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Everyday artificial intelligence unveiled: Societal awareness of technological transformation

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Abstract

Research background: As Artificial Intelligence (AI) weaves into the fabric of daily life, its societal and economic implications underscore the urgency of embracing an environment conducive to its informed adoption. This requires a sophisticated understanding of the societal perception and adaptability to AI, emphasizing the importance of developing comprehensive AI literacy.

Purpose of the article: This study inquiries into the sociodemographic underpinnings of AI literacy, aiming to demystify how knowledge about AI's capabilities in everyday tasks varies across individual population segments. It allows us to define the basic determinants that influence the differences in the individual population structures. It also reveals the potential risks associated with the use of AI.

Methods: This study investigates the awareness of Artificial Intelligence (AI) in daily lives of the Czech population, focusing on the influence of socio-demographic factors. Utilizing computer-assisted web interviewing, we surveyed 1,041 respondents in April 2023, ensuring representativeness by applying quotas for age, gender, education, region, and residential area size. Our investigation spanned AI applications in sectors like customer service, music playlist recommendation, email sorting, healthcare, online shopping, and home devices.

Findings & value added: Findings taken from descriptive statistics reveal variable AI awareness levels across different domains, with younger demographics exhibiting notably lower awareness in several areas. Regression analysis highlighted that awareness is significantly associated with gender, age, and education level. Regression analysis showed that males, younger age groups and those with higher levels of education were more likely to correctly answer majority of questions about the role of AI in everyday life. These insights are crucial for stakeholders aiming to enhance AI literacy, tailor communication strategies, and develop digital platforms, offering guidance for policymakers and market analysts in optimizing AI-related initiatives.

Introduction

The era of digital transformation, marked by significant advancements in automation, robotics, and new industrial relations, ushers in both unparalleled business opportunities and formidable challenges. This transformation, characterized by dynamic stakeholder interactions, necessitates comprehensive changes across multiple levels of the economy and society. However, the trajectory of digital transformation is not uniform across nations, as it is influenced by a myriad of factors. Recent comparative studies highlight three critical dimensions for evaluating the pace of digital transformation across countries: the digitization of society (Society 4.0), the economy's resilience in the face of technological advancements (Economy 4.0), and the integration of Information and Communication Technology (ICT) within enterprises (Enterprise 4.0) (Małkowska *et al.*, 2021). By analyzing these dimensions, researchers can quantify digital disparities and pinpoint their underlying determinants, offering valuable insights into the global landscape of digital transformation. Furthermore, the advent of Artificial Intelligence (AI) technologies emerges as a pivotal aspect of digital transformation. This development necessitates the establishment of conducive environments for the adoption and utilization of AI across various sectors of the economy and society, as well as among diverse demographic groups. Understanding the intricacies of AI integration is crucial for navigating the future of digital transformation, as it holds the potential to redefine economic and societal structures profoundly.

In the contemporary landscape, AI-based technologies are at the forefront of socio-economic disruption, catalyzing a burgeoning interest in AI education among social and political spheres (Casal-Otero *et al*., 2023). The imperative to delineate AI technology user competencies and to articulate the foundational constructs of AI literacy — comprising awareness, utilization, evaluation, and ethical considerations of AI — is underscored by the pervasive integration of AI technologies into daily life (Wang *et al.*, 2023a). In response, numerous nations are proactively enhancing AI education through diverse methodologies, including experiential learning, training programs, and interactive data visualization (Narahara & Kobayashi, 2018; Vartiainen *et al.*, 2021). Notwithstanding these efforts, the conceptualization of AI literacy and the understanding of AI technologies remain nascent and insufficiently examined (Ngai *et al.*, 2021; Cetindamar *et al.*, 2022). AI literacy's connection to digital literacy, attitudes towards robotics, and the application of AI in everyday contexts elucidates the necessity for a systematic and in-depth exploration of digital platforms and user behavior within various interactive processes (Wang *et al.*, 2023b). Such research is essential not only for advancing digital and AI literacy frameworks, but also for enabling designers to tailor AI applications to the specific literacy levels of diverse demographic segments.

This rationale underscores the compelling motivation behind our study, which endeavors to elucidate the socio-demographic factors influencing the general populace's understanding of AI's capabilities in performing everyday tasks. Our objective is to identify the fundamental determinants shaping variations across individual population segments and to uncover the potential risks associated with AI utilization.

Comprehensive research examining the broad spectrum of artificial intelligence (AI) applications encountered daily by the general population remains scarce. Existing studies typically focus on narrowly defined areas of AI application, specific demographic groups, or singular AI technologies. This narrow scope and the considerable heterogeneity among these studies complicate efforts to compare findings and holistically assess how AI technologies are integrated into daily life across different population segments. In developing our research framework, we drew inspiration from a seminal study conducted by the Pew Research Center, which surveyed 11,004 adults in the USA in 2022. While we did not aim for direct comparability between our study and the American findings — owing to the distinct factors influencing AI usage in the Czech and American contexts — this reference served as an invaluable model due to its methodological comprehensiveness and integrity. Our research aims to bridge this gap by systematically investigating the diverse factors that influence population-wide AI literacy. This approach will not only enable us to evaluate the fundamental determinants that underpin the variations in public knowledge regarding the everyday tasks AI can perform, but also to uncover potential risks associated with AI usage across different demographic structures. Such insights are crucial for developing targeted interventions and crafting robust AI literacy frameworks.

The insights garnered from this investigation are anticipated to be invaluable for professionals in strategic business management and digital platform development, facilitating the creation of sophisticated customer models through AI. Such models promise to increasingly tailor offerings to individual customer preferences, although this raises concerns about maintaining business integrity due to the anticipated variability in online merchant quality. In an era dominated by digital marketing, comprehending the behavioral nuances of different demographic groups in online shopping environments or when interacting with digital health platforms becomes paramount. An understanding of the socio-economic factors influencing these behaviors is crucial for crafting effective marketing communications. Furthermore, insights into how socio-economic determinants affect consumer perceptions and behaviors on digital platforms can empower sellers to design more effective marketing strategies, optimize the market environment, enhance the shopping platform's ecology, and, ultimately, elevate brand quality and perception.

The structure of the paper is as follows: It begins with an Introduction, setting the stage for the topic discussed. This leads into a Literature Review that explores various perspectives of the examined field. The Research Methods section details the methodology and data used in our study. Following this, the Discussion section compares our findings with existing research. Finally, the Conclusion summarizes the key insights gained and their implications.

Literature review

The recent research studies are aimed at the various aspects of the AI tools used in order to reveal new determinants and classification aspects of the differences in the individual population structures. The rapid development of the AI tools and their adoption in the population requires a deeper investigation of the relations between the determinants and at the same time, definition of the potential of these tools for their more intensive use in the future and inclusion in the various fields of social life.

Conversational agents, or chatbots, are among the AI applications poised for significant advancement in the near future (Carter, 2018; Roslan & Ahmad, 2023; Ray, 2023; Bansal *et al.,* 2024). An increasing number of companies are adopting chatbots to engage with customers, driven by the potential to enhance interaction efficiency and customer experience. While existing research on chatbot use often targets specific issues, limiting the broader applicability of findings, consensus emerges around their capacity to enhance performance, accuracy, and user experience by streamlining processes and enriching customer interactions (Paikens *et al.,* 2020). Investigations across sectors such as trade (Selamat & Windasari, 2021), tourism (Pillai & Sivathanu, 2020; Dávid & Dadkhah, 2023), telecommunications (Mnyakin, 2019), and banking (Eren, 2021; Piotrowski & Orzeszko, 2023) frequently explore the impact of chatbot design and architecture on customer service efficacy. These studies underscore the critical role of information quality and knowledge exchange between chatbots and users, distinguishing between expert-validated knowledge and mere reference information (Ngai *et al.,* 2021). The importance of thorough preparatory work for companies integrating chatbots into their optimization strategies is also highlighted (Stoilova, 2021). Hwang *et al.* (2019) categorize customer service chatbots into three types: the explorer, the soft user, and the hard user, each offering unique benefits in addressing customer needs, from complaint diagnosis to spare parts provisioning (Agnihotri & Bhattacharya, 2023). Furthermore, chatbots are credited with improving customer care and achieving cost savings through automation (Misischia *et al.,* 2022), illustrating their growing significance in enhancing business operations and customer relations.

The proliferation of chatbots across diverse sectors has spurred the development of numerous taxonomies, aimed at categorizing these AI systems based on selected domains. For instance, Janssen *et al.* (2021) devised a classification for 102 domain-specific chatbots across 17 distinct dimensions, with a particular emphasis on intelligence, interaction, and context. Meanwhile, other researchers have explored different aspects in their taxonomies, including social impulses (Feine *et al.,* 2019), as well as verbal, visual, auditory, and invisible characteristics (Diederich *et al.,* 2019; Feine *et al.,* 2020). Specifically, in the realm of customer support, Følstad *et al*. (2019) analyzed 57 chatbots. Despite the extensive development of taxonomies, a notable research gap was the lack of attention to B2B customer service chatbots. This gap was addressed by Janssen *et al.* (2021), who, utilizing the taxonomy framework by Nickerson *et al.* (2013), profiled three archetypal chatbot structures for the B2B sector, classifying 40 chatbots accordingly.

Transitioning to the music industry, the integration of AI has revolutionized not only the creation and management of sound for various media, but also introduced new dimensions to music consumption and production (Yang & Nazir, 2022). AI's implementation enhances the attractiveness of sound effects in games, potentially impacting player productivity and experience. Moreover, AI empowers the development of intelligent, interactive tools for music education, extending benefits to visually impaired individuals. The personalization capabilities provided by AI are poised to redefine consumer-brand associations within the music industry significantly (van de Haar *et al.,* 2019). As demand for sophisticated music recommendation systems increases, AI's application in music streaming services continues to expand, marking a pivotal shift in the industry's approach to meeting consumer expectations (Goh *et al.,* 2021).

Beyond traditional machine learning methods, sentiment analysis is increasingly being integrated into the development of AI-powered music streaming systems to enhance user experience. Mogale and Esiefarienrhe (2021) advocate for a comprehensive framework incorporating diverse music recommendation algorithms to optimize user engagement. Concurrently, Kaliakatsos-Papakostas *et al.* (2020) explore the potential of intuitive AI techniques for creating music that seamlessly blends or transitions between different styles. However, several research avenues remain underexplored, particularly the application of AI in fostering interactive music experiences for children, an area where Chen and Huang (2022) identify a significant research gap.

The therapeutic benefits of music, amplified by AI, represent another promising research domain. Williams *et al*. (2020) document AI-generated music's efficacy in mitigating anxiety and stress, underscoring its potential across various demographic groups. AI and machine learning techniques, through biophysiological measurements, can facilitate the creation of functional music tailored to specific health outcomes or activities, as noted by Ammari *et al*. (2019). This personalized approach extends to voice assistant technologies, which are increasingly scrutinized for their role in music consumption and influence.

Parallel to advancements in AI for entertainment and health, significant progress is noted in combating digital threats like unsolicited bulk email (UBE), which compromises global security and economic stability. Phishing emails make theft easier and are much more dangerous than UBE. Gangavarapu *et al.* (2020) emphasize the necessity for more sophisticated UBE filters, advocating for AI-driven solutions to enhance detection capabilities. Karim *et al*. (2019) contribute to this discourse with a targeted review of AI and machine learning strategies for intelligent spam detection, aiming to bolster consumer protection. Furthermore, Siddique *et al.* (2021) evaluate various machine learning algorithms for email content categorization, highlighting Long Short-Term Memory (LSTM) networks' superior accuracy. Gupta *et al.* (2022) introduce an innovative AI-based approach for spam detection, showcasing significant improvements in classification accuracy.

The integration of AI in healthcare has demonstrated significant success, underscoring the necessity of considering human factors in the design, implementation, and evaluation of AI systems. Research indicates the importance of incorporating patient and clinician perceptions to enhance the development of AI technologies (Verdicchio & Perin, 2022; Lorenzini *et al.*, 2023). Asan and Choudhury (2021) further explore how trust influences the acceptance and use of AI among healthcare providers and patients, revealing a critical gap in current studies which predominantly focus on quantitative metrics such as efficiency and accuracy, often overlooking user-centric development.

The process of building trust in AI technologies, particularly in contexts with prevalent automation biases, is intricate and prolonged. Incorporating human-centered design and cognitive ergonomics can mitigate biases and foster the development of AI within healthcare. Ethical considerations, including safety standards, informed consent, and the impact on caregivers and patients, are paramount (Blasimme & Vayena, 2020). Liu *et al.* (2023) differentiate between responsible and ethical AI, proposing a conceptual model with eight frameworks to guide responsible AI practices in healthcare, emphasizing the need to evaluate the impact of social media within these principles.

For organizations employing AI, adherence to principles of fairness, inclusiveness, transparency, security, privacy, reliability, and harmlessness is crucial in digital health marketing processes. Personalization strategies play a pivotal role in promoting healthy lifestyle changes through AI applications (Kankanhalli *et al.,* 2021). Security concerns surrounding AI technologies necessitate the development of robust security strategies (Ellahham *et al.,* 2020). Wang *et al*. (2023b) advocate for the establishment of AI literacy, encompassing awareness, use, evaluation, and ethics, to enhance user adaptability.

In the realm of customer-brand interactions, empirical studies examining AI's role in customer experience are scarce. Ameen *et al*. (2021) investigate how AI integration in purchasing processes can enhance customer experience, proposing a model based on trustworthiness. Similarly, Pereira *et al*. (2022) highlight the significance of personalized product recommendations in fashion retail, influenced by changing customer preferences and seasonal availability. The dimensions of customer experience — cognitive, emotional, physical and sensory, and social — were identified by Ladhari *et al.* (2017), emphasizing the comprehensive nature of customer interactions with brands. Factors such as perceived ease of use, trust, and performance significantly influence consumer attitudes toward online shopping applications (Kurniasari & Abd Hamid, 2020). Trust emerges as a crucial element in shaping consumer attitudes towards AI, with perceived usefulness identified as a more significant driver than ease of use (Nagy & Hajd, 2021), pointing to the complex interplay of expectations, satisfaction, and trust in the digital age.

AI has increasingly been integrated into household environments, significantly influencing both the standard of living and public perception. The decision to adopt smart home devices is shaped by a variety of factors, including socio-demographic characteristics and perceived security risks. Notable demographic disparities in smart home usage between countries have also been observed; for instance, Douha *et al*. (2023) highlight differences between users in Japan and the United Kingdom. Klobas *et al*. (2019)

report that elderly and more educated individuals tend to weigh their own assessment of security risks more heavily when deciding to adopt these technologies. Additionally, Ghoarayeb *et al*. (2021) find that direct experience with smart devices, along with the trust in professionals who install and maintain these systems, correlates with higher adoption rates.

Furthermore, the adaptation of device functionalities and features to meet the diverse needs of various population groups is crucial for enhancing adoption rates (Georgia *et al*., 2021). The perceived advantages of smart devices are significant in influencing their adoption or the replacement of existing devices. However, gender differences emerge as a strong determinant in the adoption and utilization of smart technologies (Mamonov & Benbunan-Fich, 2021). Given these factors, it is essential to address the barriers to smart home services adoption comprehensively and mitigate associated risks. Hong *et al*. (2020) recommend examining four dimensions of risk associated with smart home technologies: performance, financial, privacy, and psychological. These risks are compounded by technological uncertainty and the intangibility of services. By investigating these dimensions, we can better understand the resilience of new IT products and services and develop robust models of resilience that are aligned with existing literacy systems.

The diffusion and utilization of media technologies are significantly contingent upon their accessibility, which has increasingly expanded to encompass younger demographics in recent times. A study by Lauricella *et al*. (2014), encompassing 909 children aged 8 to 17, elucidates a growing inclination towards new mobile devices among younger cohorts, with a notable escalation in ownership of smartphones and tablets correlating with age. This trend is not merely reflective of availability, but also interwoven with diverse interests and motivations underlying media technology usage, which markedly influences consumption behaviors. Furthermore, Lissitsa and Laor (2021) contribute to the discourse by asserting that generational media preferences are deeply rooted in the media landscapes of individuals' formative years. Technologies that were either prevalent during one's childhood or emerged during their youth tend to hold a special place in their media repertoire, with each subsequent innovation playing a pivotal role in shaping their media engagement narratives (Van der Goot *et al*., 2018). This phenomenon underscores the nuanced interplay between technological availability, generational influences, and individual predispositions in determining media consumption patterns.

The outcomes of the research studies point to a rapid progress in the AI tools used in many fields of the daily life of the population and thus, appeal for their continuous systematic investigation in order to support the creation of digital information literacy and AI literacy systems. At the same time, they create a strong discussion platform and support the construction of research questions.

Research methods

This study, conducted by the Faculty of Social Sciences at Charles University in collaboration with IPSOS, aimed to assess the Czech population's awareness of Artificial Intelligence (AI) and its applications in daily life. Ipsos is the premier research agency in the Czech Republic, leading in annual turnover. Since 2007, the agency has been an integral part of the Ipsos network, which ranks among the world's most extensive research networks (IPSOS, 2024). Utilizing Computer-Assisted Web Interviewing (CAWI), we gathered data from a representative sample of 1,041 respondents, stratified by age, gender, education, region, and residential area size, between 4 and 11 April 2023. The structured questionnaire, taking an average of 10 minutes to complete, probed into various aspects of AI, including familiarity with ChatGPT, attitudes towards halting AI development, perceptions of technological advancement in Czech society, encounters with AI in daily routines, awareness levels, and the ability to distinguish between content generated by AI and humans. This approach was informed by similar research conducted by the Pew Research Center (2023), ensuring our results' comparability.

Artificial Intelligence, defined as the capability of machines or software to execute tasks typically requiring human intelligence, such as reasoning, learning, decision-making, and natural language understanding, has transformative applications across sectors like healthcare, education, entertainment, finance, and customer service. In customer service, AI enhances personalization, optimizes customer value, and boosts satisfaction by automating and tailoring services.

Our paper investigates the Czech public's knowledge regarding AI's role in everyday functions, specifically examining responses to questions about AI's use in customer service, music recommendation, email sorting and spam filtering, health monitoring, online shopping recommendations, and smart home devices.

To elucidate the socio-demographic factors influencing respondents' general knowledge of everyday tasks performed by AI, the second part of our analysis employs binary logistic regression. This statistical technique estimates the relationship between a dichotomous dependent variable and one or more independent (explanatory) variables. Binary logistic regression is particularly suited to scenarios where both the dependent variable and the outcome variable take on only two possible values, such as 'correct' or 'incorrect' responses. In this study, we use binary logistic regression to model the probability that respondents correctly answer a majority of the questions posed in the previous chapter. Specifically, we aim to model the likelihood that respondents answer at least four out of six questions correctly, based on various socio-demographic predictors. The logistic regression model is expressed by the following equation:

$$ln\left(\frac{Pr\ (most\ questions\ correct)}{1-Pr\ (most\ questions\ correct)}\right)= \\ = \beta_0+\ \beta_1 Gender_i+\beta_2 Age_i+\beta_3 Education\ _i+ \\ +\beta_4 Monthly\ income_i+\beta_5 Marital\ status_i+\beta_6 Economic\ activity_i \tag{1}$$

where $Pr\ (most\ questions\ correct)$ denotes the probability that the respondent answered at least four out of six questions correctly, while $1-Pr\ (most\ questions\ correct)$ denotes the odds that the respondent answered less than half of the questions correctly, i.e. three and fewer questions.

Results

First, we look at the percentage of respondents who answered each question correctly. For each question, we break down the responses by gender, age and education of the respondents. For each question, the correct answer is shown in the first column. The first question aimed to find out how the respondents felt about using AI to support customer service. The question reads: Which of the following uses artificial intelligence when you think about customer service? Table 1 shows respondents' answers to the first question.

Overall, 43.1% of respondents recognize a chatbot that answers customer questions instantly as an application of artificial intelligence in customer service. This is an indication of a moderate level of awareness among the survey population. There is a slight gender difference, with 45.0% of women and 41.0% of men recognizing chatbots as using AI. The difference is relatively small. This suggests that gender may not be a significant factor in shaping perceptions in this context. Younger age groups, particularly those aged 18-34, show higher percentages of recognition (56.4% to 63.9%). With increasing age there is a gradual decrease in recognition. The lowest percentage (23.8%) is found in the oldest age group (66-99). This is an indication that younger people are more likely to associate chatbots with artificial intelligence in customer service. The higher the level of education, the greater the recognition of the chatbot as an AI application. Respondents with a university education have the highest percentage (58.1%). This is followed by those with a high school education (46.3%) and primary/secondary education (34.9%). This suggests that a better understanding of AI in customer service may be associated with higher levels of education.

The purpose of the second question was to measure respondents' knowledge of the use of AI in music playlist recommendation. The question was worded as follows: Which of the following tools use artificial intelligence to play music? Responses to the second question are shown in Table 2.

The correct answer was recommending a playlist, which was chosen by 31.6% of people, but the most common answer was "I'm not sure, I don't know", which was chosen by 44.6% of people, the highest percentage of all answers. This suggests that the use of artificial intelligence in music streaming services is not something that many people are familiar with. The other three options (using Bluetooth, wireless internet connection and playing from the selected playlist) are each chosen by less than 11% of people, suggesting that they are not considered to be using artificial intelligence to play music. Regarding the correct answers to the second question, we do not observe any gender differences. Younger respondents, especially in the 18-24 age group, are less likely to correctly associate AI with recommending a playlist. This suggests a potential gap in understanding among younger demographics. Correct identification tends to increase with age, especially up to mid-age, and then decreases. The 66-99 age group has the lowest percentage. Respondents with primary/secondary and tertiary education are more likely to correctly identify the role of AI in playing music compared to those with tertiary education. This suggests that education may be a factor in people's understanding of the specific functions of AI in technology.

In our investigation into public awareness of AI applications within email services, a specific focus was placed on recognizing AI's role in classifying emails as spam. Our findings, as summarized in Table 3, indicate that only 27.3% of respondents could accurately identify spam classification as an AI-driven function. This suggests a substantial gap in the general understanding of AI's integration into everyday email usage. Notably, a considerable portion of participants (38.5%) admitted to uncertainty or a lack of knowledge regarding AI's role in this context, underscoring the imperative for enhanced educational efforts about AI technologies. Gender disparities in recognizing AI's application in spam detection were minimal, with 51.1% of women and 48.9% of men correctly identifying the function, suggesting gender does not significantly influence AI recognition in email services. Conversely, age emerged as a more defining factor in AI recognition. Our data revealed a striking gradient in correct responses across age groups; the youngest cohort (18–24 years) exhibited the lowest level of accurate identification (7.0%), while the oldest group (66–99 years) demonstrated the highest (22.2%). This counterintuitive trend implies that older individuals may possess a more accurate understanding of AI's role in email services compared to their younger counterparts.

Educational background also influenced AI recognition, with individuals holding primary/secondary education credentials showing the highest rate of correct identification (39.1%), followed by university graduates (31.3%) and high school-educated respondents (29.6%). This finding suggests that higher formal education does not necessarily correlate with better understanding of AI applications in email services. These results highlight a critical need for broad-based educational initiatives aimed at improving public understanding of AI technologies, particularly as they become increasingly embedded in daily tools such as email services. The observed demographic variations in AI awareness, especially across different age groups and educational backgrounds, call for targeted approaches in educational programs to bridge the knowledge gap.

The survey's fourth question, the answers to which are shown in Table 4, aimed at gauging the awareness of AI's role in human health products, revealed that nearly half of the respondents (46.6%) could accurately identify fitness trackers as AI-integrated health devices. This level of awareness reflects a moderate familiarity with AI applications within the realm of health and wellness technologies among the Czech population. However, a significant portion (40.5%) expressed uncertainty or admitted to a lack of knowledge regarding which health products utilize AI, indicating a considerable gap in understanding AI's penetration into healthcare technologies. Interestingly, the analysis of responses based on gender showed that women (52.2%) were marginally more likely than men (47.8%) to correctly identify fitness trackers as AI-driven health products. Although the difference is slight, it suggests a potentially higher level of engagement or interest among women in this context, aligning with broader trends of health consciousness observed in other studies.

Age appears to be a more significant determinant of AI awareness in health products, with younger age groups (18–24, 25–34, and 35–44) showing less recognition of AI applications compared to older cohorts (45–54, 55–65, and 66–99). This trend is particularly intriguing, as it challenges common perceptions that younger individuals, typically more attuned to technological advancements, would possess greater awareness of AI applications. Instead, the highest awareness levels were noted among the 45–54 age group, suggesting that middle-aged individuals might have a better grasp of AI's practical applications in health monitoring and wellness. Educational attainment also influenced the accuracy of AI recognition in health products, with respondents holding primary/secondary education demonstrating the highest correct identification rate (39.2%). This is followed by those with high school (31.1%) and university education (29.7%), presenting a contrast to the anticipated correlation between higher education and increased technology awareness. This discrepancy could be attributed to the specific nature of AI applications in health products, which may resonate differently across educational backgrounds due to varying exposure to or interest in health and wellness technologies.

These findings demonstrate the need for targeted educational and awareness campaigns to bridge the knowledge gap regarding AI's integration into health products. The demographic variances observed suggest that such initiatives should be tailored to address the specific informational needs and preferences of different age groups and educational backgrounds, to enhance public understanding and acceptance of AI in healthcare.

The survey's fifth question, the answers to which are shown in Table 5, sought to elucidate respondents' understanding of AI's integration into online shopping practices. Notably, 37.8% of participants accurately recognized that product recommendations based on previous purchase history utilize artificial intelligence, indicating a fair level of awareness regarding AI's role in enhancing the online shopping experience. However, the relatively low percentages (ranging from 3.8% to 15.1%) for other options, such as the use of AI in storing account information, tracking previous purchase records, and analyzing product reviews, suggest a prevalent ambiguity or misunderstanding about the extent of AI's application in these areas. A significant finding is that 32.6% of respondents reported uncertainty or admitted to a lack of knowledge concerning AI's employment in online shopping mechanisms. This underscores a considerable segment of the population that remains uninformed about the ways AI can optimize and personalize the online retail experience.

Gender analysis revealed a modest difference in AI awareness, with females (51.9%) slightly more likely than males (48.1%) to correctly identify AI-driven product recommendations. Although the disparity is small, it hints at a marginally higher consciousness or engagement with AI functionalities among female shoppers. The correlation between age and AI awareness in online shopping contexts exhibited a clear trend: younger respondents (18–24 years) showed the least awareness (11.2%), whereas recognition of AI applications steadily increased with age, peaking at 21.6% among the 45–54 age group. This pattern suggests that older consumers are more attuned to the AI features embedded within online shopping platforms, possibly due to a combination of greater reliance on and familiarity with e-commerce functionalities. Contrary to expectations, respondents with primary/secondary education demonstrated the highest rate of correct identification (38.2%), surpassing those with university (33.1%) and high school (28.8%) education levels. This divergence from the age-related trend underscores the nuanced relationship between educational background and specific technological awareness, highlighting that higher formal education does not automatically translate into greater comprehension of AI applications in e-commerce. These insights reveal critical gaps in public knowledge about AI's pervasive role in online shopping and underscore the need for more explicit communication regarding AI's benefits and functionalities. Addressing these knowledge gaps through targeted educational initiatives could significantly enhance consumer understanding and acceptance of AI-driven online shopping methods.

The survey's exploration into the understanding of AI in home devices has yielded significant insights, particularly in relation to security cameras equipped with AI capabilities. Responses to the sixth question are shown in Table 6. Among the respondents, 33.8% accurately recognized an AI-enabled security camera as a home device that alerts homeowners to the presence of unknown individuals. This level of awareness indicates a reasonable familiarity with AI applications in home security among the surveyed population. However, a substantial 36.4% expressed uncertainty or admitted to a lack of knowledge concerning AI's role in home devices, suggesting a considerable gap in the general understanding of AI's integration into everyday technology. Gender differences in recognizing AI applications were minimal, with women (50.3%) slightly more likely than men (49.7%) to correctly identify the function of AI in security cameras. This marginal difference points to a broadly balanced level of awareness across genders, challenging any presumptions of significant gender disparities in technological understanding.

Age demographics revealed a more pronounced variance in AI recognition, with the youngest respondents (18–24 years) showing the least awareness at 9.7%. Conversely, older age groups demonstrated a gradual increase in correct identifications, culminating in the highest awareness among those aged 45–54 years at 19.3%. This trend suggests that older generations may possess a more developed comprehension of AI's practical applications in home security, contrary to common stereotypes of generational gaps in tech-savviness. Educational background also played a crucial role in the level of AI awareness. Respondents with primary/secondary education outperformed their counterparts, with the highest rate of correct identification at 42.9%, followed by those with high school (29.5%) and university education (27.6%). This outcome indicates that higher education does not necessarily correlate with greater awareness of AI applications in home technology, particularly in the context of security systems.

These findings show the need for targeted educational efforts to enhance the public's understanding of AI's role in home devices. Given the demographic variations in awareness, such initiatives should consider age, gender, and educational background to effectively address the knowledge gaps and misconceptions about AI technology.

A number of key trends emerged when analyzing responses to questions about AI awareness in different contexts with utilization of descriptive statistics. First, there is generally a moderate level of awareness. The level of correct identification varies across different topics. In particular, correct responses often increase with age. This suggests a potential generational gap in understanding AI applications. Gender differences are generally minimal. There is little variation in correct identification. In some cases, however, women show a slightly higher level of awareness than men. Level of education appears to have a different impact on AI awareness in different contexts. In some cases, respondents with a primary/secondary level of education show a higher level of awareness, while in others, respondents with a university level of education have a higher level of understanding. The findings highlight the need for targeted educational initiatives to bridge gaps in awareness, especially among younger demographics.

Regression analysis

The regression analysis discussed in the Research Methods chapter is detailed in Table 7. In this table, 'B' represents the coefficient estimate for each predictor variable within the logistic regression equation. Each coefficient indicates the change in the log odds of the dependent variable for a one-unit increase in the predictor, assuming all other variables are held constant. 'Exp(B)', or the exponentiation of the B coefficient, is also known as the odds ratio. This value reflects the change in odds of the outcome occurring with a one-unit change in the predictor. The 'Sig.' (Significance) column assesses the statistical significance of each predictor's coefficient, determining if the observed relationships between the predictors and the outcome variable are statistically significant. The odds ratios discussed in the text can be found under the 'Exp(B)' column of Table 7. The final model has lower Akaike information criterion and Bayesian information criterion values than the intercept-only model, suggesting that it provides a better balance between goodness of fit and model complexity. The chi-squared test, with a p-value of 0.000, indicates that the final model is a significant improvement over the intercept only model. Both the likelihood ratio test and the information criteria suggest that the final model including the predictor variables is a better fitting model than the intercept only model. The results of the regression analysis, on the basis of which we make the following interpretations, are presented in Table 7.

The intercept (-1.513) represents the estimated log odds of having fewer than four correct answers when all other variables are equal to zero. The odds ratio for the intercept is approximately 0.219. This means that when all predictor variables are equal to zero, the odds of having more than four correct answers are about 0.219 times the odds of the reference category (having fewer than four correct answers). Alternatively, we can say that the odds of the reference category (having less than four correct answers) are about 4.566 times higher than the odds of the event. This fits our data perfectly, as only 262 respondents answered most questions correctly (at least four out of six questions), or alternatively up to 774 respondents answered no more than three questions correctly. The intercept is meaningful and statistically significant, so we can assume a systematic relationship between the predictor variables and the dependent variable in the context of the study.

Gender has a significant effect on the odds of answering most questions correctly. Being male increases the odds of answering most question correctly by 1.413, compared to being female. This means that males have 41.3% higher odds of answering most questions correctly than females, holding all other variables constant.

The age of the respondent also has a significant effect on the odds of answering most questions correctly. The younger the respondent, the higher the log odds and the odds of answering most questions correctly compared to the oldest age group (65+). For example, being in the 18–24 age group increases the log odds by 2.004 and the odds by 7.417 compared to being in the 65+ age group. This means that respondents in the 18–24 age group are seven times more likely to answer most questions correctly than respondents in the 65+ age group. Similarly, for the age groups 25–34, 35–44 and 45–54, respondents in these age groups are 5, 3 and 4 times more likely to answer the majority (at least four) of questions correctly than respondents aged 66+.

Education has also a significant effect on the odds of answering most questions correctly. Having a lower level of education markedly decreases the odds of answering majority of questions correctly, compared to having a university degree. Having a primary school and secondary school education decreases the log odds by -1.329 and the odds by 0.265, compared to having a university degree. This means that respondents with a primary school and secondary school education have 73.5% lower odds of answering at least four questions correctly than respondents with a university degree. Alike, individuals with high school have 52.8% lower odd of answering majority of questions correctly when compared to respondents with university degree.

Monthly income has a significant effect on the odds of answering the majority of questions correctly. Having a monthly income of less than 1000 EUR decreases the odds by 0.558, compared to having a monthly income of 1000 EUR or more. This means that respondents with a monthly income that is inferior to 1000 EUR have 44.2% lower odds of answering the majority of questions correctly as compared to respondents with a monthly income of 1000 EUR or more.

Family status has equally a significant effect on the odds of answering most questions correctly. Being married, widowed, or divorced decreases the odds of answering the majority of questions correctly, compared to being single. For example, being widowed decreases the log odds by -1.592 and the odds by 0.203, compared to being single. This means that respondents who are widowed have 79.7% lower odds of answering most questions correctly than respondents who are single. In case of divorced ones, this odd is by 57.1% smaller and in case of married ones or ones that live with partner this odd is by 34.6% smaller compared to respondents that ae single.

Also, economic activity variable has a significant effect on the odds of answering majority of questions correctly. Respondents who are employees in a management position have 104.2% higher odds of answering most questions correctly than respondents who are economically not active, holding all other variables constant. The other categories of economic activity (employee with no subordinates and self-employed and entrepreneur) are not significantly different from the reference category.

Discussion

Through our analysis, we unearthed a spectrum of findings that elucidate the public's perception and attitudes toward the integration of artificial intelligence (AI) in various facets of social and professional life. Crucially, without a clear understanding of these perceptions and attitudes, the development of comprehensive AI literacy frameworks remains elusive. We observed that a moderate 43.1% of respondents could identify the use of chatbots in customer service as an application of AI, with a marginally higher awareness noted among women. This demographic detail is significant, suggesting nuanced gender differences in AI recognition. The analysis revealed a pronounced awareness among younger age groups, peaking at 63.9% within the 25–34 age bracket. This trend is particularly noteworthy, indicating a generational divide in AI literacy that merits further exploration. Educational attainment emerged as a key factor in AI awareness; notably, respondents with university-level education exhibited the greatest awareness at 58.1% (Majumder & Mondal, 2021; Wang *et al.,* 2023a).

The role of chatbots extends beyond mere customer interaction; they are pivotal in refining the customer care ecosystem. By discerning user needs, desires, and emotions, chatbots enhance the efficiency of human agents, not by replacing them but by streamlining the processing of preliminary tasks before escalation (Majumder & Mondal, 2021; Wang *et al.,* 2023b). Nirala *et al.* (2022) corroborate the potential of AI chatbot systems in public administration, emphasizing their capacity for improved service management — a sentiment echoed by findings from the Pew Research Center (2023). The human-like attributes of chatbots, while less critical than their functional efficiency (Følstad *et al*., 2019), play a subtle yet impactful role in shaping user experiences, underscoring the importance of both assistance quality and information content over the chatbot's appearance.

In the context of AI applications in music streaming, our findings reveal a gap in public awareness, with 44.6% of respondents unfamiliar with AI's role and only 31.6% accurately identifying AI-driven playlist recommendations. This gap is especially pronounced among younger respondents (18–24), suggesting an educational opportunity to bridge this awareness divide. The correlation between increased awareness with age and higher education levels aligns with existing literature, highlighting the rich research potential in this domain. Studies by Prey (2018) and Afchar *et al.* (2022) emphasize the influence of listener context on music preferences, further supported by Ferwerda *et al*. (2015), who note the significant impact of mood, location, and social situations on musical needs. Sequential recommendation tasks play a crucial role in the consumption of music, facilitated by the automatic generation of playlists (Zamani *et al.,* 2019). Consumption characteristics, according to Hyunsuk and Jung (2016), dictate the modes of music consumption, with trends in streaming, physical purchases (Sinclair & Tinson, 2017), downloading, and piracy reflecting diverse consumer preferences. However, limitations in streaming services, as discussed by Morris and Powers (2015), highlight challenges in providing uniform access to content across various user scenarios (Pew Research Center, 2023). Despite the extensive research, the absence of gender and age differentiation in many studies underscores the significance of our findings, advocating for the inclusion of these demographic factors in future research efforts.

In terms of the role of AI in email, we find that only 27.3% of respondents correctly associate the classification of email spam with AI, highlighting a significant lack of awareness. Challenging assumptions about tech-savviness, younger age groups, particularly 18–24 year olds, show the lowest correct responses. Primary and secondary education levels show the highest correct identification (39.1%). This highlights the educational impact. One of the optimal solutions to this problem at the moment can be the introduction of the use of chatbots. This is confirmed by the study by Abdelhamid *et al.* (2023). The authors consider the use of chatbots as social collaborative agents for the protection of users against the various cybernetic attacks, while their role is also to provide answers and advice in the various threat situations. They propose a multi-layered extensible chatbot system. They explore the benefits of integrating chatbots with social network analysis for better cybersecurity and risk assessment. Kadena and Gupi (2021) state that most security problems and malicious mail are caused by human error. This is due to lack of awareness of security threats. It is also due to failure to follow instructions and poorly secured local facilities.

Additional risk dimensions arise from the use of AI, which is also associated with algorithmic personalization and the collection of personal data. People's opposition to the collection and use of sensitive personal data and the personalization of political campaigns is confirmed by Kozyreva *et al.* (2021). However, Kozyreva *et al.* (2021) suggest that attitudes towards personalization are independent of political preferences, as people across the political spectrum share the same concerns about their privacy. The provision of personalized services is often rated as more acceptable than the collection of personal data or information. Therefore, many studies argue for transparent algorithmic personalization that minimizes the use of personal data and thus respects people's preferences in personalization that is easily customizable and does not apply to political advertising. When it comes to AI in human health products, a relatively high 46.6% correctly identify fitness trackers as AI-driven health products. This suggests a reasonable level of awareness. A significant 40.5% express uncertainty, suggesting a need for more education about AI applications in health. There are notable gender and age differences. Women and older age groups show higher awareness.

The applicability of these results is also important for different groups of the population that are socially distinguished. For example, AI applications can improve the health of marginalized communities and bridge the gap between unequal access to healthcare from a geographical point of view (Okolo *et al*., 2021). Some studies also confirm improvements in health outcomes for seniors in communities (Wilmink *et al.,* 2020). However, even among young people of university age, an improvement in health status has been confirmed when using smart applications (Námesztovszki *et al*., 2020; Kinney *et al*., 2019). There is also a preventive role for fitness trackers. By increasing physical activity, they can reduce the risk of diseases such as diabetes, obesity, hypertension, etc. Vooris *et al*. (2019) investigated consumers' motivations for purchasing wearable fitness trackers and how they use them. Wearable technologies, which can be integrated into clothing or accessories worn on the body, have grown exponentially in recent years. By 2020 (Lamkin, 2016), it is estimated that 411 million wearable devices will be sold worldwide. Many of these applications sync with a smartphone (Bessant, 2016). Steinert *et al* (2018) report that tracking devices are predominantly used by younger adults, with only 16% of owners being between the ages of 55 and 64, and only 7% of owners being over the age of 65. Sarkar and Chakrabarti (2022) consider wearable fitness trackers to be a preventive mechanism for healthy lifestyles and for reducing vulnerability in old age. As the population ages, we can expect to see more widespread use of wearable trackers across the different demographics, as well as their growing importance in the preventive mechanisms of countries' healthcare systems.

Regarding AI in online shopping methods, 37.8% of respondents correctly identify product recommendations based on previous purchases as an AI-driven online shopping method. A significant 32.6% of people expressed uncertainty. This highlights potential gaps in understanding. Women slightly outperform men, and correct identification increases with age and education level. It is expected that with increasing digitization and higher internet usage across all demographics, these findings will change significantly. The previous studies have already captured this trend and the motivational aspects, such as Lian and Yen (2014), who noted an increasing use of the Internet by the elderly and the associated higher preference of the elderly to shop online. According to the authors, the main factors that lead older people to shop online are performance expectations and social influence. These are the same as for the younger population. Value, risk, and tradition are considered to be different barriers to online shopping for older people than for younger people.

For older people (Lian & Yen, 2014), no gender differences were found in the parameters studied. Differences in purchasing behavior due to experience were the focus of Hernández *et al*. (2011). The authors analyzed the extent to which individuals' socio-economic characteristics (age, gender, income) influence their shopping behavior. The respondents were experienced e-shoppers. The results of the analyses confirmed: Socio-economic variables do not influence the behavior of an experienced e-shopper. This means that the behavior of individuals does not differ according to their socio-economic characteristics once they have reached the status of an experienced e-shopper. The results of the Pew Research Center survey (Pew Research Center, 2023) also support such an approach. The importance of age as a determinant of differentiated online shopping behavior has been identified by many authors. For example, Sramova and Pavelka (2019) point to a different motivational structure on the basis of utilitarian and hedonic values in relation to the online shopping behavior of adolescents in relation to their gender. Male adolescents were shown to have a higher rate of utilitarian values related to online shopping. Similarly, the reasons and forms of using shopping channels, as well as their preferences and motivations in relation to age, were investigated by Boardman and McCormick (2018). According to their findings, multichannel shopping behavior gradually increases with age. Younger consumers in their 20s do not participate at all.

When it comes to AI in home devices, a third of the respondents correctly identify AI-powered security cameras, while a significant 36.4% are unsure about the role of AI in home devices. There is a notable age-related pattern: The youngest age group has the lowest number of correct responses. There is a surprising trend in the impact of education, with primary/secondary education level showing the highest correct identification.

Logistic regression shows that the likelihood of respondents answering the majority of questions correctly is significantly influenced by a number of demographic and socio-economic factors. For example, gender, age, education, monthly income, marital status and economic activity all play a distinct role in predicting performance on the questions. This provides valuable insights for understanding the determinants of correct answers in the given context. Regression analysis shows that the odds ratio for the intercept is about 0.219. This means that the odds of getting more than four correct answers are about 0.219 times the odds of getting less than four correct answers. Gender is a statistically significant predictor of question performance: Being male increases the odds of getting most questions correct by 41.3% compared to being female. Compared to the oldest age group (65+), younger respondents are more likely to answer most questions correctly. A lower level of education significantly reduces the odds of answering most questions correctly, in comparison with the possession of a university degree. Monthly income below 1000 EUR decreases the odds of answering most questions correctly by 44.2% compared to monthly income of 1000 EUR or more. Being married, widowed or divorced is associated decreases the odds of answering most questions correctly compared to being single. Compared to the economically inactive, respondents in a managerial position are 104.2% more likely to answer most questions correctly.

Ensuring that networked and personal information is secure is going to be important. Therefore, it is also necessary to address the issue of legal protection in relation to the development of online platforms, as laws and regulations are significantly lagging behind the development of e-commerce transactions. The results of many studies call for the improvement of the legal system in online shopping processes. This would take into account the strong technological progress in online shopping (Yan & Zhang, 2022). The reliance on AI technology and the need for an ever-increasing amount of customer data can create trust issues between customers, as Dwivedi *et al.* (2019) point out. As a number of studies confirm, it is essential to understand the impact of these and other issues in relation to the AI experience (Bharti *et al.*, 2023; Kushwaha *et al.*, 2021; Tamilmani *et al.*, 2021; Xiong, 2022).

Conclusions

The comprehensive survey conducted to evaluate public awareness of AI applications across various sectors unveils critical insights into the existing levels of AI literacy among different demographics. The findings from descriptive statistics illustrate a moderate awareness of chatbots in customer service, with younger individuals and those possessing higher education demonstrating greater familiarity. Gender differences in this context were minimal. Conversely, a significant knowledge gap was identified in AI's role in music playlist recommendation, particularly among younger demographics, indicating a potential area for educational enhancement. Similarly, in email services, the lack of awareness was pronounced among younger respondents, while older demographics exhibited a more robust understanding, revealing an unexpected generational divide in AI literacy. In the health sector, fitness trackers as AI-driven health products were widely recognized, especially among older age groups, suggesting varied levels of awareness based on age. Regarding online shopping methods, while there was a reasonable recognition of AI in product recommendations, understanding of AI's broader applications remained limited, with many expressing uncertainties. The domain of home devices using AI, notably security cameras, saw better awareness, yet significant uncertainty persisted among respondents. Education level emerged as a significant factor, with those having primary/secondary education displaying higher awareness across the board.

Regression analysis further elucidated the demographic and socioeconomic factors influencing the ability to accurately respond to questions about AI's everyday applications. Notably, men were more likely than women to answer correctly, and younger age groups outperformed the oldest cohorts. Education level significantly affected the likelihood of accurate responses, with lower education correlating with diminished odds of correct answers. Additionally, lower monthly income and certain marital statuses adversely affected the odds of answering correctly, while being in a managerial position substantially increased these odds. These findings highlight the complex interplay of factors affecting AI literacy and underscore the necessity of considering a broad spectrum of demographic and socioeconomic variables in evaluating AI understanding.

A limitation of our study is the potential for respondents to misunderstand some of the questions on the questionnaire. Given that AI is a relatively new and complex field, it is understandable that different age categories may not be equally familiar with it. This variation in familiarity could significantly influence the responses provided. Additionally, the AI literacy of the Czech population has not been extensively studied, which adds another layer of complexity to interpreting our findings. To address these challenges, our future research will focus on scrutinizing the determinants that influence AI literacy among the Czech population. By understanding these factors, we aim to better assess the risk level associated with potential misunderstandings of AI perception across different demographic groups.

This study's outcomes are pivotal for developing a comprehensive AI literacy framework that integrates information, digital, media, and health literacy. By pinpointing the determinants of AI perception across life's various domains and identifying potential security risks associated with AI usage, the research lays the groundwork for establishing benchmarking indicators. These indicators are crucial for national and international comparative analyses, essential for constructing effective literacy systems amidst the challenges posed by globalization and its associated risks.

The findings of this study carry significant political and practical implications.

Political implications

Despite rapid technological advancements, significant variations remain in how different individuals perceive the relevance of AI. These perceptions influence decision-making processes in both professional and private contexts. Our study sheds light on the crucial need to further explore how various population groups understand the daily tasks that AI can perform. As new technologies evolve, they often bring concerns about potential risks, including cybersecurity threats and the impact of misinformation, fears of fraud, and misuse. It is essential to investigate the extent of population differences in the perception of everyday AI tasks, explore strategies for mitigating these differences, and identify both the knowledge and recognition of the potential benefits that AI tools and technologies offer for individual and societal advancement. While we anticipate a narrowing of age-related disparities in digital literacy, factors such as attitudes toward technology, educational background, employment type, and views on the future of technological development will continue to play significant roles. Accordingly, this knowledge enables the development not only of comprehensive digital literacy frameworks — including AI, algorithmic, and information literacy — but also supports the formulation of active educational, labor market, social, economic, and environmental policies. The findings of our study are invaluable for policymakers, enhancing the development of benchmarking indicators crucial for assessing the effectiveness of these policies. Additionally, our results underscore the urgent need for systematic research in this domain at an individual level, necessitating access to more detailed data and the support of relevant governmental and non-governmental institutions.

Practical implications

Our study highlights the imperative for ongoing monitoring of how the population perceives technological development, the rapid dissemination of knowledge, and the integration of technological processes and tools into everyday life. While AI impacts nearly all aspects of daily life, its adoption varies widely. In different life domains, these technologies can have distinct roles, and contrary to common assumptions, older age does not necessarily correlate with lower technological acceptance. Current frameworks that examine the phases of AI adoption across various demographic structures do so in a very limited scope, influenced by socio-demographic factors and socio-political constructs. This limited perspective may contribute to the insufficient progress in AI utilization, resulting in notable disparities between countries. A significant role could be played by various associations, enterprises, and institutions in providing economically accessible training in cybersecurity, the use of various applications (such as those monitoring location, health, and activity), and their effects on enhancing quality of life. While the quality of life concepts has evolved over decades, their connection to everyday technology use remains underexplored.

Intergenerational and generational experience sharing could also prove significant. Furthermore, it is crucial to investigate technological availability and the impact of technological gaps on population digital literacy. The 2022 resolution of the European Parliament (2022) highlights the profound social differences caused by digitization and the need to make technology accessible to older generations through tailored programs and initiatives. However, the issue of digital deprivation also severely affects children, particularly those in poverty or material need lacking internet access. The disparities in digitalization rates and technological development across European Union member states are creating socio-economic divides, requiring investment and infrastructure enhancements. International institutions are advocating for a detailed examination of population needs concerning digital development and innovation, especially for vulnerable groups, to gauge the level of new technology usage. It is essential to identify barriers preventing these groups, including the elderly, less educated, individuals with learning disabilities, and low-income earners, from fully participating in electronic services like banking and administrative services. Without intervention, these populations risk social exclusion and loss of economic opportunities. Each country should support solutions that enable all groups to adapt swiftly and effectively to digitalization, ensuring that digital transformation within the European Union benefits everyone.

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Annex

Table 1. Which of the following uses artificial intelligence when you think about customer service?

		Which of the following uses artificial intelligence when you think about customer service?				
		Chatbot that instantly answers customer questions (%)	An online questionnaire sent to customers to allow them to provide feedback (%)	Contact page with a form available for customers to provide feedback (%)	Detailed website with frequently asked questions (%)	I'm not sure, I don't know (%)
Overall		**43.1**	**12.1**	**9.7**	**6.9**	**28.1**
Gender	Male	41.0	11.6	11.9	7.1	28.5
	Female	45.0	12.5	7.9	6.8	27.9
Age	18 - 24	56.4	11.5	10.3	7.7	14.1
	25 - 34	63.9	12.0	6.8	4.5	12.8
	35 - 44	49.4	11.9	11.9	6.9	20.0
	45 - 54	48.0	14.7	6.9	7.8	22.5
	55 - 65	41.3	9.8	9.2	9.2	30.4
	66 - 99	23.8	12.1	12.1	5.7	46.5
Education	Primary/Secondary	34.9	12.1	9.8	6.9	36.3
	High school	46.3	13.8	9.1	6.7	24.2
	University	58.1	9.9	10.4	7.2	14.4

Table 2. Which of the following tools use artificial intelligence to play music?

		Which of the following tools use artificial intelligence to play music?				
		Recommending a playlist to be played (%)	Using Bluetooth to connect to wireless speakers (%)	Wireless internet connection to stream music (%)	Playing from the selected playlist (%)	I'm not sure, I don't know (%)
Overall		**31.6**	**5.3**	**8.5**	**10.1**	**44.6**
Gender	Male	50.8	47.3	51.1	55.2	39.9
	Female	49.2	52.7	48.9	44.8	60.1
Age interval	18 - 24	12.8	5.5	10.2	1.9	4.7
	25 - 34	21.9	7.3	11.4	7.6	8.4
	35 - 44	19.8	16.4	18.2	16.2	11.4
	45 - 54	21.0	30.9	19.3	20.0	17.2
	55 - 65	13.4	14.5	18.2	24.8	19.4
	66 - 99	11.2	25.5	22.7	29.5	38.8
Education	Primary/ Secondary	36.5	61.8	48.9	52.4	58.0
	High school	28.6	27.3	30.7	28.6	28.4
	University	35.0	10.9	20.5	19.0	13.6

Table 3. Which of the following uses of e-mail make use of artificial intelligence?

		Which of the following uses of e-mail make use of artificial intelligence?				
		Email service that classifies email as spam (%)	Email service that marks email as read after a user opens it (%)	Email service that allows a user to schedule an email to be sent at a specific time in the future (%)	Email service that sorts emails by time and date (%)	I'm not sure, I don't know (%)
Overall		**27.3**	**8.2**	**15.3**	**10.8**	**38.5**
Gender	Male	48.9	34.1	44.7	51.8	45.9
	Female	51.1	65.9	55.3	48.2	54.1
Age interval	18 - 24	7.0	10.6	14.5	10.7	3.5
	25 - 34	18.0	4.7	17.0	13.4	9.0
	35 - 44	15.8	15.3	17.0	17.9	13.7
	45 - 54	21.5	17.6	22.0	19.6	17.7
	55 - 65	15.5	20.0	11.9	16.1	21.4
	66 - 99	22.2	31.8	17.6	22.3	34.7
Education	Primary /Secondary	39.1	51.8	40.9	57.1	59.1
	High school	29.6	28.2	37.1	29.5	24.4
	University	31.3	20.0	22.0	13.4	16.5

Table 4. Which of the following human health products has the use of artificial intelligence?

		Which of the following human health products has the use of artificial intelligence?				
		Fitness trackers that analyse the movement and sleeping habits of users (%)	Digital thermometers that are placed at the base of the tongue to measure fever (%)	Home tests for the detection of the COVID-19 (%)	Pulse oximeters that measure the level of oxygen in a person's blood (%)	I'm not sure, I don't know (%)
Overall		**46.6**	**3.1**	**3.0**	**6.8**	**40.5**
Gender	Male	47.8	53.1	35.5	52.1	43.6
	Female	52.2	46.9	64.5	47.9	56.4
Age interval	18 - 24	10.3	12.5	9.7	12.7	2.8
	25 - 34	16.1	3.1	16.1	15.5	9.0
	35 - 44	18.1	18.8	16.1	12.7	12.3
	45 - 54	22.5	21.9	19.4	14.1	17.1
	55 - 65	13.2	25.0	16.1	15.5	22.7
	66 - 99	19.8	18.8	22.6	29.6	36.0
Education	Primary/ Secondary	39.2	59.4	67.7	46.5	61.1
	High school	31.1	37.5	16.1	29.6	25.8
	University	29.7	3.1	16.1	23.9	13.0

Table 5. Which of the following methods of online shopping use artificial intelligence?

		Which of the following online shopping methods uses artificial intelligence?				
		Product recommendations based on previous purchases (%)	Storing account information, such as shipping addresses (%)	Previous purchase records (%)	Product reviews from other customers (%)	I'm not sure, I don't know (%)
Overall		**37.8**	**15.1**	**10.8**	**3.8**	**32.6**
Gender	Male	48.1	45.9	42.0	42.5	46.0
	Female	51.9	54.1	58.0	57.5	54.0
Age interval	18 - 24	11.2	5.1	8.9	12.5	3.2
	25 - 34	15.5	10.2	15.2	10.0	10.3
	35 - 44	19.1	12.1	16.1	12.5	12.7
	45 - 54	21.6	18.5	18.8	25.0	17.4
	55 - 65	14.2	19.7	15.2	10.0	22.4
	66 - 99	18.3	34.4	25.9	30.0	33.9
Education	Primary/Secondary	38.2	58.0	46.4	65.0	59.6
	High school	28.8	29.3	36.6	20.0	26.5
	University	33.1	12.7	17.0	15.0	13.9

Table 6. Which of the following home devices use artificial intelligence?

		Which of the following home devices use artificial intelligence?				
		A security camera that sends an alert when an unknown person appears at the door (%)	Setting the home thermostat to change the room temperature at a certain time (%)	Setting a timer that controls when lights turn on and off in the home (%)	Indicator light that turns red when the water filter needs to be replaced (%)	I'm not sure, I don't know (%)
Overall		**33.8**	**10.0**	**14.4**	**5.4**	**36.4**
Gender	Male	49.7	47.1	42.7	39.3	45.1
	Female	50.3	52.9	57.3	60.7	54.9
Age interval	18 - 24	9.7	9.6	11.3	3.6	4.0
	25 - 34	17.6	8.7	13.3	16.1	8.7
	35 - 44	18.2	14.4	12.7	26.8	12.4
	45 - 54	19.3	18.3	26.0	14.3	18.5
	55 - 65	16.5	16.3	18.7	12.5	19.5
	66 - 99	18.8	32.7	18.0	26.8	36.9
Education	Primary/ Secondary	42.9	50.0	44.0	60.7	57.5
	high school	29.5	26.9	30.7	28.6	27.4
	university	27.6	23.1	25.3	10.7	15.0

Table 7. Regression analysis

Answered majority of questions correctly [a]	B	Std. Error	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
					Lower Bound	Upper Bound
Intercept	-1.513	.252	.000	0.219	0.134	0.358
Gender						
Male	.346	.154	.025	1.413	1.045	1.911
Female	0[b]	.	.	.	.	.
Age						
18 - 24	2.004	.314	.000	7.417	4.005	13.736
25 - 34	1.760	.276	.000	5.810	3.385	9.974
35 - 44	1.179	.275	.000	3.252	1.898	5.573
45 - 54	1.417	.258	.000	4.125	2.487	6.841
55 - 65	.650	.284	.022	1.916	1.097	3.346
66+	0[b]	.	.	.	.	.
Education						
Primary and secondary school	-1.329	.192	.000	.265	.182	.385
High school	-.739	.203	.000	.478	.321	.711
University	0[b]	.	.	.	.	.
Monthly Income						
<1000 EUR	-.584	.176	.001	.558	.395	.788
1000+ EUR	0[b]	.	.	.	.	.
Family status						
Married, partnership, registered partnership	-.425	.177	.016	.654	.463	.924
Widowed	-1.592	.549	.004	.203	.069	.597
Divorced	-.846	.260	.001	.429	.258	.714
Single	0[b]	.	.	.	.	.
Economic activity						
Employee with no subordinates	.253	.202	.211	1.288	.867	1.914
Employee - management position	.714	.248	.004	2.042	1.257	3.318
Self-employed and entrepreneur	.165	.323	.609	1.179	.626	2.221
Economically not active	0[b]	.	.	.	.	.

a. The reference category is: did not answer the majority of questions correctly.

b. This parameter is set to zero because it is a reference variant.