THE INFLUENCE OF PSYCHOLOGICAL AND CULTURAL FACTORS ON THE DEVELOPMENT OF HUMAN CAPITAL IN THE DIGITAL ECONOMY

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Abstract

The research examines the impact of psychological and cultural factors on human capital development in the context of the digital economy in Bosnia and Herzegovina. While access to infrastructure and accessibility of information and communication technologies (ICT) remain key, the research findings highlight that attitudes, perceptions, and cultural factors significantly shape digital adoption and skills acquisition. The survey results show that barriers such as lack of confidence, fear of technology, and limited perceived needs are significant obstacles to full participation in the digital economy, even when basic infrastructure is present. Regression analysis confirmed that psychological and cultural factors have a statistically significant impact on human capital development, explaining a significant part of the variance in outcomes. The presented results highlight that digital transformation cannot be reduced to a purely technical challenge but must also address the human and cultural dimensions of technology use. Policies that combine infrastructure investments with programs designed to build trust, build and change perceptions, and align digital tools with local cultural practices will be most effective in reducing the digital divide and strengthening human capital for future growth. The research sample consisted of 1547 citizens (n = 1547) from Bosnia and Herzegovina, selected using the snowball sampling method. The basic motive for the realization of this research is the fact that there are no relevant studies in Bosnia and Herzegovina that focus on the influence of psychological and cultural factors on human capital in the digital economy.

Keywords: psychological factors, cultural factors, human capital, digital economy

JEL: O33, J24, L86

1. Introduction

The digital economy has fundamentally transformed the basis of competitive advantage, shifting emphasis from traditional factors of production toward knowledge, innovation, and human capabilities. In this paradigm, human capital encompasses skills, competencies, and adaptive capacities which become central to economic growth and social development. However, the transition to a digitally driven economy extends beyond technological infrastructure and access to digital tools, which is directly impacted with psychological and cultural dimensions that shape how individuals perceive, adopt, and utilize digital technologies.

While considerable scholarly attention has focused on technical and infrastructural aspects of the digital divide, such as broadband penetration and device accessibility, less emphasis has been placed on non-material barriers impeding digital participation. Psychological factors, including digital confidence, fear of technology, self-efficacy, and motivation, critically determine whether individuals engage with information and communication technologies (ICT) even when access is available. Cultural factors, rooted in shared values, norms, and social practices, influence the perceived relevance and acceptability of digital tools within different communities. These dimensions are particularly salient in contexts with diverse socio-economic conditions, where traditional behavioral patterns may not align with the demands of rapid digitization.

Bosnia and Herzegovina presents a compelling case for exploring these dynamics. The country faces persistent digital inclusion challenges, characterized by significant urban-rural disparities, generational divides, and varying educational levels. Despite increasing investments in digital infrastructure and ICT

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adoption policies, progress remains uneven. A substantial portion of the population exhibits low digital engagement, not due to lack of access, but rather attitudinal, perceptual, and cultural barriers. Understanding these barriers is essential for designing effective interventions beyond infrastructure provision. Contemporary human capital theory extends beyond formal education to encompass cognitive, emotional, and social competencies. In the digital economy, human capital development requires not only digital skills acquisition but also psychological resilience, openness to change, and cultural adaptability. Research increasingly recognizes that mental well-being, self-confidence, and culturally informed attitudes toward technology are essential to successful integration into digital labor markets. Yet, empirical studies examining the relationship between these psychological and cultural factors and human capital formation remain limited, particularly in the Western Balkans.

The significance of this research lies in both its empirical contribution to understanding digital divides and its practical implications. By demonstrating that psychological and cultural factors account for substantial variance in human capital development, this study underscores the necessity of complementing infrastructure investments with initiatives aimed at shifting attitudes, building confidence, and aligning digital technologies with cultural contexts. It contributes to understanding digital transformation as a socio-cultural process rather than merely a technological one, advancing both theoretical understanding and practical strategies for fostering inclusive human capital development in the digital age.

2. Literature review

The digital economy, a socio-economic system driven by digital technologies, data, and innovation, fundamentally redefines the role and nature of human capital. Unlike traditional industrial economies dependent on natural and physical resources, the digital economy emphasizes intellectual capacities, creativity, adaptability, and lifelong learning. As rapid technological advancements, including artificial intelligence (AI), automation, and digital communication tools, become ubiquitous across economic systems, human capital development becomes a critical driver of competitiveness, productivity, and social progress. However, the transformation is not purely technological; psychological and cultural factors play crucial roles in shaping individuals' ability and willingness to develop and leverage digital skills, thus influencing economic outcomes.

From a theoretical perspective, the relationship between psychological and cultural factors and digital engagement can be grounded in established models of technology adoption and digital inclusion. The Technology Acceptance Model (TAM) is a theoretical model that explains and predicts how users come to accept and use technology. It proposes that two key beliefs drive a person's intention to use a system: perceived usefulness and perceived ease of use as primary determinants of technology adoption, both of which are strongly influenced by individual attitudes and confidence (Davis, 1989; Venkatesh & Davis, 2000; Zaineldeen et.al., 2020). Similarly, the Unified Theory of Acceptance and Use of Technology (UTAUT) incorporates social influence and facilitating conditions, highlighting the role of cultural norms and collective expectations (Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh, Thong, & Xu, 2012). Recent extensions such as UTAUT2 further emphasize hedonic motivation, habit, and price value, which are particularly relevant for understanding everyday digital engagement beyond the workplace (Venkatesh et al., 2012). Digital inclusion frameworks complement these adoption models by shifting attention from individual behavioral intentions to structural and contextual determinants of engagement. Multidimensional approaches distinguish between access, skills, usage, and outcomes, and explicitly embed these dimensions in broader socio-cultural and institutional environments (Helsper, 2012; van Deursen & Helsper, 2015; van Dijk, 2020). These frameworks highlight that psychological factor (e.g., self-efficacy, motivation, perceived control) and cultural factors (e.g., norms, values, language, trust) shape not only whether people adopt digital technologies, but also how they convert access into meaningful benefits. By integrating TAM, UTAUT/UTAUT2, and digital inclusion perspectives, this study positions psychological and cultural factors not as peripheral variables, but as central mechanisms shaping human capital formation in the digital economy. Digital technologies are profoundly transforming the way we live, work, and connect, with far-reaching implications for both individual well-being and societal cohesion. As these tools become embedded in daily routines from AI-powered healthcare to assistive devices that enhance accessibility, they offer unprecedented opportunities for empowerment, education, and economic participation. Yet, alongside these benefits come complex risks: mental health strains, the spread of misinformation, and growing concerns over data privacy. Raising awareness of these challenges is essential, but true empowerment demands more. It requires equipping individuals with the skills and agency to navigate digital environments responsibly and confidently (OECD, 2024). This emphasis on agency and capability aligns with capability-based approaches to digital inclusion, which focus on people's real freedoms to achieve valued outcomes rather than mere access or use (Robeyns, 2017; Kleine, 2015).

The digital economy transcends simple digitization of existing processes; it represents a shift to innovation-led growth, where knowledge, skills, and creativity define competitive advantage. Human capital encompasses not only formal education and training but also cognitive capacities, psychological resilience, cultural values, and socio-emotional skills essential to adapt to new technologies and work environments (Qilicheva, 2025). Although more than 90 percent of the population in high-income countries was online in 2022, only one in four people in low-income countries used the internet, and the speed of their connection was typically only a small fraction of that in wealthier countries (World Bank, 2024). Studies indicate that economies investing in digital literacy, skill enhancement, and continuous learning mechanisms reap significant benefits in productivity and innovation capacity (Salmi, Amegah, & Shinde, 2025; OECD, 2021). However, the rapid pace of change creates challenges such as skill obsolescence, digital divides, and inequality, which are heavily mediated by psychological and cultural contexts. In digital inclusion terms, these reflect first-level (access), second level (skills and usage), and third-level (outcome) divides, which often intersect with socio-demographic and cultural cleavages (van Deursen & van Dijk, 2019).

Psychological well-being significantly influences individuals' capacity to acquire and apply digital skills. The intense engagement with digital environments has brought new mental health challenges, including digital addiction, anxiety, fear of missing out (FOMO), and emotional stress, which can impair learning and productivity (Nguyen et al., 2022; Fioravanti et al., 2021). Digital environments are characterized by anonymity, disembodiment, and disinhibition, which can influence behavior and self-perception. While anonymity can offer freedom for self-expression, it may also decrease accountability and foster harmful behaviors like cyberbullying, which have adverse psychological effects on victims including depression and social isolation (Wachs & Wright, 2019). Emotional barriers such as fear and anxiety related to digital technologies can hinder technology adoption and skill development, emphasizing the need for psychological support mechanisms. These psychological constructs are closely related to core variables in technology acceptance models, such as computer anxiety, perceived behavioral control, and self-efficacy, which have been shown to affect perceived ease of use and behavioral intention (Venkatesh, 2000; Chen & Chan, 2014).

Furthermore, digital disembodiment allows users to create idealized online identities, often causing dissociation and unrealistic beauty or skill standards, negatively impacting self-esteem especially among youth (Whitty and Young, 2017). Decreased social cues in digital communication contribute to disinhibition, sometimes manifesting as aggressive or antisocial behaviors online, further complicating psychological safety in digital contexts. Mental health promotion, digital literacy education, and protective mechanisms such as privacy safeguards and curated digital content are therefore essential. Governments and organizations increasingly integrate psychological safety features and AI-based moderation tools to mitigate risks, supporting healthier digital engagement that fosters rather than impairs human capital development. Ultimately, responsible digital use is essential for safeguarding data privacy, supporting democratic values and respecting ethical standards. While digital technologies have the power to level the playing field, they can deepen existing inequalities if access and skills are unevenly distributed (OECD, 2024). These interventions can be interpreted as “facilitating conditions” in the UTAUT framework, shaping both the opportunity structure for technology use and individuals’ confidence in using digital tools. Culture, broadly defined as shared values, norms, and behaviors, profoundly affects how individuals and societies engage with digital technologies. Ethnic, national, and regional cultures shape learning styles, motivation, trust in institutions, and openness to innovation, thereby influencing human capital formation (Vitolla et al., 2022; Rubino, 2020). For example, studies highlight the role of cultural dimensions such as gender egalitarianism, performance orientation, and collectivism/individualism in explaining variations in digital literacy, technology adoption, and economic innovation (Zheng et al., 2021; Rantanen, 2024). Countries with cultures that encourage gender equality and performance-driven values tend to make more significant advances in sustainable development and digital skills acquisition. In the context of technology acceptance, these cultural dimensions map onto “social influence” in UTAUT and shape subjective norms around digital participation (Straub, Keil, & Brenner, 1997; Srite & Karahanna, 2006).

On the other hand, traditional cultural values tied to family roles and rural community life can affect economic resilience and the preservation of cultural identity but also create barriers to digital inclusion, contributing to persistent rural-urban digital divides and uneven access to education and employment opportunities. Digital inequalities often reflect deeper socio-cultural divides, including language barriers, ethnic segregation, and socio-economic status, which exacerbate challenges in accessing and benefiting from digital economies (Berdiev et al., 2020). These disparities stress the importance of culturally sensitive policies and programs that address not only skill gaps but also social and cultural dimensions of inclusion. Empirical work on digital inclusion emphasizes the need to tailor interventions to local cultural logics and trust structures to avoid reinforcing existing forms of exclusion (Helsper & van Deursen, 2017).

The interaction between psychological and cultural factors is complex and mutually reinforcing. Cultural norms influence psychological attitudes toward technology, risk-taking, and learning, while psychological health affects cultural engagement and social capital. Simultaneously, digital environments challenge cultural traditions through exposure to diverse worldviews and new social norms, requiring psychological adaptation (Valkenburg et al., 2022). Understanding this interplay is crucial for designing interventions that promote digital literacy, mental well-being, and inclusive human capital development. Approaches combining technical training with psychological support and cultural competence are more likely to succeed in fostering resilient digital workforces. Effective human capital development in the digital economy demands integrated strategies addressing psychological and cultural factors alongside technological and educational measures. Framing these strategies within well-established technology acceptance and digital inclusion frameworks allows for a more systematic explanation of how psychological and cultural variables translate into concrete patterns of digital engagement, skill development, and economic outcomes.

Policy and practical implications for advancing human capital development in the digital economy must address psychological and cultural factors comprehensively to be effective and inclusive. Promoting digital literacy programs should extend beyond technical skills to encompass education about psychological risks in digital environments, such as internet addiction, cyberbullying, anxiety, and fear of missing out (FOMO). Teaching individuals’ strategies to manage these risks can foster healthier online behavior and improve mental well-being, which supports sustainable engagement and skill development (OECD, 2023; Nguyen et al., 2022). This holistic approach to digital literacy ensures that users are not only competent in the use of technology but also resilient to challenges that may hinder their participation and growth in the digital economy. In line with digital inclusion frameworks, such policies should simultaneously target access, skills, motivation, and outcomes, and be informed by technology acceptance insights on perceived usefulness, ease of use, and social influence to ensure that investments in digital infrastructure translate into equitable human capital gains.

Cultural diversity is another critical consideration in designing learning and inclusion initiatives. Cultural contexts shape attitudes toward technology, learning motivation, and access to digital tools. Policies tailored to respect cultural values and address language, gender, and regional differences can reduce barriers and close digital divides, especially for marginalized groups facing complex socio-cultural challenges (Vitolla et al., 2022; Glatkova et al., 2021). By incorporating cultural sensitivity into these programs, policymakers can better engage in diverse populations and foster equitable opportunities for skill acquisition and economic participation.

Building safe, supportive digital spaces is essential. Stakeholders can leverage artificial intelligence and immersive technologies to develop platforms that shield users from harassment, misinformation, and privacy violations. Features like AI-based content filtering, usage time management tools, and virtual personal space boundaries contribute to psychological safety and build user trust, which is vital for human capital formation (OECD, 2022). These measures not only protect mental health but also encourage active and confident engagement in digital environments, promoting overall digital inclusion.

Supporting lifelong learning environments is imperative as rapid technological change demands continuous upskilling. Education systems, workplaces, and governments must collaborate to provide flexible, culturally adaptive learning pathways to meet diverse learner needs and maximize skill acquisition. Lifelong learning initiatives equipped to address psychological and cultural factors ensure adaptability and sustain competitiveness within the digital economy. Finally, public-private partnerships enable the pooling of expertise and resources to tackle multifaceted challenges effectively. They foster innovation in educational technologies, promote inclusive policymaking, and ensure digital ecosystems evolve to safeguard psychological well-being and cultural inclusiveness (OECD, 2023; Rantanen, 2024). Such collaborations build comprehensive and adaptive strategies necessary for addressing the complexity of digital transformation and human capital development. In conclusion, development of human capital in the digital economy is a multifaceted process shaped by intertwined psychological and cultural factors. These non-technical dimensions are as crucial as digital skills for fostering an adaptive, innovative, and inclusive workforce. Ensuring mental wellbeing, addressing cultural barriers, and promoting supportive digital environments will enable individuals and societies to maximize the benefits that digital technologies offer while mitigating their risks. Future research and policy should continue to explore this nexus, focusing on creating holistic strategies that integrate psychological health, cultural diversity, and technological proficiency. Only by acknowledging and acting on these interconnected factors can sustainable human capital growth be achieved in the rapidly evolving digital landscape.

3. Research methodology

As part of the primary research (field research), data were collected using the survey method, with a questionnaire serving as a technical means of data collection. The collection of primary data for this research was a part of a wider research. Primary data were collected using the snowball method, which was partly done electronically using Google Forms, the platform for online surveys, and partly by personally surveying the respondents. In principle, the main advantage of the snowball or multiple sample is the economic efficiency of the procedure. The process begins with the researcher who, on a case-by-case basis, identifies the initial participants who have the characteristics under study, and then asks them to identify other respondents with the same trait. In other words, based on the information obtained from the initial respondents, the subsequent ones are identified, and so on, hence the metaphorical name of the "snowball" sample.

In the process of data collection, the answers of 1547 respondents were collected, based on which empirical research was carried out for this section of the study. The survey questionnaire, except for the question on territorial affiliation, was structured using closed-ended questions, whereby the respondents had the opportunity to evaluate their degree of agreement with certain statements using a five-point Likert response scale. This methodological design allowed the research to capture not only socio-demographic variables like territorial distribution and gender but also detailed subjective evaluations of digital skills and human capital, thereby linking psychological and cultural dimensions to economic participation capabilities.

The methods used in the presented scientific research work to investigate and present the results of scientific research are inductive and deductive, the methods of analysis and synthesis, comparative methods, and statistical methods. During the research, the analysis of relevant scientific research and studies in the form of books, textbooks, magazines, official publications, websites, as well as other relevant literature was carried out. The inductive method was applied in the reverse direction to derive general propositions from individual facts. The deductive method was used to derive appropriate concrete assumptions and conclusions from general statements.

The method of analysis enabled the explanation of the problem and the research subject by breaking them down into simpler parts and researching each part separately concerning other parts. This enabled the observation, discovery, and study of the scientific truth about mutual relationships. The synthesis method was used to combine the obtained research results into a coherent whole, thereby establishing and examining the interrelationships among the individual findings. The comparative method was used to compare the same or related facts, phenomena, processes, and relationships, i.e., it helped to establish their similarities in behavior and intensity, as well as the differences between them. Following the usual research standards in the social sciences, the data obtained from the questionnaire were processed using the SPSS software package for statistical analysis. Bearing in mind that the research hypotheses were formulated in such a way as to test the influence (causality) of one variable on another, rather than the connection between the defined variables, regression analysis was used in the paper. The method of description was used to describe facts and their empirical confirmation but without scientific interpretation and explanation.

Although the snowball sampling method enabled efficient data collection and access to a large number of respondents, it introduced limitations regarding representativeness. The sample demonstrates a strong urban bias (approximately 79% were the urban respondents), which may overestimate digital engagement levels and underrepresent rural-specific barriers. Therefore, the findings should be interpreted with caution when generalizing to the entire population of Bosnia and Herzegovina. Future research should consider stratified or probability-based sampling techniques to improve generalizability.

4. Research variables

The variables observed in the context of empirical research are:

The independent variable relates to psychological and cultural factors. Psychological and cultural factors as determinants of the digital divide refer to internal, mental and social characteristics that influence individuals or groups in accessing, using, and accepting digital technologies. Psychological factors include attitudes, perceptions, confidence in using technology, sense of belonging or self-efficacy related to digital platforms. Cultural factors represent values, norms, beliefs, and patterns of behavior specific to certain communities or societies that can create a mismatch or barrier in the acceptance and use of digital resources (e.g., mismatch of cultural norms with digital requirements).

For the empirical testing, the psychological and cultural dimensions were treated as a unified composite construct. Although conceptually distinguishable, these dimensions are empirically interrelated within the context of digital participation, as individual attitudes and confidence are often shaped by broader socio-cultural norms and value systems. Therefore, the study models them as an integrated attitudinal orientation toward ICT use.

The psychological and cultural factors are operationalized through an indicator as follows:

- The attitude and perception of the respondents towards the active use of ICT

More specifically, this construct was measured through six Likert-scale items capturing confidence in ICT use, perceived competence, motivational readiness, perceived necessity of ICT in daily life, emotional comfort when using digital tools, and perceived compatibility of digital technologies with personal values and lifestyle.

The respondents rated their level of knowledge for each of these indicators on a scale from 1 to 5, where the rating 1 indicates insufficient, 2 - sufficient, 3 - good, 4 - very good and 5 - excellent level of knowledge of the subject category, so the value of the variable represents the sum of the respondents' responses to these six indicators.

The composite index was constructed using additive aggregation, whereby the responses across six items were summed to generate a continuous variable representing the overall psychological and cultural orientation toward ICT. Higher values indicate stronger positive disposition, greater confidence, and higher perceived alignment with digital technologies. This additive approach is consistent with standard practice in social science research when measuring multidimensional attitudinal constructs. *The dependent variable "human capital"* was operationalized through functional digital competency indicators aligned with digital economy requirements. These include knowledge of basic computer applications, communication skills in digital environments, ability to transfer files and manage digital resources, software installation and configuration skills, and general digital literacy. Each item was measured using the same five-point Likert scale. Similar to the independent construct, the responses were aggregated additively to create a composite human capital index.

In this study, human capital is conceptualized within the framework of the digital economy, where digital competencies represent a core productive capability. The operationalization therefore focuses specifically on functional digital skills as observable manifestations of human capital relevant to participation in digitally mediated economic activities.

Indicators for measuring dependent variables Human capital are as follows:

- Level of knowledge of basic computer applications
- Level of communication skills
- Level of knowledge of transferring files from a computer to another device,
- Level of knowledge of installing software and changing settings on devices
- Level of computer literacy (creating, moving, and storing documents and files), and finding necessary information on the internet

The composite human capital index was calculated as the sum of these five indicators, producing a continuous measure of digital competence. Higher index values reflect stronger digital capability and greater readiness for participation in the digital economy. The measurement scales used in this study were constructed based on established theoretical frameworks in digital divide and digital economy research. The items reflecting psychological and cultural factors were derived from prior literature addressing self-efficacy, digital confidence, and socio-cultural compatibility with ICT usage. Similarly, the indicators used to operationalize human capital were aligned with widely recognized digital competency dimensions, including functional ICT literacy and applied digital skills. All items were measured using a five-point Likert scale to ensure consistency and comparability across the constructs. The use of a uniform scale format enhances measurement stability and reduces response bias. Prior to data collection, the questionnaire was reviewed for clarity, internal coherence, and conceptual alignment with the study's theoretical model. Construct validity was supported through theoretical consistency between conceptual definitions and operational indicators, ensuring that each item directly reflected the underlying construct it was intended to measure. The planned research was based on the application of scientific methods of secondary and primary research.

5. Results and discussion

The majority of the respondents (63%) were from the Federation of Bosnia and Herzegovina, while 32.45% were from Republika Srpska. Only 4.55% of the respondents were from the Brčko District, highlighting a notable underrepresentation of this entity. This distribution roughly reflects the real population share but shows that the survey leaned more towards the Federation of Bosnia and Herzegovina. Such differences are important to consider when generalizing results, as regional differences in ICT usage may exist.

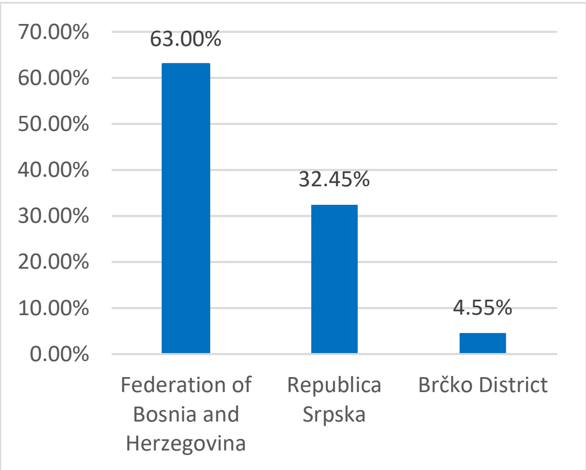

Figure 1. Respondent demographics based on entity
Source: Author's research

The overwhelming majority of the respondents (78.98%) live in urban areas, compared to only 21.02% from rural areas. This imbalance is significant, as access to ICT infrastructure is typically much higher in urban settings. As a result, rural barriers to ICT use might be underrepresented in the dataset. On the other hand, the strong urban sample gives a realistic picture of ICT adoption in city environments. The contrast between rural and urban respondents may explain differences in skills, affordability, and motivation observed later in the survey.

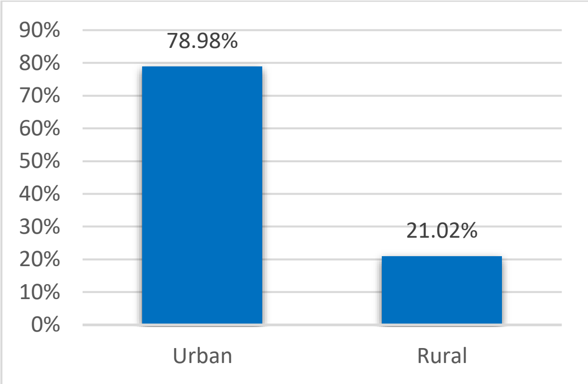

Figure 2. Respondent demographics based on urban vs. rural
Source: Author's research

The respondents were almost evenly split between genders, with 51.09% male and 48.91% female. This balance is useful, as it ensures that findings are not overly skewed towards one gender. A nearly equal gender distribution also allows for more accurate interpretation of psychological, cultural, and financial barriers. Since digital divides can sometimes be gendered, the equal representation increases the robustness of the results.

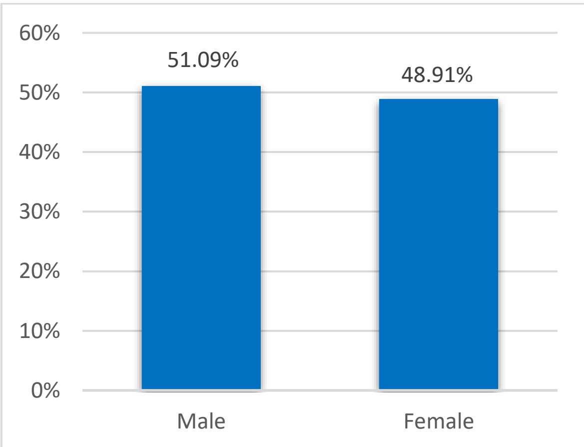

Figure 3. Respondent demographics based on gender
Source: Author's research

A large majority of the respondents showed positive engagement with ICT: 63.67% strongly agreed and 10.92% agreed that they actively use ICT. A smaller group (12.28%) reported mixed opinions ("both agree and disagree"), while only 11.05% strongly disagreed and 2.07% disagreed. This indicates that nearly three-quarters (74.59%) of the respondents regularly and actively use ICT. The findings highlight a generally strong adoption of digital tools among the sample. However, the existence of about 13% with low or no ICT usage suggests persistent barriers worth addressing.

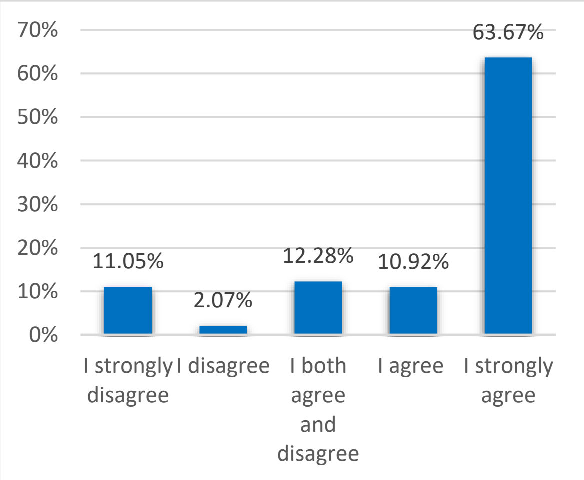

Figure 4. Distribution of responses based on respondents' level of active ICT use
Source: Author's research

The largest reported barrier was lack of digital skills/knowledge (80.7%), which dominated all other reasons. Other notable barriers included lack of motivation (36.84%), lack of confidence (26.9%), and lack of time (8.19%). Since the respondents could choose more than one option, these percentages overlapped and should not be read as exclusive categories. Instead, they showed the relative frequency of barriers most often cited. It is also important to note that these values reflect only those respondents who selected "I strongly disagree" when asked about ICT readiness.

This means the numbers represent a concentrated group of individuals with the strongest resistance to ICT use, rather than the entire sample. Taken together, the findings emphasize that the skills gap remains the most critical barrier, and it often overlaps with issues of confidence and motivation, creating a compounded effect.

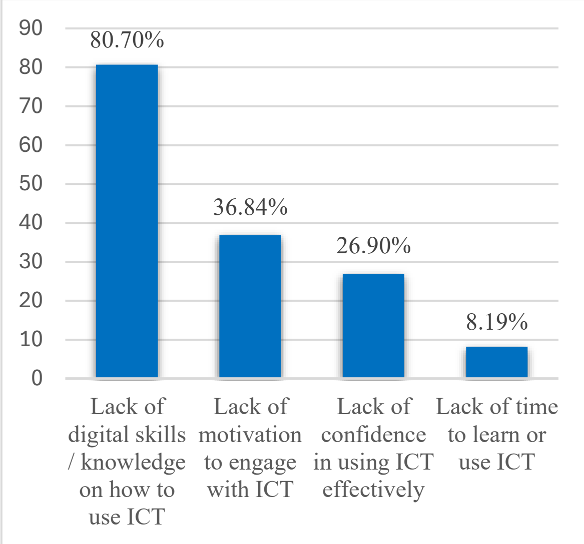

Figure 5. Distribution of responses on the lack of digital skills and knowledge
Source: Author's research

Nearly half of the respondents (46.78%) said they cannot afford ICT tools or services, while 10.53% noted limited opportunities or access. Financial issues were therefore a major structural barrier to ICT use. This indicates that even when infrastructure exists, affordability is not guaranteed. Lowering costs through subsidies or shared-access initiatives could make a significant difference.

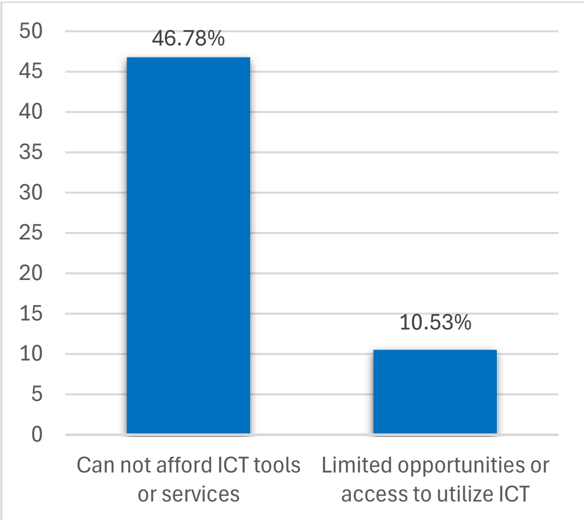

Figure 6. Distribution of responses on financial barriers and limited access to ICT
Source: Author's research

About 37.43% of the respondents reported having no personal interest in ICT, while 35.67% admitted to fear or anxiety when using it. This suggests that nearly three-quarters of the respondents faced some psychological or attitudinal barrier. Fear, disinterest, and lack of confidence undermine adoption even when infrastructure and affordability are present. Awareness campaigns and targeted support may help build positive attitudes toward ICT.

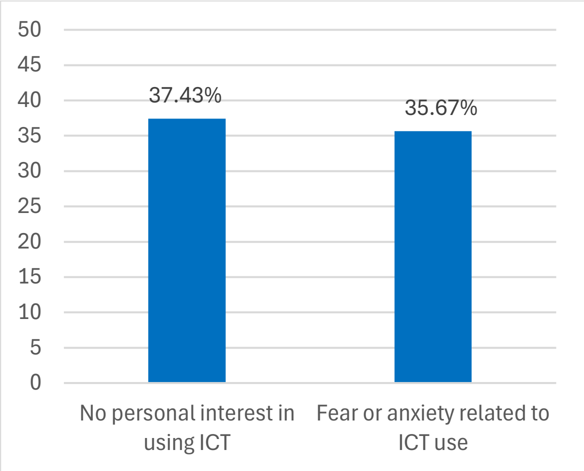

Figure 7. Distribution of responses on psychological barriers and emotional attitudes in using ICT
Source: Author's research

One-third of the respondents (33.33%) reported no perceived need for ICT in their daily lives, while 4.68% said ICT is not compatible with their cultural or personal values.

The cultural barrier was relatively small, but the lack of perceived need was significant. This indicates that many do not yet see ICT as essential. Efforts to show practical benefits could help change these perceptions.

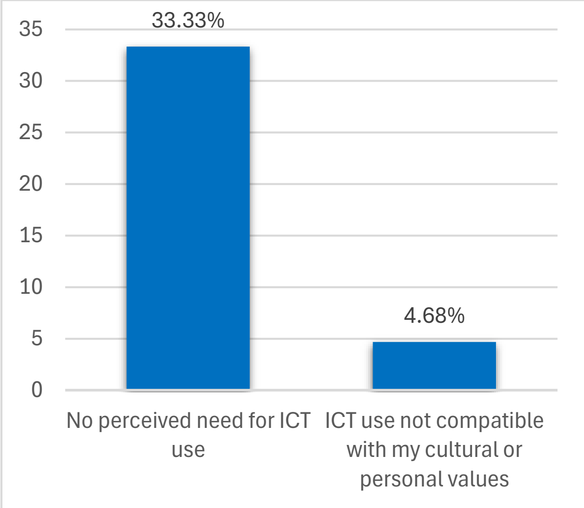

Figure 8. Distribution of responses on perceived need and cultural factors in using ICT
Source: Author's research

For basic applications, the respondents rated their skills as: insufficient (14.60%), sufficient (19.40%), good (22.20%), very good (24.60%), and excellent (19.20%). For technical knowledge, the results were similar: insufficient (15.20%), sufficient (19%), good (21.60%), very good (24%), and excellent (20.20%). The largest groups are in the good-to-very-good categories, showing a reasonable level of competence across the sample.

Still, about one-third remain at insufficient or sufficient levels, highlighting ongoing skill gaps.

At the other end, roughly 40–45% identified as very good or excellent, forming a strong base of digitally capable individuals. This distribution suggests both progress in digital literacy as well as the areas requiring targeted support.

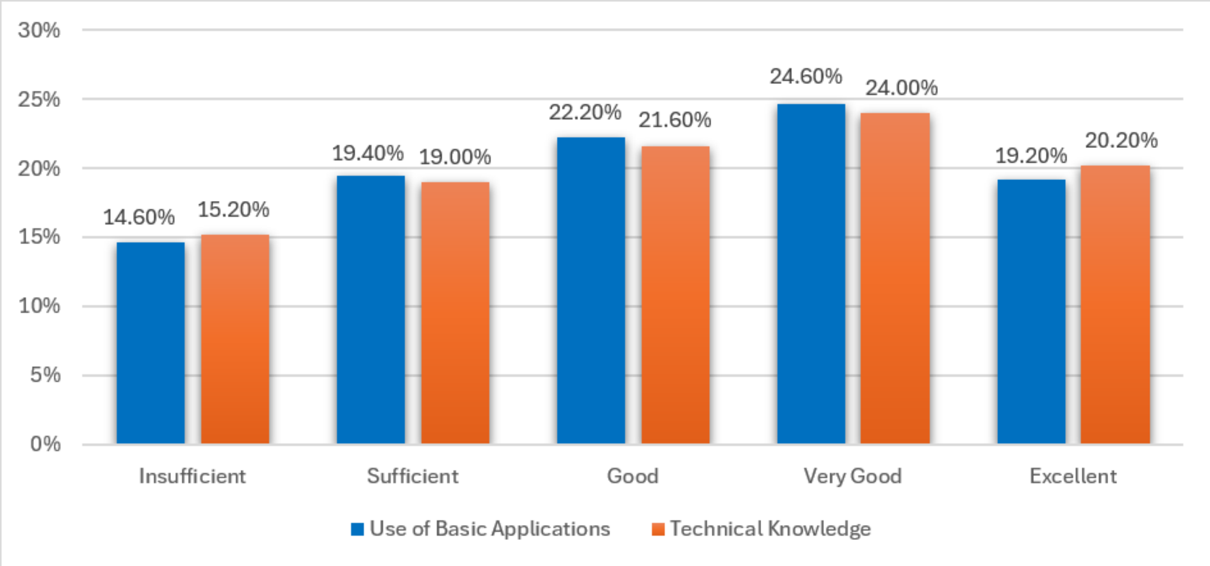

Figure 9. Distribution of responses on perceived practical digital skills
Source: Author's research

For digital communication, the ratings were: insufficient (14.80%), sufficient (18.60%), good (21.80%), very good (24.40%), and excellent (20.40%). For digital literacy, the results were: insufficient (14.40%), sufficient (18.80%), good (22%), very good (24.80%), and excellent (20%).

Again, most respondents fall into the good-to-very-good categories, while around one-third are at the lower end (insufficient or sufficient). About 40–45% see themselves as very good or excellent, indicating strong confidence in digital interaction.

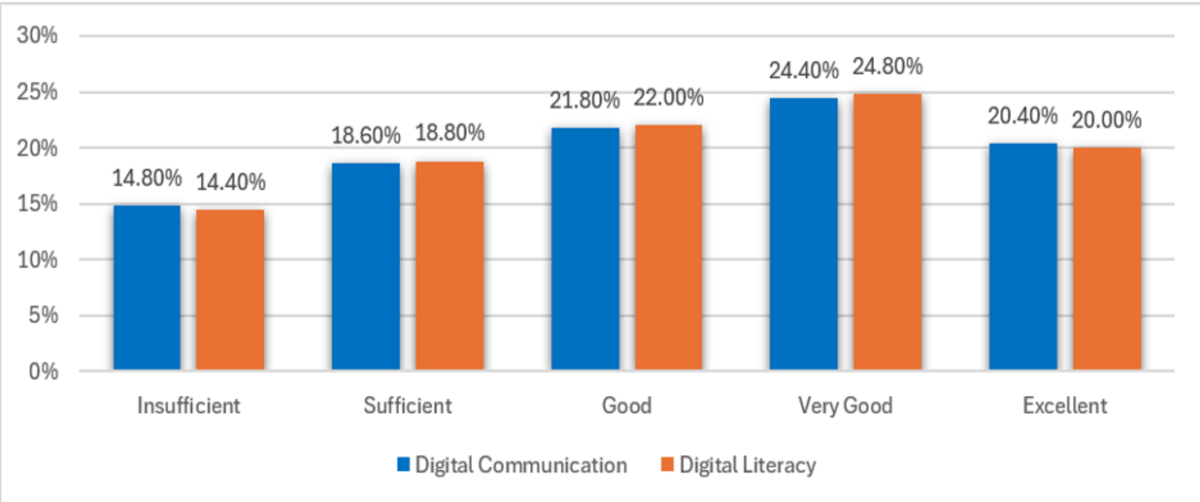

Figure 10. Distribution of responses on perceived digital interaction skills
Source: Author's research

The regression analysis shows a correlation of R = 0.529, with a coefficient of determination (R^2) = 0.280. This means that 28% of the variance in human capital is explained by psychological and cultural factors. The adjusted R^2 (0.279) confirms the model's reliability. The regression coefficient (β = 0.529) is statistically significant at $p < 0.001$, indicating a strong positive relationship. In other words, improvements in psychological and cultural attitudes toward ICT significantly increase human capital. While 72% of the variance is explained by other factors, this result confirms that attitudes and cultural dimensions play a substantial role. This underlines the importance of not only infrastructure investment but also targeted programs to shift perceptions and build confidence.

In terms of effect size interpretation, an R^2 value of 0.28 represents a substantial level of explanatory power within social science research, particularly when examining complex socio-economic phenomena such as human capital formation. The standardized coefficient (β = 0.529) further indicates a strong positive effect, confirming the structural relevance of psychological and cultural dimensions.

Table 1. Results of regression analysis of the model of influence of psychological and cultural factors on human capital

Summary of model[b]					ANOVA	Coefficients	
Model	R	Coefficient of determination	Corrected coefficient of determination	Standard error of estimate	Sig.	Beta	Sig.
1	0.529[a]	0.280	0.279	4.639	0.000	0.529	0.000
a. Predictor: PSYCHOLOGICAL AND CULTURAL FACTORS							
b. Dependent variable: HUMAN CAPITAL							

Source: Author's research

Additional diagnostic indicators confirm the statistical stability of the model. The Variance Inflation Factor (VIF = 1.000) and tolerance values (1.000) indicate the absence of multicollinearity concerns. The condition index (6.302) remains well below critical thresholds, confirming model stability.

Residual analysis shows standardized residuals within acceptable limits (±3), while Cook's distance values remain far below 1, indicating that no influential outliers distort the regression estimates. These diagnostic results strengthen the robustness and reliability of the reported findings.

6. Discussion

The findings of this research offer robust empirical support for the argument that digital transformation cannot be adequately understood through infrastructural or economic determinants alone. While traditional analyses of the digital divide emphasized broadband penetration, affordability, and device access, the present results demonstrate that psychological and cultural factors represent structurally significant determinants of human capital development within the digital economy. The statistical evidence confirms that non-material dimensions of digital engagement possess measurable and substantial explanatory power, particularly within transition economies such as Bosnia and Herzegovina.

The regression analysis indicates that psychological and cultural factors account for twenty-eight percent of the variance in human capital. Within the domain of social sciences, and especially in the study of multifaceted constructs such as human capital, this level of explanatory strength is considerable. Human capital formation is typically influenced by a wide constellation of determinants, including formal education systems, labor market dynamics, institutional stability, macroeconomic conditions, and socio-demographic characteristics. Against this backdrop, the independent contribution of attitudinal and cultural variables underscores the necessity of reconceptualizing digital transformation as a socio-psychological process rather than a purely technological shift. These findings reinforce established theoretical perspectives such as the TAM Model and the UTAUT, which emphasize perceived usefulness, perceived ease of use, and social influence as predictors of digital engagement (Venkatesh et al., 2003; Zaineldeen et al., 2020). However, this study extends these models by empirically linking psychological and cultural dispositions directly to measurable indicators of human capital, thereby situating internal attitudes as foundational to economic participation in the digital era.

The descriptive results further illuminate the layered nature of digital inclusion and exclusion. Although a substantial majority of the respondents reported active use of information and communication technologies, the structure of reported barriers revealed deeper complexities. The predominance of self-reported skill deficits aligns with global findings emphasizing the persistence of digital literacy gaps (World Bank, 2024; OECD, 2023). Yet the simultaneous presence of low confidence, technological anxiety, and absence of personal interest indicates that skill acquisition is embedded within a broader psychological framework. These elements do not operate independently; rather, they interact in a reinforcing manner. Individuals lacking technical competence frequently experience diminished self-efficacy, which in turn reduces motivation to engage with digital tools. As highlighted by Nguyen et al. (2022) and Whitty and Young (2017), digital environments may generate stressors that intensify apprehension and avoidance behaviors. In such contexts, infrastructure expansion and training programs, while necessary, are insufficient if not accompanied by interventions aimed at strengthening psychological readiness and resilience.

Financial constraints remain a salient structural barrier, as evidenced by the substantial proportion of the respondent's identifying affordability as a limiting factor. Nevertheless, the regression findings demonstrate that psychological and cultural attitudes retain independent explanatory capacity even when material constraints are acknowledged. This aligns with the work of Zheng et al. (2021) and Rantanen (2024), who emphasize that cultural values and individual dispositions significantly shape digital skill development and sustainable economic progress. Cultural resistance in the explicit sense appears limited; however, the more pervasive challenge lies in the perception among a significant segment of the respondents that digital technologies are not necessary in their daily lives. This perception reflects deeper socio-cultural narratives concerning relevance, utility, and compatibility with established patterns of social and economic activity. As Vitolla et al. (2022) and Rubino et al. (2020) argue, national and regional cultural characteristics influence openness to innovation and the perceived legitimacy of technological change. In environments where traditional economic structures remain prominent, digitalization may not yet be internalized as integral to everyday functioning.

This study contributes to an underexplored empirical field, particularly within the Western Balkans. While official statistical reports provide valuable quantitative insights into ICT penetration and usage rates, they rarely capture the attitudinal and cultural dimensions that mediate digital participation. By operationalizing psychological and cultural constructs and linking them directly to functional indicators of digital competence, this research advances literature beyond descriptive assessments of access and toward a more nuanced understanding of internal determinants. The operationalization of human capital through practical digital competencies, including application knowledge, communication skills, file management, software configuration, and digital literacy, ensures alignment with contemporary digital economy requirements. The distribution of responses suggests both progress and vulnerability, with a substantial share of the respondents demonstrating strong competence while a significant minority remains at lower proficiency levels. This duality indicates that digital advancement within the population is uneven and potentially fragile.

From a theoretical standpoint, the findings support a reconceptualization of the digital divide as a multi-layered phenomenon encompassing access, skills, psychological readiness, and cultural alignment. Policy discourse frequently concentrates on infrastructure expansion and technical training, yet the present results empirically validate the structural importance of psychological confidence and cultural compatibility. The statistically significant positive relationship between psychological and cultural factors and human capital confirms that improvements in attitudes, self-efficacy, and normative acceptance of digital tools materially enhance digital competencies. This reinforces the broader socio-psychological perspective articulated by Valkenburg et al. (2022), who argue that digital environments reshape identities, norms, and behavioral expectations, requiring adaptive cultural and psychological responses.

The practical implications of these findings are substantial. Given that 80.7% of the respondents identified digital skill deficits and over one-third reported technological anxiety or lack of perceived necessity, policy measures should prioritize confidence-building digital literacy programs, culturally contextualized communication strategies, and interventions that demonstrate tangible everyday relevance of digital tools. Digital economy strategies must move beyond hardware deployment and curriculum reform to incorporate confidence-building mechanisms, culturally sensitive communication strategies, and community-level engagement initiatives that demonstrate tangible local relevance. In transition economies characterized by socio-cultural heterogeneity and post-industrial restructuring, failure to address psychological and cultural dimensions risks perpetuating latent forms of exclusion even where infrastructure is available. Effective human capital policy must therefore integrate technical training with initiatives that normalize digital engagement, reduce technological anxiety, and align digital tools with everyday social and economic practices.

This research substantiates that psychological and cultural factors function as central determinants of human capital development within the digital economy. Their measurable explanatory power confirms that digital transformation is inherently socio-cultural in nature. By empirically quantifying the magnitude of these influences in a transition economy context, the study contributes to both theoretical advancement and policy relevance. Sustainable digital progress depends not only on access and skill provision but also on cultivating confidence, perceived relevance, and cultural alignment. The human dimension of digitalization, far from being peripheral, constitutes one of its most decisive foundations.

Several methodological limitations should be acknowledged. The reliance on self-reported Likert-scale measures may introduce subjective bias and potential social desirability effects, as responses reflect individual perceptions rather than externally verified competencies. Although the theoretical framework supports the internal coherence of the composite constructs, the absence of reported reliability coefficients limits the statistical confirmation of internal consistency. Additionally, the use of snowball sampling restricts sample representativeness and constrains the generalizability of findings beyond the observed group of the respondents. Despite these constraints, the methodological framework remains theoretically grounded and appropriate for examining the relationship between psychological-cultural factors and digital human capital within the defined research context.

7. Concluding remarks

The results of this study point to a layered and complex relationship between psychological and cultural factors and the development of human capital in the digital economy. While access to technology, affordability, and infrastructure remain important determinants of digital inclusion, what emerges clearly is that individual perceptions, attitudes, and cultural dispositions often carry equal, if not greater, weight in shaping whether people will actively engage with ICT. Skills gaps and financial constraints can be addressed through targeted policies, but unless individuals themselves believe in the value of digital tools, feel confident in their ability to use them, and see them as compatible with their way of life, the adoption of ICT will remain uneven. This demonstrates that the digital divide is not merely a question of availability but also of acceptance and motivation, making the human dimension of digital transformation critical to its success.

Although regression analysis tests directional relationships, the cross-sectional design of the study limits strict causal inference. The results therefore indicate statistically significant associations consistent with theoretical expectations, rather than definitive causal mechanisms.

The psychological barriers observed in this study such as lack of confidence, fear of using technology, and absence of personal interest illustrate how deeply digital participation is tied to mindset and emotional readiness. Human capital development depends not only on providing formal education and training but also on cultivating resilience, adaptability, and curiosity among individuals. A workforce that is hesitant, disengaged, or culturally resistant to digital tools cannot fully realize the potential of new technologies, even if the tools are made widely available. This suggests that human capital policies must integrate psychological and cultural considerations into their design, moving beyond traditional education models to include awareness campaigns, mentorship programs, and efforts that normalize digital engagement in daily life.

Cultural dimensions also play a meaningful role in shaping digital behavior. While only a minority express explicit cultural resistance to ICT, the more subtle issue lies in whether communities perceive digital tools as necessary or aligned with their everyday practices. In societies where traditional patterns of interaction and work remain dominant, the digital economy may appear detached from immediate needs. This perception weakens incentives for individuals to invest time and energy in learning digital skills, reinforcing a cycle of exclusion. Breaking this cycle requires making digital tools visibly relevant to local contexts, whether through e-government services, accessible healthcare technologies, or platforms that support small business and agriculture. When cultural narratives embrace technology as a facilitator of progress rather than as a disruption, the path to stronger human capital becomes clearer.

Theoretically, this study contributes to literature by empirically demonstrating that psychological and cultural factors are not peripheral variables within digital inclusion frameworks, but measurable and statistically significant determinants of human capital formation. By linking attitudinal and cultural dimensions directly to functional indicators of digital competencies, the research extends established technology acceptance models and digital divide theories into the domain of human capital development within transition economies. In doing so, it advances the conceptualization of the digital divide as a multi-layered socio-psychological phenomenon rather than a purely infrastructural or economic gap. The findings provide empirical grounding for integrating psychological readiness and cultural alignment into contemporary human capital theory in the digital economy context.

From a policy perspective, the results indicate that digital transformation strategies must move beyond infrastructure deployment and technical training alone. Given that a substantial proportion of the respondents reported skill deficits, lack of confidence, and absence of perceived need, policy interventions should combine digital literacy programs with confidence-building mechanisms, culturally sensitive communication strategies, and localized demonstrations of digital relevance. Public institutions should design targeted interventions aimed at reducing technological anxiety, strengthening self-efficacy, and embedding digital tools within everyday economic and social practices. Without such integrated approaches, investments in infrastructure risk generating limited returns in terms of sustainable human capital development.

Future research should expand this analysis in several directions. First, longitudinal studies would allow for stronger causal inference regarding the dynamic relationship between psychological dispositions and human capital development over time. Second, comparative cross-country analyses within the Western Balkans or other transition economies could test the external validity of these findings. Third, future studies should consider separating psychological and cultural constructs into distinct analytical dimensions to examine their independent and interactive effects. Finally, incorporating additional structural variables such as income level, employment status, and educational attainment could provide a more comprehensive model of digital human capital formation.

In conclusion, the development of human capital in the digital economy cannot be separated from the psychological and cultural environment in which individuals operate. Technology adoption is as much a social process as it is a technical one, requiring alignment between skills, infrastructure, and personal as well as collective attitudes. To foster inclusive digital growth, policies must therefore aim not only to bridge the access gap but also to dismantle psychological and cultural barriers that slow or prevent full participation. Human capital will reach its potential only when individuals feel both capable and motivated to embrace digital transformation, and when societies as a whole perceive technology as integral to their future. The results of this study reinforce that the human side of digitalization deserves equal attention to the technical side, as it is here that the true enablers and obstacles to sustainable digital economies reside.

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Additional Statistical Evidence

Descriptive Statistics

	Mean	Std. Deviation	N
HUMAN CAPITAL	14.24	5.464	1547
PSYCHOLOGICAL AND CULTURAL FACTORS	4.14	1.348	1547

Correlations

		HUMAN CAPITAL	PSYCHOLOGICAL AND CULTURAL FACTORS
Pearson Correlation	HUMAN CAPITAL	1.000	.529
	PSYCHOLOGICAL AND CULTURAL FACTORS	.529	1.000
Sig. (1-tailed)	HUMAN CAPITAL		.000
	PSYCHOLOGICAL AND CULTURAL FACTORS	.000	
N	HUMAN CAPITAL	1547	1547
	PSYCHOLOGICAL AND CULTURAL FACTORS	1547	1547

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	PSYCHOLOGICAL AND CULTURAL FACTORS[b]		Enter

a. Dependent Variable: HUMAN CAPITAL

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.529[a]	.280	.279	4.639

a. Predictors: (Constant), PSYCHOLOGICAL AND CULTURAL FACTORS

b. Dependent Variable: HUMAN CAPITAL

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12902.717	1	12902.717	599,552	.000[b]
	Residual	33249.310	1545	21.521		
	Total	46152.027	1546			

a. Dependent Variable: HUMAN CAPITAL

b. Predictors: (Constant), PSYCHOLOGICAL AND CULTURAL FACTORS

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	5.369	.381		14.090	.000	4.621	6.116					
	PSYCHOLOGICAL AND CULTURAL FACTORS	2.142	.087	.529	24.486	.000	1.971	2.314	.529	.529	.529	1.000	1.000

a. Dependent Variable: HUMAN CAPITAL

Collinearity Diagnostics[a]

Model		Eigenvalue	Condition Index	Variance Proportions	
				(Constant)	PSYCHOLOGICAL AND CULTURAL FACTORS
1	1	1.951	1.000	.02	.02
	2	.049	6.302	.98	.98

a. Dependent Variable: HUMAN CAPITAL