alpha = 0.59$) and Conscientiousness ($\alpha = 0.63$). While such reliability levels are not uncommon in brief personality measures, they may introduce additional measurement error and potentially attenuate observed relationships. Finally, the cross-sectional nature of the data limits the ability to draw causal conclusions. To validate and extend these findings, future research should employ larger, more diverse samples across various institutions and disciplines, utilize comprehensive personality scales, incorporate objective usage logs, and adopt longitudinal or experimental designs to evaluate how these relationships evolve over time outside of operationally intensive ERP contexts.

Overall, this study provides a more nuanced understanding of the role of generative artificial intelligence in higher education, particularly within system-oriented learning environments. By emphasizing the interaction between technology use and personality traits, it offers insights that can inform more effective and balanced approaches to AI-supported learning.

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