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WHO DID AI LEAVE BEHIND? SOCIAL INEQUALITY PERCEPTIONS IN THE USE OF AI TOOLS IN CROATIA

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ABSTRACT

Generative artificial intelligence (AI) is increasingly embedded in everyday life, raising questions about how its use may reinforce or mitigate social inequalities. This study examines perceptions of affordability, self-assessed knowledge, practical accessibility, and usefulness of AI tools in Croatia, focusing on how gender, age, and frequency of AI use shape emerging digital divides. Drawing on survey data from a nationally representative sample, descriptive analyses, group comparisons, exploratory factor analysis, and multiple linear regressions were conducted to identify patterned inequalities across Lutz's three sequential levels of digital inequality: access, skills, and outcomes. Factor analysis indicates that the inequality items do not form a single coherent scale, suggesting that AI-related inequality is multidimensional and that affordability, knowledge, practical accessibility, and usefulness represent distinct but related facets. Group comparisons and regression models reveal that frequency of AI use is the most consistent predictor across all facets: frequent users report higher affordability, greater perceived knowledge, lower reliance on assistance, and stronger perceptions of usefulness, while non-users cluster at the opposite end of each dimension. Age further differentiates respondents in perceived knowledge and practical accessibility, with younger cohorts feeling more competent and less dependent on help, whereas gender only marginally shapes confidence and loses significance once age and use frequency are controlled. Overall, the findings support and extend sequential models of digital inequality by demonstrating that, in the Croatian context, GenAI inequality is driven less by static sociodemographic attributes and more by practice-based divides between those who engage with AI tools and those who remain non-users.

KEY WORDS

generative AI, digital divides, AI engagement, access and skills, Croatia

CLASSIFICATION

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INTRODUCTION

After several "winters" that, over the past 70 years, have been marked by occasional interruptions in research funding and a decline in broader societal and scientific interest [1], artificial intelligence (AI) has re-emerged as an unavoidable topic in contemporary debates on the societal implications of technological development. These debates span multiple domains – from geopolitics and military affairs to the economy and labour, public policy and legislation, sustainability and energy, education, and demography. At the micro level, particularly through the rapid commercialization of ChatGPT, AI tools have become embedded in people's everyday lives, shaping experiences from autonomous vehicles and smart homes to individual concerns related to health and employment. At both societal and individual levels, concerns regarding how AI may reinforce or reduce social inequalities have become increasingly salient [2, 3].

In the social sciences, the implications of AI are situated within the broader question of the relationship between technology and society and currently constitute one of the most prominent dimensions of accelerated digitalization. Liu [4] systematizes sociological interest in the social character and challenges of AI use into three analytical perspectives. The first understands AI as a scientific research domain in which systems of scientific knowledge are socially constructed. The second perspective views AI as a metatechnology, emphasizing the societal consequences of its multiple applications and branching into a series of sub-technologies. Liu's third analytical perspective focuses on the broader social effects of AI development and the sociocultural contexts of its use, largely shaped by ongoing digital transformation [4].

Although these perspectives represent analytical ideal types that frequently overlap in empirical research, Liu's third perspective is particularly relevant to this study. In some research, AI is implicitly treated as an autonomous force capable of deepening or reducing inequality [5]. Concurrently, media narratives and popular discourse often frame generative AI (GenAI) as a radically disruptive force – one that transforms communication, reshapes social structures, and challenges established norms. Such arguments, however, rest on the assumption that technology acts independently upon individuals and groups. What is overlooked is that acceptance or rejection of technology is mediated by pre-existing structures of everyday meaning-making, which influence whether individuals embrace, ignore, resist, or fail to recognize technological change. Studies have consistently shown that the uses and effects of new technologies, including AI, are shaped by existing forms of social inequality [6, 7]. The "old" often defines the "new", meaning that pre-existing social inequalities shape new forms of digital inequality, including those emerging around GenAI [6, 7]. Technological innovation thus frequently reaffirms and extends existing social divides.

This article examines how AI is used in everyday life in Croatia, focusing on the extent to which social categories (gender, age, and place of residence) shape perceptions of AI's usefulness, affordability, practical accessibility, and self-assessed knowledge. Each of these categories has long represented a core dimension in the study of digital inequalities. For example, research shows that gender significantly mediates content orientations and online activities [8, 9]. Although recent evidence suggests a narrowing of the digital gender gap in the most developed countries, gendered digital inequalities persist in emerging economies [10], raising questions about the acceptance and use of AI in semi-peripheral contexts such as Croatia.

Research also suggests that age, education, and digital skills are important predictors of digital inequalities [9, 10]. While initial age-related differences in basic digital skills have become more nuanced over time, as older cohorts have gradually adopted foundational digital competencies, critical skills related to evaluating digital content remain important across all age groups [9]. Furthermore, studies point to substantial heterogeneity among older adults, not only in knowledge and education but also in affordability, cognitive ability, willingness and need to use digital technologies, and trust in their usefulness [10]. These age-related dynamics are particularly relevant in Croatia, a society undergoing pronounced demographic ageing.

Finally, significant digital inequalities have been shown to manifest in global, regional, or national differences [11]. This is likewise evident in Croatia, where, despite the rapid global uptake of GenAI, empirical research on AI-related digital inequalities remains limited.

THEORETICAL BACKGROUND

The digital era has produced new forms of inequality – commonly termed digital inequalities. Early research focused primarily on the digital divide as a problem of accessibility [12]. Over time, however, scholars recognized that digital divides are embedded within the broader social structure and reflect inequalities that predate the digital sphere [13]. Van Dijk [14] argues that digital inequality cannot be understood solely through access (e.g. to devices or internet). Instead, digital divides emerge through a multi-stage process encompassing: (1) motivation, (2) physical access, (3) digital skills, and (4) patterns of usage. Each stage both reflects and reinforces pre-existing social inequalities. When the technological and structural dimensions of the social life are tightly interconnected, digital inequalities become expressions of both technological developments (and the technological divides generated by the implementation of technology) and enduring structural divides [14]. Combining access, skills (knowledge), and usage patterns with individuals' social positions therefore reveals not only inequalities themselves but also the reciprocal shaping of technology and society.

To understand digital inequalities in that regard, researchers have focused on social categories that structure inequality more broadly: 1) economic position, 2) gender, 3) age, and race [15]. Economically, individuals with greater knowledge and internet access can secure employment more easily and earn higher incomes, enhancing their prospects for social inclusion, whereas those who lack such resources have fewer opportunities and face a greater risk of exclusion [16]. When it comes to gender as a predictor of digital inequalities, studies from the United States, Finland, Greece, and the United Kingdom show that boys tend to use computers more frequently, and more often for educational purposes, than girls [17]. As noted earlier, age represents a central dimension of digital inequality. Generational differences in knowledge and everyday meaning-making affect individuals' capacities to adapt to rapid technological and social change. Since knowledge is partly linked to generational location [18], those closer to technological innovations in their formative years tend to adopt and use them more easily. This is supported by various research, as evidence from many countries suggests that adults aged 65 and older use digital media (email, websites, social networks, mobile phones, and tablets) significantly less than younger cohorts [19, 20]. Race also acts as an important predictor of digital inequality. A recent Free Press report finds that racial disparities remain significant even after controlling for income and education, as structural discrimination in the United States continues to produce unequal offline and online conditions, particularly for non-White groups in urban areas [21].

Integrating access, skills (knowledge), and structural dimensions of inequality (economic position, gender, age, race) leads to a multidimensional understanding of digital inequality. This aligns with contemporary conceptualizations of digital inequalities in the context of GenAI, such as Lutz's three-level framework [2]. The first level concerns unequal access to digital technologies, including disparities in devices, connectivity, and the ability to adopt emerging AI-powered systems. The second involves inequalities in digital skills and usage patterns, whereby individuals with higher cultural, social, or educational capital are better positioned to navigate, understand, and meaningfully use AI tools. The third level focuses on unequal outcomes, capturing how different groups benefit from, or are harmed by, digital technologies through processes such as datafication, algorithmic decision-making, and the distribution of opportunities and risks [2].

Applied to AI, Lutz shows that these levels of digital inequality operate sequentially: limited access restricts skill development, and both jointly shape the benefits individuals can obtain from AI. Moreover, AI tends to amplify existing organizational power structures, granting additional advantages to already privileged actors while exposing disadvantaged groups to intensified surveillance, precarity, or automation. At the macro level, GenAI interacts with processes of market concentration, enabling dominant firms and institutions to accumulate disproportionate resources and data, and to influence and thus deepen existing societal inequalities [22].

Building on this conceptualization, digital inequalities in the age of GenAI are expected to manifest across distinct but interconnected dimensions of access, skills and uses, and outcomes, further shaped by structural characteristics such as age, gender, and economic affordability. These levels operate sequentially, meaning that restricted access limits AI-related skills development, while both shape the potential benefits individuals derive from AI-enabled environments. Although race represents an important axis of digital inequality in many international contexts, it is not examined in this article, as Croatia remains a predominantly racially homogeneous society in which racialized mechanisms are not meaningful in shaping digital inequality.

METHODOLOGY

RESEARCH DESIGN

The part of the questionnaire intended to measure social inequality in the use of AI tools in Croatia comprised four statements: 1) "I can afford to pay a monthly subscription fee for AI tools such as ChatGPT (e.g., 25 euros per month)"; 2) "I believe I have sufficient knowledge about artificial intelligence tools such as ChatGPT"; 3) "Without assistance, it would be difficult for me to successfully master the use of AI tools such as ChatGPT"; and 4) "AI tools such as ChatGPT are not personally useful to me". Respondents rated these items on a five-point Likert scale from 1 ("strongly disagree") to 5 ("strongly agree"), with a score of 3 indicating neutrality. The frequency of AI tool usage was assessed on a four-point scale ("Never", "Rarely", "Sometimes" and "Often"). To reduce redundancy, sociodemographic details are not included in the methodology, as they are discussed in the editorial section.

DATA ANALYSIS

Data were analysed using JASP version 0.95.4. Initially, descriptive statistics were calculated, including arithmetic means for each item and frequencies of agreement and disagreement with the statements. Group differences based on sociodemographic characteristics (gender, age, city size, region, and county) and frequency of AI tool usage were tested using t-tests and one-way analysis of variance (ANOVA). Subsequently, exploratory factor analysis was conducted on the four social inequality items to assess whether they form a unified construct of inequality. Finally, linear regression analysis was performed with sociodemographic variables and AI tool usage frequency as predictors of social inequality, enabling identification of significant associations between these attributes and the measured dimensions of inequality.

RESULTS

The results of this study are organized to provide a comprehensive overview of patterns and predictors of social inequality in the context of AI tool use. First, the distribution of responses to survey items related to perceived inequality and access is presented, providing an initial mapping of attitudes across the sample. This is followed by an examination of differences in these perceptions as a function of sociodemographic characteristics and frequency of AI tool usage. Next, the underlying structure of the social inequality construct is explored through factor analysis, assessing whether the survey items collectively measure a coherent dimension of inequality. Finally, regression analysis is used to evaluate the extent to which sociodemographic attributes and usage frequency predict variation in perceived AI inequality.

MAPPING PERCEPTIONS OF AI INEQUALITY

The descriptive analysis revealed moderate to low mean values on the items assessing social inequality in AI use. The item addressing financial barriers to access to AI tools yielded the lowest mean score ($\bar{x}$ = 2,35, SD = 1,239). This mean is substantially below the neutral midpoint of 3, indicating a collective tendency toward disagreement. Specifically, as it can be seen in Table 1, over half of the respondents (56%) either “strongly disagreed” or “mostly disagreed” with this statement, suggesting that the cost of subscription fees presents the most significant perceived barrier to equitable AI access among the measured dimensions.

The remaining three items were clustered closer to the neutral point. The mean score of respondents’ perceived knowledge about AI tools slightly skews towards disagreement ($\bar{x}$ = 2,71, SD = 1,170), suggesting that while respondents do not strongly feel they lack knowledge, the average individual does not confidently assert sufficient understanding. This is also evident in the response frequencies in Table 1, according to which almost 30% of respondents “strongly” or “mostly” agree, while 42% “strongly” or “mostly” disagree with the statement.

Almost identical mean score for statement regarding the need for assistance for mastering AI tools ($\bar{x}$ = 2,72, SD = 1,195) indicates respondents’ slight disagreement with the premise of intrinsic difficulty of those tools. However, as is evident in Table 1, a significant amount of them (26,4%) agrees with that statement.

Table 1. Response distribution on perceived social inequality items.

Item	Level of agreement	*n*	%
I can afford to pay a monthly subscription fee for AI tools such as ChatGPT (e.g. 25 euros per month).	Strongly disagree	171	34,3
	Mostly disagree	109	21,7
	Neither agree nor disagree	118	23,6
	Mostly agree	76	15,1
	Strongly agree	26	5,3
I believe I have sufficient knowledge about artificial intelligence tools such as ChatGPT.	Strongly disagree	101	20,2
	Mostly disagree	109	21,8
	Neither agree nor disagree	150	30,0
	Mostly agree	115	23,0
	Strongly agree	25	4,9
Without assistance, it would be difficult for me to successfully master the use of AI tools such as ChatGPT.	Strongly disagree	94	18,7
	Mostly disagree	126	25,2
	Neither agree nor disagree	149	29,8
	Mostly agree	91	18,3
	Strongly agree	40	8,1
AI tools such as ChatGPT are not personally useful to me.	Strongly disagree	69	13,8
	Mostly disagree	122	24,4
	Neither agree nor disagree	191	38,2
	Mostly agree	68	13,6
	Strongly agree	50	10,0

Finally, the mean score of the item assessing personal usefulness of AI tools falls below the neutral point ($\bar{x}$ = 2,82, SD = 1,140), which suggests a mild collective opinion that the tools are, in fact, personally useful. However, it is important to note that this same item exhibited the highest proportion of neutral responses among all social inequality items (38,2%), an amount equivalent to the combined frequency of “strongly disagree” and “mostly disagree” responses, as presented in Table 1. This pronounced neutrality, along with expressed limited confidence in using AI tools, indicates a prevailing sense of uncertainty or ambivalence among respondents.

THE DIVIDE REVEALED: PERCEIVED INEQUALITY ACROSS DEMOGRAPHIC AND AI USE GROUPS

The ANOVA and independent samples t-tests employed to identify significant differences in the perception of social inequality items across various categorical variables, found statistically significant differences on one or several items based on gender, age and frequency of AI tools use. Conversely, ANOVAs conducted for other sociodemographic variables – city size, region, and county – did not identify any statistically significant differences in responses across these groups (all $p > 0{,}05$), suggesting that these attributes do not distinguish respondents in terms of their agreement or disagreement with any of the four dimensions of perceived inequality.

Gender differences in perceived AI inequality

An independent samples t-test revealed a statistically significant difference between men and women on the item assessing respondents’ ability to master AI tools such as ChatGPT without assistance (t = 2,696, df = 498, p = 0,007). As seen in Figure 1, men reported a higher mean score ($\bar{x}$ = 2,87, SD = 1,171) compared to women ($\bar{x}$ = 2,58, SD = 1,203), suggesting that men perceive the barrier to achieving competence with AI tools without external support to be statistically higher than women do. Although the difference in means between genders is modest, this finding represents one aspect of social inequality where women report greater confidence than men.

Figure 1. Differences in perceived need for assistance when using AI tools by gender.

Age differences in perceived AI inequality

In contrast to the previous section, analysis of age differences revealed significant variations across nearly all social inequality items, except for the item related to the assessment of AI tools’ monthly subscription fee affordability. More precisely, ANOVAs showed statistically significant differences between the age groups on items assessing respondents' perceived knowledge about AI tools (F = 13,922, df = 4, p = 0,000), ability to master those tools without assistance (F = 21,856, df = 4, p = 0,000), and the perceived usefulness of the tools for the respondents (F = 4,339, df = 4, p = 0,002).

According to the Games-Howell post-hoc test, with regard to the item assessing the perceived knowledge of AI tools, statistically significant differences are found between the youngest age group (15-24) and all other groups except for the adjacent cohort (25-34). Likewise, differences are significant between the eldest group (55+) and others except for the 45-54 one. Apart from that, the group 25-34 has statistically different answers on this item than the group 45-54. As can be seen in Figure 2, the youngest respondents are the ones expressing the highest level of knowledge ($\bar{x}$ = 3,37), with the perceived level of knowledge dropping with each older cohort, reaching a knowledge level one full point lower in the 55+ group ($\bar{x}$ = 2,37).

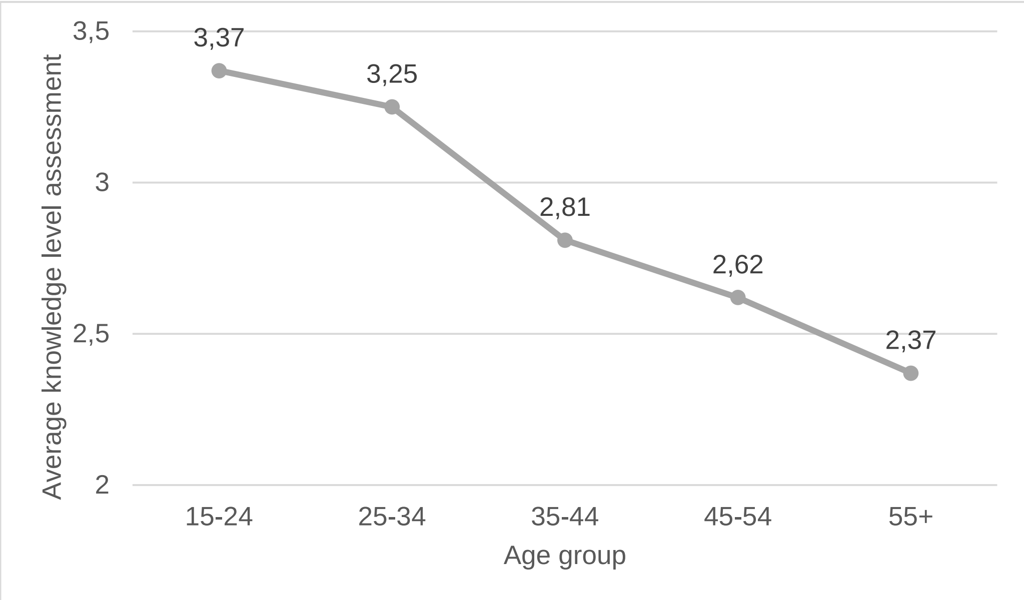

Figure 2. Differences in perceived level of knowledge of AI tools by age group.

Similar to the previous item, Scheffe's post-hoc test conducted on the item regarding respondents' perceived necessity for assistance while using AI tools revealed statistically significant differences between the eldest cohort (55+) and all the others and between the youngest one (15-24) and all except the second-to-youngest (25-34). Again, as is evident from Figure 3, the youngest cohort is the most confident in their independent mastering of AI tools ($\bar{x}$ = 1,8). The uncertainty in their abilities rises across cohorts, reaching the highest level by the age group 55+ ($\bar{x}$ = 3,17).

Considerably smaller number of statistically significant differences among age cohorts is found by the Games-Howell post-hoc test conducted on the item assessing perceived usefulness of AI tools. The only such differences are found between the eldest respondents and those belonging to the youngest and second-oldest cohorts. As Figure 4 shows, the respondents over 50 regard these tools as less useful ($\bar{x}$ = 3) than those who are part of age groups 15-24 ($\bar{x}$ = 2,43) and 45-54 ($\bar{x}$ = 2,54).

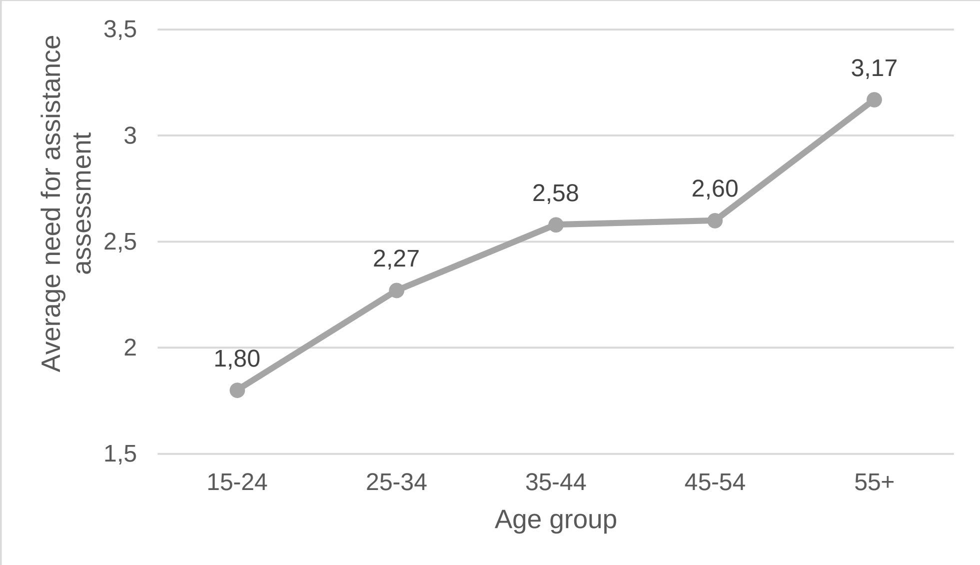

Figure 3. Differences in perceived need for assistance when using AI tools by age group.

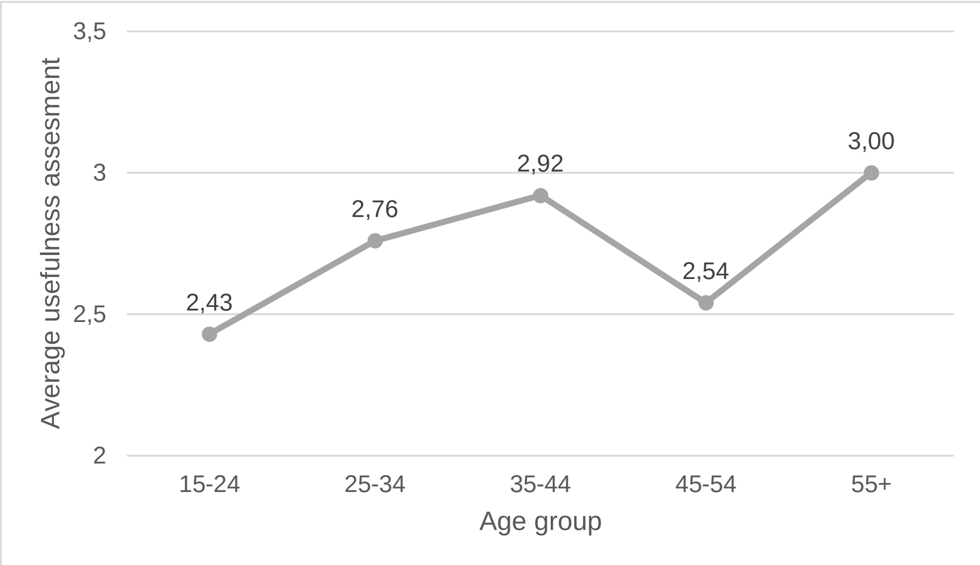

Figure 4. Differences in perceived usefulness of AI tools by age group.

Frequency of AI tools use differences in perceived AI inequality

Employing ANOVA to explore differences by frequency of AI tool use revealed significant variations across all inequality measures: respondents' perceived affordability of AI tools (F = 5,350, df = 3, p = 0,001), AI tools knowledge (F = 41,457, df = 3, p = 0,000), their ability to master those tools without assistance (F = 22,949, df = 3, p = 0,000), and perceived usefulness of those tools (F = 48,294, df = 4, p = 0,000).

On the affordability item, as seen in Figure 5, respondents who use AI tools more frequently report fewer affordability concerns. Games-Howell post-hoc test indicates that those who never use AI tools ($\bar{x}$ = 2,00) perceive the affordability of paid AI tools as significantly lower than those who use them sometimes ($\bar{x}$ = 2,37) or often ($\bar{x}$ = 2,61). As expected, respondents who never use AI tools report the lowest affordability perception level, while those who use them often have the highest one, albeit still below the neutral point.

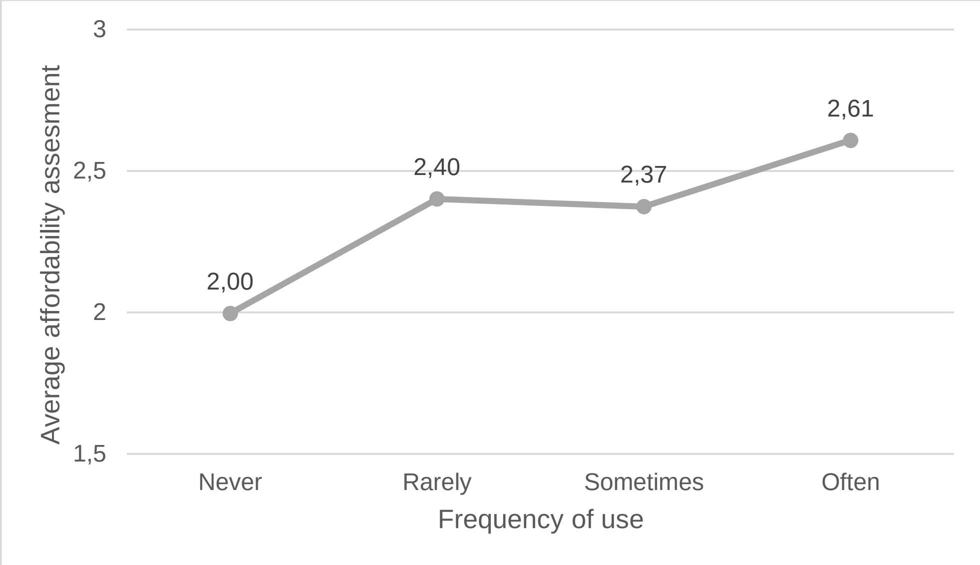

Figure 5. Differences in perceived affordability of AI tools by frequency of their use.

Similar but more pronounced patterns of difference are observed on the knowledge item, where higher usage frequency is associated with increased perceived knowledge of AI tools. Here the Games-Howell post-hoc test reveals statistically significant differences among all frequency-of-use groups. As shown in Figure 6, those who never use AI tools rate their knowledge of said tools the lowest ($\bar{x}$ = 1,98), those who use them rarely ($\bar{x}$ = 2,41) and sometimes ($\bar{x}$ = 2,92) significantly higher, but still below the neutral point, while frequent users are the only ones that perceive their knowledge of it as sufficient ($\bar{x}$ = 3,37).

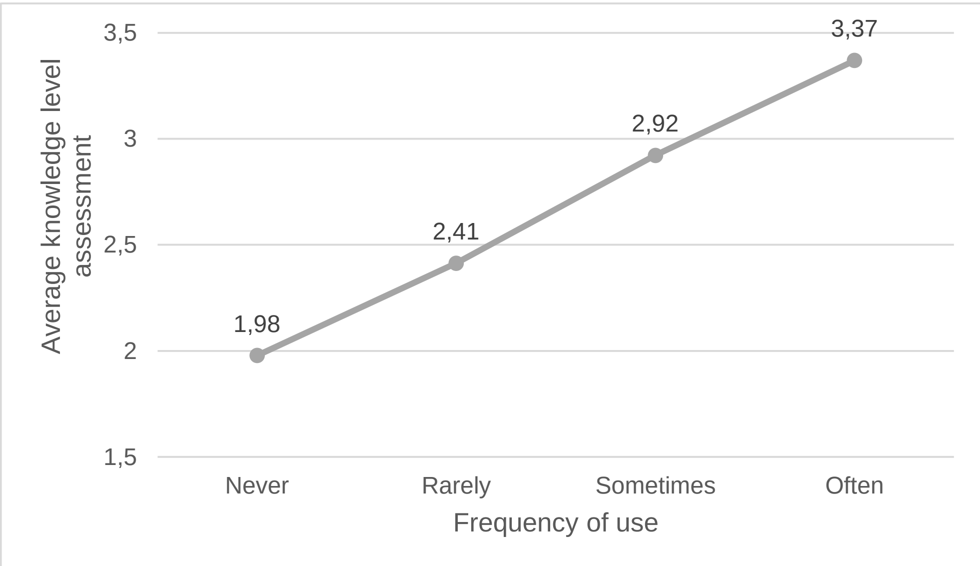

Figure 6. Differences in perceived level of knowledge of AI tools by frequency of their use.

For perceived need for assistance, statistically significant differences exist between frequent users of AI tools and all other groups, as well as between those who use those tools sometimes and never. As evident in Figure 7, respondents who never use AI tools are the only group with a mean above the neutral point ($\bar{x}$ = 3,25), indicating their reliance on assistance while using AI tools, while other groups report independence in this matter, with frequent users ($\bar{x}$ = 2,11) being the most confident ones.

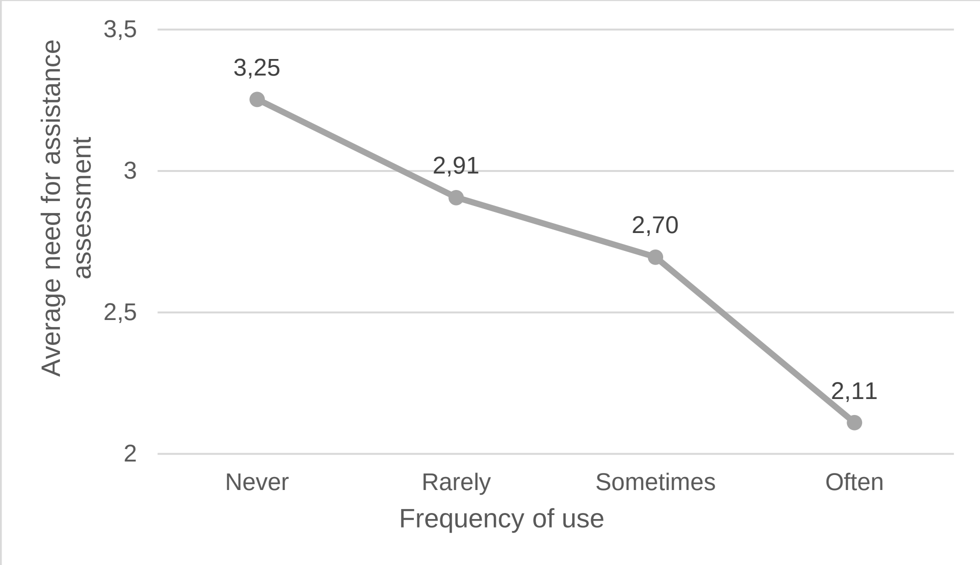

Figure 7. Differences in perceived need for assistance when using AI tools by frequency of their use.

Finally, as was the case with knowledge, the Games-Howell post-hoc test reveals statistically significant differences among all the groups of different usage frequencies. As is visible in Figure 8, respondents who never use AI tools ($\bar{x}$ = 3,56) or use them rarely ($\bar{x}$ = 3,11) do not perceive AI tools as useful, unlike those who use those tools sometimes ($\bar{x}$ = 2,65) or often ($\bar{x}$ = 2,10).

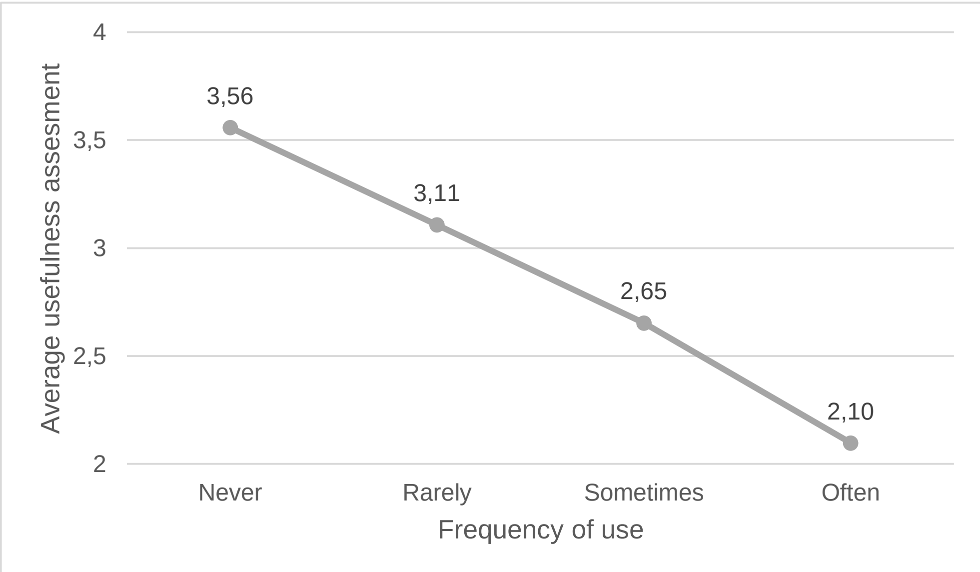

Figure 8. Differences in perceived usefulness of AI tools by frequency of their use.

To summarize results of t-test and ANOVA analysis, women report slightly greater confidence than men in mastering AI tools without assistance, suggesting that, on at least one competence-related indicator, men perceive a higher barrier to autonomous AI use. Age differences and those regarding the frequency of AI use are more systematic and pronounced. Younger respondents, especially those aged 15-24, report the highest levels of AI knowledge, the lowest need for assistance, and greater perceived usefulness of AI tools, with these advantages diminishing progressively across older cohorts. In contrast, the eldest age group (55+) consistently reports the lowest knowledge, the strongest reliance on help when using AI, and the weakest perception of AI's usefulness, indicating a generational gradient in both perceived competence and benefit perception. Individuals who use AI tools more often express fewer affordability concerns, higher perceived knowledge, greater independence from external assistance, and a stronger sense of AI's usefulness, whereas non-users and infrequent users cluster at the opposite end of each scale.

Taken together with the absence of statistically significant differences among respondents based on other sociodemographic factors (city size, region, and county), these results suggest that divides in perceived AI inequality are less a function of place-based or regional contexts and more a function of gendered confidence, life stage, and, crucially, actual engagement with AI tools, which appears to reinforce both perceived competence and perceived value.

CONFIRMING THE CONSTRUCT: VALIDATING THE SOCIAL INEQUALITY SCALE

The exploratory factor analysis did not support the assumption that the four social inequality items form a single, coherent latent construct. The principal components solution produced two components with eigenvalues above 1 (1,746 and 1,030), jointly explaining 69,4% of the variance. The component loading matrix revealed that the item related to knowledge of AI tools cross-loaded, while the one related to affordability formed a specific factor, indicating multidimensionality rather than a unified social inequality factor. The overall internal consistency of the four-item scale was very low ($\alpha = -0{,}068$), further demonstrating that these items together do not behave as indicators of one underlying dimension. Item-level diagnostics suggested a possible increase in reliability with removal of the affordability item, but its coefficient would remain unacceptably low ($\alpha = -0{,}374$).

Given this weak factor structure and poor reliability, treating the four statements as a single additive index would be both statistically and conceptually problematic. Instead, it is more appropriate to analyse each item separately in subsequent linear regression models, which allows estimation of how gender, age, and frequency of AI tool use relate to distinct facets of perceived social inequality in AI (e.g., financial barriers, knowledge barriers, or perceived usefulness), thereby building directly on the group differences already identified with t-tests and ANOVA.

PREDICTORS OF PERCEIVED INEQUALITY: GENDER, AGE AND ENGAGEMENT

To examine the relative influence of sociodemographic predictors on distinct dimensions of perceived social inequality in AI use, separate linear regression models were estimated for each of the four inequality items. These models include only the variables identified as statistically significant in prior t-tests and ANOVA analyses – namely gender, age, and frequency of AI tool use – allowing assessment of which predictors exert the strongest effects on specific inequality facets (e.g., affordability, knowledge, assistance needs, usefulness).

Since linear regression requires binary or categorical predictors suitable for dummy coding, age and AI use frequency variables were recoded into dichotomous formats. The original five age groups were collapsed into two: "younger" (combining 15-24 and 25-34 cohorts) and "older" (combining 35-44, 45-54, and 55+ cohorts). Similarly, the four AI use frequency categories were dichotomized: "infrequent" (combining "never" and "rarely" answers) versus "frequent" (combining "sometimes" and "often" answers).

Predictors of perceived AI affordability

Since previous analysis showed that the only factor influencing the perceived affordability of AI tools is frequency of their use, this is the only predictor included in the linear regression (LR) for that aspect of social inequality. The LR analysis indicates that frequency of AI tool use is a statistically significant but substantively modest predictor of perceived AI affordability.

As seen in Tables 2 and 3, the overall model including frequency of use is significant (p = 0,002) and explains 1,9% of the variance in perceived affordability (R^2 = 0,019), suggesting that higher use is reliably but weakly associated with more positive affordability perceptions.

Table 2. LR model summary of frequency of use predicting perceived AI affordability**.**

					Durbin-Watson		
Model	**R**	**R²**	**Adjusted R²**	**RMSE**	**Autocorrelation**	**Statistic**	***p***
M_0	0,000	0,000	0,000	1,236	0,105	1,786	0,017
M_1	0,137	0,019	0,017	1,225	0,102	1,793	0,020

Table 3. ANOVA of LR model (frequency of use predicting perceived AI affordability).

Model		Sum of Squares	df	Mean Square	F	*p*
M_1	Regression	14,32	1	14,324	9,540	0,002
	Residual	749,25	499	1,501		
	Total	763,57	500			

As is shown in Table 4, the coefficient for frequency of use (β = 0,339, p = 0,002) shows that respondents who use AI tools more frequently score, on average, about one third of a scale point higher on perceived affordability than infrequent users.

Table 4. Coefficient of the LR model (frequency of use predicting perceived AI affordability).

Model		Unstandardized	Standard Error	*t*	*p*
M_0	(Intercept)	2,347	0,055	42,516	< 0,001
M_1	(Intercept)	2,165	0,081	26,847	< 0,001
	Frequency of use	0,339	0,110	3,089	0,002

Substantively, this means that more frequent engagement with AI tools is linked to viewing them as somewhat more affordable, but the small proportion of explained variance indicates that most differences in affordability perceptions are driven by other, unmeasured factors.

Predictors of perceived AI knowledge

The multiple linear regression (MLR) analysis on knowledge on AI tools as a dependent variable, included age and frequency of AI tools use as predictors, since previous ANOVAs confirmed their influence on this aspect of AI inequality. As is evident in Tables 5 and 6, this MLR analysis indicates that age and frequency of AI use together are strong, significant predictors of perceived AI knowledge. The full model is statistically significant ($p < .001$) and explains 22% of the variance in perceived AI knowledge (R^2 = 0.220), which represents a substantial effect.

Table 5. MLR model summary of age and frequency of use predicting perceived AI knowledge.

					Durbin-Watson		
Model	**R**	**R²**	**Adjusted R²**	**RMSE**	**Autocorrelation**	**Statistic**	***p***
M_0	0,000	0,000	0,000	1,166	0,119	1,760	0,007
M_1	0,469	0,220	0,217	1,032	0,047	1,905	0,281

Table 6. ANOVA of MLR model (age and frequency of use predicting perceived AI knowledge).

Model		Sum of Squares	df	Mean Square	F	*p*
M_1	Regression	149,9	2	74,963	70,39	< 0,001
	Residual	530,4	498	1,065		
	Total	680,3	500			

Examination of the coefficients available in Table 7 shows that both age and frequency of AI use are significant predictors of perceived AI knowledge, but their effects differ in strength and direction. Age emerges as a significant negative predictor (β = –0,603, p < 0,001), indicating that as age increases, perceived AI knowledge decreases. This suggests that older respondents tend to feel less knowledgeable about AI technologies such as ChatGPT. In contrast, frequency of AI use is a strong positive predictor (β = 0,872, p < 0,001), showing that individuals who use AI tools more frequently report substantially higher levels of perceived knowledge.

Table 7. Coefficients of the MLR model (age and frequency of use predicting perceived AI knowledge).

Model		Unstandardized	Standard Error	*t*	*p*
M_0	(Intercept)	2,695	0,052	51,708	< 0,001
M_1	(Intercept)	2,685	0,117	22,983	< 0,001
	Age	–0,603	0,111	–5,433	< 0,001
	Frequency of use	0,872	0,094	9,233	< 0,001

When comparing the magnitude of the effects, frequency of use is the stronger predictor. Its coefficient (0,872) is larger in absolute value than that of age (–0,603), indicating that differences in how often individuals engage with AI tools have a greater impact on their perceived knowledge than differences in age. In practical terms, this means that active, hands-on engagement with AI tools contributes more strongly to people's sense of competence and understanding than demographic factors such as age.

This is confirmed by the overview of partial correlations of the predictors, where age (R = 0,217), without the influence of frequency of AI tools use and their overlap, accounts for 4,7% of the variance in perceived AI knowledge, while frequency of use (0.382) in the same way explains 14,6% of that variance.

Predictors of perceived AI practical accessibility

Since previously run t-test and ANOVAs showed that differences in independent mastering of AI tools, i.e. practical accessibility, can be explained by gender, age and frequency of use of AI tools, those were the variables included as predictors in the MLR analysis of that AI inequality aspect. As Tables 8 and 9 show, the model is statistically significant (p < 0,001), explaining 14,3% of the variance in perceived AI practical accessibility (R^2 = 0,143) which is a modest but meaningful effect of the predictors overall.

Table 8. MLR model summary of gender, age and frequency of use predicting perceived AI practical accessibility.

					Durbin-Watson		
Model	R	R²	Adjusted R²	RMSE	Autocorrelation	Statistic	*p*
M_0	0,000	0,000	0,000	1,188	0,019	1,961	0,666
M_1	0,378	0,143	0,138	1,103	–0,006	2,012	0,917

Table 9. ANOVA of MLR model (gender, age and frequency of use predicting perceived AI practical accessibility).

Model		Sum of Squares	df	Mean Square	F	*p*
M_1	Regression	101,0	3	33,656	27,69	< 0,001
	Residual	604,1	497	1,216		
	Total	705,1	500			

An inspection of the coefficients (Table 10) shows that although age and frequency of use emerge as significant predictors, gender does not. Age has a positive and statistically significant effect (β = 0,702, p < 0,001), indicating that older respondents tend to perceive AI tools as less independently manageable. Frequency of use also significantly contributes to the model (β = 0,702, p < 0,001), suggesting that greater engagement with AI tools is associated with a higher perceived ability to successfully master their use. In contrast, gender is not a significant predictor (β = –0,115, p = 0,253), implying no measurable difference between men and women in their perceptions of AI practical accessibility once age and use frequency are controlled.

Table 10. Coefficients of the MLR model (gender, age and frequency of use predicting perceived AI practical accessibility).

Model		Unstandardized	Standard Error	*t*	*p*
M_0	(Intercept)	2,729	0,053	51,430	< 0,001
M_1	(Intercept)	2,535	0,142	17,910	< 0,001
	Gender	–0,115	0,100	–1,144	0,253
	¤ Age	0,702	0,121	5,822	< 0,001
	Frequency of use	–0,528	0,101	–5,229	< 0,001

As opposed to the earlier MLR, in this model, age emerges as the strongest predictor (0,702), followed by frequency of AI use (β = –0,528, $p < 0{,}001$), suggesting that age difference has a greater impact on perceived independence in AI tools use than the frequency of use of said tools itself, although the difference in effect of these predictors is not as prominent as was in the MLR model predicting perceived knowledge.

Partial correlations confirm these effects. In this model, age (R = 0,253), while controlling the influence of other two predictors, explains 6,4% of variance in perceived AI practical accessibility, while frequency of use (R = 0,228) explains 5,2% of it.

Predictors of perceived AI usefulness

Finally, since ANOVAs revealed the differences in perceived usefulness of AI tools based on respondents age and AI tools frequency of use, these variables were included as predictors of said AI inequality aspect in the MLR. This model, as seen in Tables 11 and 12, is also statistically significant ($p < 0{,}001$) and explains 17,8% of variance in perceived usefulness, meaning that the predictors jointly provide a meaningful explanation of how useful people find AI tools.

Table 11. MLR model summary of age and frequency of use predicting perceived AI usefulness.

					Durbin-Watson		
Model	**R**	**R²**	**Adjusted R²**	**RMSE**	**Autocorrelation**	**Statistic**	***p***
M_0	0,000	0,000	0,000	1,134	0,044	1,900	0,263
M_1	0,422	0,178	0,175	1,030	–0,012	2,016	0,870

Table 12. ANOVA of MLR model (age and frequency of use predicting perceived AI usefulness).

Model		Sum of Squares	df	Mean Square	F	*p*
M_1	Regression	114,6	2	57,296	53,99	< 0,001
	Residual	528,5	498	1,061		
	Total	643,1	500			

The coefficients overview, provided in Table 13, show that frequency of use is a strong and significant predictor, while age does not contribute significantly to the model. Specifically, frequency of use has a negative and statistically significant coefficient (β = –0,956, $p < 0{,}001$), indicating that individuals who use AI tools more frequently tend to rate them as more useful. In contrast, age is not a significant predictor of perceived usefulness (β = 0,021, $p = 0{,}851$), meaning that older and younger respondents do not differ in their evaluations of how useful AI tools are once frequency of use is accounted for.

Table 13. Coefficients of the MLR model (age and frequency of use predicting perceived AI usefulness).

Model		Unstandardized	Standard Error	*t*	*p*
M_0	(Intercept)	2,816	0,051	55,584	< 0,001
M_1	(Intercept)	3,316	0,117	28,425	< 0,001
	Age	0,021	0,111	0,187	0,851
	Frequency of use	–0,956	0,094	–10,137	< 0,001

Overall, frequency of AI use clearly emerged as the stronger and only meaningful predictor of perceived usefulness. This suggests that actual engagement with AI technologies, and not demographic factors such as age, shapes individuals' perceptions of how beneficial these tools are.

Across all four models, frequency of AI use consistently emerges as the strongest and most reliable predictor of perceived AI inequality dimensions, particularly perceived knowledge and usefulness, where its effects are substantial. Age also plays an important role, most notably in shaping perceived independence in mastering AI tools and perceived knowledge, whereas gender does not meaningfully predict any inequality dimension once other variables are controlled.

Compared with the earlier t-tests and ANOVAs, which identified multiple significant group differences, the regression analyses reveal a more precise and hierarchical pattern: apparent group differences largely reduce to two core factors – age and especially actual AI engagement. While bivariate tests suggested broader demographic disparities, regression results show that frequency of use is the single most influential and consistent predictor, overshadowing demographic differences when variables are examined simultaneously.

DISCUSSION

The findings of this study closely align with and empirically reinforce Lutz's conceptualization of digital inequalities as a sequential, multilayered process spanning across access, skills and uses, and outcomes. Rather than manifesting as a single, uniform divide, AI-related inequalities in Croatia emerge as patterned differentiations across these levels, revealing how GenAI becomes embedded in existing social structures.

At the first level of digital inequality – access – affordability emerges as the most immediate and widely experienced constraint. More than half of respondents report being unable to pay for subscription-based AI tools, placing economic barriers at the forefront of inequality. Yet regression analysis shows that perceived affordability is shaped not by sociodemographic characteristics, such as age or gender, but by frequency of use. This suggests that access is not merely a structural condition but also a practice-dependent phenomenon: individuals who already use AI perceive it as more affordable, while non-users experience stronger economic barriers.

The second level – skills and patterns of use – reveals significant generational differences. Younger respondents report higher perceived knowledge, lower need for assistance (practical accessibility), and stronger confidence in navigating AI tools, whereas older cohorts report weaker skills and greater dependency. The strong link between use frequency and perceived competence reinforces previous findings that skill inequalities intensify when individuals lack opportunities for meaningful practice [23]. GenAI amplifies this dynamic: those who engage with the tools develop higher competence, while non-users fall further behind, widening the skill gap over time. Gender differences, although limited, also offer theoretically meaningful insights at this level. Although research on digital inequalities often positions men as more confident technology users and content producers in digital sphere [24], in this sample women report greater confidence in independently using AI tools. This finding aligns with Turkle's [25] distinction between hard mastery (rule-based, system-oriented, technical manipulation) and soft mastery (explorative, relational, conversational engagement). Because GenAI relies heavily on iterative dialogue, interpretation, and the ability to frame meaningful prompts, it aligns more closely with soft mastery [25], potentially explaining women's greater confidence in this study. However, once use frequency and age are controlled for, gender no longer predicts any inequality dimension, suggesting that it functions as a secondary moderator that slightly shapes confidence in AI mastery rather than a foundational axis of AI stratification in Croatia.

The third level – outcomes – is reflected in perceived usefulness. Only respondents who already use AI tools frequently perceive GenAI as personally valuable, whereas non-users and infrequent users largely do not. After controlling for use frequency, age no longer predicts usefulness of AI, indicating that outcomes are determined primarily by experiential integration rather than demographic attributes. This supports Lutz's claim [2] that digital inequality is increasingly defined not by who individuals are but by how they use technology. It also reaffirms findings from other research showing that digital inequality today is defined less by who has access or skills, and more by who can translate AI use into meaningful, sustainable, and equitable outcomes [26]. Unequal benefits emerge because GenAI rewards patterns of engagement, creating a feedback loop in which users gain both competence and value, while non-users neither gain nor perceive these advantages.

While the results affirm Lutz's sequential model, they also extend it in several meaningful ways. First, the Croatian case demonstrates that use-nonuse divides now overshadow traditional digital divides based on sociodemographic attributes such as gender, age, region, or settlement size. This suggests that, in the context of GenAI, inequalities emerge less from infrastructural deficits and more from differentiated capacities to incorporate AI into everyday routines. Differences that appear demographic at the surface diminish once use frequency is considered, illustrating a transition toward a new configuration of digital inequality in which practice becomes the central stratifying mechanism. This complements previous research showing that once online, older adults experience more pronounced benefits than younger cohorts – challenging digital native assumptions [27]. The weak factor cohesion among the inequality indicators further reinforces Lutz's argument that digital inequality should be conceptualized not as a single construct but as a differentiated, sequential, and multi-level process in which each stage shapes and constrains the next.

CONCLUSION

This study demonstrates that digital inequality in the age of GenAI is a multilayered phenomenon unfolding across the sequential levels of access, skills, and outcomes. Although affordability remains the most prominent basic barrier, with over half of respondents reporting they cannot pay for subscription-based AI tools, this level of inequality only partially explains differences in GenAI use. Age and gender shape perceived knowledge, confidence, and usefulness, but their effects diminish once engagement with AI tools is considered.

Across all MLR models, frequency of AI use consistently emerges as the strongest predictor, influencing perceptions of affordability, knowledge, accessibility, and usefulness. This indicates that, in the Croatian context, GenAI inequality is increasingly constituted through practice rather than structural access alone. Frequent users of AI tools experience cumulative advantages: higher perceived competence, lower reliance on assistance, and a stronger sense of personal benefit. Non-users, by contrast, remain excluded from both skill development and the recognition of AI's value, reinforcing their non-use.

This shift from demographic disparities toward practice-driven inequalities has important implications. It suggests that the most pressing digital inequalities of GenAI cannot be addressed solely through expanding access to infrastructure or basic digital skills. Instead, interventions must focus on what might be termed a "literacy of usefulness" – that is, the ability to understand, evaluate, and meaningfully integrate AI tools into everyday tasks. Traditional digital literacy remains a prerequisite, but it is no longer sufficient. Without targeted initiatives to support meaningful engagement, particularly among older adults and non-users, the gap between those who derive benefits from AI and those who do not will deepen.

These findings have two key implications. First, they highlight the broader social meaning of generative AI in Croatia. Although public debate on AI often centres on ethical dilemmas [28], labour transformation [29], or educational impact [30], little is known about how the general population perceives AI's usefulness. This study fills that gap by showing that GenAI operates as a socially stratifying practice embedded in everyday life, with benefits unevenly distributed according to engagement rather than structural access. Second, the results extend theoretical understandings of digital inequality. While Lutz's sequential framework is fully supported, findings of this study show that inequalities increasingly form around patterns of use rather than stable demographic categories. This confirms the maturation of digital ecosystems in which practice (frequency of use, experience, and perceived usefulness) becomes the dominant mechanism producing stratification. In semi-peripheral societies such as Croatia, sustained engagement and perceived value appear essential for individuals to progress from basic access toward meaningful benefit. Without these, new forms of digital exclusion are likely to persist.

These insights underscore the need for policy efforts that go beyond infrastructure or basic digital literacy. Future interventions should cultivate the "literacy of usefulness" by supporting individuals, particularly older adults and non-users, in recognising how AI can be meaningfully integrated into their everyday lives. Only when people recognise usefulness in their own terms can meaningful engagement develop, allowing the praxis of usage to grow.

LIMITATIONS AND FUTURE RESEARCH

A key limitation of this study is the absence of detailed socio-economic indicators such as education level, occupation, income, or household resources. Since the survey was part of a broader research project, only perceived affordability was included as a proxy for economic position. While affordability offers an initial insight, richer socio-economic data would likely reveal additional mechanisms shaping AI inequalities.

The study also captures general perceptions of using GenAI but does not differentiate between domains of use (e.g., work, education, creative production). Since perceived usefulness is context-dependent, future research should examine domain-specific patterns to identify where and why inequalities emerge most strongly.

Finally, the cross-sectional design does not allow for causal inference. Although Lutz's sequential framework provides a strong theoretical rationale, longitudinal or mixed-method studies are needed to track how inequalities evolve as GenAI becomes more integrated into society. Qualitative studies, particularly ethnographic approaches, could further illuminate how individuals make sense of AI in everyday life and how meaning-making processes shape engagement and inequality over time.

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