Research Article

Personality and Adaptive Coping in the Digital Age: Psychological Pathways to Emerging Technology Adoption, with a Focus on Artificial Intelligence

Daniela-Elena Lițan*

Department of Psychology, Faculty of Psychology and Educational Sciences, West University of Timișoara, Timișoara, Timiș 300223, Romania

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Background

Rapidly developing technologies, including artificial intelligence (AI), the Internet of Things (IoT), and blockchain, continue to reshape social structures, professional domains, and daily life.

Objective

This study investigates how individual personality characteristics shape people's willingness to adopt and engage with such innovations.

Methods

A cross-sectional survey was conducted with 202 Romanian adults (aged 18–61), who completed validated measures assessing personality traits (Big Five agency, beliefs, conscientiousness, dynamism, and morality), cognitive–emotional coping strategies (cognitive emotion regulation questionnaire), and the use of AI, IoT, and blockchain technologies (hours per day). Data were analyzed using Jamovi, applying descriptive statistics, correlations, multiple regression with Bonferroni corrections, and mediation/moderation analyses with bootstrap resampling.

Results

The analyses indicated no evidence of common method bias. Among the three tested models, only AI use was significantly predicted by personality factors, with extraversion exerting a positive effect and maturity a negative effect. Age moderated the extraversion–AI relationship, suggesting stronger effects among younger participants. Mediation analyses showed that adaptive coping strategies did not play a significant mediating role.

Conclusion

Personality factors, particularly extraversion and maturity, play a central role in the adoption of AI, while coping strategies showed limited explanatory power. The moderating effect of age suggests that younger individuals may benefit more from extraversion in engaging with digital technologies. These findings underscore the importance of considering psychological factors in understanding digital transformation and call for further research into how individual differences shape technology use.

1. INTRODUCTION

The rapid development of digital technologies is producing profound changes across societies, influencing how people work, communicate, and carry out daily activities. This continuously evolving landscape creates new expectations for individuals and organizations, requiring ongoing adaptation to emerging tools and systems.[1] This study focuses on artificial intelligence (AI), Internet of Things (IoT), and blockchain—technologies that are increasingly

***Corresponding author:**
Daniela-Elena Lițan
Department of Psychology, Faculty of Psychology and Educational Sciences, West University of Timișoara, Timișoara, Timiș 300223, Romania.
E-mail: daniela.litan@e-uvt.ro

adopted on a large scale in contemporary society. The aim is to examine the relationship between personality and the use of these technologies, as well as the contribution of emotion-focused and cognitive-coping mechanisms, with particular emphasis on adaptive forms of coping. Although prior studies have explored personality traits, coping mechanisms, or technology adoption independently, few have investigated the interplay among these variables in a single integrative framework. This lack of integrative evidence is particularly significant in the Romanian setting, where psychological adaptation to digital transformation has received limited empirical attention. Broader discussions on digital innovation and cloud-based learning environments further emphasize the psychological and organizational challenges associated with rapid technological change, particularly in educational and professional contexts.[2]

AI refers to a diverse set of computational technologies capable of processing information and generating outputs that simulate intelligent behavior. These systems, grounded in algorithmic processing, support a wide range of applications, from everyday recommendation tools to more complex forms of machine reasoning.[3] Broadly speaking, AI encompasses technologies that can carry out functions traditionally associated with human cognitive abilities.[4]

Meanwhile, IoT technology describes an interconnected system of physical devices equipped with sensors and communication components that allow them to exchange information and react to both internal states and environmental conditions.[5] In essence, IoT involves linking a wide range of devices with varying technical specifications and functionalities, enabling them to operate within a shared digital ecosystem. This concept already underpins numerous practical applications, including smart home systems, healthcare monitoring, drone communication, and intelligent parking solutions.[6]

Initially introduced as the foundational technology for cryptocurrency exchanges, blockchain has since been adopted across multiple sectors, including education, healthcare, media, public administration, smart computing, and various business domains.[7] It has also become relevant to the development and management of digital identity systems.[8] A key feature of blockchain is its decentralized architecture, in which transaction records are distributed and synchronized across all participating nodes, eliminating the need for a single central authority to oversee the database.[7]

A society undergoing rapid technological change requires continuous adaptation, particularly at the professional level. Virtual assistants, autonomous vehicles, technology-assisted medical diagnosis, smart homes monitored through connected devices, virtual currencies, and smart contracts are examples of modern automation solutions that bring transformation, innovation, and rapid responses to societal needs. At the same time, these developments also introduce significant challenges related to human adaptation and psychological adjustment. In this context, several questions arise: to what extent have individuals adapted to these changes, and to what extent can personality predict the acceptance and use of AI, IoT, and blockchain technologies? Do cognitive–emotional coping strategies, especially adaptive strategies, mediate the relationship between personality and adjustment to this digital transformation?

Personality is a psychological construct intended to explain the wide variety of human behaviors in terms of a few individual, stable, and measurable characteristics.[9] Personality determines the pattern of individual behavior and influences individual behavior, group behavior, and even social development.[10] On the other hand, coping has been defined as cognitive and behavioral efforts to control, tolerate, and reduce the burden that overloads or overwhelms a person's resources.[11(p219)] Coping represents an internal psychological resource power that mediates a person's reaction to perceived stress, regardless of its origin.[12] However, personality can influence the effectiveness of coping strategies by facilitating or interfering with their successful implementation.[13]

To clarify the objectives and hypotheses of this study, we reviewed prior work addressing the broader "digital revolution." This body of research highlights several relevant aspects, including emerging forms of workplace dissatisfaction,[14] the challenges individuals face when adapting to rapid digital change, and the increasing need to acquire competencies required for operating new digital tools.[15,16] Recent contributions to the field further indicate that effective adjustment to the digital era relies on skills such as critical thinking, collaborative teamwork, adaptability, autonomous decision-making, and the ability to function under uncertainty while managing complex analytical tasks that demand creativity and improvisation.[17] At the same time, personality, as a construct that reflects the essential characteristics of an individual, may serve as a key factor in narrowing the gap between humans and technological systems.[9]

A review of recent studies highlights associations between psychological outcomes and the use of AI technologies in several Asian contexts, including China and South Korea, where the implementation of such systems has progressed far more rapidly than in Romania. In 2022, China remained the global leader in the deployment of industrial and service robots, with countries such as Japan, the United States (US), South Korea, Germany, Italy, and Taiwan following at a considerable distance.[18] The literature reports that AI use is positively linked to indicators of psychological well-being,[19,20] while other findings show inverse associations with depression, anxiety, and burnout levels.[21-23] Considering this pattern reflected in the existing literature, and given that Romania is expected to follow similar trajectories of AI implementation, the present study places particular emphasis on how adaptive coping processes that integrate cognitive and emotional components shape the association between personality factors and engagement with AI-, IoT-, and blockchain-based technologies. However, most of these findings come from highly technologized societies. In contrast, Romania lacks empirical studies that systematically address psychological adaptation to AI, IoT, and blockchain adoption, despite an increasing national push for digital integration. Identifying these gaps may inform public education and psychological preparedness, potentially reducing technology-related distress.

The present study focuses on a single maladaptive coping strategy, namely blaming others. In general, people are sensitive to negative events,[24] and the change brought about by digitalization can cause concern, fear, and distrust. Compared to positive or neutral events, negative events require attention. They are more widely represented in language, have a stronger impact on behavior, and once detected, can trigger evaluative responses and activate the judgment mechanism. Judgment in this context can be directed, for example, toward decision-makers and technology (based on the fear of replacement, automation, etc.).

Recent international research provides additional support for the relevance of psychological factors in shaping engagement with digital and AI-based technologies.

Empirical studies show that users' evaluations and acceptance of AI systems are closely linked to perceived usefulness, trust, and related cognitive and emotional appraisals, as evidenced by both multi-site empirical investigations and integrative reviews of the literature.[25,26] More recent studies based on samples from Western countries, including participants from the United Kingdom and the US, further indicate that emotional regulation and coping-related processes are important in shaping individuals' responses to complex digital environments, including technology-related stress and broader psychological outcomes.[27] In addition, recent conference-based research suggests that attitudes toward AI are influenced by individual differences, including demographic and personality-related factors, and may differ from attitudes toward technology use in general.[28] Overall, these findings support the view that psychological processes and individual differences play an important role in technology adoption, while also highlighting the relevance of socio-cultural context.

Drawing on the considerations outlined above, the present study articulates its research objectives as follows:

- To examine how personality factors relate to engagement with digital technologies, with a focus on AI, IoT, and blockchain technologies.
- To investigate whether adaptive coping processes that integrate cognitive and emotional components mediate the association between personality factors and engagement with digital technologies (AI, IoT, and blockchain).

By addressing these objectives, the present study aims to advance an integrative understanding of how individual personality factors and adaptive coping processes that integrate cognitive and emotional components jointly shape engagement with emerging digital technologies, providing new empirical insights grounded in the Romanian population.

1.1. PERSONALITY FACTORS AND DIGITAL TECHNOLOGIES

The hypotheses developed in this study were grounded in an integrative framework that brings together established models of technology adoption (such as the technology acceptance model [TAM] and the unified theory of acceptance and use of technology [UTAUT]), the Big Five model of personality, and cognitive-emotional coping theory. This combination allows for a nuanced analysis of both dispositional and situational psychological factors that may influence technology use.

Blockchain, IoT, and AI are key technologies driving the next wave of digital transformation[29]; however, individual personality traits play an important role in shaping behavior toward emerging technologies. The adoption of technologies by the population has already been studied over time. In the literature, we identified a number of theories in this regard:

- TAM[30] proposes that individuals' willingness to adopt a system is shaped by their perceptions of how useful the technology is and how easy it is to operate, both of which inform their intention to use.
- Within the UTAUT framework,[31] individuals' engagement with technology is shaped by performance and effort expectations, alongside social and organizational influences, while demographic and experiential characteristics condition the strength of these effects.[32]
- UTAUT2 extends this framework by adding three determinants, hedonic motivation, perceived value, and habit, further explaining why individuals engage with a technology, especially when use involves personal satisfaction or routine behavior.[33]
- The Technological Impact Model suggests that the effects of technology on users vary depending on how the technology is applied and on the expectations people hold about its consequences.[34] The perceived impact arises from comparing outcomes achieved with the technology to those experienced beforehand.

Across these models, technology adoption is conceptualized primarily as a function of cognitive evaluations and contextual factors, leaving room for individual differences to further explain variability in technology use.

When discussing technology acceptance, particularly of emerging technologies and their use, a key common factor, regardless of the model considered, whether mentioned above or found in existing literature, is the individual's personality. Analyzing the factors underlying the adoption of agricultural technology, it was found that non-cognitive skills affect both technical efficiency and decisions to adopt new technologies.[35] More specifically, the results suggest that personality traits are significant predictors of technology adoption, with effects approximately double those of standard human capital variables. Moreover, personality traits directly improve technical efficiency, unlike education, whose estimated effect was not significant.

Further analysis of existing literature shows that studies regarding the influence of personality traits on the decision to use technology or digital platforms have been conducted in various contexts. The Big Five model[36,37] is currently the most established and best-validated model of personality factors. It is often used as a reference framework in studies on socio-emotional competencies. This model includes five global dimensions: extraversion, agreeableness, conscientiousness, emotional stability, and openness to experience.[38] The current research used the Big Five agency, beliefs, conscientiousness, dynamism, and morality (ABCD-M) personality questionnaire. The Big Five ABCD-M, according to the technical and interpretative manual,[39] operationalizes the Big Five model of personality in the Romanian linguistic and cultural space. The five factors represent the fundamental dimensions involved in the personality's structuring and dynamics. The factors are defined by groups of intercorrelated traits. The traits are called facets, and each group of facets forms a domain (a factor), as follows:

- Extraversion: According to the ABCD-M manual,[39] this factor accounts for 15.59% of behavioral variability and reflects the extent to which individuals are socially engaged, expressive, and energized by interactions with others. It includes tendencies such as sociability, openness in communication,[40] and vitality in social situations.[41]
- Maturity: This factor captures 14.06% of behavioral variance and refers to how individuals regulate negative emotions, manage impulsivity, and maintain psychological stability, as described in the ABCD-M manual.[39]
- Agreeableness: Representing 14.02% of variability,[39] this factor reflects interpersonal warmth, empathy, and the ability to relate to others in a supportive and cooperative manner. It includes prosocial tendencies such as trust and willingness to collaborate.[42]
- Conscientiousness: Accounting for 10.12% of behavioral variation,[39] this dimension involves self-regulation,

organization, persistence, and the ability to plan and complete tasks effectively, essentially describing a disciplined and goal-oriented behavioral style.[43]

- Self-actualization: As reported in the ABCD-M manual,[39] this factor explains 8.73% of behavioral variance and reflects motivational and attitudinal aspects related to personal growth and the pursuit of one's potential.

Building on these theoretical considerations, the following hypotheses were developed:

(i) H_1: Personality is a significant predictor of acceptance (use) of digital transformation (represented by AI, IoT, and blockchain).

(ii) $H_{1.1}$: Extraversion is a significant positive predictor of acceptance (use) of digital transformation (represented by AI, IoT, and blockchain).

(i) $H_{1.2}$: Maturity is a significant positive predictor of acceptance (use) of digital transformation (represented by AI, IoT, and blockchain).

(ii) $H_{1.3}$: Agreeableness is a significant positive predictor of acceptance (use) of digital transformation (represented by AI, IoT, and blockchain).

(iii) $H_{1.4}$: Conscientiousness is a significant positive predictor of acceptance (use) of digital transformation (represented by AI, IoT, and blockchain).

(iv) $H_{1.5}$: Self-actualization is a significant positive predictor of acceptance (use) of digital transformation (represented by AI, IoT, and blockchain).

Next, an important question that emerges from existing literature,[31,33] some of which was discussed earlier in this paper, is the extent to which age and gender moderate the relationships between personality factors and the use of emerging technologies (AI, IoT, and blockchain). Therefore, the following set of hypotheses is proposed:

(v) $H_{1.6}$: Gender moderates the relationship between personality factors and the use of digital technologies (AI, IoT, and blockchain).

(vi) $H_{1.7}$: Age moderates the relationship between personality factors and the use of digital technologies (AI, IoT, and blockchain).

1.2. MEDIATION BETWEEN PERSONALITY AND THE USE OF DIGITAL TECHNOLOGIES

In the first part of this research, the aim is to identify the personality factors associated with the acceptance (use) of emerging technologies (represented by AI, IoT, and blockchain), as well as the moderating role of gender and age. In the second part, the focus shifts to examining whether adaptive coping processes that integrate cognitive and emotional components function as mediators between personality factors and engagement with digital technologies. Existing literature suggests that personality traits not only shape individual behavior but also influence the selection and effectiveness of coping strategies in response to technological demands. Thus, coping may serve as a psychological mechanism that explains how personality affects adaptation to digital change. The model starts from the premise that the use of digital technology (represented by AI, IoT, and blockchain), a relatively novel technology that is not yet widely understood by the general population, can trigger cognitive-emotional coping strategies.

Emotion regulation represents all the external and internal processes that an individual uses to monitor, evaluate, and modify the nature and course of an emotional response so that they can appropriately cope with environmental demands and achieve desired goals.[44-47] The use of emerging technologies such as AI, IoT, and blockchain has become a necessity in several sectors. In Romania, for example—though not limited to these cases—these technologies are integral to support services and call centers, the control and use of certain household appliances, and virtual currencies. This trend aligns with global development: the AI market exceeded 184 billion US dollars in 2024, almost 50 billion dollars more than in 2023, with projected growth expected to exceed 826 billion US dollars by 2030.[48] In addition, Romania's National Strategy on AI 2024–2027 envisions the implementation of AI with a substantial impact at the societal level.[49] In this context, the present study explores coping responses elicited by digital transformation, with particular emphasis on adaptive forms of coping, including acceptance, positive refocusing, planning refocusing, positive reappraisal, and perspective-taking. It further examines how these strategies are associated with personality factors and engagement with emerging digital technologies (AI, IoT, and blockchain). Regarding maladaptive strategies, this study focuses on evaluating the strategy of blaming others. This strategy is often used unconsciously when people avoid being judged negatively by others or even by themselves,[50] particularly in situations of non-adaptation to the environment. In the context of the present study, environment refers to the use of emerging technologies such as AI, IoT, and blockchain.

In the current research, in order to assess cognitive-emotional coping strategies, the cognitive emotion regulation questionnaire (CERQ) for adults, adapted and standardized for the Romanian population,[51] was used. The following scales were used from CERQ:

- Acceptance: this scale, according to the manual[51] refers to thoughts of resignation toward what happened.
- Positive refocusing: This scale, according to the manual[51] refers to thoughts about pleasant things and not about the event itself.
- Planning refocusing: this scale, according to the manual[51] refers to thoughts about the steps to follow to confront the event.
- Positive reappraisal: this scale, according to the manual[51] refers to thoughts through which a positive meaning is attributed to the event in terms of personal development.
- Perspective-taking: this scale, according to the manual,[51] refers to thoughts that minimize the seriousness of the event when compared to other events.
- Blaming others: this scale, according to the manual,[51] refers to thoughts of blaming others for what happened.

Coping strategies cover individual, interpersonal, and institutional dimensions, each of which is an integral part of resilience and stress management.[52,53] At the individual level, techniques such as cognitive reappraisal and action-oriented coping effectively reduce anxiety and improve well-being.[53,54]

Building on the theoretical arguments outlined above, the present study advances a second set of hypotheses:

(i) H_2: Adaptive coping processes integrating cognitive and emotional components account for the association between personality factors and engagement with digital technologies (AI, IoT, and blockchain).

(ii) $H_{2.1}$: Acceptance is expected to play a positive mediating role in the association between personality factors and engagement with digital technologies (AI, IoT, and blockchain).

(iii) $H_{2.2}$: Positive refocusing is expected to play a positive mediating role in the association between personality factors and engagement with digital technologies (AI, IoT, and blockchain).
(iv) $H_{2.3}$: Planning refocusing is expected to play a positive mediating role in the association between personality factors and engagement with digital technologies (AI, IoT, and blockchain).
(v) $H_{2.4}$: Positive reappraisal is expected to play a positive mediating role in the association between personality factors and engagement with digital technologies (AI, IoT, and blockchain).
(vi) $H_{2.5}$: Perspective-taking is expected to play a positive mediating role in the relationship between personality factors and engagement with digital technologies (AI, IoT, and blockchain).
(vii) $H_{2.6}$: Blaming others is expected to play a negative mediating role in the association between personality factors and engagement with digital technologies (AI, IoT, and blockchain).

Figure 1 illustrates the hypothesized theoretical framework integrating hypotheses H_1 and H_2.

2. METHODS

2.1. STUDY DESIGN

This study employed a cross-sectional survey design to examine the psychological factors associated with the use of emerging technologies. The proposed model tested both direct and indirect effects, assuming that personality factors predict the frequency of interaction with AI, IoT, and blockchain technologies. Cognitive–emotional coping strategies were included as mediating variables, while age and gender were tested as potential moderators of these relationships.

2.2. PARTICIPANTS

Eligibility criteria for participation included Romanian citizenship, an age range between 18 and 65 years, the ability to understand written Romanian at a basic level, and voluntary participation. All participants provided informed consent prior to inclusion in the study.
The sample consisted of 202 Romanian participants with 48.8% identifying as men, 50.7% as women, and 0.5% choosing not to disclose their gender. Participants ranged in age from 18 to 61 years (M = 33.84 years, standard deviation [SD] = 11.55). Other demographic data regarding the group of study participants are as follows:

- Marital status: 41.9% married, 58.1% unmarried (widowed, divorced, single, in a romantic relationship of 1 year or less);
- Professional status: 68.5% employed, 1% retired, 9.9% self-employed, 0.5% housewives, 19.2% students, 1% unemployed;
- Residential area: 85.2% urban, 14.8% rural;
- Number of children: 59.4% no children, 20.3% one child, 16.8% two children, 3.5% three children.

It is necessary to mention that three participants (1.49%) did not declare their year of birth, but agreed and confirmed that they had read the explanations and met the requirements of the study, which state that the age required to participate must be over 18 and less than or equal to 65. Therefore, their responses were retained in the analysis, and their age was recorded as 18 in the study database.

An a priori power analysis was conducted using G*Power, indicating that a minimum sample size of 92 participants was required to detect a medium effect size with a statistical power of 0.80, an alpha level of 0.05, and 5 predictors.

Conditions for excluding responses included incomplete questionnaire submissions (no such cases were identified) and refusal to provide informed consent to participate

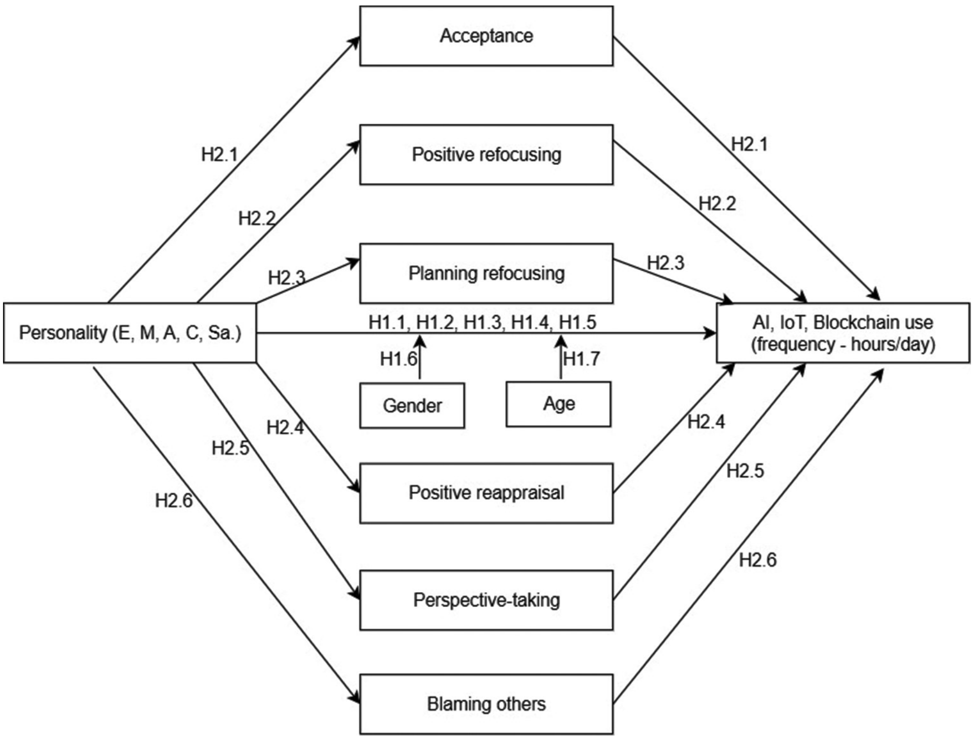

Figure 1. The hypothetical model integrating hypotheses H_1 and H_2
Abbreviations: A: Agreeableness; AI: Artificial intelligence; C: Conscientiousness; E: Extraversion; IoT: Internet of Things; M: Maturity; Sa.: Self-actualization.

(informed consent was required prior to the presentation of the study items).

2.3. EVALUATION MEASURES

To test the study hypotheses, we used standardized self-report measures to assess the main constructs of interest: personality factors (predictors), cognitive–emotional coping strategies (mediators), technology use (dependent variable), and demographic variables (age and gender as moderators).

The survey consisted of several measurement instruments, which are described below:

- The Big Five ABCD-M personality questionnaire[39] (Romanian Big Five). As the name suggests, the questionnaire is intended for personality assessment. It is a concise assessment adapted to the Romanian mentality to comprehensively assess the adult and stabilized personality through the 5 scales intended for the 5 broad personality domains—namely extraversion, maturity, agreeableness, conscientiousness, and self-actualization—and through the 25 scales intended for traits (personality facets). The questionnaire consists of 150 short items formulated in the first person singular, with a natural language, accessible to a Romanian speaker with an elementary level of education. Participants' responses were recorded on a Likert scale with 5 options, from 0 (totally disagree) to 4 (totally agree). The ABCD-M questionnaire can be used in clinical and medical assessments. For the present sample, the five personality scales demonstrated strong internal consistency, with Cronbach's alpha coefficients of 0.928 (extraversion), 0.954 (maturity), 0.923 (agreeableness), 0.933 (conscientiousness), and 0.878 (self-actualization). This instrument was used to operationalize the five personality dimensions that serve as predictors in both the direct effect hypotheses ($H_{1.1}$–$H_{1.5}$), the moderation hypotheses ($H_{1.6}$ and $H_{1.7}$), and the mediation hypotheses ($H_{2.1}$–$H_{2.6}$).
- The CERQ for adults was adapted and standardized for the Romanian population.[51] CERQ is a multidimensional questionnaire, designed to identify the cognitive coping strategies that one uses after experiencing certain negative/specific events or situations. It is a self-report instrument comprising 36 items, designed for use in both non-clinical and clinical samples, including adolescents from the age of 12 and adults. The questionnaire measures nine coping strategies: Self-blame, acceptance, rumination, positive refocusing, planning refocusing, positive reappraisal, perspective-taking, catastrophizing, and blaming others. Participants' responses were recorded on a 5-point Likert scale, from 1 (almost never) to 5 (almost always). In the current study, six cognitive–emotional coping scales had good internal consistency, with Cronbach's alpha values: 0.854 (acceptance), 0.851 (positive refocusing), 0.799 (planning refocusing), 0.833 (positive reappraisal), 0.852 (perspective-taking), 0.881 (blaming others). These strategies were tested as mediators of the relationship between personality factors and technology use, in accordance with hypotheses $H_{2.1}$–$H_{2.6}$.
- Acceptance of digital transformation/use of digital technology (represented by AI, IoT, and blockchain). The participants answered the questions:
  - (i) How many hours do you spend daily interacting with AI (e.g., ChatGPT, call center AI, other AI-based applications)?
  - (ii) How many hours do you spend daily using the IoT technology (e.g., controlling your home, appliances, and other similar devices)?
  - (iii) How often do you use blockchain technology (e.g., cryptocurrencies)?

Respondents could choose the answer to each of the 3 questions above from the following list of options: 0 h/day, <1 h/day, 1 h/day, 2 h/day., 12 h/day, >12 h/day, 1–2 times/week, and once every 2–3 months. To capture a realistic representation of participants' engagement with digital technologies, a broad set of response options was provided. After all responses relevant to the study were collected, the data were subsequently standardized as follows:

(i) Answer: <1 h/day was equivalent to 0.5 h/day;
(ii) Answer: once every 2–3 months was equivalent to 0 h/day, as the frequency per day was very low, close to 0; and
(iii) Answer: >12 h/day was equivalent to 12 h/day.

The answer 1–2 times/week was not necessary to standardize because it was not found in any of the answers received.

The rest of the answers: 0 h/day; 1 h/day; 2 h/day;. 12 h/day, were kept as they were received from the respondents. Therefore, in the database, the values acquired for the three questions above extend over a range from 0.5 h/day to 12 h/day, with hourly increments starting with 1 h/day (0.5 h/day, 1 h/day, 2 h/day, 3 h/day., 12 h/day).

A similar approach to evaluating the population in relation to technology, based on the number of hours, is also found in a recent study.[55]

The three digital technology variables (AI, IoT, and blockchain use) were treated as separate dependent variables in the analysis, and three distinct models were tested accordingly.

2.4. ETHICAL CONSIDERATIONS

Data collection was carried out online using a questionnaire hosted on Google Forms, available between October 12 and November 9, 2024. Participation was entirely voluntary, and no incentives were offered. All digital data were kept on a computer secured with password protection.

Ethical approval was obtained on August 2, 2024, from the Ethics Committee of the West University of Timișoara, Romania (process number: 53163/02.08.2024). All procedures followed the principles of the Declaration of Helsinki (World Medical Association). All ethical procedures were rigorously implemented in accordance with institutional regulations and internationally recognized standards for research involving human participants. The study was reported in accordance with the Strengthening the Reporting of Observational Studies in Epidemiology guidelines for cross-sectional studies.

2.5. PROCEDURE

The study was preregistered on the Open Science Framework (https://osf.io/e9apx/?view_only=e62096bfa5d34131bbd32d314125313b), where the objectives, hypotheses, methodological approach, data collection procedures, variables, and planned analyses were documented. The present study is part of a larger research initiative titled "The role of cognitive–emotional coping strategies in the relationship between personality and the digitalization process."

The questionnaire, administered in Romanian, first gathered demographic information (age, gender, marital status, employment status, residential environment, and number of children). Participants were then presented with three standardized instruments: the CERQ, the Big Five ABCD-M questionnaire, and single-item questions measuring estimated daily interaction time with AI, IoT, and blockchain technologies.

Before accessing the survey items, participants were shown an information page outlining the purpose of the study, confidentiality principles, and participant rights. Only individuals who provided informed consent could proceed. All responses were anonymous, and participants were reminded that they could discontinue participation at any time without consequences. Each section of the questionnaire included brief instructions, and the average completion time was approximately 50 min.

The survey link was distributed via social networks, professional online groups, and mobile messaging platforms. A total of 205 individuals initially accessed the questionnaire; three declined to provide consent, resulting in 202 valid responses included in the final dataset.

2.6. STATISTICAL ANALYSIS

All statistical procedures were carried out in the Jamovi software environment (version 2.3.28.0[56]). The analysis plan included descriptive statistics, correlational analyses, an assessment of potential common method bias, multiple linear regression models, mediation analyses, and bootstrap resampling.

Mediation and moderation models were estimated using the Medmod module in Jamovi. Several cognitive–emotional coping strategies, namely acceptance, positive refocusing, planning refocusing, positive reappraisal, perspective-taking, and blaming others, were examined as potential mediators in the association between personality traits (predictors) and use of emerging technologies (outcomes). Additional tests were performed to examine whether age and gender moderated these associations.

3. RESULTS

3.1. COMMON METHOD BIAS ANALYSIS

To assess the potential influence of common method bias, all responses from the questionnaire items were analyzed. For this purpose, a principal component analysis was conducted using Jamovi. The first extracted component explained 26.6% of the total variance, remaining well below the commonly accepted 50% criterion, suggesting that common method bias was unlikely to pose a problem.[57]

Complementary evidence was obtained by examining the correlation matrix, which showed that the highest correlation between constructs did not exceed 0.558, remaining below the 0.90 cut-off value.[58] In addition, multicollinearity was assessed using the variance inflation factor (VIF) and tolerance indices.[59,60] All VIF values were well below 5, with the highest being 2.024 for the construct positive reappraisal. All tolerance values were >0.10. These results confirm that multicollinearity was not a significant issue and that common method bias was unlikely to have affected the findings.

3.2. PRELIMINARY ANALYSIS

Descriptive statistics and intercorrelations among all study variables are presented in Table 1. Examination of the data indicated several significant relationships. The cognitive–emotional coping strategy construct, blaming others, showed positive correlations with the frequency of interaction (use) with AI technologies ($r = 0.208$, $p<0.01$), IoT technologies ($r = 0.183$, $p<0.01$), and blockchain technologies ($r = 0.139$, $p<0.05$).

Regarding personality factors, extraversion significantly correlated positively with AI use ($r = 0.151$, $p<0.05$), which is consistent with $H_{1.1}$. In contrast, maturity showed significantly negative associations with both AI use ($r = -0.205$, $p<0.01$) and blockchain use ($r = -0.209$, $p<0.01$).

The potential moderating variables, age and gender, displayed weak correlations with the main study variables (predictors and outcomes), as illustrated in Table 1.

3.3. PERSONALITY FACTORS AS PREDICTORS OF THE USE OF EMERGING TECHNOLOGIES

To examine H_1 and $H_{1.1}$–$H_{1.5}$, a multiple linear regression analysis was conducted, with the five personality factors entered as predictors and the frequency of AI, IoT, and blockchain use as the dependent variable. To facilitate the interpretation of the results, all predictors and the dependent variable were standardized using z-scores. Because three parallel regression models were tested (dependent variables: AI, IoT, and blockchain use), we applied the Bonferroni correction and therefore used a significance level of 0.0167 (instead of 0.05) to control the Type I error rate (a similar approach can be found in the literature[61]).

Three multiple linear regression models were examined simultaneously (Table 2). The results indicated that the only statistically significant model was the use of AI ($p<0.001$). Therefore, subsequent analyses focused on the AI-use model.

Since the regression model on AI use has already been rigorously evaluated at the family-wise level using Bonferroni correction, and the Type I error is already under control, a significance threshold of 0.05 was applied within the model to avoid unnecessary reductions in statistical power and to minimize the risk of Type II errors that could obscure potentially meaningful associations (a similar approach can be found, also in the literature[62]).

The multiple linear regression model predicting AI use indicated that the five personality factors jointly explained 12.1% of the variance, with the overall model reaching statistical significance ($F[7, 194] = 3.813$, $p<0.001$). Among the five personality dimensions, only extraversion ($\beta = 0.168$, 95% confidence interval [CI] = [0.004, 0.332], $p=0.044$) and maturity ($\beta = -0.189$, 95% CI = [−0.333, −0.046], $p=0.01$) emerged as significant predictors. Gender and age were included as covariates to account for their potential influence and to reduce alternative explanations.

Taken together, the results indicate that, with respect to AI use, H_1 received partial empirical support, as only $H_{1.1}$ was confirmed. In contrast, the findings related to $H_{1.2}$ did not align with the hypothesis. Specifically, the maturity factor showed a negative association with AI use when controlling for the other predictors included in the model. This inverse relationship indicates that higher levels of maturity are associated, on average, with lower levels of AI use.

Table 1. Descriptive statistics and correlations between the investigated variables

Variables	Mean	SD	Acceptance	Positive refocusing	Planning refocusing	Positive reappraisal	Perspective- taking	Blaming others	Extraversion
Acceptance	3.344	1.041	-						
Positive refocusing	3.389	0.974	0.416***	-					
Planning refocusing	4.147	0.767	0.214**	0.309***	-				
Positive reappraisal	4.198	0.788	0.273***	0.466***	0.541***	-			
Perspective-taking	3.64	0.953	0.305***	0.413***	0.320***	0.445***	-		
Blaming others	2.171	0.949	0.289***	0.245***	0.092	−0.013	0.185**	-	
Extraversion	2.866	0.574	0.042	0.300***	0.284***	0.355***	0.205**	−0.005	-
Maturity	3.204	0.695	−0.040	−0.138	0.043	0.177*	−0.025	−0.379***	0.098
Agreeableness	2.748	0.571	0.285***	0.302***	0.321***	0.303***	0.353***	0.038	0.343***
Conscientiousness	2.9	0.573	0.058	0.204**	0.295***	0.347***	0.205**	−0.142*	0.530***
Self-actualization	2.953	0.46	0.146*	0.320***	0.321***	0.407***	0.184**	−0.052	0.492***
AI use (frequency)	0.891	1.791	0.082	0.124	0.057	0.042	0.029	0.208**	0.151*
IoT use (frequency)	0.609	1.601	0.019	0.029	−0.064	0.047	0.034	0.183**	0.027
Blockchain use (frequency)	0.193	0.922	0.022	0.099	−0.023	0.100	0.104	0.139*	0.018
Age (years)	33.84	11.55	0.014	0.175*	0.080	0.266***	0.070	−0.066	0.155*
Gender (0/1/2)			0.044	0.023	0.186**	0.135	0.035	−0.013	−0.001

Variables	Maturity	Agreeableness	Conscientiousness	Self-actualization	AI use (frequency)	IoT use (frequency)	Blockchain use (frequency)	Age (years)	Gender (0/1/2)
Acceptance									
Positive refocusing									
Planning refocusing									
Positive reappraisal									
Perspective-taking									
Blaming others									
Extraversion									
Maturity	-								
Agreeableness	0.039	-							
Conscientiousness	0.250***	0.456***	-						
Self-actualization	0.078	0.521***	0.558***	-					
AI use (frequency)	−0.205**	−0.040	0.052	0.090	-				
IoT use (frequency)	−0.109	−0.037	0.003	0.050	0.350***	-			
Blockchain use (frequency)	−0.209**	0.084	0.064	0.040	0.196**	0.164*	-		
Age (years)	0.183**	0.163*	0.189**	0.120	−0.187**	−0.013	−0.131	-	
Gender (0/1/2)	0.235***	0.199**	0.007	0.060	−0.178*	−0.017	−0.138*	0.275***	-

Notes: *p<0.05, **p<0.01, **p<0.001; Gender (0=Male, 1=Female, 2=Not applicable). Abbreviations: AI: Artificial intelligence; IoT: Internet of Things; SD: Standard deviation.

Table 2. Regression analyses to test the relationship between personality factors and the use of emerging technologies

Predictor	AI use (frequency; hours/day) (R^2=0.121, p<0.001)			IoT use (frequency; hours/day) (R^2=0.021, p=0.755)			Blockchain use (frequency; hours/day) (R^2=0.081, p=0.02)		
	β	SE	p	β	SE	p	β	SE	p
Intercept	0	0.067	1	0	0.071	1	0	0.069	1
Extraversion	0.168	0.083	0.044*	0.020	0.088	0.817	−0.029	0.085	0.732
Maturity	−0.189	0.073	0.010*	−0.125	0.077	0.105	−0.201	0.074	0.007
Agreeableness	−0.113	0.084	0.177	−0.098	0.088	0.271	0.095	0.086	0.270
Conscientiousness	0.049	0.093	0.596	0.021	0.098	0.833	0.124	0.095	0.191
Self-actualization	0.079	0.090	0.383	0.084	0.095	0.380	−0.032	0.092	0.729
Gender	−0.071	0.074	0.334	0.026	0.078	0.734	−0.081	0.075	0.287
Age (years)	−0.159	0.072	0.028	0.001	0.076	0.992	−0.103	0.073	0.164

Notes: β: Standardized coefficient (Beta); SE: Standard error; p: p-value (statistical significance); R^2: Coefficient of determination; *p<0.05. Abbreviations: AI: Artificial intelligence; IoT: Internet of Things.

Next, the moderating effects of gender and age on the relationship between personality factors and AI use were analyzed ($H_{1.6}$ and $H_{1.7}$). Correlations between the moderators (age, gender) and the criterion and/or predictors were generally small (Table 1). The only moderating effect of the relationship between personality factors and AI use was identified for the moderator age and the personality factor extraversion (B = −0.146, 95% CI = [−0.279, −0.013], p=0.032; Table 3). The relationship between extraversion and AI use depended on the age threshold: people younger than the average age of the analyzed sample and with a higher level of extraversion use AI more frequently (Low [−1SD): B = 0.313, 95% CI = [0.134, 0.492], p<0.001) than older people (Table 4).

3.4. MEDIATION MODEL ANALYSES (AI)

Table 5 summarizes the findings of the parallel mediation analyses examining the role of adaptive cognitive–emotional coping strategies (acceptance, perspective-taking, positive reappraisal, planning refocusing, and positive refocusing), as well as the maladaptive strategy of blaming others, in the association between the five personality factors (extraversion, maturity, agreeableness, conscientiousness, and self-actualization) and AI use. The results of the mediation model demonstrated that blaming others emerged as a significant mediating mechanism linking the maturity personality factor to AI use (indirect effect, β = −0.058, 95% CI = [−0.114, −0.003], p<0.05), accounting for 24.89% of the total effect. This finding provides support for $H_{2.6}$ in the context of AI technology. None of the remaining adaptive cognitive–emotional coping strategies demonstrated a significant mediating effect in the relationship between personality factors and AI use. Results presented in Table 5 indicate a robust direct association between the personality factor maturity and AI use across coping strategies included in the model, both for the direct and the total effects. This pattern is consistent with the findings obtained from the multiple linear regression analysis.

For the model including positive refocusing coping, Table 5 indicates a significant direct association between the personality factor agreeableness and AI use (direct effect, β = −0.162, 95% CI = [−0.322, −0.001], p<0.05). The same direct relationship between the personality factor agreeableness and the use of AI was found in the analysis corresponding to the type of coping acceptance (direct effect, β = −0.183, 95% CI = [−0.347, −0.019], p<0.05). However, being a weak relationship, this was not detected following the multiple linear regression analysis. Notably, the direct relationship between the extraversion personality factor and the use of AI was also confirmed (direct effect, β = 0.163, 95% CI = [0.002, 0.324], p<0.05) for the analysis corresponding to the coping strategy of acceptance, as identified above, and in the case of multiple linear regression.

However, in the case of mediation analyses, among the aforementioned relationships, those referring to the personality factor maturity can be considered strong; the others remain weak. The sample size might limit the robustness of these effects without invalidating the observed patterns. The significance of the multiple mediation model was evaluated using a bootstrap resampling procedure with 5,000 iterations.[21,63,64] Effects were statistically significant when the 95% CI did not include 0.

4. DISCUSSION

This study examined how personality factors derived from the Big Five ABCD-M model and cognitive–emotional coping processes, particularly adaptive coping, are associated with the use of emerging technologies (AI, IoT, and blockchain). Gender and age differences were also analyzed regarding the relationship between personality factors and AI use.

Descriptive analyses indicated that extraversion was positively associated with AI use, as well as higher levels of maturity associated with both AI and blockchain technologies. With regard to adaptive coping, no significant correlations were identified with the use of AI, IoT, and blockchain technologies. In contrast, significant relationships were observed between the maladaptive coping strategy, blaming others, and the use of the three types of technologies. It is noteworthy that respondents did not report employing any of the five adaptive coping strategies examined in the study in relation to emerging technologies—technologies that require adaptation, learning, and, in general, resource consumption, elements that lead to stress, challenges, and emotional and psychological difficulties. This finding contrasts with previous studies that reported a positive association between adaptive coping strategies and digital adaptation,[27,65] suggesting that in the Romanian context, psychological barriers or limited emotional resources may inhibit the use of such strategies. In contrast, the identified correlations between the use of

Table 3. The moderation effect for the variables of hypotheses $H_{1.6}$ and $H_{1.7}$

Parameter	Estimate (B)	SE	95% confidence interval		p
			Lower	Upper	
$H_{1.6}$					
Extraversion	0.124	0.069	−0.012	0.260	0.074
Gender	−0.187	0.068	−0.320	−0.054	0.006**
Extraversion * Gender	−0.120	0.066	−0.249	0.008	0.066
Maturity	−0.158	0.070	−0.297	−0.020	0.025*
Gender	−0.142	0.068	−0.275	−0.008	0.038*
Maturity * Gender	0.053	0.072	−0.089	0.195	0.467
Agreeableness	−0.006	0.069	−0.142	0.129	0.926
Gender	−0.179	0.069	−0.314	−0.043	0.010*
Agreeableness * Gender	−0.041	0.071	−0.179	0.097	0.561
Conscientiousness	0.060	0.069	−0.075	0.195	0.382
Gender	−0.182	0.069	−0.317	−0.047	0.008**
Conscientiousness * Gender	−0.099	0.069	−0.235	0.037	0.153
Self-actualization	0.100	0.069	−0.035	0.235	0.147
Gender	−0.186	0.069	−0.321	−0.052	0.007**
Self-actualization * Gender	−0.046	0.067	−0.177	0.085	0.494
$H_{1.7}$					
Extraversion	0.167	0.068	0.035	0.300	0.013*
Age	−0.207	0.067	−0.338	−0.075	0.002**
Extraversion * Age	−0.146	0.068	−0.279	−0.013	0.032*
Maturity	−0.175	0.068	−0.309	−0.041	0.010*
Age	−0.155	0.068	−0.288	−0.021	0.023*
Maturity * Age	0.021	0.069	−0.115	0.157	0.763
Agreeableness	−0.003	0.069	−0.139	0.133	0.967
Age	−0.191	0.069	−0.326	−0.056	0.006**
Agreeableness * Age	0.053	0.070	−0.084	0.190	0.446
Conscientiousness	0.092	0.069	−0.043	0.227	0.181
Age	−0.201	0.069	−0.336	−0.066	0.003**
Conscientiousness * Age	−0.035	0.067	−0.166	0.096	0.604
Self-actualization	0.116	0.069	−0.019	0.250	0.092
Age	−0.199	0.069	−0.334	−0.065	0.004**
Self-actualization * Age	−0.013	0.068	−0.147	0.120	0.845

Notes: Estimate (B): Unstandardized regression coefficient (B); SE: Standard error; *p*: *p*-value (statistical significance); $*p< 0.05$, $**p< 0.01$.

Table 4. Simple slope analysis corresponding to the interaction of extraversion and age

Parameter	Estimate (B)	SE	95% confidence interval		p
			Lower	Upper	
Average	0.167	0.068	0.034	0.301	0.014*
Low (−1 SD)	0.313	0.091	0.134	0.492	<0.001***
High (+1 SD)	0.022	0.102	−0.177	0.221	0.83

Notes: Estimate (B): Unstandardized regression coefficient (B); SE: Standard error; *p*: *p*-value (statistical significance); $*p<0.05$, $***p<0.001$.

emerging technologies and the maladaptive coping strategy of blaming others indicate a tendency to externalize responsibility for difficulties encountered in understanding, learning, and adapting to the demands of the "new digital era."

Hypotheses $H_{1.1}$–$H_{1.5}$ examined associations between personality factors and the use of AI, IoT, and blockchain technologies. Before the actual testing of the five hypotheses, for the three types of technologies, it was decided to apply the Bonferroni correction to control the Type I error rate (false positive statistical effect). Following this selection, the only valid model retained in the research was the model regarding AI use. Hence, the analysis focused exclusively on this technology. Accordingly, the interpretations and conclusions presented in this section primarily reflect psychological pathways related to AI use. In contrast, IoT and blockchain are discussed at a descriptive and contextual level due to their limited adoption in the studied sample.

Table 5. Results of the mediation analysis of cognitive–emotional coping

Coping strategy	Type	Effect	Estimate (β)	SE	95% confidence interval		*p*
					Lower	Upper	
Acceptance	Indirect	Extraversion⇒Acceptance⇒AI use	−0.005	0.009	−0.022	0.013	0.613
		Maturity⇒Acceptance⇒AI use	−0.003	0.008	−0.018	0.012	0.665
		Agreeableness⇒Acceptance⇒AI use	0.032	0.023	−0.014	0.078	0.167
		Conscientiousness⇒Acceptance⇒AI use	−0.009	0.011	−0.030	0.013	0.441
		Self-actualization⇒Acceptance⇒AI use	0.006	0.010	−0.014	0.025	0.581
	Direct	Extraversion⇒AI use	0.163	0.082	0.002	0.324	0.047*
		Maturity⇒AI use	−0.23	0.069	−0.366	−0.094	<0.001***
		Agreeableness⇒AI use	−0.183	0.084	−0.347	−0.019	0.029*
		Conscientiousness⇒AI use	0.058	0.091	−0.121	0.236	0.525
		Self-actualization⇒AI use	0.077	0.089	−0.098	0.252	0.387
Perspective-taking	Indirect	Extraversion⇒Perspective-taking⇒AI use	0.002	0.008	−0.013	0.017	0.769
		Maturity⇒Perspective-taking⇒AI use	−0.001	0.004	−0.010	0.007	0.777
		Agreeableness⇒Perspective-taking⇒AI use	0.007	0.024	−0.040	0.054	0.763
		Conscientiousness⇒Perspective-taking⇒AI use	0.001	0.004	−0.007	0.009	0.791
		Self-actualization⇒Perspective-taking⇒AI use	−0.001	0.005	−0.011	0.008	0.782
	Direct	Extraversion⇒AI use	0.156	0.083	−0.006	0.319	0.059
		Maturity⇒AI use	−0.232	0.070	−0.369	−0.095	<0.001***
		Agreeableness⇒AI use	−0.158	0.085	−0.324	0.008	0.062
		Conscientiousness⇒AI use	0.048	0.091	−0.131	0.227	0.597
		Self-actualization⇒AI use	0.084	0.090	−0.092	0.260	0.349
Positive reappraisal	Indirect	Extraversion⇒Positive reappraisal⇒AI use	0.005	0.013	−0.020	0.030	0.712
		Maturity⇒Positive reappraisal⇒AI use	0.004	0.010	−0.016	0.023	0.713
		Agreeableness⇒Positive reappraisal⇒AI use	0.003	0.008	−0.012	0.017	0.719
		Conscientiousness⇒Positive reappraisal⇒AI use	0.001	0.005	−0.008	0.011	0.749
		Self-actualization⇒Positive reappraisal⇒AI use	0.007	0.018	−0.029	0.043	0.710
	Direct	Extraversion⇒AI use	0.154	0.084	−0.010	0.317	0.066
		Maturity⇒AI use	−0.237	0.070	−0.375	−0.099	<0.001***
		Agreeableness⇒AI use	−0.153	0.081	−0.313	0.006	0.060
		Conscientiousness⇒AI use	0.048	0.091	−0.131	0.227	0.600
		Self-actualization⇒AI use	0.076	0.092	−0.103	0.255	0.406
Planning refocusing	Indirect	Extraversion⇒Planning refocusing⇒AI use	0.004	0.009	−0.014	0.022	0.653
		Maturity⇒Planning refocusing⇒AI use	0	0.002	−0.005	0.004	0.927
		Agreeableness⇒Planning refocusing⇒AI use	0.006	0.013	−0.020	0.032	0.644
		Conscientiousness⇒Planning refocusing⇒AI use	0.003	0.007	−0.010	0.016	0.673
		Self-actualization⇒Planning refocusing⇒AI use	0.004	0.010	−0.014	0.023	0.654
	Direct	Extraversion⇒AI use	0.154	0.083	−0.008	0.317	0.063
		Maturity⇒AI use	−0.233	0.070	−0.370	−0.096	<0.001***
		Agreeableness⇒AI use	−0.157	0.082	−0.318	0.004	0.056
		Conscientiousness⇒AI use	0.046	0.092	−0.133	0.226	0.611
		Self-actualization⇒AI use	0.078	0.090	−0.098	0.255	0.384
Positive refocusing	Indirect	Extraversion⇒Positive refocusing⇒AI use	0.012	0.015	−0.017	0.042	0.413
		Maturity⇒Positive refocusing⇒AI use	−0.011	0.013	−0.037	0.015	0.410
		Agreeableness⇒Positive refocusing⇒AI use	0.011	0.013	−0.015	0.037	0.419
		Conscientiousness⇒Positive refocusing⇒AI use	−0.001	0.006	−0.013	0.010	0.806
		Self-actualization⇒Positive refocusing⇒AI use	0.011	0.013	−0.016	0.037	0.428
	Direct	Extraversion⇒AI use	0.146	0.084	−0.018	0.310	0.080
		Maturity⇒AI use	−0.222	0.071	−0.361	−0.084	0.002**
		Agreeableness⇒AI use	−0.162	0.082	−0.322	−0.001	0.049*
		Conscientiousness⇒AI use	0.051	0.091	−0.128	0.230	0.577
		Self-actualization⇒AI use	0.072	0.090	−0.105	0.249	0.425
Blaming others	Indirect	Extraversion⇒Blaming others⇒AI use	0.013	0.014	−0.015	0.041	0.357
		Maturity⇒Blaming others⇒AI use	−0.058	0.028	−0.114	−0.003	0.038*
		Agreeableness⇒Blaming others⇒AI use	0.017	0.015	−0.012	0.046	0.253

(Cont'd...)

Table 5. ***(Continued)***

Coping strategy	Type	Effect	Estimate (β)	SE	95% confidence interval		p
					Lower	Upper	
		Conscientiousness⇒Blaming others⇒AI use	−0.018	0.016	−0.050	0.014	0.271
		Self-actualization⇒Blaming others⇒AI use	−0.009	0.015	−0.038	0.020	0.538
	Direct	Extraversion⇒AI use	0.145	0.082	−0.015	0.306	0.075
		Maturity⇒AI use	−0.175	0.074	−0.319	−0.030	0.018*
		Agreeableness⇒AI use	−0.168	0.081	−0.325	−0.010	0.037*
		Conscientiousness⇒AI use	0.067	0.091	−0.110	0.245	0.457
		Self-actualization⇒AI use	0.092	0.089	−0.082	0.266	0.301
Total		Extraversion⇒AI use	0.158	0.083	−0.004	0.321	0.056
		Maturity⇒AI use	−0.233	0.070	−0.370	−0.096	<0.001***
		Agreeableness⇒AI use	−0.151	0.081	−0.310	0.009	0.064
		Conscientiousness⇒AI use	0.049	0.092	−0.130	0.229	0.590
		Self-actualization⇒AI use	0.083	0.090	−0.094	0.259	0.358

Notes: All paths represent standardized estimates obtained after z-scoring the variables; β: Standardized coefficient (Beta); SE: Standard error; *p*: *p*-value (statistical significance); *p<0.05, **p<0.01, ***p<0.001.
Abbreviation: AI: Artificial intelligence.

These descriptive findings are consistent with official national statistics, which indicate relatively low levels of adoption of IoT and blockchain technologies within the Romanian population. Analysis of the initial data received from the respondents identified that only 26 out of 202 respondents had used blockchain at the time of the study, with 18 of these respondents reporting usage of no more than 0.5 h/day. Similarly, in the IoT usage model, 97 out of 202 respondents mentioned using this technology, of whom 68 reported usage limited to a maximum of 0.5 h/day. Although these two models could not be included in the final analysis, national-level statistics suggest that openness toward IoT adoption in Romania was limited as early as 2022, a trend that appears to persist according to the present findings.

Specifically, the National Institute of Statistics of Romania reported in the study "Reasons why IoT devices are not used in Romania in 2022" that 61% of the population (16–74 years old) believed that they did not need IoT technology.[66] Regarding the blockchain technology, most often associated with the cryptocurrency market, a financial instrument familiar to many Romanians, in 2022, 84% of respondents planned to purchase this instrument in the future.[67] However, 2 years later, in 2024 (the year of the current study), projections remained modest: the number of users is expected to increase to reach 1.97 million by 2028, corresponding to an adoption rate of 10.65% in Romania.[68] Overall, a comparison between the current questionnaire data and official statistics indicates convergence in trends, with both sources reflecting similarly low levels of adoption, as evidenced by the descriptive analyses.

For the valid model, AI use, retained in the analysis, hypotheses $H_{1.1}$–$H_{1.5}$ were tested. The findings indicate that extraversion and maturity showed significant associations with AI use. Unexpectedly, self-actualization did not correlate with AI use as initially anticipated. This factor, which encompasses intellect and openness to experience, reflects motivational and attitudinal aspects on both personal and professional levels. The absence of association may indicate stagnation or a tendency to maintain familiar patterns, focusing on immediate fulfillment of motivations and needs rather than pursuing progress. It may also indicate that the motivational dimensions of self-actualization are not sufficiently triggered by AI use in the studied context. Similar findings have been reported in previous studies, where openness to experience was not linked to adoption unless the technology was perceived as personally relevant or aligned with individual values.[69] In addition, no significant association was observed between conscientiousness and AI use. This factor relates to perseverance, self-improvement, duty fulfillment, and planning. Given that AI technology is neither fully understood nor widely used in Romania, the lack of association between the personality factor agreeableness and AI use can be explained primarily by the skepticism toward this new, largely uncontrollable technology.

The extraversion personality factor was associated with AI use as a predictor. This is not surprising given that extraverts tend to be dynamic, sociable, and open to change. Certain aspects of AI technology facilitate interactions and bring about stimulating, transformative, and modern effects. This result is consistent with findings from previous studies, showing that individuals high in extraversion tend to adopt new technologies more readily, especially when these technologies facilitate social interaction or novelty.[70-72]

From a psychological standpoint, AI applications may satisfy extraverted individuals' preference for stimulation, rapid feedback, and exploratory interaction, thereby reinforcing more frequent use. Conversely, higher levels of maturity, characterized by emotional regulation, impulse control, and reliance on internal coping resources, may be associated with a more cautious or selective engagement with AI, particularly in contexts where trust and perceived utility are still evolving. Thus, lower AI use among individuals with high maturity should not necessarily be interpreted as resistance or non-adoption, but rather as a more deliberate and critical evaluation of when and how to use such technologies.

The last personality factor analyzed, maturity, showed a significant inverse relationship with AI use. In other words, as people demonstrate greater control over their reactions and trust in themselves and others, their frequency of AI use tends to decrease. This finding aligns with research indicating that higher emotional regulation and cognitive control levels, characteristics of high maturity, can sometimes be associated with more cautious or selective technology use,[73] particularly when perceived utility or trust is low.

The hypotheses $H_{1.6}$ and $H_{1.7}$ tested the moderating effect of gender and age in the relationship between personality factors and AI use. The statistical analysis highlighted that gender has no influence as a moderator. Currently in Romania, access to technology is achieved regardless of gender, minimizing any potential difference. Meanwhile, age functions as a moderator of the association between extraversion and AI use. Specifically, higher levels of AI use were observed among individuals who are younger than the sample average age and who also reported higher levels of extraversion. This result reinforces the previous conclusion that the personality factor extraversion is a predictor of AI use. However, the conclusion becomes valid only in the case of younger people. Other works have demonstrated that as age increases, the value of the extraversion factor decreases.[74,75]

These findings have practical and theoretical implications. The lack of gender differences suggests a democratization of AI access and usage across genders in the Romanian context, contrasting with earlier studies that found significant gender-based disparities in technology use.[76-78] Meanwhile, the moderating effect of age on extraversion and AI use underscores the need for targeted interventions when promoting digital engagement in older populations. Younger, more extraverted individuals may adopt AI more easily due to openness to novelty and lower technostress.[79-81] At the same time, older users may benefit from tailored digital literacy or motivational programs to bridge this engagement gap. These patterns highlight the importance of designing technology adoption strategies that are sensitive to both personality and age dynamics.

The second group of hypotheses focused on examining whether the association between personality factors and the use of digital AI technology is mediated by cognitive–emotional coping strategies, including adaptive strategies (acceptance, positive refocusing, planning refocusing, positive reappraisal, and perspective-taking) and a maladaptive strategy (blaming others). The results were largely consistent with earlier observations. Specifically, blaming others was identified to mediate the association between the personality factor maturity and AI use, with the direction of the effect being inverse. Higher levels of maturity were associated with lower levels of blaming others, which in turn corresponded to reduced engagement with AI technologies. This result is in line with previous results showing that maturity negatively predicts AI use, supporting the broader theoretical framework,[13] which suggests that personality traits influence coping styles, and that maladaptive coping can diminish the likelihood of proactive behaviors, including technology engagement.

Within the context of the present study, the blaming others coping strategy appears particularly relevant for understanding individual differences in engagement with AI technologies. Given that maturity is associated with lower blaming others, and blaming others is positively related to AI use, maturity may indirectly contribute to a decrease in AI use via reduced blaming others. However, blaming others–AI use relationships can be influenced by a series of elements, such as a negative attitude toward change (a situation already discussed previously regarding the absence of relationships between the personality factors self-actualization/conscientiousness and AI use) and distrust in AI technology. In addition, the direct relationship between maturity and AI use was present as both a direct and total effect in all analyses for all cognitive–emotional coping strategies performed. This result is consistent with previous literature that demonstrated certain negative emotional tendencies being reduced as maturity increases.[82]

The mediation model also revealed a weak but significant inverse direct relationship between agreeableness and AI use—an association not detected in the multiple linear regression analysis. This was identified both when acceptance and blaming others were the mediators. This relationship indicates that individuals score higher in agreeableness—that is, as they become more cooperative, pleasant, and generous in their relationships with others—their use of AI decreases. In other words, more agreeable individuals tend to prefer direct interactions over technology-mediated relationships. This finding is supported by existing literature.[83]

At the same time, it is important to note that the direct relationship between extraversion and AI use was also confirmed by the mediation model in the analysis involving the cognitive–emotional coping strategy of acceptance.

While the results of this work align with existing literature, the main finding raises questions regarding psychological readiness. Specifically, the sample population does not appear to adopt adaptive cognitive–emotional coping strategies in response to change, such as the introduction of AI technology into society, which represents a major transformation. According to the literature, several factors may explain this reluctance: (i) a fear of losing control, often cited as a primary cause of resistance to change[84,85]; (ii) resistance to abandoning old habits, which is a common characteristic of change reluctance[85]; (iii) a high level of stress or anxiety regarding digital technologies, which can inhibit adaptive coping and instead promote maladaptive strategies that offer only temporary relief but fail to address underlying stressors[86]; (iv) a lack of positive adaptive cognitive–emotional coping strategies[87]; and (v) a lack of personal and social resources necessary to effectively apply such adaptive coping strategies.

This interpretation is further supported by broader evidence on occupational stress and burnout across Europe. According to a survey conducted in Europe in 2022, 67% of Romanian respondents reported suffering from burnout or feeling on the verge of it, placing Romania second in Europe after Poland.[88] The World Health Organization classifies burnout as a syndrome resulting from chronic, unmanaged workplace stress.[88] This survey underscores a widespread reality: modern life has become tense and hectic, with emotional and stress-related disturbances often triggering conflicts. Such conflicts and internal stress can cause complex psychological and physical changes in the body, with emotional disagreement leading to a state of stress.[89] Even an analysis limited to this survey helps to better understand the findings of the present study.

Coping mechanisms often operate unconsciously.[86] However, since Romania is still at an early stage in the implementation of emerging technologies on a macro/society scale, decision-makers can still implement measures to develop programs aimed at educating the population regarding these technologies. These efforts could include state-supported psychological services focusing on adaptive emotion and change management techniques, social support groups, and initiatives to promote the benefits of emerging technologies (AI, IoT, and blockchain), which currently face low levels of public trust. Prioritizing psychological education is essential, as choosing effective coping strategies is crucial for preventing adverse outcomes,[86] especially taking into account that coping styles can indirectly affect physical health through psychological responses.[90]

5. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

The current study is descriptive, exploratory, differential, and correlational in nature. While it provides a series of valuable insights as the first study on this topic among the Romanian population, it has several limitations. First, the cross-sectional design precludes the ability to draw causal inferences. Longitudinal or experimental designs could further clarify the directionality of these relationships, such as whether personality traits predict changes in AI use over time or whether sustained AI use influences personality-related behaviors.

The sample size (n = 202) exceeded the minimum required by an a priori power analysis using G*Power, which indicated a minimum of 92 participants for a model with five predictors, assuming a medium effect size, a statistical power of 0.80, and α of 0.05. However, the use of a Romanian convenience sample limits the generalizability of the findings. Cultural norms, access to emerging technologies, and socio-economic conditions specific to the Romanian context may influence both personality expression and technology engagement, thereby restricting the applicability of results to other cultural or national settings.

In addition, despite a relatively broad age range, the study design does not allow for developmental or cohort-based interpretations. The predominantly urban and employed sample may underrepresent rural or socio-economically disadvantaged groups. Consequently, it cannot be determined whether the observed moderating effect of age on the relationship between extraversion and AI use reflects developmental changes or cohort-specific patterns of technology exposure and adoption.

Another limitation lies in the assessment of emerging technologies. Specifically, AI, IoT, and blockchain use were measured solely in terms of daily usage time, reflecting the absence of a validated Romanian questionnaire capturing these behaviors with greater precision. This approach may have limited the detection of qualitative differences in engagement (e.g., purpose, complexity, or perceived usefulness of AI use), potentially attenuating observed associations and moderation effects.

An important direction emerging from these findings concerns the assessment of stress and anxiety levels in relation to the use of emerging technologies. This aspect is particularly relevant given that the present study identified a lack of adaptive coping strategies in response to the implementation of these transformative technologies at a macro/societal level. Therefore, future research should address these limitations by incorporating longitudinal designs, larger and more representative samples, and additional mediators or moderators such as educational level, professional status, and residential area.

Finally, future studies may benefit from incorporating alternative personality frameworks or more fine-grained trait facets beyond the global Big Five dimensions. Constructs such as technology readiness, need for cognition, and facet-level personality traits may yield a more nuanced understanding of individual differences underlying emerging technology adoption, especially in early-stage implementation contexts such as IoT and blockchain.

6. CONCLUSION

This study investigated how personality factors and cognitive–emotional coping strategies are associated with the use of emerging technologies, specifically AI, IoT, and blockchain, among adults in Romania. The results revealed that extraversion and maturity are significantly linked to AI use: Extraversion is positively associated with usage, whereas maturity shows an inverse relationship.

Adaptive coping strategies were not found to mediate technology use. In contrast, the maladaptive strategy of blaming others served as a significant mediator between maturity and AI engagement. In addition, age moderated the extraversion–AI use association, with younger, more extraverted individuals reporting greater usage. Gender, by contrast, had no moderating effect, indicating relatively equitable access to AI across men and women respondents.

These findings underscore the importance of targeted interventions to foster digital engagement, particularly among older adults and individuals whose personality profiles may hinder proactive technology use. The limited use of adaptive coping mechanisms in this context raises further questions about psychological readiness for digital transformation, inviting future research into emotional, motivational, and educational barriers.

The results of the present study also have several practical implications for initiatives aimed at supporting digital transformation. Individual differences in personality and age appear to play an important role in how emerging technologies, particularly AI, are adopted and used. For this reason, programs designed to enhance AI engagement among older adults or individuals with lower levels of extraversion may benefit from structured guidance, clear demonstrations of usefulness, and the gradual development of trust in these technologies, rather than relying exclusively on self-directed exploration.

At the same time, the inverse association between maturity and AI use suggests that concerns related to control, autonomy, and trust should not be overlooked, especially among individuals who rely strongly on internal regulation and self-efficacy. In this context, interventions that integrate digital skills training with psychological support and the development of adaptive coping strategies may be more effective than approaches focused solely on technical instruction.

Future studies using longitudinal or experimental designs may further clarify the causal mechanisms underlying these associations and help refine evidence-based strategies for supporting psychologically sustainable digital adoption. Although the study was framed within the broader context of emerging technologies, the primary inferential conclusions are driven by findings related to AI, reflecting the higher level of engagement with this technology in the present sample.

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CONFLICT OF INTEREST

The author declares no competing interests.

AUTHOR CONTRIBUTIONS

This is a single-authored article.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study was conducted in accordance with the Declaration of Helsinki. All participants provided informed consent prior to completing the survey. Ethical approval was granted by the Scientific Council of University Research and Creation, West University of Timişoara, Romania (process number: 53163/02.08.2024).

CONSENT FOR PUBLICATION

All participants provided written informed consent for anonymized data to be published in aggregated form.

DATA AVAILABILITY STATEMENT

All data supporting the findings of this study are included in this article. Additional information can be requested from the corresponding author.

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