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Exploring the Moderating Role of Personality Traits in Technology Acceptance: A Study on SAP S/4 HANA Learning Among University Students

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Abstract

The aim of this study is to examine the impact of personality traits on students' intention to accept the SAP S/4HANA business software. Grounded in the Big Five Factor (BFF) model of personality and the Technology Acceptance Model (TAM), the research analyzed the role of individual differences in students' learning performance using this ERP system. The study was conducted on a sample of N = 418 first-year students who underwent a quasi-experimental treatment based on realistic business scenarios. The results indicate that conscientiousness emerged as a positive predictor, while agreeableness demonstrated negative predictive value in learning SAP S/4HANA, whereas neuroticism did not exhibit a significant effect. Moderation analysis revealed that both Perceived Usefulness and Actual Usage of technology moderated the relationship between conscientiousness and SAP learning performance, enhancing its predictive strength. These findings underscore the importance of individual differences in the process of SAP S/4HANA acceptance within an educational context and suggest that instructional strategies should be tailored to students' personality traits in order to optimize learning outcomes.

Keywords: technology acceptance; personality traits; SAP S/4HANA

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1. Introduction

In parallel with the advancement of modern technologies, increasing attention has been devoted to understanding how users accept and utilize new technological systems. The acceptance of new technologies represents a complex phenomenon influenced not only by the characteristics of the technology itself but also by a range of individual and social factors, including users' needs, attitudes, personality traits, cognitive styles, and emotional responses, as well as social norms and ethical considerations [1,2].

Although the scholarly pursuit of a deeper understanding of individual differences and the determinants underlying users' acceptance or rejection of emerging technologies dates back to the 1970s [3], this subject remains highly relevant today. The study of technology adoption and the use of information technology (IT) and information systems (ISs) constitutes a well-established academic domain that has evolved, in parallel with the pervasive integration of technology, into diverse spheres of human activity [1].

1.1. The Importance of Technology Acceptance Theories in Contemporary IS Research

Numerous theoretical frameworks have been developed to explain end-user behavior in the adoption of new technological solutions [3,4]. Given the inherent complexity of the

interaction between humans and technology, the investigation of technological innovation acceptance necessitates the application of IT and psychological theories and models, which facilitate a deeper understanding of the factors shaping individuals' perceptions of the utility and value of emerging devices and systems. At the core of effective technological implementation and utilization lies the capacity of ICT producers to identify and comprehend the multifaceted factors that influence user adoption and acceptance. Equipped with such insights into user behavior, IT experts and other decision-makers responsible for technological strategies are better positioned to undertake informed and impactful measures aimed at enhancing user engagement with technological systems.

Technology acceptance theories are grounded in a diverse array of theoretical frameworks, from social psychology, sociology and social science to IT. The literature presents a variety of Technology Acceptance Models [3,4], each characterized by distinct conceptual features, like the Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB), the Theory of Interpersonal Behavior (TIB), the Technology Acceptance Model (TAM), the Extension of TAM (ETAM), Igbaria's Model (IM), Social Cognitive Theory (SCT), the Innovation Diffusion Theory (IDT), the Perceived Characteristics of Innovating Theory (PCIT), the Motivational Model (MM), the Uses and Gratification Theory (U&G), the Model of PC Utilization (MPCU), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Compatibility UTAUT (C-UTAUT). Despite emerging from distinct theoretical frameworks and differing in their conceptual focus, these models have consistently proven effective in predicting and explaining a broad spectrum of human behaviors across multiple contexts [4]. Theories and models originating from psychology and sociology primarily emphasize behavioral aspects of technology acceptance, whereas those developed within the field of IT concentrate on system-related characteristics and their influence on user adoption [3]. For example, the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB) differ from the Innovation Diffusion Theory (IDT) in their primary focus: while TRA and TPB concentrate on individual behavioral intentions, IDT emphasizes adoption decisions shaped by organizational attributes rather than personal determinants [4]. Meanwhile, the Social Cognitive Theory and The Theory of Planned Behavior (TPB) incorporate the concept of perceived outcomes in behavioral forecasting, while IDT and the Technology Acceptance Model (TAM) concentrate primarily on users' beliefs about the technology itself [4].

Davis's Technology Acceptance Model (TAM) stands as one the most frequently employed models in research studies on technology acceptance [5–8]. It is considered a straightforward, predictive, and reliable framework for explaining the process of adoption and utilization of information technologies [9,10]. This model was developed within the field of information technology following the introduction of information systems into organizational environments [7]. TAM predicts users' acceptance of technology based on three fundamental constructs: Perceived Usefulness (PU), Perceived Ease of Use (PeU), and Behavioral Intention (BI) [6]. The model suggests that users who exhibit the intention to use a given technology will ultimately do so, and that this intention is influenced by their perceptions of the technology's usefulness and ease of use. TAM not only provides a theoretical framework for explaining user behavior in adopting new technologies but also serves as a practical tool for investigating the implementation processes in both educational [11] and business contexts [12]. The fundamental concept of technology acceptance is inherently focused on individual reactions to technological systems, which are undoubtedly influenced by users' personality characteristics [13]. Among the earliest studies examining the influence of personality on technology acceptance, the Big Five Inventory (BFI)—a standardized psychometric instrument assessing the five fundamental traits of the Big Five personality model (extraversion, agreeableness, conscientiousness, neuroticism, and

openness to experience)—was utilized in combination with the Technology Acceptance Model (TAM). This approach aimed to investigate the impact of personality traits on the intention to use collaborative technologies, with the goal of developing an extended model of technology adoption that would better elucidate the role of personality in the context of Business Intelligence (BI) tool adoption [13].

1.2. Innovative ERP Learning for Students Using SAP S/4HANA

Understanding the interaction between user-specific and situational factors related to IS acceptance effectively facilitates IS implementation in business practice [14]. This is particularly important when dealing with complex and expensive business ISs such as Enterprise Resource Planning (ERP). ERP, including SAP/ERP systems, is an integrated software suite that connects all aspects of a business and its processes into a unified information technology architecture, providing a comprehensive overview of operations [15,16]. SAP provides a next-generation intelligent ERP system that enables companies to achieve digital transformation.

SAP S/4HANA Cloud, the SaaS version of SAP's integrated ERP suite, enables organizations to perform core business functions with real-time analytics, scalability, and automation [16]. The main S/4HANA Cloud business modules include finance, sourcing and procurement, sales, professional services, and manufacturing (see Figure 1). Cloud-based deployment of SAP S/4HANA enables organizations to utilize its full range of functionalities without the need to invest in physical infrastructure, database management systems, or dedicated IT personnel. The service includes technologies that can help bring intelligence into ERP applications, including machine learning, voice-enabled technology and an artificial intelligence offering with SAP Business AI [16].

The increasing use of SAP/ERP systems in business has increased the demand for a skilled workforce, which has led universities to incorporate training programs into their curricula to prepare students for mastering business process concepts within the ERP environment [17–21]. The global SAP University Alliance program, undertaken by SAP companies, is an educational initiative that provides member universities with essential technical resources and educational support for training students in SAP/ERP technologies [22]. By doing so, it enhances the supply of qualified professionals with SAP/ERP competencies in the labor market, enabling employers to access graduates proficient in emerging IT concepts and software tools.

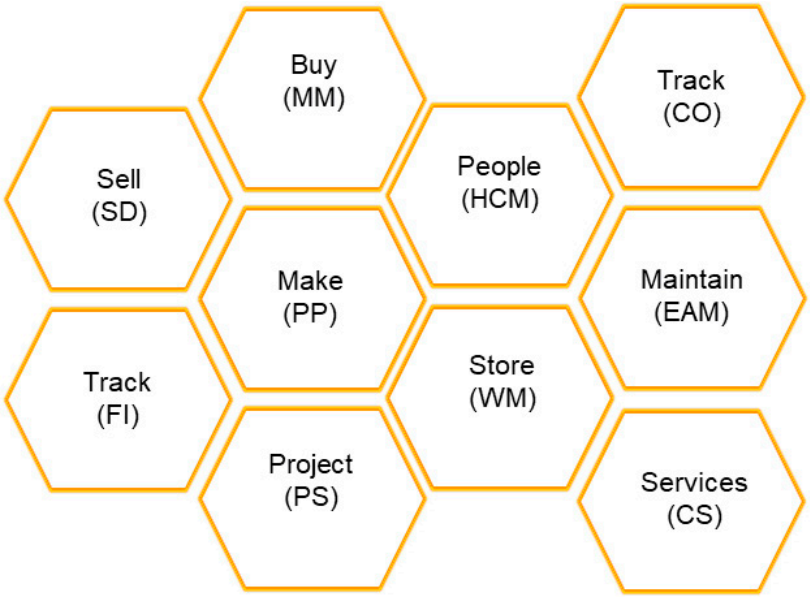


Figure 1. SAP S/4HANA: overview of key modules. Source: [23].

The SAP S/4HANA system, as an educational platform, provides an in-depth exploration of complex business processes through the fictional bicycle manufacturer Global Bike. Each learning module, illustrated in Figure 1, features a slide deck that introduces key processes, along with detailed explanations of the organizational, master, and transactional data used within the SAP S/4HANA system.

To support learning, the platform includes introductory exercises, case studies, and practical challenges designed to help students and educators grasp and engage with typical business operations. All exercises and case studies are conducted via the browser-based SAP Fiori Launchpad, offering streamlined and user-friendly access to the SAP environment, as shown in Figure 2.

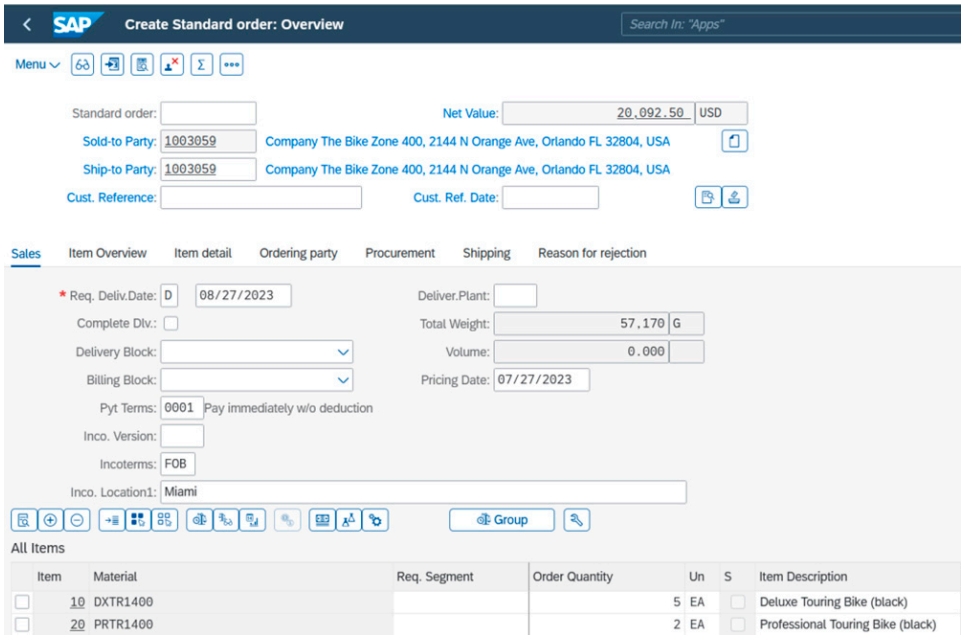


Figure 2. Sales order creation in SAP S/4HANA: A transactional interface illustrating key fields for order processing and logistics coordination. Source: [24].

The technical architecture of SAP S/4HANA is built on three layers, the database, application, and presentation layers, as illustrated in Figure 3. SAP HANA, the core component of the SAP S/4HANA system, has significantly advanced data processing within enterprise environments. As an in-memory computing engine, it allows for lightning-fast processing of large volumes of data, a stark contrast to traditional database systems. The architectural design of SAP S/4HANA supports accelerated data processing and contributes to improved cybersecurity measures [25].

By presenting security-related components in a comprehensible and structured format, Fiori UX contributes to reducing user error and enhancing operational reliability in complex digital environments. Its structure enables streamlined navigation and improves the visibility of system functionalities, contributing to more efficient user interaction [25].

Finally, advanced analytics and real-time data processing are integral components of SAP S/4HANA. The system enables the processing of complex analytical operations and calculations in real time, providing immediate access to relevant information within business processes. The integration of advanced analytics into the system supports more precise risk management and allows for the definition of quantitative indicators for monitoring security performance [25].

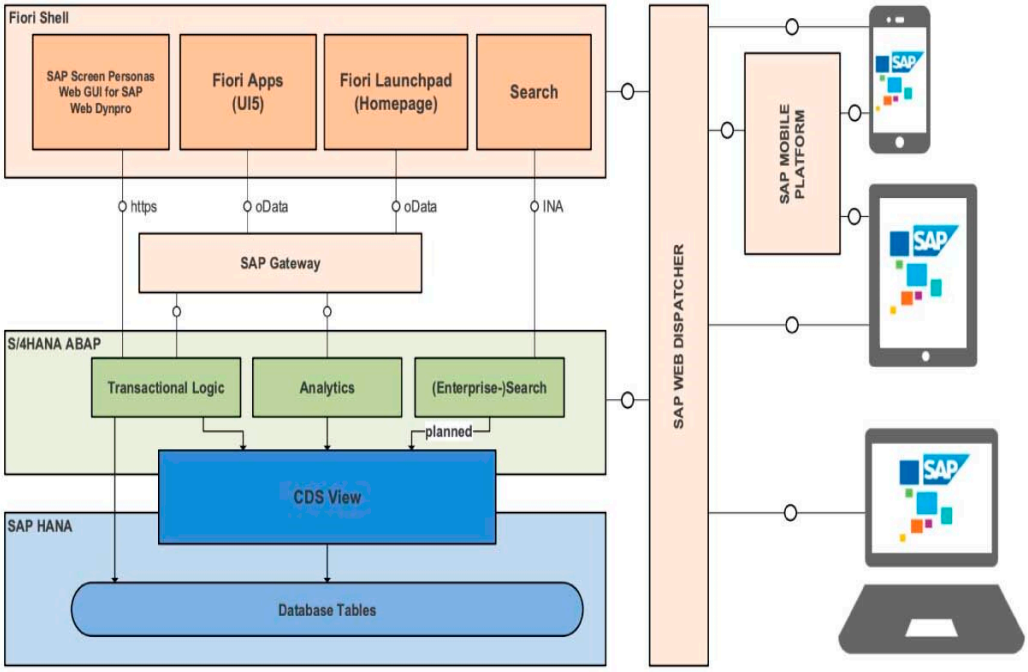


Figure 3. SAP S/4HANA Architecture. Source: [25].

1.3. Student Adoption of Technology: The Role of Personal Differences and the TAM Framework

The use of SAP S/4HANA software in university education not only enhances students' knowledge and technical skills, but also provides a valuable foundation for conducting research on ERP adoption and usage among student populations [18,26,27].

The underlying reasons for individuals' use of new technologies and their behavioral patterns with regard to their use are predominantly explored within the field of psychology, given its focus on personality as a key determinant of human behavior [28]. Personality reflects a combination of inborn and acquired attributes that tend to remain consistent over time and across various situations [29]. The Big Five Inventory (BFI) is widely used in personality and technology acceptance research, as it measures five key traits—conscientiousness, neuroticism, extraversion, openness, and agreeableness—based on typical patterns of thought, emotion, and behavior [30].

In educational settings, personality traits such as conscientiousness, openness, and agreeableness have been positively associated with academic achievement [31]. Among these, conscientiousness is identified as the strongest predictor of academic success [32], and reflects the extent to which a person is organized, disciplined, and goal-oriented [33]. Individuals with high levels of conscientiousness typically demonstrate strong self-control, determination, reliability, and a pronounced drive to achieve [34]. Neuroticism and extraversion tend to show negative associations with academic performance [35]. Neuroticism reflects an individual's level of emotional stability, anxiety, and impulse control. Those scoring high in neuroticism tend to experience frequent mood swings and are more prone to feelings such as anxiety, worry, fear, anger, frustration, jealousy, guilt, and loneliness [35,36]. Extraversion describes the degree of sociability, talkativeness, and assertiveness. Highly extraverted individuals are typically cheerful, outgoing, and confident in social interactions [33,34]. Openness to experience captures a person's intellectual curiosity and preference for novelty and diversity. Individuals with high openness are receptive to new ideas, introspective, and drawn to varied and stimulating experiences [34]. Agreeableness is defined by traits such as helpfulness, cooperation, and empathy. People with high agreeableness are often perceived as kind, warm, friendly, tactful, and optimistic [36].

While personality traits are associated with academic performance, their impact may vary depending on learning styles and educational contexts [32].

The TAM framework is applicable to a broad spectrum of end-users of computer technologies and can also serve as a developmental model for technology adoption in learning environments [11]. Research on personality traits combined with the Technology Acceptance Model (TAM) suggests that personality traits influence users' behavioral intentions to use technology [13,37–39]. Studies have shown that personality, as measured by the BFI, has an indirect impact on technology acceptance and usage: conscientiousness moderated the relationship between expected performance and behavioral intentions, while conscientiousness, extraversion, and agreeableness moderated the relationship between social influences and behavioral intentions [13]. According to the same study, neuroticism was negatively associated with expected success, whereas openness to experience and agreeableness were positively correlated with expected performance. A study reported that users' personalities indirectly influenced their behavioral intentions to use technology: openness to experience and agreeableness had a positive impact on expected performance [38]. According to scientific research [37], personality traits affect behavioral intentions to use software both directly and indirectly through expected performance (Perceived Usefulness), expected effort (Perceived Ease of Use), and subjective norms (Social Influence). The authors further emphasize that extraversion positively affects expected performance, while conscientiousness influences PeU and Social Influence. Neuroticism negatively affects BI and PeU, but has a positive effect on Social Influence. Finally, openness to experience positively influences ease of use [37].

Assuming that certain individual characteristics enhance students' receptiveness to adopting and acquiring new technological knowledge [27,31–34], this empirical study broadly aims to deepen our understanding of how personality traits influence university students' intention to use SAP/ERP tools. Given the importance of users' cognitive, emotional and behavioral responses in the process of adopting new technologies, the following central research question arises: to what extent can personality traits predict successful adoption of SAP/ERP systems, and are these relationships mediated by elements of the Technology Acceptance Model?

This theoretical foundation gives rise to the following:

1.4. Hypothesys Development

Based on the above, the primary hypotheses of this study are as follows:

H1. *Personality traits are correlated with success in acquiring knowledge in the domain of SAP/ERP (SAP Learning Performance Index).*

The literature on the BFI suggests that, in the context of learning and acquiring new skills among university students, personality traits such as extraversion, conscientiousness, agreeableness, and openness to experience are likely to facilitate learning [32,35,37]. In contrast, negative emotionality (or neuroticism) is more likely to act as a risk factor [35,36]. Certain studies suggest that, to some extent, motivation for learning can be predicted based on proactivity and personality traits such as extraversion, openness, and conscientiousness, including intention, planning, and initiation of action [40].

H1.1. *Neuroticism is negatively correlated with the SAP Learning Performance Index.*

Neuroticism is frequently identified as a predictor of lower performance in cognitive tasks [35,36,41]. In the context of technology acceptance, several studies have demonstrated

its negative influence, as anxious and emotionally unstable individuals often avoid new technologies due to perceived stress [42].

H1.2. *Conscientiousness is positively correlated with the SAP Learning Performance Index.*

Conscientiousness, on the other hand, is generally associated with greater motivation and stronger academic achievement [32,43], as well as discipline, organization, and consistent work habits [34,44], all of which may contribute to more effective learning outcomes. Conscientious individuals are organized, persistent in fulfilling their duties and tasks, and reliable. They respect rules and guidelines; value achievement, order, hard work, and efficiency [45]; and are more likely to exhibit an assertive behavioral style [46]. This personality trait is particularly relevant to academic success [47].

H1.3. *Openness to experience is positively correlated with the SAP Learning Performance Index.*

Individuals with high openness tend to exhibit intellectual curiosity and show creativity. They adapt easily to new experiences [48] and are more receptive to adopting new learning methods, such as online education [49]. Openness to experience is recognized as the best predictor of individuals' motivation to participate in training [40,50–52]. It is associated with curiosity and innovativeness [53], which can facilitate adaptation and experimentation with new technologies. Additionally, they display a greater tendency toward prosocial behavior [54]. As a personality trait, openness is also a significant predictor of one's ability to recognize emotions, understand others' perspectives, and offer mutual emotional support in friendships [55]. In light of the documented findings, the following hypothesis is proposed:

H2. *Personality traits can predict success in acquiring SAP ERP knowledge (SAP Learning Performance Index).*

Building on the previously discussed findings regarding the relationship between personality traits and academic success [31–37,41–53], it is reasonable to assume that similar patterns may emerge in situations involving the adoption of new technologies such as SAP/ERP.

H3. *The intention to use new technology, as defined by TAM, may moderate (strengthen) the relationship between personality traits and the SAP Learning Performance Index.*

The relationship between personality traits and the SAP Learning Performance Index is influenced by the intention to use new technology, as defined by the Technology Acceptance Model. Specifically, higher levels of Perceived Usefulness (PU) and Perceived Ease of Use (PeU) strengthen the positive effects of personality traits on learning performance.

H4. *Students enrolled in IT-related fields of study demonstrate higher effectiveness in acquiring SAP/ERP competencies compared to students from Management fields.*

Empirical findings suggest that different academic groups adopt varied approaches to learning and technology acceptance [56]. Information Technology (IT) students typically possess greater experience with digital tools, while Management students may rely on alternative learning strategies and demonstrate distinct technological needs. Given the nature of SAP/ERP systems—which require specific prior business and technical knowledge [19,57]—these platforms can pose cognitive challenges even for students in technical disciplines [58]. Nevertheless, the very choice of study program among IT students allows

us to conclude that the intention to adopt new technologies is already embedded in their professional orientation.

2. Research Method

This research was conducted during February and March 2024 at the Faculty of Organizational Sciences, University of Belgrade, the leading public institution in Serbia in the fields of information systems, technology, organization, and management, and a member of the SAP University Alliance.

The study was conducted in the computer lab of the faculty, in a single session (90 min) of the course Introduction to Information Systems used for the implementation of a quasi-experimental treatment. The computer lab was equipped with 50 networked computers, and the experiment was carried out in groups of 50 students. A total of N = 437 first-year students participated in the experimental training, with 418 valid responses, resulting in a response rate of 95.6%. All participants voluntarily took part in the study and did not receive any incentives for their participation.

In the first phase of the study, participants were subjected to a quasi-experimental procedure involving training in the use of the SD (Sales and Distribution) module, based on real business scenarios involving this software. The training consisted of using structured, pre-defined instructional content fully aligned with the SAP University Alliance curriculum for SAP S/4 HANA. The usage scenario served both as an educational and a research tool, and it is defined as "A narrative involving one or more actors aimed at directed activity with an interactive computer system. It includes an activation context (e.g., social or physical environment), the actors' motivation, and the actions and reactions during the activity (context of use)" [59] (p. 67).

Each student, as a participant in the study, was provided access to the SAP S/4 HANA Fiori software, version 3.0, through a virtual organization. After activating the SAP Fiori interface, participants received the following information regarding SAP and the SD module: What is SAP?, SAP Fiori, Types of data in SAP, Information about the company The Global Bike, Sales Order document, Create Sales Order based on Quotation command, Create Delivery Order, and Create Invoice). The total duration for presenting the basic elements of the SD module in the SAP S/4 HANA software was 45 min.

In the second phase, the degree of knowledge acquired about the SD module of SAP was assessed through a knowledge test, which served as a measure of the efficiency of technology adoption. Each participant completed their respective battery of online questionnaires, which were hosted on the SoSci Survey platform. The participants were assured of their anonymity and the protection of their personal data. All aspects of the students' participation in the study, as well as the methods and purposes of data collection and analysis, were reviewed and approved by the Ethics Committee of the Faculty of Organizational Sciences prior to the commencement of the research. All students were informed about the objectives of the study and provided their consent before completing the surveys.

The valid sample for the research consisted of a total of N = 418 first-year students from the Faculty of Organizational Sciences at the University of Belgrade, from two study programs: Management and Organization (N = 155 or 37% of the students) and Information Systems and Technologies (N = 263 respondents or 63%). The average age of the participants was 18.98 years (SD = 1.93). Female participants represented 61% of the total sample.

The study used three key instruments:

Personality traits were measured using the BFI-44, a short form of the Big Five Inventory comprising 44 Likert-scale items that assess five key personality traits: extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience [60].

To evaluate the effectiveness of knowledge acquisition in relation to SAP/ERP technologies, the authors developed the SAP Learning Performance Test, which focuses on the SAP SD module and includes ten closed-ended questions. Each correct answer is awarded one point, yielding a total score ranging from 0 to 10.

Finally, the Technology Acceptance Model (TAM) instrument [7] was used to assess participants' motivation to adopt new technologies, based on four key factors: Perceived Usefulness (PU), Perceived Ease of Use (PeU), Behavioral Intention (BI), and Actual Use (AU). The TAM instrument was adapted and translated into Serbian [61], and comprises 14 items rated on a seven-point Likert scale.

A descriptive analysis was performed to assess the distribution of the variables used. Pearson's correlation coefficient was then applied to assess the relationships between personality traits, SAP learning performance, and the intention to use new technologies. To evaluate the moderating effect of the intention to use new technologies on the relationship between personality traits and SAP learning (see Figure 4), a moderation analysis (Model 1) was conducted using the PROCESS macro for IBM SPSS Statistics (Version 28) [62]. To categorize the moderating variable (intention to use new technologies), the median split method was used [62].

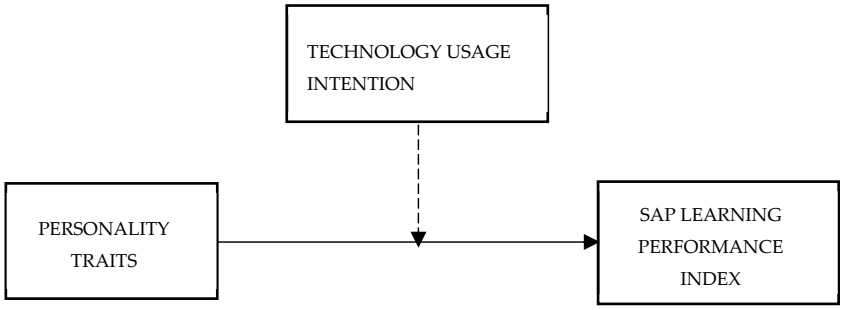


Figure 4. The relationship between personality traits and success in SAP learning: hypothetical framework of the moderating effect of the intention to use new technologies. Source: Own illustration.

The moderation analysis by study program (IT/Management) was conducted within the same macro framework, utilizing Model 3 (Figure 5), where the study program was incorporated as an additional moderator. This approach aimed to examine the moderating role of the intention to use new technologies in the relationship between personality dimensions and the SAP efficiency index while considering the students' respective study programs.

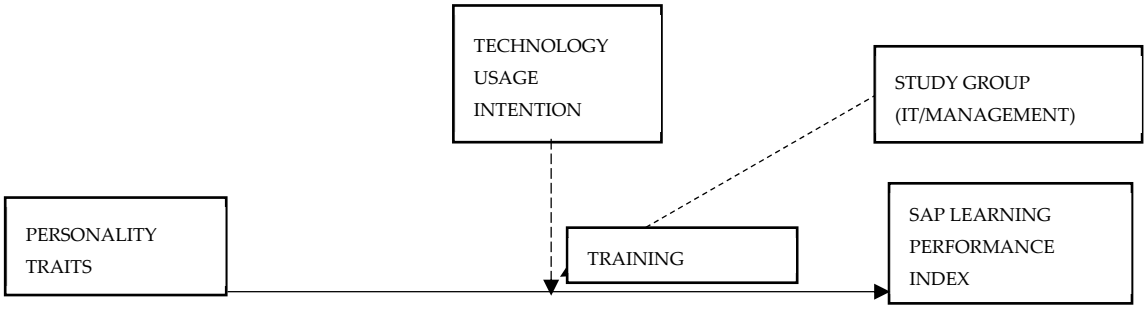


Figure 5. Relationships between personality traits and SAP acceptance: a hypothetical framework of the interactive moderating effect of the intention to use new technologies with the study group. Source: Own illustration.

3. Results

3.1. Descriptive Statistics and Reliability Analysis of Variables

A descriptive statistics analysis was conducted to examine the distribution of the obtained data (Table 1). Upon reviewing the skewness and kurtosis indicators of the overall average scores, it was concluded that their values generally fall within appropriate ranges (skewness and kurtosis between −3.00 and 3.00), in accordance with the more lenient criteria outlined by [63].

Table 1. Descriptive statistics and reliability of the variables used.

Variable	M	SD	min	max	Sk	Ku	α
SAP L.P. Index	1.64	1.15	0.00	6.00	0.72	0.74	0.86
Perceived Usefulness (TAM)	4.57	1.15	1.00	7.00	0.09	0.03	0.90
Perceived Ease of Use (TAM)	4.38	0.93	1.00	7.00	0.44	1.87	0.84
Behavioral Intention (TAM)	4.50	1.06	1.00	7.00	0.02	1.23	0.70
Actual Use (TAM)	4.45	1.04	1.00	7.00	0.14	1.32	0.85
Extraversion (BFI)	3.36	0.72	1.13	5.00	−0.12	−0.22	0.87
Neuroticism (BFI)	3.09	0.60	1.50	5.00	0.12	−0.01	0.84
Agreeableness (BFI)	3.70	0.64	1.67	5.00	−0.10	−0.59	0.81
Conscientiousness (BFI)	3.52	0.67	1.33	5.00	−0.09	−0.28	0.72
Openness (BFI)	3.48	0.60	1.50	4.70	0.11	−0.41	0.88

In the TAM questionnaire, respondents scored highest on the Perceived Usefulness scale and lowest on the Perceived Ease of Use scale. The maximum score on the SAP Learning Performance Test was 6 points, while the minimum score was 0. Reliability analysis of the measurement variables, using the coefficient of internal consistency (Cronbach's α), revealed that all variables can be considered reliable, as all exceed the threshold score of 0.60, which is recommended as the minimum for the reliability of psychological measurement instruments [63].

3.2. Analysis of Interrelationships Among Variables

The correlational analysis addressed the first set of hypotheses (H1) on the relationship between personality traits and success in acquiring knowledge in the ICT domain. Pearson's correlation analysis (Table 2) revealed that SAP Learning Performance scores positively correlate with Perceived Ease of Use and conscientiousness, and negatively with agreeableness. Neuroticism shows a low but significant positive correlation with Behavioral Intention (BI). On the other hand, openness also shows low but significant positive correlations with Actual Use (AU).

This analysis also provides an answer to the hypotheses proposed in the first set of specific hypotheses. It confirmed positive correlations with conscientiousness (H1.2), found no significant effect for neuroticism (H1.1), and unexpectedly revealed a negative correlation with agreeableness. Thus, the hypotheses regarding conscientiousness and openness were supported.

In order to examine the collective contribution and the effects of personality traits on the success of SAP learning, multiple regression analysis was employed (Table 3). Regression analysis showed that personality traits explain 4% of the variance in the SAP Learning Performance Test, with lower agreeableness significantly predicting higher SAP scores. This finding supports H2.

Table 2. Intercorrelations of the variables used in the study.

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
SAP l.p.index	-															
PU (TAM)	0.01	0.05	-													
PeU(TAM)	0.09 *	−0.01	0.52 **	-												
BI (TAM)	−0.02	0.01	0.62 **	0.56 **	-											
AU (TAM)	0.01	−0.05	0.68 **	0.54 **	0.74 **	-										
Extraversion	−0.08	0.05	0.06	0.05	0.04	0.07	0.01	0.03	−0.01	0.04	−0.03	−0.02	-			
Neuroticism	−0.04	0.02	0.02	−0.08	0.12 *	0.02	−0.01	−0.03	−0.03	0.01	0.01	0.03	−0.09	-		
Agreeableness	−0.17 **	0.02	0.06	−0.02	0.01	−0.02	0.09	0.06	0.05	0.09	−0.01	0.05	0.40 **	−0.02	-	
Conscientiousness	0.15 **	−0.09 *	0.01	0.03	0.01	−0.02	0.01	−0.02	0.02	0.02	−0.02	0.01	0.32 **	0.17 **	0.49 **	-
Openness	−0.05	0.13 **	−0.01	−0.04	−0.05	0.10 *	0.11 *	0.07	0.01	0.10 *	0.02	0.06	0.35 **	0.03	0.35 **	0.24 **

Note: PU—Perceived Usefulness; PeU—Perceived Ease of Use; BI—Behavioral Intention; AU—Actual Use. * $p < 0.05$. ** $p < 0.01$.

Table 3. The combined contribution of personality traits to SAP acceptance.

	SAP Learning Performance Index		
	β	***T***	***p***
Extraversion	−0.02	−0.33	0.74
Neuroticism	−0.08	−1.51	0.13
Agreeableness	−0.13	−2.01	0.04
Conscientiousness	0.10	1.66	0.09
Openness	0.03	0.50	0.61
Model Significance	$F(5, 359) = 3.10$, $p < 0.01$, $R = 0.20$, $R^2 = 0.04$		

Note: F—value of the F-test; R—multiple correlation coefficient; R^2—coefficient of multiple determination; β—partial contribution of the predictor; t—value of the *t*-test.

A series of moderation analyses was conducted using the PROCESS macro for SPSS [64] to address Hypothesis H3.

The macro estimates the moderation model's overall significance and the interaction effect between predictor and moderator variables. Moderation is confirmed only if this interaction is statistically significant. If so, it can be visualized using syntax from the PROCESS output. Significance is further supported when the confidence interval (ULCI–LLCI) excludes the value 0.00. To establish the levels of the moderating variables, the median-split method was employed [62]. This approach divides participants into two relatively equal groups based on the scores of the moderating variable, categorizing them as individuals with either higher or lower levels of the moderator. These groups then serve as a categorical variable required for conducting moderation analysis, particularly when examining the nature of the moderator and its potential interactive effects with the predictor variable.

Based on the median-split criterion, participants were grouped according to the levels of the moderating variables, as shown in Table 4.

Table 4. Participant categorization according to the moderator variable (TAM) of intention to use new technologies.

Moderator	Lower Scores	Highers Scores
Perceived Usefulness (PU)	50.5% participants	49.5% participants
Perceived Ease of Use (PeU)	54.9% participants	45.1% participants
Behavioral Intention (BI)	53.5% participants	46.7% participants
Actual Use (AU)	53.3% participants	46.7% participants

The first set of moderation analyses focused on the relationship between personality traits and the SAP Learning Performance Index, with intention to use new technologies serving as the moderating variable in this relationship (Table 5).

Perceived Ease of Use (PeU) showed a significant interaction with extraversion and SAP acceptance, adding 1% to explained variance, evident only in high PeU scores (β = −0.29, SE = 0.12, t = −2.48, $p < 0.01$, LLCI = −0.51, ULCI = −0.06), and not among those with low PeU scores (β = 0.04, SE = 0.11, t = 0.36, $p = 0.72$, LLCI = −0.17, ULCI = 0.26). In this case, students with higher levels of extraversion and higher PeU scores demonstrated lower performance in the SAP Learning Performance test.

Behavioral Intention (BI) as a moderator revealed a significant interaction between extraversion and SAP learning performance, explaining an additional 1% of variance. This effect was significant only among participants with high BI (β = −0.29, $p < 0.01$), indicating that highly extraverted students with strong intentions to use new technologies tend to perform worse in SAP learning tasks.

Table 5. Moderating effect of intention to use modern technologies (TAM) on the relationship between BFI and SAP Learning Performance Index.

Extraversion	**Model Significance Parameters**	**Interaction Significance**
Perceived Usefulness (PU)	F = 1.17; R^2 = 0.01; p = 0.32	ΔR^2 = 0.00; F = 1.32; p = 0.25
Perceived Ease of Use (PeU)	F = 2.35; R^2 = 0.02; p = 0.07	ΔR^2 = 0.01; F = 4.14; p = 0.04
Behavioral Intention (BI)	F = 2.29; R^2 = 0.02, p = 0.08	ΔR^2 = 0.01; F = 3.67; p = 0.05
Actual Use (AU)	F = 1.33; R^2 = 0.01, p = 0.26	ΔR^2 = 0.01; F = 2.08; p = 0.15
Neuroticism	**Model Significance Parameters**	**Interaction Significance**
Perceived Usefulness (PU)	F = 0.17; R^2 = 0.00; p = 0.92	ΔR^2 = 0.00; F = 0.00; p = 0.98
Perceived Ease of Use (PeU)	F = 1.19; R^2 = 0.01; p = 0.31	ΔR^2 = 0.00; F = 1.22; p = 0.27
Behavioral Intention (BI)	F = 0.62; R^2 = 0.00, p = 0.60	ΔR^2 = 0.00; F = 0.57; p = 0.45
Actual Use (AU)	F = 0.28; R^2 = 0.00, p = 0.84	ΔR^2 = 0.00; F = 0.27; p = 0.60
Agreeableness	**Model Significance Parameters**	**Interaction Significance**
Perceived Usefulness (PU)	F = 4.67; R^2 = 0.03; p = 0.00	ΔR^2 = 0.00; F = 0.18; p = 0.67
Perceived Ease of Use (PeU)	F = 5.79; R^2 = 0.04; p = 0.00	ΔR^2 = 0.00; F = 1.99; p = 0.16
Behavioral Intention (BI)	F = 4.84; R^2 = 0.04, p = 0.00	ΔR^2 = 0.00; F = 1.02; p = 0.31
Actual Use (AU)	F = 4.33; R^2 = 0.03, p = 0.01	ΔR^2 = 0.00; F = 0.03; p = 0.86
Openness	**Model Significance Parameters**	**Interaction Significance**
Perceived Usefulness (PU)	F = 0.66; R^2 = 0.01; p = 0.57	ΔR^2 = 0.00; F = 0.56; p = 0.45
Perceived Ease of Use (PeU)	F = 1.37; R^2 = 0.01; p = 0.25	ΔR^2 = 0.00; F = 1.33; p = 0.25
Behavioral Intention (BI)	F = 0.82; R^2 = 0.04, p = 0.48	ΔR^2 = 0.00; F = 0.59; p = 0.44
Actual Use (AU)	F = 0.43; R^2 = 0.00, p = 0.73	ΔR^2 = 0.00; F = 0.03; p = 0.86
Conscientiousness	**Model Significance Parameters**	**Interaction Significance**
Perceived Usefulness (PU)	F = 5.17; R^2 = 0.04; p = 0.00	ΔR^2 = 0.01; F = 4.97; p = 0.03
Perceived Ease of Use (PeU)	F = 4.71; R^2 = 0.03; p = 0.00	ΔR^2 = 0.01; F = 2.52; p = 0.11
Behavioral Intention (BI)	F = 3.85; R^2 = 0.03, p = 0.01	ΔR^2 = 0.00; F = 0.97; p = 0.32
Actual Use (AU)	F = 4.70; R^2 = 0.03, p = 0.00	ΔR^2 = 0.01; F = 4.03; p = 0.05

Note: F—test value F-test; R^2—coefficient of multiple determination; p—significance level.

The results also indicate a statistically significant effect of Perceived Usefulness and Actual Use in interaction with conscientiousness. Specifically, PU contributes an additional 1% to the explanation of the relationship between conscientiousness and the SAP Learning test. This effect is significant only among participants with lower levels of PU (β = −0.47, SE = 0.12, t = −3.85, $p < 0.01$, LLCI = −0.72, ULCI = −0.23), while no significant effect is observed among those with higher PU scores (β = −0.10, SE = 0.12, t = −0.82, p = 0.41, LLCI = −0.33, ULCI = 0.13).

The interaction with Actual Use contributes an additional 1% to explaining the link between conscientiousness and SAP learning performance. A significant effect is observed only among participants who exhibit lower levels of AU of new technologies (β = −0.44, SE = 0.12, t = −3.66, $p < 0.01$, LLCI = −0.68, ULCI = −0.20), but not among those with higher levels of PU (β = −0.10, SE = 0.12, t = −0.83, p = 0.41, LLCI = −0.34, ULCI = 0.14). Although participants with higher levels of conscientiousness tend to achieve better outcomes, those with lower levels of AU score lower on the SAP learning performance test.

Overall, Hypothesis 3 is confirmed by the interactions of extraversion with PeU and BI, and conscientiousness with PU and AU. Each of these interactions strengthen the relationship with SAP scores by 1%, thereby supporting Hypothesis 3. However, these interactions accounted for only an additional 1% of the variance in SAP performance scores, suggesting that, while the moderating effects are statistically significant, their contribution to the overall explanation of learning success in SAP S/4HANA software is fairly modest.

And finally, for the evaluation of Hypothesis 4, a descriptive analysis of the variables used across student groups was conducted, taking into account the student groups that participated in the study: Management students and IT students (Table 6).

Table 6. Descriptive statistics and reliability of the variables used—presented by student group.

Information Systems	**M**	**SD**	**min**	**max**	**Sk**	**Ku**
SAP Learning Performance Index	1.68	1.13	0.00	6.00	0.54	0.27
Perceived Usefulness (PU) (TAM)	4.45	1.13	1.00	7.00	0.20	0.21
Perceived Ease of Use (TAM)	4.34	0.88	1.00	7.00	0.49	2.34
Behavioral Intention (TAM)	4.33	1.02	1.00	7.00	−0.05	1.92
Actual Use (TAM)	4.30	0.99	1.00	7.00	−0.02	1.98
Extraversion (BFI)	3.25	0.73	1.13	5.00	−0.01	0.02
Neuroticism (BFI)	3.07	0.60	1.50	5.00	0.09	0.15
Agreeableness (BFI)	3.65	0.66	1.67	5.00	−0.05	−0.47
Conscientiousness (BFI)	3.45	0.67	1.33	5.00	−0.01	−0.04
Openness (BFI)	3.44	0.61	1.50	4.70	0.03	0.27
Management	**M**	**SD**	**min**	**max**	**Sk**	**Ku**
SAP Learning Performance Index	1.57	1.19	0.00	6.00	1.01	1.52
Perceived Usefulness (PU) (TAM)	4.80	1.16	1.00	7.00	−0.12	0.04
Perceived Ease of Use (TAM)	4.47	1.00	1.00	7.00	0.32	1.33
Behavioral Intention (TAM)	4.66	1.13	1.00	7.00	0.09	0.24
Actual Use (TAM)	4.71	1.08	1.00	7.00	0.26	0.43
Extraversion (BFI)	3.56	0.66	1.75	4.75	−0.26	−0.62
Neuroticism (BFI)	3.13	0.59	1.63	4.63	0.18	−0.32
Agreeableness (BFI)	3.79	0.60	2.56	5.00	−0.15	−0.94
Conscientiousness (BFI)	3.64	0.67	1.78	5.00	−0.04	−0.64
Openness (BFI)	3.55	0.58	1.80	4.60	−0.38	−0.32

By comparing the two student groups across the examined variables using an independent samples t-test, it was found that differences could be detected for several variables: Perceived Usefulness (PU) ($t = -2.97$, $p < 0.01$), Behavioral Intention (BI) ($t = -3.03$, $p < 0.01$), Actual Use (AU) ($t = -3.80$, $p < 0.01$), extraversion ($t = -4.32$, $p < 0.01$), agreeableness ($t = -2.12$, $p < 0.05$) and conscientiousness ($t = -2.77$, $p < 0.01$).

On all of these variables, Management students achieved higher scores compared to IT students. Management students were more likely to exhibit higher levels of intention to use new technologies (TAM) and also showed higher levels of extraversion, agreeableness, and conscientiousness than IT students. No statistically significant differences were found between the two groups for the remaining variables.

To examine the moderating effects of TAM factors on the relationship between personality traits and SAP learning performance among IT and Management students, the same statistical principles of moderation and median split were applied. This framework enabled the comparison of moderating effects across the two student groups, in accordance with the requirements of Hypothesis 4, and facilitated the assessment of potential differences in the moderator effects between the two groups of students.

The results of the moderation analysis, as shown in Table 7, revealed no differences between the two student groups, leading Hypothesis 4 to be rejected.

Table 7. Moderating effect of intention to use modern technologies (TAM) on the relationship between personality traits (BFI) and SAP Learning Performance Index across student subgroups.

Extraversion	**Model Significance Parameters**	**Interaction Significance**
Perceived Usefulness × Group	F = 1.12; R^2 = 0.02; p = 0.35	ΔR^2 = 0.00; F = 0.10; p = 0.75
Perceived Ease of Use × Group	F = 2.19; R^2 = 0.04; p = 0.03	ΔR^2 = 0.01; F = 3.44; p = 0.06
Intention to Use × Group	F = 1.53; R^2 = 0.03, p = 0.16	ΔR^2 = 0.00; F = 0.26; p = 0.61
Actual Use × Group	F = 1.34; R^2 = 0.02, p = 0.33	ΔR^2 = 0.00; F = 0.29; p = 0.59
Neuroticism	**Model Significance Parameters**	**Interaction Significance**
Perceived Usefulness × Group	F = 0.66; R^2 = 0.01; p = 0.77	ΔR^2 = 0.00; F = 0.00; p = 0.96
Perceived Ease of Use × Group	F = 1.33; R^2 = 0.02; p = 0.24	ΔR^2 = 0.00; F = 0.61; p = 0.43
Intention to Use × Group	F = 0.91; R^2 = 0.02, p = 0.50	ΔR^2 = 0.00; F = 0.00; p = 0.99
Actual Use × Group	F = 0.87; R^2 = 0.02, p = 0.53	ΔR^2 = 0.00; F = 0.00; p = 0.95
Agreeableness	**Model Significance Parameters**	**Interaction Significance**
Perceived Usefulness × Group	F = 2.72; R^2 = 0.05; p = 0.01	ΔR^2 = 0.00; F = 0.03; p = 0.86
Perceived Ease of Use × Group	F = 3.45; R^2 = 0.06; p = 0.00	ΔR^2 = 0.00; F = 1.12; p = 0.29
Intention to Use × Group	F = 2.80; R^2 = 0.05, p = 0.01	ΔR^2 = 0.00; F = 0.02; p = 0.89
Actual Use × Group	F = 2.86; R^2 = 0.05, p = 0.01	ΔR^2 = 0.00; F = 0.15; p = 0.70
Conscientiousness	**Model Significance Parameters**	**Interaction Significance**
Perceived Usefulness × Group	F = 3.04; R^2 = 0.05; p = 0.00	ΔR^2 = 0.00; F = 0.01; p = 0.92
Perceived Ease of Use × Group	F = 3.31; R^2 = 0.06; p = 0.00	ΔR^2 = 0.01; F = 3.24; p = 0.07
Intention to Use × Group	F = 2.28; R^2 = 0.04, p = 0.03	ΔR^2 = 0.00; F = 0.08; p = 0.78
Actual Use × Group	F = 3.16; R^2 = 0.05, p = 0.00	ΔR^2 = 0.00; F = 0.00; p = 0.99
Openness	**Model Significance Parameters**	**Interaction Significance**
Perceived Usefulness × Group	F = 1.58; R^2 = 0.03; p = 0.14	ΔR^2 = 0.00; F = 0.79; p = 0.37
Perceived Ease of Use × Group	F = 1.97; R^2 = 0.03; p = 0.06	ΔR^2 = 0.00; F = 0.78; p = 0.38
Intention to Use × Group	F = 1.48; R^2 = 0.03, p = 0.17	ΔR^2 = 0.00; F = 0.62; p = 0.43
Actual Use × Group	F = 1.42; R^2 = 0.03, p = 0.20	ΔR^2 = 0.00; F = 0.33; p = 0.57

4. Discussion

The findings of this study present clear evidence that personality traits have an impact on technology acceptance. Conscientiousness and openness were positively associated with SAP knowledge acquisition, supporting prior findings on their relevance for academic and professional success [31,32]. However, the expected negative correlation between neuroticism and SAP performance was not observed, diverging from studies linking neuroticism to lower academic achievement and reduced technology adoption [13,35,41]. This may be due to the brief exposure to SAP/ERP (45 min, one module), which likely did not elicit sufficient stress for neuroticism-related effects to emerge. The unexpected finding—the negative correlation between agreeableness and the SAP Learning Performance Index—contrasts with the majority of prior research in the fields of technology acceptance [37,65] and academic achievement [32]. This result suggests that students with lower levels of agreeableness—typically more individualistic and competitive—may be more prone to adopting a proactive approach to learning SAP, leading to better outcomes. It may also be attributed to the specific nature of SAP/ERP software, which requires a high degree of self-sufficiency. These insights underscore the relevance of interpersonal traits, and they open avenues for further research into their impact on the acquisition of technological skills.

The interaction of extraversion with Perceived Ease of Use (PeU) and Behavioral Intention (BI), as well as the interaction of conscientiousness with Perceived Usefulness (PU) and Actual Use (AU), each contributed to a 1% increase in SAP performance scores.

Despite being statistically significant, these effects explained only an additional 1% of the total variance in SAP learning outcomes, indicating that their overall influence on learning success within SAP software is marginal.

Finally, our results suggest that IT and Management students show no significant differences in the way technology acceptance moderates the relationship between personality traits and SAP learning performance. This may be a consequence of the nature of SAP/ERP software, which requires specific prior business and technical knowledge [19,57] that may present similar challenges for both student groups, given that they are first-year students.

5. Practical Implications

The initial aim of this study was to contribute to the existing theoretical framework by enhancing our understanding of student characteristics in the context of ERP technology acceptance.

The findings support the possibility of designing tailor-made training programs during the SAP/ERP education process, which would be adapted to users' personality traits in order to facilitate more efficient and accessible learning. More contemporary training approaches—such as gamified learning—could be employed, especially considering that game-based methods have proven to be more effective than traditional training in enhancing user motivation to adopt new IT systems [66]. Furthermore, according to the same study, Perceived Ease of Use also had a stronger influence on users' intention to adopt the system among individuals who undertook game-based training [66].

For example, since extroverted individuals often prefer learning through interaction and hands-on experiences, training in the form of interactive SAP gaming is recommended for this type of user, as it provides a sufficiently stimulating environment. This approach includes group-based processes, various types of simulations and interactive challenges within the SAP context, which can lead to improved learning performance through the kinds of team interaction and experiential engagement that suit extroverted individuals. Extraverted individuals often favor learning through interaction and hands-on experiences, whereas mastering ERP systems typically demands high levels of focus and analytical thinking, and may represent a less stimulating environment for them. This pattern aligns with theoretical frameworks linking extraversion to a preference for external stimuli and social interactions [33,34,62].

On the other hand, students with lower levels of agreeableness [36], characterized by higher tendencies toward disagreeableness, egocentrism, and competitiveness, may exhibit greater intrinsic motivation to independently engage with and acquire new technologies such as SAP. For these individuals, engaging tasks would include individual assignments and competitive problem-solving activities without necessarily relying on peer collaboration. Self-paced training with a variety of learning resources, available in multiple formats and hands-on exercises within live SAP training systems, would be recommended for them.

A second practical implication emerging from this study concerns the acceptance and learning of SAP/ERP systems. Specifically, the findings suggest that general SAP/ERP training standardized in terms of content and information delivery and designed independently of students' academic background could be adapted to individual personality traits. As demonstrated by this research, personality traits have a greater impact than the specific academic major on knowledge acquisition related to SAP/ERP systems. These findings are relevant only to students in the fields of Information Systems and Technology, Organizational Sciences, and Management.

The third practical implication refers to applying insights from this study to help organizations tailor training programs to better match employee characteristics during the implementation of SAP ERP systems, although this may potentially limit the generalizabil-

ity of the findings to broader employee populations beyond the study sample [13,67]. As employee frustration often stems from insufficient IT knowledge and skills, end-user training plays a key role in shaping attitudes toward technology. Failures in its adoption can lead to reduced productivity and a loss of competitive advantage [68,69]. Therefore, tailor-made training solutions according to individual differences could be valuable solution.

6. Conclusions

The results of this study offer valuable contributions to our understanding of the role of personality traits and technology acceptance among first-year university students in the context of SAP/ERP system learning, emphasizing the critical importance of individual personality differences across academic disciplines. Specifically, the results demonstrate that lower levels of agreeableness emerge as a significant predictor of SAP/ERP learning success, accounting for 4% of the explained variance.

The intention to use new technology, as defined by TAM, influenced the strength of the relationship between personality traits and the SAP Learning Performance Index. However, the effect was marginal, indicating that the overall contribution of these factors to learning outcomes remains limited.

Ultimately, IT and Management students showed no notable differences in how technology acceptance intentions influenced the relationship between personality traits and SAP learning, suggesting that this effect remains consistent across academic disciplines.

Overall, considering the results obtained in this study, the findings have practical implications for the design of educational programs, highlighting the importance of tailoring learning methods to individual personality characteristics. Aligning instructional strategies with these traits may enhance the effectiveness of SAP learning and foster greater user engagement with ERP technologies.

7. Limitations

Certain limitations should be considered when interpreting these findings. The use of student samples in information system (IS) research remains a frequently debated methodological choice, potentially limiting the generalizability of findings [13,67]. However, within the context of this study, the convenience sample consisting of first-year IT and Management students may be considered appropriate, as it was their first exposure to an enterprise technology, such as SAP/ERP, that aligns with their selected academic and professional fields. However, it must be noted that the participants were at the very beginning of their studies (freshmen in the early second semester), and thus may not yet have possessed the necessary prior business knowledge—particularly regarding sales processes—that would facilitate a deeper understanding and easier adoption of the system [19,61]. Moreover, the sample was restricted to students from IT and Management groups, thereby excluding other academic and professional groups that may exhibit different learning patterns and technology acceptance behaviors [54].

8. Recommendations for Future Studies

Due to the time limitations of this research design, the inclusion of additional SAP modules was not feasible. Consequently, future research could expand upon these findings by incorporating multiple SAP modules and including other factors, such as the digital competencies of students, which may further influence the process of ERP technology acceptance.

For future research, it is recommended to include students from higher years of study, who possess broader business and technical knowledge, as well as students from diverse academic disciplines. Such an approach would provide deeper insights into how these relationships vary across different fields of study and how they evolve over time,

following the processes of adaptation to and adoption of SAP/ERP systems. Moreover, the experimental design should be further refined to incorporate additional factors that may influence learning success and technology acceptance.

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Abbreviations

The following abbreviations are used in this manuscript:

TAM	Technology Acceptance Model
TRA	Theory of Reasoned Action
TPB	Theory of Planned Behavior
TIB	Theory of Interpersonal Behavior
ETAM	Extension of TAM
IM	Igbaria's Model
SCT	Social Cognitive Theory
PCIT	Perceived Characteristics of Innovating Theory
MM	Motivational Model
U&G	Uses and Gratification Theory
MPCU	Model of PC Utilization
UTAUT	Unified Theory of Acceptance and Use of Technology
C-UTAUT	Compatibility UTAUT
PU	Perceived Usefulness
BI	Behavioral Intention
RU	Real Use
PeU	Perceived Ease of Use
IDT	Innovation Diffusion Theory
BFI	Big Five Inventory
BFF	Big Five Factor
ERP	Enterprise Resource Planning

References

1. Taiwo, A.A.; Downe, A.G. The theory of user acceptance and use of technology (UTAUT): A meta-analytic review of empirical findings. *J. Theor. Appl. Inf. Technol.* **2013**, *49*, 48–59.
2. Chaudhry, B.M.; Shafeie, S.; Mohamed, M. Theoretical models for acceptance of human implantable technologies: A narrative review. *Informatics* **2023**, *10*, 69. [CrossRef]
3. Momani, A.M.; Jamous, M.M.; Hilles, S.M. Technology Acceptance Theories: Review and Classification. *Int. J. Cyber Behav. Psychol. Learn.* **2017**, *7*, 1–14. [CrossRef]
4. Taherdoost, H. A review of technology acceptance and adoption models and theories. *Procedia Manuf.* **2018**, *22*, 960–967. [CrossRef]
5. King, W.R.; He, J. A meta-analysis of the technology acceptance model. *Inf. Manag.* **2006**, *43*, 740–755. [CrossRef]
6. Davis, F.D. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q.* **1989**, *13*, 319–340. [CrossRef]

7. Davis, F.D.; Bagozzi, R.P.; Warshaw, P.R. User acceptance of computer technology: A comparison of two theoretical models. *Manag. Sci.* **1989**, *35*, 982–1003. [CrossRef]
8. Lee, D.; Lee, S.M.; Olson, D.L.; Chung, S.H. The effect of organizational support on ERP implementation. *Ind. Manag. Data Syst.* **2010**, *110*, 269–283. [CrossRef]
9. Venkatesh, V.; Davis, F.D. A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Manag. Sci.* **2000**, *46*, 186–204. [CrossRef]
10. Lu, J.; Yu, C.; Liu, C.; Yao, J.E. Technology acceptance model for wireless Internet. *Internet Res.* **2003**, *13*, 206–222. [CrossRef]
11. Alomary, A.; Woollard, J. How is technology accepted by users? A review of technology acceptance models and theories. In Proceedings of the IRES 17th International Conference, London, UK, 21 November 2015; pp. 1–4.
12. Zheng, J.; Li, S.; Zheng, Y. Students' technology acceptance, motivation and self-efficacy towards the eSchoolbag: An exploratory study. *Int. J. Inform.* **2017**, *10*, 1350–1358. [CrossRef]
13. Devaraj, S.; Easley, R.F.; Crant, J.M. Research note—How does personality matter? Relating the five-factor model to technology acceptance and use. *Inf. Syst. Res.* **2008**, *19*, 93–105. [CrossRef]
14. Ramírez-Correa, P.; Grandón, E.E.; Alfaro-Pérez, J.; Painén-Aravena, G. Personality types as moderators of the acceptance of information technologies in organizations: A multi-group analysis in PLS-SEM. *Sustainability* **2019**, *11*, 3987–4002. [CrossRef]
15. Klaus, H.; Rosemann, M.; Gable, G.G. What is ERP? *Inf. Syst. Front.* **2000**, *2*, 141–162. [CrossRef]
16. Gillis, A.S.; Jim, O. What Is SAP S/4HANA Cloud? TechTarget, 4 February 2025. Available online: https://www.techtarget.com/searchSAP/resources/SAP-S4HANA-Cloud/969435@ (accessed on 27 September 2025).
17. O'Sullivan, J. Validating academic training versus organizational training: An analysis in the enterprise resource planning (ERP) field. *J. Commun. Comput.* **2013**, *10*, 1261–1270.
18. Charland, P.; Léger, P.M.; Cronan, T.P.; Robert, J. Developing and Accessing ERP Competencies: Basic and Complex Knowledge. *J. Comput. Inform. Syst.* **2016**, *56*, 31–39. [CrossRef]
19. Boyle, T.A.; Strong, S.E. Skill requirements of ERP graduates. *J. Inf. Syst. Educ.* **2006**, *17*, 403–412.
20. Hawking, P.; Foster, S.; Bassett, P. An applied approach to teaching HR concepts using an ERP system. In Proceedings of the Informing Science and IT Education Conference, Cork, Ireland, 19–21 June 2002. Informing Science.org.
21. Blount, Y.; Abedin, B.; Vatanasakdakul, S.; Erfani, S. Integrating Enterprise Resource Planning (SAP) in the Accounting Curriculum: A Systematic Literature Review and Case Study. *Account. Educ.* **2016**, *25*, 185–202.
22. McCann, D.K.; Grey, D. SAP/ERP Technology in a Higher Education Curriculum and the University Alliance Program. *Issues Inf. Syst.* **2009**, *10*, 176–182.
23. SAP UCC Magdeburg. *Introduction to SAP S/4HANA. Next Generation Business Suite*; PowerPoint presentation; University Competence Center Magdeburg, SAP University Alliances: Magdeburg, Germany, 2023.
24. Wagner, B.; Weidner, S. *SAP S/4HANA 2022: Global Bike—Sales and Distribution Case Study*; Version 4.2, Beginner Level, Fiori 3.0 Interface; SAP University Alliances: Walldorf, Germany, 2023.
25. Redwood Software. SAP S/4HANA Architecture: A Complete Guide. Redwood: Carson City, Nevada, 2025. Available online: https://www.redwood.com/resource/sap-s-4hana-architecture-guide/ (accessed on 27 September 2025).
26. Garača, Ž. Factors related to the intended use of ERP systems. *Manag.-J. Contemp. Manag. Issues* **2011**, *16*, 23–42.
27. Lea, B.-R.; Mirchandani, D.; Sumner, M.; Yu, K. Personality types in learning enterprise resource planning (ERP) systems. *J. Comput. Inf. Syst.* **2022**, *62*, 359–371. [CrossRef]
28. Özbek, V.; Alnıaçık, Ü.; Koc, F.; Akkılıç, M.E.; Kaş, E. The impact of personality on technology acceptance: A study on smart phone users. *Procedia-Soc. Behav. Sci.* **2014**, *150*, 541–551. [CrossRef]
29. Fink, M.; Bäuerle, A.; Schmidt, K.; Rheindorf, N.; Musche, V.; Dinse, H.; Moradian, S.; Weismüller, B.; Schweda, A.; Teufel, M.; et al. COVID-19-Fear Affects Current Safety Behavior Mediated by Neuroticism—Results of a Large Cross-Sectional Study in Germany. *Front. Psychol.* **2021**, *12*, 671768. [CrossRef]
30. Soto, C.J.; John, O.P. The Next Big Five Inventory (BFI-2): Developing and Assessing a Hierarchical Model with 15 Facets to Enhance Bandwidth, Fidelity, and Predictive Power. *J. Personal. Soc. Psychol.* **2017**, *113*, 117–143. [CrossRef]
31. Laidra, K.; Pullmann, H.; Allik, J. Personality and Intelligence as Predictors of Academic Achievement: A Cross-Sectional Study from Elementary to Secondary School. *Personal. Individ. Differ.* **2007**, *42*, 441–451. [CrossRef]
32. Poropat, A.E. A Meta-Analysis of the Five-Factor Model of Personality and Academic Performance. *Psychol. Bull.* **2009**, *135*, 322–338. [CrossRef]
33. Komarraju, M.; Karau, S.J.; Schmeck, R.R.; Avdic, A. The Big Five personality traits, learning styles, and academic achievement. *Personal. Individ. Differ.* **2011**, *51*, 472–477. [CrossRef]
34. Grehan, P.M.; Flanagan, R.; Malgady, R.G. Successful graduate students: The roles of personality traits and emotional intelligence. *Psychol. Sch.* **2011**, *48*, 317–331. [CrossRef]
35. O'cOnnor, M.C.; Paunonen, S.V. Big Five Personality Predictors of Post-Secondary Academic Performance. *Personal. Individ. Differ.* **2007**, *43*, 971–990. [CrossRef]

36. Thompson, E. Development and validation of an international english big-five mini-markers. *Personal. Individ. Differ.* **2008**, *45*, 542–548. [CrossRef]
37. Svendsen, G.B.; Johnsen, J.-A.K.; Almås-Sørensen, L.; Vittersø, J. Personality and Technology Acceptance: The Influence of Personality Factors on the Core Constructs of the Technology Acceptance Model. *Behav. Inf. Technol.* **2011**, *32*, 323–334. [CrossRef]
38. Lin, M.Y.C.; Ong, C.S. Understanding information systems continuance intention: A five-factor model of personality perspective. In Proceedings of the Fourteenth Pacific Asia Conference on Information Systems, Taipei, China, 9–12 July 2010; p. 367.
39. Terzis, V.; Moridis, C.N.; Economides, A.A. How Student's Personality Traits Affect Computer-Based Assessment Acceptance: Integrating BFI with CBAAM. *Comput. Hum. Behav.* **2010**, *28*, 1985–1996. [CrossRef]
40. Major, D.A.; Turner, J.E.; Fletcher, T.D. Linking Proactive Personality and the Big Five to Motivation to Learn and Development Activity. *J. Appl. Psychol.* **2006**, *91*, 927–935. [CrossRef]
41. Anglim, J.; Horwood, S.; Smillie, L.D.; Marrero, R.J.; Wood, J.K. Predicting Psychological and Subjective Well-Being from Personality: A Meta-Analysis. *Psychol. Bull.* **2020**, *146*, 279–323. [CrossRef]
42. Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D. User Acceptance of Information Technology: Toward a Unified View. *MIS Q.* **2003**, *27*, 425–478. [CrossRef]
43. Kappe, R.; van der Flier, H. Using Multiple and Specific Criteria to Assess the Predictive Validity of the Big Five Personality Factors on Academic Performance. *J. Res. Personal.* **2010**, *44*, 142–145. [CrossRef]
44. Barrick, M.R.; Mount, M.K. The big five personality dimensions and job performance: A meta-analysis. *Pers. Psychol.* **1991**, *44*, 1–26. [CrossRef]
45. Roberts, B.W.; Chernyshenko, O.S.; Stark, S.; Goldberg, L.R. The Structure of Conscientiousness: An Empirical Investigation Based on Seven Major Personality Questionnaires. *Pers. Psychol.* **2005**, *58*, 103–139. [CrossRef]
46. Bagherian, M.; Mojambari, A.K. The relationship between Big Five personality traits and assertiveness. *Tendenzen* **2016**, *25*, 111–119.
47. Judge, T.A.; Ilies, R. Relationship of personality to performance motivation: A meta-analytic review. *J. Appl. Psychol.* **2002**, *87*, 797. [CrossRef]
48. McAdams, D.P. Three Lines of Personality Development: A Conceptual Itinerary. *Eur. Psychol.* **2015**, *20*, 252–264. [CrossRef]
49. Lepine, J.A.; Colquitt, J.A.; Erez, A. Adaptability to Changing Task Contexts: Effects of General Cognitive Ability, Conscientiousness, and Openness to Experience. *Pers. Psychol.* **2000**, *53*, 563–593. [CrossRef]
50. Gollwitzer, P.M. Implementation Intentions: Strong Effects of Simple Plans. *Am. Psychol.* **1999**, *54*, 493–503. [CrossRef]
51. Gollwitzer, P.M.; Parks-Stamm, E.J.; Jaudas, A.; Sheeran, P. Flexible Tenacity in Goal Pursuit. In *Handbook of Motivation Science*; James, Y.S., Wendi, L.G., Eds.; Guilford Press: New York, NY, USA, 2008; pp. 325–341.
52. Gollwitzer, P.M.; Gabriele, O. Goal Pursuit. In *The Oxford Handbook of Human Motivation*; Ryan, R.M., Ed.; Oxford University Press: Oxford, UK, 2012; pp. 208–231.
53. DeYoung, C.G.; Peterson, J.B.; Higgins, D.M. Higher-Order Factors of the Big Five Predict Conformity: Are There Neuroses of Health? *Personal. Individ. Differ.* **2002**, *33*, 533–552. [CrossRef]
54. Kline, R.; Bankert, A.; Levitan, L.; Kraft, P. Personality and Prosocial Behavior: A Multilevel Meta-Analysis. *Political Sci. Res. Methods* **2019**, *7*, 125–142. [CrossRef]
55. McCrae, R.R.; Greenberg, D.M. Openness to Experience and Its Social Consequences. In *Handbook of Individual Differences in Social Behavior*; Leary, M.R., Hoyle, R.H., Eds.; Guilford Press: New York, NY, USA, 2009; pp. 257–273.
56. Sánchez-Prieto, J.C.; Olmos-Migueláñez, S.; García-Peñalvo, F.J. MLearning and pre-service teachers: An assessment of the behavioral intention using an expanded TAM model. *Comput. Hum. Behav.* **2017**, *72*, 644–654. [CrossRef]
57. Kang, D.; Santhanam, R. A Longitudinal Field Study of Training Practices in a Collaborative Application Environment. *J. Manag. Inf. Syst.* **2003**, *20*, 257–281. [CrossRef]
58. Chen, H.-Y.; Chen, Y.-C.; Wu, H.-C.; Chiu, T. Exploring the Difficulties in Learning ERP Systems from Students' Perspective: The Case of Oracle E-Business Suite ERP. *Int. J. Data Netw. Sci.* **2022**, *6*, 1201–1214. [CrossRef]
59. Stone, D.; Caroline, J.; Mark, W.; Shailey, M. *User Interface Design and Evaluation*; Morgan Kaufmann Publishers: Burlington, MA, USA, 2005.
60. John, O.P.; Naumann, L.P.; Soto, C.J. Paradigm shift to the integrative big five trait taxonomy. In *Handbook of Personality: Theory and Research*; Guilford Press: New York, NY, USA, 2008; pp. 114–158.
61. Bošković, D. Model prihvatanja tehnologije i primena na komunikacione platforme. In *Doctoral Dissertation*; University of Novi Sad: Novi Sad, Serbia, 2021.
62. DeCoster, J.; Gallucci, M.; Iselin, A.M.R. Best Practices for Using Median Splits, Artificial Categorization, and Their Continuous Alternatives. *J. Exp. Psychopathol.* **2011**, *2*, 197–209. [CrossRef]
63. Tabachnick, B.G.; Fidell, L.S.; Ullman, J.B. *Using Multivariate Statistics*, 7th ed.; Pearson: Boston, MA, USA, 2019.
64. Hayes, A.F. *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*; Guilford Publications: New York, NY, USA, 2017.

65. McElroy, J.C.; Hendrickson, A.; Townsend, A.M.; DeMarie, S.M. Dispositional factors in internet use: Personality versus cognitive style. *MIS Q.* **2007**, *31*, 809–820. [CrossRef]
66. Venkatesh, V.; Speier, C. Computer Technology Training in the Workplace: A Longitudinal Investigation of the Effect of Mood. *Organ. Behav. Hum. Decis. Process.* **1999**, *79*, 1–28. [CrossRef]
67. Compeau, D.; Marcolin, B.; Kelley, H.; Higgins, C. Research Commentary—Generalizability of Information Systems Research Using Student Subjects: A Reflection on Our Practices and Recommendations for Future Research. *Inf. Syst. Res.* **2012**, *23*, 1093–1109. [CrossRef]
68. Chen, C.C.; Law, C.C.; Yang, S.C. Managing ERP Implementation Failure: A Project Management Perspective. *IEEE Trans. Eng. Manag.* **2009**, *56*, 157–170. [CrossRef]
69. Rouhani, S.; Mehri, M. Empowering Benefits of ERP Systems Implementation: Empirical Study of Industrial Firms. *J. Syst. Inf. Technol.* **2018**, *20*, 54–72. [CrossRef]

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