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GENERATION Z AND ARTIFICIAL INTELLIGENCE: USAGE PATTERNS AND DELEGATION BOUNDARIES

Adam P. Balcerzak
Brno University of Technology, Czechia;
University of Warmia and Mazury in Olsztyn, Poland
ORCID 0000-0003-0352-1373

Marek Zinecker
Brno University of Technology, Czechia
Nicolaus Copernicus University in Torun, Poland
ORCID 0000-0003-1764-0904

Jiří Mičánek
Brno University of Technology
Czechia
ORCID 0009-0001-7237-9369

Abstract: *This study examines the use of artificial intelligence (AI), delegation preferences, and perceptions of the future of work among Generation Z representatives, shedding light on emerging patterns of human-AI interaction and delegation. The analysis is based on a cross-sectional survey. The results indicate widespread and frequent engagement with AI, particularly for learning-related tasks and chatbot interaction, as well as high levels of mobile-based use. Despite this intensive adoption, the willingness to delegate tasks to AI systems remains limited. Most respondents reject delegation across contexts such as financial decisions, monitoring, and communication, and, where accepted, delegation is typically conditional on human oversight rather than full autonomy. Perceptions of the future of work emphasise transformation rather than displacement. Respondents most commonly expect hybrid models in which human work is supported by AI tools, alongside a strong expectation of the need for retraining. Overall, the findings highlight a tension between high AI usage and constrained trust in autonomous decision-making, suggesting that Generation Z engages with AI as a supportive resource while maintaining strong preferences for human control. This contributes to ongoing discussions on human-technology relationship in which Gen Z engages AI primarily as a supportive tool while safeguarding human control, thereby contributing to understandings of trust, agency, and socio-technical change in future work practices.*

Keywords: *AI adoption; youth; generation Z; human-AI collaboration; delegation; automation; future of work*

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INTRODUCTION

Artificial intelligence (AI) has evolved from niche applications to an integral part of everyday life, seamlessly embedded in educational, communication, and productivity tools. Its integration into modern technologies has been linked to improvements in efficiency, innovation, and productivity, while also introducing new dependencies, risks, and governance challenges (Balcerzak et al., 2025a; 2025d; Škare et al., 2025a; Yarovenko et al., 2024; van der Vlist et al., 2024; Aldoseri et al., 2024).

As AI becomes increasingly embedded in daily practices, understanding how individuals interact with and adopt these systems has become a central concern in research and policy (Moravec et al., 2024; Lazaroiu et al. 2025; Abbas et al., 2025). A substantial body of research has examined the determinants of AI adoption, consistently highlighting its socio-technical nature. Technological factors such as perceived usefulness, ease of use, and compatibility with existing workflows play a significant role in adoption decisions (Chatterjee et al., 2021; Wang, et al., 2025; Lazaroiu et al., 2024; Kliestik et al., 2024). However, research also shows that organizational conditions, including digital skills, resource availability, and leadership support, are equally important in shaping adoption outcomes (Balcerzak & Valaskova, 2024; Khanfar et al., 2025; Horani et al., 2025; Balcerzak et al., 2025d). Furthermore, individual-level factors, such as attitudes toward technology, perceived risks and trust, strongly influence willingness to engage with AI systems (Hassan et al., 2024; Ismatullaev et al., 2024; Balcerzak et al. 2025e). Recent studies further emphasise that successful AI adoption depends on aligning technological capabilities with human and organisational factors, rather than focusing on technical performance (Balcerzak et al., 2025b).

Within this broader landscape, the rapid diffusion of AI tools among young cohorts has attracted increasing scholarly attention (Balcerzak et al., 2025a; García-Martínez et al., 2023; Kozová et al., 2024; Spychalski, 2023; Wojciechowski & Korjonen-Kuusipuro, 2023). AI-enabled educational technologies, including intelligent tutoring systems, chatbots, and adaptive learning platforms, have been shown to improve learning outcomes, engagement, and knowledge retention, particularly in higher education and STEM fields (Eltahir and Babiker, 2024; García-Martínez et al., 2023; Chen et al., 2020; Abbas et al., 2025; Bilan et al., 2026). At the same time, the literature identifies important challenges associated with AI use in educational contexts. These include risks of over-reliance, reduced creativity, emotional strain, and ethical concerns related to transparency and fairness (Lin and Chen, 2024; Zawacki-Richter et al., 2019). Importantly, a consistent conclusion across studies is that AI is most effective when used as a support tool that enhances human learning and decision-making, rather than replacing human agency.

Beyond education, AI is increasingly influencing broader technological and economic systems, contributing to digital transformation and reshaping work practices. Research highlights that AI acts as a driver of innovation, enabling new business models, improving decision-making processes, and enhancing productivity across industries (Gama and Magistretti, 2023; Dwivedi et al., 2021; Škare et al., 2025b). However, these developments also raise concerns about skill requirements, labour market transformation, and the need for continuous adaptation. Studies on AI and the future of work suggest that, rather than fully replacing jobs, AI is more likely to transform tasks and require reskilling and human-AI collaboration (Babashahi et al., 2024).

Despite the growing body of literature on AI adoption, education, and the future of work, there remains limited understanding of how young users navigate the balance between extensive AI use and maintaining control over decision-making. While existing studies have primarily addressed adoption drivers, system performance, and institutional perspectives (Balcerzak et al., 2025; Țuclea et al., 2026), far less attention has been given to how users themselves define acceptable levels of AI autonomy in daily contexts or the relationship between high-frequency use and reluctance to delegate responsibility (Yankouskaya, 2026).

To address this gap, the present study examines how Generation Z engages with AI, their delegation preferences, and their perceptions of AI's impact on the future of work. Guided by three research questions – on frequency and purposes of AI use, willingness to delegate tasks, and perceptions of AI's role in employment – the study draws on survey-based data and theoretical insights on human-AI interaction and control. In total 262 respondents aged 16–25 from Czechia were surveyed between December 2025 and January 2026. As already noted, the research sample was selected using purposive sampling to include representatives of Generation Z, as this cohort demonstrates particularly high exposure to and active use of artificial intelligence–based technologies in everyday life, education, and work contexts. Focusing on Generation Z enables a deeper understanding of attitudes, practices, and competencies related to AI that are shaped by early and continuous interaction with digital innovations. This purposive sampling enhances the study's analytical relevance by capturing insights from a group that is especially representative of emerging AI usage patterns. Finally, the attitudes of represnetatives of this generation will shape the path of socio-technological developments and AI proliferation for the next decades (Spychalski, 2023).

The key findings of this study reveal the coexistence of high AI adoption and limited delegation, offering insights into how young users integrate AI into their activities while maintaining boundaries around c ontrol and responsibility.

The rest of this paper is structured as follows. The next section reviews the relevant literature on patterns of AI adoption by generation Z. This is followed by the research methodology, including the data collection, and analytical approach. The subsequent sections present the results, discussion, and conclusions with implications for theory, aplication, and policy.

THEORETICAL FRAMEWORK

This study is grounded in the Technology Acceptance Model (TAM) and Socio-Technical Systems (STS) theory, which together provide a robust lens for examining how Generation Z representatives engage with AI while actively negotiating human control and agency.

TAM (Davis, 1989; extended in later applications, e.g., Chatterjee et al., 2021) posits that perceived usefulness and perceived ease of use are primary drivers of technology adoption and behavioural intention. In the context of AI, these factors help explain the widespread and frequent use of generative tools for learning, creativity, and daily tasks among young users. Recent extensions of TAM to AI among Generation Z representatives confirm that usefulness and ease of use strongly predict adoption intensity, yet they often fall short in accounting for concerns around trust, risk, and loss of control (Balcerzak et al., 2025a; Koteczki and Eisinger Balassa, 2025). TAM thus illuminates the high engagement observed in educational and personal domains but requires supplementation to address why intensive use does not automatically translate into full delegation or uncritical reliance.

To capture the deeper relational and contextual dynamics of human-AI interaction, the study also draws on Socio-Technical Systems (STS) theory. STS views technology and social elements as interdependent subsystems that must be jointly optimized for effective outcomes (Trist and Bamforth, 1951; updated for AI in Xu and Gao, 2024; Desveaud and Bawack, 2026). In AI contexts, STS theory emphasises that successful integration depends not only on technical capabilities but also on their alignment with human and social factors – including agency, trust, organisational and educational conditions, and wider societal expectations.

Taken together, TAM and STS theory reveal a nuanced human-technology relationship: high AI adoption does not equate to passive acceptance or loss of control. Instead, young users actively negotiate boundaries around usage, delegation, and future expectations within interdependent socio-technical systems.

Existing empirical evidence suggests that young users engage with AI tools frequently and for a wide range of purposes, reflecting the increasing integration of AI into daily life. In case of education purposes, studies show that a majority of students – from secondary education to university level – report using AI tools regularly, particularly for academic tasks such as homework completion, essay writing, summarisation, and concept clarification (Granström and Oppi, 2025; Fošner, 2024; Klarin et al., 2024; von Garrel and Mayer, 2023). Usage is not limited to formal education; young users also engage with AI for creative experimentation, entertainment, communication, and emotional support, including interactions with conversational agents and mental health chatbots (Brandtzaeg et al., 2025; Canady, 2025). Furthermore, patterns of use appear to vary by age, digital literacy, and cognitive characteristics, with older students and those facing academic challenges often demonstrating higher reliance on AI tools (Klarin et al., 2024).

Although AI adoption is widespread, the literature also highlights important tensions associated with frequent use. Several studies raise concerns about over-reliance on AI systems, particularly in educational settings, where excessive dependence may lead to reduced critical thinking, diminished creativity, and surface-level learning (Gerlich, 2025; Sharma et al., 2025). These findings reinforce earlier work suggesting that AI is most effective when used as a complementary tool that augments human cognition, rather than replacing it (Lin and Chen, 2024; Zawacki-Richter et al., 2019). As such, high levels of engagement do not necessarily imply uncritical acceptance or complete reliance, pointing to a more complex relationship between usage and control.

This complexity becomes particularly evident in research on AI delegation and decision-making. A growing body of literature demonstrates that users exhibit conditional and context-dependent willingness to delegate tasks to AI systems, rather than uniformly accepting automation. Trust has consistently been identified as a central determinant of delegation behaviour, with higher perceived reliability and competence of AI systems increasing the likelihood of delegation (Song and Lin, 2024; Lubars and Tan, 2019). At the same time, users tend to prefer retaining control in situations involving subjective judgment, ethical considerations, or high perceived risk (Leyer and Schneider, 2019; Gogoll and Uhl, 2018).

Task characteristics also play a critical role. Users are generally more willing to delegate routine, objective, or low-stakes tasks, while demonstrating reluctance to delegate complex or identity-relevant decisions (Husairi and Rossi, 2024; Candrian et al., 2022). Additionally, perceived autonomy significantly influences acceptance, as users resist AI systems that limit their sense of control or agency (Husairi and Rossi, 2024) . Research further suggests that users often prefer human-AI collaboration (augmentation) over full automation, indicating a preference for shared decision-making rather than complete delegation (Pinski and Benlian, 2023). These findings highlight that even in contexts of frequent AI use, individuals actively negotiate the extent to which they are willing to rely on AI outputs.

Beyond immediate interactions, AI is also reshaping broader socio-economic systems, particularly in relation to the future of work and employment. AI technologies are widely recognised as drivers of digital transformation, enabling increased efficiency, innovation, and data-driven decision-making across industries (Gama and Magistretti, 2023; Dwivedi et al., 2021; Král' et al., 2025; Stefko et al., 2025). At the same time, they are associated with significant changes in labour markets, including task automation, job redesign, and evolving skill requirements (Babashahi et al., 2024; Balcerzak et al., 2025b; Roshchyk et al., 2024). Importantly, the literature suggests that AI is more likely to transform jobs rather than fully replace them, increasing the demand for hybrid skills that combine technical knowledge with human capabilities such as creativity, critical thinking, and emotional intelligence.

For young users, who are entering or preparing to enter the workforce, these developments are particularly salient. Studies indicate that they are increasingly aware of both the opportunities and risks associated with AI, including improved productivity and new career paths, in addition to concerns about job displacement, skill obsolescence, and increased competition (Balcerzak et al., 2025a). However, empirical research examining how these perceptions relate to actual AI use and delegation behaviour remains limited.

Taken together, these strands of research reveal a significant gap in research. Although existing studies provide valuable insights into AI usage, delegation behaviour, and future work perceptions as separate phenomena, there is a lack of integrated research examining how these dimensions interact within a single population. In particular, the coexistence of high-frequency AI use, selective delegation, and ambivalent perceptions of AI's societal impact has not been sufficiently explored.

Consequently, this study aims to address this gap by examining these dynamics among Generation Z through the following research questions:

- RQ1: *How frequently do young users engage with AI tools, and for what purposes?*

This question is motivated by empirical evidence of widespread but heterogeneous AI use across academic, creative, and personal domains, necessitating a more detailed understanding of usage patterns and motivations (Granström and Oppi, 2025; von Garrel and Mayer, 2023; Brandtzaeg et al., 2025).

- RQ2: *To what extent are users willing to delegate tasks and decision-making to AI systems?*

Given that prior research highlights the importance of trust, autonomy, and task characteristics in shaping delegation behaviour, this question seeks to clarify how young users balance efficiency gains with the desire to retain control (Song and Lin, 2024; Lubars and Tan, 2019; Husairi and Rossi, 2024).

- RQ3: *How do young users perceive the impact of AI on future work and employment?*

As AI continues to transform labour markets and skill requirements, this question addresses the need to understand how young users interpret these changes and their implications for future career trajectories (Babashahi et al., 2024; Dwivedi et al., 2021; Mishchuk et al., 2025).

By examining these dynamics through a survey of 262 Generation Z respondents, this study contributes to ongoing discourse on human agency, trust, and socio-technical change in AI-infused societies. It highlights how young users integrate AI as a supportive resource while safeguarding human control, offering insights into the design of education, work practices, and policies that promote responsible and empowering human-AI relations.

METHODS

This study adopts a quantitative, cross-sectional survey design to examine patterns of AI use, delegation preferences, and perceptions of the future of work among young individuals. This design is appropriate to capture self-reported behaviours, attitudes, and perceptions at a single point in time, particularly in the context of rapidly evolving technologies such as AI.

The study is descriptive and exploratory in nature, aiming to identify distributions, behavioural tendencies, and response patterns rather than to establish causal relationships or test hypotheses. This approach enables a systematic examination of how frequently young users engage with AI tools, the extent to which they are willing to delegate tasks and decision-making, and how they perceive the implications of AI for future employment.

The use of a survey-based methodology is consistent with prior research in this field, where similar designs have been employed to investigate AI usage and perceptions among young populations. For instance, survey-based studies have been used to analyse student engagement with AI tools (Granström et al., 2025), attitudes toward AI in higher education (Fošner, 2024), and patterns of AI use in academic contexts (von Garrel and Mayer, 2023). Similarly, research on adolescents has relied on survey data to examine AI usage and perceived usefulness, as well as broader student knowledge and engagement with AI technologies (Klarin et al., 2024).

Overall, a quantitative cross-sectional survey design provides a methodologically appropriate and well-established framework for addressing the research objectives, as it allows for the efficient collection of comparable data across a sample population and facilitates the analysis of emerging patterns in human-AI interaction.

Data were collected using a structured, online questionnaire implemented via Google Forms. The survey was distributed through digital channels, including networks and educational environments, targeting primarily secondary school and university populations. Participation was voluntary and anonymous, and no personally identifiable information was collected. A total of 262 valid responses were obtained from participants mostly enrolled in secondary and tertiary education institutions in the Czech Republic. All responses were included in the analysis, as no incomplete or duplicate entries requiring exclusion were identified.

The survey instrument was structured into six sections (A-F), each designed to capture a specific dimension of human-AI interaction. The instrument was developed in alignment with prior research that employs survey-based measures to examine AI usage patterns, attitudes, and behavioural tendencies among users under investigation (von Garrel and Mayer, 2023; Fošner, 2024; Granström and Oppi, 2025; Klarin et al., 2024).

The structure of the questionnaire directly reflects the study's research questions (RQ1-RQ3), ensuring conceptual consistency between the measurement and the research objectives.

Section A includes demographic and contextual variables such as age, gender, education, role, region, digital access, and language use in AI interactions. These variables serve as control and segmentation factors, enabling the analysis of differences in AI usage and perceptions across groups. The inclusion of such background characteristics is consistent with prior survey-based studies on AI adoption and use among students (von Garrel and Mayer, 2023).

Section B measures the frequency of AI interaction across multiple contexts, including chatbot use, AI embedded in applications, and active exploration of new AI tools. Responses are captured using ordinal frequency scales ranging from "not applicable" to "daily or almost daily". This operationalisation follows established approaches in the literature, where AI engagement is measured through self-reported frequency of use across platforms and contexts (Granström et al., 2025; Klarin et al., 2024). These measures directly address RQ1, capturing how frequently young users engage with AI technologies.

Section C focusses on the purposes of AI use, including understanding or explaining concepts, writing and summarising text, solving problems, saving time, and improving work quality. These items are measured using Likert-type ordinal scales ("never" to "very often"). This approach reflects prior research that conceptualises AI use in terms of task-specific applications, particularly in educational contexts (Fošner, 2024; von Garrel and Mayer, 2023). By distinguishing between different functional uses of AI, this section complements frequency-based measures and further addresses RQ1, providing insight into why users engage with AI.

Section D assesses the willingness of respondents to delegate tasks and decision-making to AI systems across a range of scenarios (e.g., scheduling, communication, monitoring, financial decisions, workflow decisions). Responses are measured using ordered categorical scales ranging from "no delegation" to "full delegation." This measurement is grounded in research on human-AI delegation, which conceptualises delegation as a continuum shaped by trust, perceived autonomy, and task characteristics (Husairi and Rossi, 2024; Song and Lin, 2024; Lubars and Tan, 2019). Previous studies show that willingness to delegate varies across contexts and task types, supporting the use of scenario-based items. This section directly addresses RQ2, capturing the extent and conditions under which users are willing to rely on AI systems.

Section E captures the perceptions of AI's impact on the future of work, including expectations related to job displacement, changes in workplace organisation, AI beneficiaries, and the need for retraining. These variables are measured using categorical and ordinal response formats. This approach aligns with existing research that examines how individuals perceive AI-driven labour market transformations, including changes in job structures, skill requirements, and employment opportunities (Babashahi et al., 2024; Dwivedi et al., 2021). This section directly addresses RQ3, focussing on forward-looking expectations and attitudes.

Finally, Section F includes items that capture changes in AI use over time, expected future reliance on AI, perceived normalisation of AI, and perceived dependence on AI. These indicators provide a better understanding of how users' relationships with AI evolve. Such attitudinal measures are commonly included in AI research to capture longer-term behavioural trends and perceptions of technological integration (Brandtzaeg et al., 2025; Gerlich, 2025) . This section complements all three research questions by linking usage, delegation, and future expectations.

Across the instrument, variables are primarily ordinal (Likert-type and frequency scales) and nominal categorical variables, which is consistent with established practices in survey-based research on technology use and perceptions. This measurement approach is suitable for capturing subjective evaluations, behavioural tendencies, and categorical distinctions, without requiring continuous data.

Given the categorical and ordinal nature of the data, the analysis was conducted using descriptive statistical techniques, including absolute frequencies (*n*) and relative frequencies (*%*), to summarise response distributions across all variables. This approach is consistent with prior research examining AI usage and perceptions, where survey-based data are commonly analysed using descriptive methods to identify behavioural patterns and trends (Granström and Oppi, 2025; von Garrel and Mayer, 2023).

For ordinal variables, the analysis focused on the distribution of responses across categories, with particular attention to dominant response patterns. According to established practices in survey research, selected categories were aggregated (eg, “often” and “very often”, or “several times a week” and “daily”) to enhance interpretative clarity while preserving the ordinal structure of the data. Similar approaches have been applied in studies examining AI engagement and usage intensity, where the emphasis is placed on identifying general tendencies rather than precise numerical differences (Granström and Oppi, 2025; Klarin et al., 2024).

No inferential statistical analyses (e.g., hypothesis testing or regression modelling) were conducted. This decision reflects the descriptive and exploratory nature of the study, which aims to identify patterns of AI use, delegation preferences, and perceptions rather than test causal relationships or make population-level generalisations. Previous research in this domain has similarly relied on descriptive survey analysis when the objective is to provide an overview of user behaviour and attitudes, particularly in emerging research areas where constructs are still being explored (Fošner, 2024; von Garrel and Mayer, 2023).

Accordingly, the analytical approach is consistent with a descriptive statistical framework, which is methodologically appropriate for the research objectives and the type of data collected.

Participation in the study was voluntary, and respondents were informed about the purpose of the research prior to completing the questionnaire. No sensitive personal data was collected and all responses were fully anonymised. The study adheres to standard ethical principles for research involving human participants, including informed consent, confidentiality, and data protection.

AI-based tools were used during manuscript preparation solely for language refinement and structural support. The authors retained full responsibility for the research design, data collection, analysis, and interpretation of findings. The use of AI tools was limited to improving clarity and readability and did not influence the substantive content or scientific conclusions of the study.

RESULTS

Sample characteristics

As already noted, the analytical sample (N = 262) consists predominantly of Generation Z respondents. As shown in Table 1, the age distribution is concentrated in the 19–25 category (58.0%), followed by 16–18 (34.7%) and 10–15 (7.3%), with no respondents in older age groups. The sample is strongly student-oriented, with university undergraduates (48.9%) and secondary school students (42.4%) forming the majority. Smaller proportions include graduate students (5.0%) and minimal representation from employed or other categories. Gender distribution, also reported in Table 1, includes 57.3% women and 40.5% men, with a small proportion identifying as non-binary (0.8%) or preferring not to disclose (1.5%). Geographically, the sample is highly concentrated in Czechia (99.2%).

Table 1. Socio-demographic characteristics (N = 262) [Source: own processing]

Variable	Category	n	%
Age group	10–15	19	7.3
	16–18	91	34.7
	19–25	152	58.0
Gender	Woman	150	57.3
	Man	106	40.5
	Non-binary / third gender	2	0.8
	Prefer not to say	4	1.5
Current main role	Elementary school student	4	1.5
	High school student	111	42.4
	University undergraduate	128	48.9
	University graduate student	13	5.0
	Employed	2	0.8
	Self-employed / freelance	3	1.1
	Retired	1	0.4
Highest level of education completed	Primary	80	30.5
	Secondary	165	63.0
	Bachelor's degree	8	3.1
	Master's degree	1	0.4
	Doctorate	1	0.4
	None above	7	2.7
Region currently lived in	Europe	260	99.2
	Africa	1	0.4
	Prefer not to say	1	0.4

Digital access and language context characteristics are summarised in Table 2. The results indicate a highly connected population, with 76.3% of respondents reporting smartphone or tablet use of at least three hours per day (56.5% for 3–6 hours and 19.8% for more than 6 hours). In addition, 83.2% report reliable or always available internet access (46.9% reliable most of the time and 36.3% always available).

Table 2. Digital Access and Language Context (N = 262) [Source: own processing]

Variable	Category	n	%
Daily smartphone or tablet use	Less than 1 hour	3	1.1
	1–3 hours	59	22.5
	3–6 hours	148	56.5
	More than 6 hours	52	19.8
Daily computer or laptop use	Less than 1 hour	87	33.2
	1–3 hours	108	41.2
	3–6 hours	56	21.4
	More than 6 hours	11	4.2
Internet access quality	Rare or unstable	4	1.5
	Sometimes available	40	15.3
	Reliable most of the time	123	46.9
	Always available	95	36.3
Main language used with AI tools	Only my native language	39	14.9
	Mostly my native language	114	43.5
	Both equally	64	24.4
	Mostly English	35	13.4
	Only English	3	1.1
	I don't use AI tools	7	2.7

AI Usage Intensity

The distribution of AI usage frequency indicates a high level of adoption across the sample. As shown in Table 3, for chatbot use, the modal categories were "several times per week" (42.4%) and "daily or almost daily" (40.8%). When combined, these categories represent 83.2% of respondents, indicating that frequent AI use is the dominant behavioural pattern.

A similar distribution is observed for AI use on mobile devices. As presented in Table 3, 41.2% reported usage several times per week and 39.7% reported daily use. This results in 80.9% of respondents engaging with AI on mobile platforms at high frequency, suggesting that mobile environments are a primary access point for AI interaction.

In contrast, AI use on computers or laptops shows a more dispersed distribution across frequency categories: 27.1% of respondents reported several times per week use and 19.8% reported daily use, while a substantial proportion of respondents reported lower-frequency engagement. This indicates that computer-based AI interaction is less central compared to mobile usage.

Use of AI features embedded within applications (e.g., search engines, office tools, maps) was also less intensive: only 17.6% reported using such features several times per week and 11.5% daily, while the largest proportions were observed in lower-frequency categories (e.g., less than monthly and monthly/weekly).

Finally, active exploration of new AI tools was relatively limited. The most frequent responses were "less than monthly" (37.4%) and "monthly or weekly" (27.9%), while only 14.5% of respondents reported actively seeking new AI tools on a weekly or daily basis.

Table 3. AI Usage Intensity (N = 262) [Source: own processing]

Response category	Chatbot use	AI in apps	AI on phone/tablet	AI on computer/laptop	Seek out new AI tools
Not applicable/I don't use AI	6 (2.3)	10 (3.8)	5 (1.9)	6 (2.3)	11 (4.2)
Never	5 (1.9)	58 (22.1)	10 (3.8)	27 (10.3)	53 (20.2)
Less than monthly	14 (5.3)	76 (29.0)	10 (3.8)	48 (18.3)	98 (37.4)
Monthly or weekly	45 (17.2)	61 (23.3)	42 (16.0)	77 (29.4)	73 (27.9)
Several times per week	111 (42.4)	46 (17.6)	108 (41.2)	71 (27.1)	23 (8.8)
Daily or almost daily	107 (40.8)	30 (11.5)	104 (39.7)	52 (19.8)	15 (5.7)

Temporal comparisons shown in Table 4 indicate an increasing trajectory of AI use. A total of 37.4% of respondents reported that their AI use is "slightly higher" than one year ago, and 29.4% reported it as "much higher," resulting in 66.8% indicating increased usage.

Future expectations align with this trend. A total of 62.2% of respondents agreed and 7.6% strongly agreed that they expect to rely more on AI in the future.

Normalization of AI is also evident. A total of 63.4% of respondents agreed and 20.6% strongly agreed that AI is becoming a normal part of everyday work and life, resulting in 83.9% expressing agreement.

Finally, responses to a counterfactual scenario suggest emerging functional dependence on AI. When asked how their daily activities would change if AI were unavailable, 31.7% indicated that they would be "slightly harder," and 11.5% "much harder," while the largest group (43.1%) reported no major change.

Table 4. Behavioural and Attitudinal Indicators (N = 262) [Source: own processing]

Variable	Category	n	%
If AI were unavailable tomorrow, my daily activities would be	Much harder	30	11.5
	Slightly harder	83	31.7
	No major change	113	43.1
	Slightly easier	27	10.3
	Much easier	9	3.4
Compared to one year ago, my AI use is	Much lower	14	5.3
	Slightly lower	22	8.4
	About the same	51	19.5
	Slightly higher	98	37.4
	Much higher	77	29.4
I expect to rely more on AI in the future than I do now	Strongly disagree	17	6.5
	Disagree	62	23.7
	Agree	163	62.2
	Strongly agree	20	7.6
I would prefer a job or activity that involves working with AI (N = 255)	Strongly disagree	24	9.4
	Disagree	87	34.1
	Agree	131	51.4
	Strongly agree	13	5.1
Overall, AI is becoming a normal part of everyday work and life	Strongly disagree	14	5.3
	Disagree	28	10.7
	Agree	166	63.4
	Strongly agree	54	20.6

AI Use Purposes

Analysis of AI use purposes reveals a clear hierarchy of functional applications. As shown in Table 5, the most frequently reported use case was understanding or explaining concepts. A total of 38.9% of respondents reported using AI "very often" for this purpose, and 32.8% reported "often," resulting in a combined high-frequency usage rate of 71.8%. This indicates that AI is primarily utilised as a cognitive support tool.

Other use cases exhibit lower but still notable levels of engagement. For problem-solving tasks, 24.4% of respondents reported "often" and 14.5% "very often," resulting in a combined high-frequency usage rate of 38.9%. Similarly, AI use for improving the quality of work was reported "often" by 27.9% and "very often" by 10.7% of respondents (38.6% combined).

Writing-related uses (e.g., summarising or rewriting text) were reported less frequently, with 19.8% indicating "often" and 12.2% "very often," resulting in 32.0% high-frequency usage. The use of AI to save time on routine or repetitive tasks was also relatively moderate, with 30.9% reporting frequent use ("often" or "very often").

Across all use categories, lower-frequency responses (e.g., "rarely" and "sometimes") remain substantial, indicating that while AI is widely adopted, its application is selective and context-dependent. Overall, the distribution suggests that AI is used more intensively for knowledge-related tasks than for automation or efficiency-driven purposes.

Table 5. Purposes of AI Use (N = 262) [Source: own processing]

Response category	Understand / explain	Write / rewrite / summarize	Solve tasks / problems	Save time on routine work	Improve quality of work
Not applicable/I don't use AI	5 (1.9)	9 (3.4)	4 (1.5)	7 (2.7)	8 (3.1)
Never	5 (1.9)	19 (7.3)	18 (6.9)	29 (11.1)	13 (5.0)
Rarely	13 (5.0)	55 (21.0)	61 (23.3)	64 (24.4)	50 (19.1)
Sometimes	51 (19.5)	95 (36.3)	77 (29.4)	81 (30.9)	90 (34.4)
Often	86 (32.8)	52 (19.8)	64 (24.4)	50 (19.1)	73 (27.9)
Very often	102 (38.9)	32 (12.2)	38 (14.5)	31 (11.8)	28 (10.7)

Delegation and Automation Readiness

Across all delegation-related variables, the dominant response category was "no," indicating a general reluctance to delegate tasks to AI systems. As shown in Table 6, this pattern is consistent across both low-stakes and high-stakes scenarios.

For task coordination (e.g., scheduling), 54.6% of respondents indicated that they would not allow AI to perform this function. Similarly, 61.8% reported that they would not allow AI to draft messages on their behalf. For monitoring tasks (e.g., deadlines or opportunities), 71.0% selected "no," indicating strong resistance even in relatively low-risk contexts.

Resistance to delegation was most pronounced in high-stakes contexts: 74.0% of respondents reported that they would not allow AI to make purchases or payments on their behalf, while 57.3% indicated that they would not allow AI to decide the next step in a task or workflow.

Among respondents who expressed some willingness to delegate, the most common response was "yes, but only with strict human approval". Fully autonomous delegation ("fully delegated") was selected by only a small minority (typically fewer than 10 respondents per item), indicating that complete trust in AI decision-making is rare within the sample.

Table 6. Automation and Delegation Readiness (N = 262) [Source: own processing]

Response category	Schedule / coordinate	Draft messages	Monitor / notify	Purchases / payments	Decide next step
Not applicable/I don't want or can't do this	18 (6.9)	20 (7.6)	21 (8.0)	24 (9.2)	15 (5.7)
No	143 (54.6)	162 (61.8)	186 (71.0)	194 (74.0)	150 (57.3)
Yes, but only with strict human approval	56 (21.4)	57 (21.8)	35 (13.4)	26 (9.9)	73 (27.9)
Yes, with occasional check-ins	38 (14.5)	18 (6.9)	16 (6.1)	12 (4.6)	15 (5.7)
Yes, fully delegated	7 (2.7)	5 (1.9)	4 (1.5)	6 (2.3)	9 (3.4)

Perceptions of the Future of Work

Respondents' expectations regarding the impact of AI on the labour market reflect a distribution centred around transformation rather than disruption. As shown in Table 7, the most frequently selected response (53.4%) was that AI will reduce some jobs while creating others. This suggests that respondents perceive AI as both a disruptive and generative force.

Other responses were less frequent, including "mostly change tasks, not job numbers" (16.4%) and "reduce total jobs" (11.1%). A smaller proportion (9.9%) indicated that AI would increase productivity with minimal job loss, while 9.2% reported uncertainty.

In terms of the structure of future work, nearly half of respondents (48.9%) indicated that the most likely model is human-led work supported by AI tools. An additional 29.4% selected AI-led systems with human oversight, while 11.8% selected fully automated systems and only 3.1% expected work to remain entirely human-based.

Perceptions of retraining needs were also pronounced: 49.2% of respondents indicated that significant retraining is "somewhat likely", and 20.2% reported it as "very likely", resulting in 69.4% indicating anticipated skill adaptation.

In terms of emotional responses, the most frequent category was "neutral or mixed" (43.1%), followed by "slightly worried" (27.9%). Positive responses were less frequent, suggesting a cautious or uncertain outlook rather than strong optimism.

Table 7. Perceptions of the Future of Work (N = 262) [Source: own processing]

Variable	Category	n	%
In the next 10 years, AI will mostly	Reduce total jobs	29	11.1
	Reduce some jobs but create others	140	53.4
	Mostly change tasks, not job numbers	43	16.4
	Increase productivity with little job loss	26	9.9
	Unsure	24	9.2
The most likely future of work is	Work done entirely by humans	8	3.1
	Human-led work with AI tools	128	48.9
	AI-led work with human oversight	77	29.4
	Mostly automated systems	31	11.8
	Unsure	18	6.9
AI will mainly benefit	Employers much more than workers	50	19.1
	Employers slightly more	52	19.8
	Workers and employers equally	87	33.2
	Workers more than employers	31	11.8
	Unsure	42	16.0
Most people will need significant retraining because of AI	Very unlikely	6	2.3
	Somewhat unlikely	35	13.4
	Somewhat likely	129	49.2
	Very likely	53	20.2
	Unsure	39	14.9
Overall, AI will make finding good jobs	Much harder	22	8.4
	Slightly harder	92	35.1
	No major change	61	23.3
	Easier	58	22.1
	Unsure	29	11.1
AI will mostly replace	Only repetitive or boring jobs	50	19.1
	Some skilled jobs as well	86	32.8
	Many current profession	66	25.2
	Very few jobs overall	34	13.0
	Unsure	26	9.9
Personally, AI makes me feel about my future work	Much more worried	34	13.0
	Slightly worried	73	27.9
	Neutral / mixed	113	43.1
	Slightly optimistic	31	11.8
	Very optimistic	11	4.2

DISCUSSION

The aim of this study was to examine patterns of artificial intelligence (AI) use, delegation preferences, and perceptions of the future of work among Generation Z. The findings reveal a consistent pattern of high AI adoption combined with limited willingness to delegate control, providing a more nuanced understanding of human-AI interaction. Importantly, these results both confirm and extend existing findings reported in prior academic studies.

For RQ1, the results indicate that AI has become deeply embedded in young users' everyday practices. A large majority reported frequent engagement with chatbots and mobile-based AI, with concept explanation emerging as the dominant application. These patterns align with existing evidence of widespread AI adoption among younger generation cohorts for cognitive support and learning enhancement (Lin & Chen, 2024; García-Martínez et al., 2023).

In terms of functional use, the most prominent application of AI was for understanding or explaining concepts, confirming that AI is primarily used as a cognitive support tool. Other uses were less intensive and more distributed, including problem-solving, improving work quality, writing-related tasks, and saving time. These findings align with previous studies suggesting that AI is most frequently used in learning-related and knowledge-support contexts, where it enhances understanding and productivity (Balcerzak et al., 2025a; Koteczki & Eisinger Balassa, 2025; Zawacki-Richter et al., 2019).

Regarding RQ2, the findings indicate a clear reluctance to delegate tasks and decision-making to AI systems. Rejection rates were high across contexts, including financial decisions, monitoring, and even routine activities such as scheduling or message drafting. Among those who expressed some willingness to delegate, the dominant preference was conditional use, particularly "yes, but only with strict human approval", while fully autonomous delegation remained rare (generally below 5% across tasks).

These findings are consistent with prior research emphasising that trust, perceived risk, and the need for control are central determinants of AI acceptance (Hassan et al., 2024; Ismatullaev et al., 2024) . They extend the literature by demonstrating that resistance to delegation appears as a general feature of human-AI relations, not limited to high-risk scenarios, suggesting that young users actively safeguard their agency (Balcerzak et al., 2025b).

In relation to RQ3, respondents' perceptions of the future of work indicate a predominantly adaptive rather than disruptive outlook. The most frequently selected response was that AI will reduce some jobs while creating others, suggesting that respondents perceive AI as both transformative and generative. This aligns with previous research indicating that AI is expected to reshape rather than fully replace jobs, requiring adaptation and reskilling (Babashahi et al., 2024).

These expectations are further supported by views on future work structures. The majority of respondents anticipated human-led work supported by AI tools, followed by AI-led systems with human oversight. Only a small proportion expected mostly automated or entirely human-based work. This preference for hybrid models aligns with prior research emphasising human-AI collaboration over full automation (Gama & Magistretti, 2023; Dwivedi et al., 2021). This orientation towards human-centred augmentation echoes analogous trends in digital service innovation, where platform-based models such as Mobility as a Service demonstrate how technology can enhance rather than displace human decision-making in complex environments (Vovk et al., 2024).

Perceptions of retraining reinforced this adaptive outlook, with a large majority considering significant reskilling likely. At the attitudinal level, responses were predominantly neutral or cautiously mixed, indicating a pragmatic and transitional rather than polarized view of AI's role in future work.

Taken together, the findings reveal a clear tension in human-AI interaction: high levels of AI use coexist with limited willingness to delegate control. This divergence – evident in frequent engagement with chatbots and concept explanation alongside strong rejection of delegation in both routine and high-stakes tasks – supports prior research portraying AI primarily as a supportive tool rather than an autonomous agent (Zawacki-Richter et al., 2019). The present study extends these insights by demonstrating that usage intensity and delegation willingness constitute distinct dimensions of AI engagement.

From a theoretical perspective, these results suggest that traditional models such as the Technology Acceptance Model (TAM) (Chatterjee et al., 2021), which focus on perceived usefulness and ease of use, provide only partial explanations. A more comprehensive understanding requires complementary socio-technical perspectives that account for the interdependent relationship between technical capabilities and human factors, including trust in autonomy, perceived control, and responsibility (Trist and Bamforth, 1951; Desveaud and Bawack, 2026; Xu and Gao, 2024).

CONCLUSIONS

This study examined patterns of AI use, delegation preferences, and perceptions of the future of work among Generation Z. The results show that AI is widely and frequently used, particularly for cognitively supportive tasks such as understanding concepts, while willingness to delegate tasks and decision-making to AI remains consistently low across contexts. At the same time, respondents expressed an adaptive view of the future of work, expecting both job transformation and the need for ongoing reskilling.

Taken together, these findings highlight a key insight: high levels of AI use do not imply acceptance of AI autonomy, but rather reflect a model of selective and controlled integration. Young users appear to value AI primarily as a support tool rather than as an independent decision-maker.

Several questions remain unanswered. First, it is unclear why frequent AI users continue to resist delegation, suggesting that trust and perceived responsibility require further investigation. Second, it remains uncertain whether increased exposure to AI will lead to greater acceptance of autonomy over time, or whether resistance will persist. Finally, the relatively neutral perceptions of future work indicate a need for further research into how education and experience shape long-term expectations of AI.

The following limitations of this study should be acknowledged. First of all, the survey was conducted within the Czech educational context. Thus, future research should replicate this design with larger and more diverse STEM cohorts, incorporate other countries, and examine longitudinal effects of AI integration.

IMPLICATIONS FOR RESEARCH AND APPLICATION

The findings of this study contribute to prior research on AI adoption, human-AI interaction, and the future of work by providing empirical evidence from a Generation Z sample.

From a theoretical perspective, the results extend existing adoption frameworks, such as the Technology Acceptance Model (TAM) and Socio-Technical Systems (STS), by demonstrating that high levels of AI use do not correspond to acceptance of autonomous decision-making. Instead, the findings highlight a distinction between usage intensity and delegation, contributing to emerging concepts of bounded trust and selective delegation in AI interaction.

From the application perspective, the results suggest that AI systems targeting young users should prioritise support for cognitive tasks rather than full automation. The strong rejection of delegation across tasks indicates that users prefer systems that enhance performance while maintaining human control.

In terms of policy-making application, the findings support the need for AI literacy and reskilling initiatives, given that more than third of respondents expect significant retraining. Policies should focus on equipping users with skills for effective and critical AI use while ensuring that human agency remains central in AI-mediated environments.

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Authors' Note

All correspondence should be addressed to

Adam P. Balcerzak
Brno University of Technology, Faculty of Business and Management, Czechia
University of Warmia and Mazury in Olsztyn, Faculty of Economic Sciences, Poland
pl. Cieszyński 1/327
10-720 Olsztyn
Email address:
a.balcerzak@uwm.edu.pl

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