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Challenges and Opportunities of AI in Market Research: Virtual Interviewers

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Abstract
Purpose – This study explores the integration of artificial intelligence (AI) into marketing research, focusing specifically on the acceptance and perceptions of AI-based virtual interviewers. It examines respondents' willingness to engage with AI-driven survey tools, analyzing perceived advantages and concerns, while identifying key demographic and attitudinal drivers influencing acceptance.
Design/methodology/approach – A representative survey of 1,077 adult respondents in Hungary was conducted using the Computer-Assisted Telephone Interviewing (CATI) method. The sample was weighted by gender, age, education, settlement type, and region. Statistical analyses included z-tests, ANOVA, factor analysis, and cluster analysis to assess demographic and experiential factors influencing AI perceptions and to segment respondents into attitude-based clusters.
Findings – The Hungarian population shows general hesitance toward AI-based interviewers. While 46% of AI adopters expressed willingness to engage with a virtual interviewer, only 11% of AI rejecters reported the same. Experience with AI tools, such as chatbots or virtual assistants, significantly increases openness. Two factors influenced willingness to respond: perceived benefits (e.g., speed, curiosity) and perceived risks (e.g., job loss, data privacy). Cluster analysis identified three segments: Open Sceptics, Technology Sceptics, and Technology Friends, differentiated by age, gender, technological experience, and attitudes toward AI.
Originality – This is one of the early empirical studies investigating public acceptance of AI-based virtual interviewers in the context of marketing research. It provides actionable insights for researchers and practitioners into how technological experience, demographic factors, and emotional responses influence acceptance. The study also offers practical recommendations for implementing hybrid survey models and segment-specific communication strategies to foster greater engagement with AI-driven research tools.

Keywords: artificial intelligence, market research, responsiveness, survey

1. Introduction

Over recent decades, it has become evident that data play a crucial role in corporate success (Awan et al., 2021; Sundström, 2019). Accurate and reliable data facilitate more informed and effective decision-making (Awan et al., 2021), foster innovation, and enhance competitiveness (Sundström, 2019). Conversely, poor or incomplete data can lead to suboptimal decisions, potentially damaging a company's performance and long-term prospects (Fehrenbacher et al., 2023; Goknil et al., 2023). Therefore, reliable and accurate data are essential in strategy development, enabling companies to adapt to shifting market conditions and competitive pressures (Mahendra et al., 2022; Zedginidze & Berikashvili, 2023). They also play a vital role in process optimization (Davenport & Harris, 2007) and innovation and R&D activities (West & Bogers, 2014). The significance of data-driven decision-making is undeniable, regardless of the industry. Despite the vast amounts of information available (Thakur & Kushwaha, 2023) and the continuous accumulation of data, only a few are actively utilized (e.g., Mustak et al., 2021). Artificial intelligence (AI) is becoming increasingly pivotal in helping companies use such data.

This study aims to explore artificial intelligence (AI)'s impact on marketing research, focusing on practical applications. We provide an overview of currently available tools and discuss their potential uses. In our primary research, we examined the attitudes of the Hungarian population toward AI, paying particular

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attention to how respondents would react to being surveyed by an AI-based robot instead of a human interviewer. The Computer-Assisted Telephone Interviewing (CATI) survey was conducted in June 2024 with 1,077 respondents. The sample is representative of the adult Hungarian population by gender, age, education, settlement type, and region.
The structure of the paper is as follows: After reviewing the relevant literature and practical applications and outlining the methodology, we present the results of our primary research. Our findings summarize the main advantages and disadvantages of using AI, especially AI-based interviewers, in marketing research.

2. Literature review and practical solutions

In addition to the growing importance of data-driven decision-making, artificial intelligence (AI) is increasingly transforming various fields, including marketing research (Brynjolfsson & McAfee, 2017). Technological developments support new approaches and methods that improve our understanding of consumer behavior and preferences. These innovations can help make more efficient use of data and information. AI-based systems, especially those that rely on big data, as seen in marketing more broadly (Simay et al., 2021), have the potential to improve customer service in marketing research and provide a more engaging experience for respondents.

One of the main challenges in the industry is staying innovative while keeping up with rapid technological change. George et al. (2024) noted that traditional market research methods may be less effective in this fast-evolving environment. For smaller research organizations or academic institutions, limited programming knowledge and a lack of resources can present serious difficulties. In addition, concerns about data security remain common in the field.

The next section presents current solutions for using AI in marketing research. We also summarize the use of AI agents in other sectors and offer insights from their practical applications.

2.1 AI in marketing research

Many academic articles explore the relationship between marketing and artificial intelligence (AI), with some addressing marketing research; however, few focus specifically on this topic. A central aspect of AI's role in marketing is the personalization and automation of big data analytics (Huang & Rust, 2020). Jarek and Mazurek (2019) found that AI functions such as image recognition and generation, text creation, and decision-making are commonly used in marketing. Applications include personalization (e.g., products, campaigns, recommendations, pricing), dynamic pricing, data collection, data analysis, and predictive analytics to forecast trends and consumer behavior. AI is also used in customer service, especially chatbots, virtual assistants, and content generation (Davenport et al., 2019; Huang & Rust, 2020; Jarek & Mazurek, 2019).
Beyond analytics and forecasting, a few studies examine AI's potential in marketing research. For example, Danyi et al. (2020) highlight the application of sentiment analysis and netnography in tourism research, while Szűcs et al. (2023) discuss AI's role in avatar-based interviews and automated surveys.
We used the framework developed by Huang and Rust (2020) to explore how artificial intelligence (AI) can be applied in marketing research. This model organizes AI applications into three levels: mechanical, understanding, and sentient tasks. Mechanical-level AI performs simple, routine, and algorithm-based tasks that follow predefined rules (Huang & Rust, 2020). Examples include generating questionnaires, translating them into other languages, testing them using automated responses, collecting data (e.g., online surveys or IoT devices), and visualizing data. AR/VR technologies may also gather behavioral data in virtual stores, conduct product and prototype tests, or evaluate packaging.

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At the understanding level, more advanced AI can recognize and analyze context, provide appropriate responses, and make decisions. According to Huang and Rust (2020), AI at this level can interpret real-time data and interact meaningfully with human communication. Applications include consumer segmentation, forecasting market trends and consumer behavior, and collecting data via chatbots.

For sentient-level AI, Huang and Rust (2020) point out that it can recognize and respond to human emotions and interact with a degree of emotional sensitivity. Sentiment-based AI is especially suited for emotionally nuanced tasks. Marketing research might include managing customer interactions, developing empathetic chatbots, or analyzing emotional responses. We believe such capabilities could be useful during questionnaire-based data collection, for example, by detecting when a respondent is fatigued, disengaged, or ready to stop.

Some concrete examples of AI applications in marketing research are presented below, each corresponding to different levels of AI. For instance, Pollfish (2024) and SurveyMonkey (2024) offer questionnaire design tools to generate a full survey outline within seconds based on a brief input. The questions can then be adjusted to meet specific needs. Some platforms also provide functions such as generating test responses for debugging or refining questionnaires. The Indeemo online platform (2024) enables observational and ethnographic studies using AI, allowing researchers to analyze video, image, and text-based content. Similarly, AudEERING's (2024) AI-based tools can interpret human voice and mood, offering insights into consumers' emotional reactions that may be relevant for marketing research.

A common feature of these tools is that they still depend on consumer input. However, some emerging solutions no longer require direct consumer interaction, relying instead on previous research data to conduct analyses and make predictions. One example is Kantar's LINK AI creative testing solution (2024), which evaluates TV and digital advertisements in about 15 minutes and produces a heat map and key performance indicators. Another example is Hell Energy AI's sensory testing process (2024), which uses e-nose and e-mouth technologies to simulate taste and smell testing based on prior data, removing the need for human participants (Storeinsider, 2024).

Soul Machines (2024) offers virtual avatars capable of real-time conversation using AI. These avatars produce natural-sounding speech and interact with users through facial expressions and emotional responses. Within the Soul Machines interface, a virtual interviewer can administer a Google Forms questionnaire by asking questions and reacting to answers. Additionally, experiments are underway to replace human respondents in interview scenarios with AI-based synthetic respondents, as Arora et al. (2025) demonstrated. These examples show that integrating AI into marketing research is already in progress and presents several potential benefits.

The use of AI in marketing research brings advantages and disadvantages, some of which are already apparent. AI improves efficiency, reducing both time and cost (Mirwan et al., 2023; Szűcs et al., 2023), and it is particularly effective in analyzing large datasets (Chintalapati & Pandey, 2021). It can process vast amounts of data that would be difficult for humans to handle, identifying correlations and patterns researchers might not notice (Mustak et al., 2021). AI improves quality and accuracy by supporting questionnaire testing, data cleaning, and respondent authentication.

Further progress is expected in enhancing the respondent experience, particularly through personalization and emotionally responsive AI. However, challenges remain. Ethical concerns, such as potential job losses and privacy risks, are widely discussed (Davenport et al., 2019). Moreover, while AI can detect subtle patterns beyond human capacity, this strength makes it difficult to identify and correct errors when they occur (Ma & Sun, 2020). Although AI is increasingly capable of simulating emotional responses, it still lacks intuition, raising questions about its limitations. There are also concerns that the widespread use of AI may diminish the role of individual opinions, creativity, and unique perspectives.

Researchers and practitioners should consider several practical factors to support the successful implementation of AI-based virtual interviewers. First, applying hybrid models in which AI tools assist may be useful, but they do not fully replace human interviewers. These models combine the efficiency of AI with the empathy and adaptability of human interaction. Second, audience segmentation may be important

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when introducing AI tools to diverse populations. Adapting the design and communication of virtual interviewer systems to suit different demographic groups could improve user acceptance and engagement, especially among individuals with less digital experience.

2.2 AI in other fields

Beyond marketing research, AI has a range of applications, many of which focus on capturing the voice of the customer and incorporating it into organizational practices across sectors.

In higher education, AI is becoming increasingly common, changing the roles of both students and teachers (Ali et al., 2021; Blau & Shamir-Inbal, 2018; Niemi, 2020). On the one hand, AI contributes to the development of teaching staff and course content. On the other hand, with appropriate preparation and support, AI services can improve the efficiency and productivity of educational processes (Liu et al., 2022). One of the main areas where AI is being applied is through AI-based chatbots (Dempere et al., 2023; Neuman et al., 2023; Rudolph et al., 2023). Despite their potential, the broad use of chatbots and similar tools—whether in individual courses or at the institutional level—has yet to become standard practice (Topol, 2020). These tools can help students prepare for exams, replace frequently asked questions, assist with administrative tasks, conduct exams, or collect feedback.

Another significant application of AI in the healthcare sector is in back-office services. It is commonly used to organize and analyze patient data, gather feedback, and educate patients and their families, often through chatbot interfaces. Some of the most frequent uses are in radiology (diagnostic imaging) and ophthalmology, where AI tools pre-evaluate images and generate preliminary diagnostic descriptions (Kulkov, 2023). AI is also applied to evaluate risk factors for patients with multiple health conditions or injuries, helping to inform suitable treatment plans (Topol, 2019). According to Megaro (2023), AI holds the potential to support the development of a more patient-centered, adaptive, and responsive healthcare system, with data-driven decision support playing a key role. These systems can accelerate various processes and help make diagnosis, treatment, and therapy more tailored to individual needs (Kulkov, 2023). Still, as Megaro (2023) notes, patients continue to rely on doctors and clinical staff, as trust in AI remains limited. However, signs of growing acceptance, such as the rising popularity of telemedicine, are beginning to emerge.

AI is also being integrated into human resources processes. Advances in technology have intensified competition among organizations to attract high-performing employees, which is often central to operational success (Arora & Mittal, 2024). AI can assist in screening candidates by applying algorithms to match qualifications, support training systems, and enhance performance evaluations. According to Sattu et al. (2024), AI also improves the candidate experience by refining the metrics used in recruitment and accelerating the selection process.

Analyzing financial and behavioral habits to create personalized offers is particularly important in banking and finance. This approach can reduce the limitations of traditional financial channels and lower the cost of information gathering (Shao et al., 2021). AI-enabled FinTech solutions may also support environmentally responsible investments by making the identification of sustainable opportunities more accessible and accurate. As Nair et al. (2024) observe, AI-based personal finance tools can guide individuals and organizations toward more sustainable financial practices, such as green investments, energy-efficient consumption, and socially responsible banking.

Across a range of sectors, AI is now applied to tasks such as customer service, automating data collection, analyzing and visualizing feedback (from customers, employees, or the public—for instance, in political elections), delivering information (e.g., FAQs and digital help desks), and identifying consumer behavior patterns (e.g., purchase histories). However, a high-quality, regularly updated database is essential to ensure effective AI support. Compliance with data protection regulations such as GDPR and managing the so-called AI "black box" represents one of the most significant challenges for adopters (Megaro, 2023). The opacity of some AI systems can make it difficult to interpret or audit automated decision-making processes.

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While these challenges are broadly relevant across sectors, the emphasis on specific risks and priorities may vary. In healthcare, the secure handling of personal and sensitive data is especially important, along with questions of responsibility in medical decision-making. Accountability and transparency in AI-supported processes will likely be central regulatory concerns in finance. In human resources, a key challenge is ensuring that overly standardized algorithms do not exclude exceptional or unconventional candidates. The risk of job displacement is also a shared concern in finance and HR. In education, preserving room for original thinking and unique perspectives may be particularly important, as these are often drivers of innovation. These examples suggest that although the technological foundation of AI may be similar across sectors, its ethical and operational implications should be interpreted within each field's specific cultural and professional context.

Therefore, the major challenge is to ensure the ongoing quality and transparency of databases and AI systems.

Based on the current state of research, our study focuses on the following research questions:

1) How do people perceive artificial intelligence? Are there differences between demographic groups (e.g., age, gender, education) in their views on this issue?
2) How do people respond to a virtual interviewer—a research question asked by a fully human-voiced, AI-based robot?
3) To what extent are attitudes toward a virtual interviewer influenced by specific positive and negative factors? Based on these factors, what clusters of respondents can be identified?

3. Materials and methodology

As previously mentioned, one potential application of AI in market research is the partial or complete replacement of human interviewers with AI-based virtual interviewers. This concept formed the basis of our study, in which 1,077 individuals were interviewed via CATI (Computer-Assisted Telephone Interviewing) in June 2024. Our questions were included in an omnibus-style survey conducted by a public opinion research institute. Respondents were selected using randomly generated mobile phone numbers to ensure representativeness. To account for sample bias, the data were weighted by gender, age, education, municipality type, and region. As a result, the sample is representative of the adult Hungarian population along these key demographic variables.

The main demographic characteristics of the sample are as follows: 47% male and 53% female; 17% aged 18–29, 15% aged 30–39, 20% aged 40–49, 15% aged 50–59, and 33% aged 60 and above. Regarding educational attainment, 23% had completed primary school or less, 21% had attended vocational school or an apprenticeship, 34% held a high school diploma, and 21% held a higher education degree.

To address the three research questions, we employed a combination of statistical methods, including z-tests, ANOVA, factor analysis, and cluster analysis. Z-tests and ANOVA were used to identify significant differences across demographic groups and levels of knowledge about AI. Factor and cluster analyses were then conducted to explore the potential for segmenting respondents into distinct "customer" groups based on their attitudes and perceptions.

4. Results

The potential application of an AI-based virtual interviewer was examined in relation to the three proposed research questions.

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4.1 *First research question*

As part of our research, we aimed to understand how the Hungarian population perceives artificial intelligence by categorizing respondents based on their attitudes. Using a five-point Likert scale, we identified three main groups:

- **AI Rejecters**: Respondents (N=225) with a very negative (1) or negative (2) opinion of AI.
- **Neutral toward AI**: This group (N=547) includes those who either could not express an opinion (answer 9) or selected the neutral option (3).
- **AI Adopters**: Respondents (N=305) with a positive (4 or 5) opinion of AI.

Notably, the neutral group—representing 51% of the sample—was more than twice as large as the rejecting (21%) or accepting (28%) groups. This distribution suggests that a substantial portion of the population remains undecided about AI, possibly adopting a wait-and-see stance.
To better understand the drivers behind these attitudes, we further examined the influence of demographic characteristics and specific technological experiences. The results are presented in Table 1.

Table 1 Differences in Opinions on Artificial Intelligence by Demographic Factors

			Total National Sample, Column %	Opinion about MI*: AI Rejecters	Neutral Towards AI	AI Adopters
			N=1077	N=225	N=547	N=305
DEMOGRAPHY	Gender	Man	47%	48%	42%	55%
		Woman	53%	52%	58%	45%
	Age	18-29	17%	16%	12%	26%
		30-39	15%	12%	14%	20%
		40-49	20%	21%	20%	20%
		50-59	16%	20%	17%	9%
		60+	32%	31%	37%	25%
	Education	Primary school or less	45%	46%	49%	37%
		High school diploma	34%	40%	30%	37%
		Higher education diploma	21%	14%	21%	26%
	Region	West-Hungary	30%	29%	32%	29%
		Central-Hungary	35%	35%	34%	37%
		East-Hungary	35%	36%	34%	34%
	Settlement type	Budapest	18%	23%	16%	18%
		County seat	20%	19%	20%	20%
		City	33%	30%	31%	38%
		Village	30%	28%	33%	25%
	Occupation	Active	50%	45%	48%	55%
		Non-active	50%	55%	52%	45%
KNOWLEDGE	Communicated with a virtual assistant	Yes	50%	41%	46%	63%
		No	50%	59%	54%	37%
	Chabot usage	Regular user	6%	2%	1%	18%
		Occasionally	11%	3%	9%	21%
		Tried but do not use	13%	13%	11%	17%
		Not tried	69%	82%	79%	43%

* Based on a statement measured on a five-point Likert scale: rejecters include responses of 1 or 2, neutral includes responses of 3 and "don't know," and acceptors include responses of 4 or 5.

Significantly higher than the total sample ($p < 0.05$).
Significantly lower than the total sample ($p < 0.05$).

Source: Own analysis

The main differences across demographic groups are summarized below. In terms of gender, the AI adopters group contains a significantly higher proportion of men (55%) and a lower proportion of women (45%) compared to the total sample (47% male, 53% female). Concerning age, individuals aged 18–29 are

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overrepresented among AI adopters and underrepresented in the neutral group. This trend likely reflects their greater familiarity and experience with technological innovation, which may encourage them to form more decisive opinions on AI. Conversely, older respondents (particularly those aged 50–59 and 60+) are significantly less likely to fall into the AI adopter group. This may be due to lower levels of digital literacy and heightened concerns about data security and job displacement—factors commonly associated with skepticism toward emerging technologies. As will be discussed further below, our findings suggest that younger generations are generally more open to adopting new technologies, while older generations are more cautious and uncertain.

Differences by educational attainment are somewhat less pronounced. However, it is noteworthy that AI rejecters include fewer university graduates than the overall sample (14% vs. 21%). This may indicate that individuals with higher education are more technologically literate and thus more open to AI-related innovations. Their education may have also provided a broader perspective on AI's benefits and potential applications, reducing the likelihood of outright rejection.

Another key finding from the analysis is the significantly higher proportion of AI adopters (63%) who have experience with AI-based virtual assistants (e.g., Telekom Vanda) compared to the overall sample (50%). We also examined the prevalence of chatbot use, specifically referencing "ChatGPT or similar chatbots." Among AI rejecters and neutral respondents, the proportion of individuals who have never used chatbots is considerably higher than in the total sample (82% and 79% vs. 69%, respectively). In contrast, AI adopters include a significantly larger share of regular (18% vs. 6%) and occasional (21% vs. 11%) chatbot users.

These findings suggest that direct interaction with AI technologies positively influences adoption. Users who have already engaged with virtual assistants or chatbots are likelier to perceive tangible benefits, such as increased service efficiency, faster customer support, and an improved user experience, and are correspondingly less apprehensive about the technology. Conversely, the high rates of non-use among AI rejecters and neutrals indicate that unfamiliarity may serve as a barrier to acceptance. In this context, digital experience emerges as a critical factor in shaping favorable attitudes and fostering trust in AI systems.

In summary, attitudes toward AI within the Hungarian population vary substantially based on demographic characteristics and prior technological experience. While the proportions of AI adopters and rejecters are relatively similar, a notably large segment of the population remains undecided. This signals that AI adoption continues to be met with uncertainty across society. Our demographic analysis indicates that younger, more digitally literate individuals and men tend to be more open to AI, while older adults are more likely to be skeptical. Direct exposure to technologies such as chatbots correlates strongly with greater acceptance. These findings imply that increasing access to and familiarity with AI-based tools may help shift public attitudes positively.

4.2 Second research question

The research also explored respondents' feelings about being interviewed by an AI-based system using a fully human-like voice. Willingness to participate was measured on a five-point Likert scale, and the main findings are presented in Figure 1.

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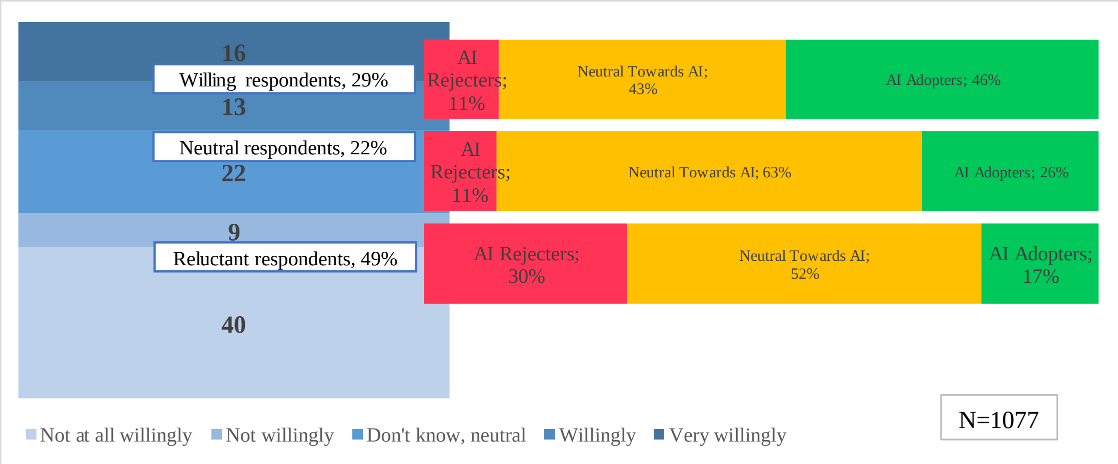

Figure 1. Willingness to Respond to a Human-Voiced AI Interviewer

The results indicate that nearly half of the respondents (49%) expressed reluctance to answer questions posed by a human-voiced AI interviewer. Meanwhile, 22% were neutral, and 29% were willing to respond. We further examined how respondents' general attitudes toward AI correlated with their willingness to participate in such interviews.

Among the reluctant respondents, 52% held a neutral opinion of AI, 30% rejected it, and only 17% accepted it. The high reluctance level among AI rejecters is understandable, as they are generally skeptical of the technology and unlikely to welcome interactions with it. The predominance of neutrals in this group suggests that uncertainty or hesitation may also lead to avoidance, especially in unfamiliar or intrusive contexts.

Notably, 17% of reluctant respondents belonged to the AI-accepting group. This indicates that general approval of AI does not necessarily translate into a willingness to engage with it in all contexts. Concerns about data privacy or a preference for traditional, human-to-human communication may influence their reluctance.

In the neutral response group, 63% were neutral toward AI, 26% were accepting, and 11% were rejecting. This distribution aligns more broadly with their stance on AI. Individuals undecided about AI tend to adopt a similarly cautious or ambivalent position toward AI-based interviewing. Interestingly, this group's lower-than-average proportion of AI rejecters suggests that even those skeptical of AI may adopt a neutral or pragmatic stance in specific situations, particularly when the perceived risk is low or participation allows them to share their views.

Among the respondents willing to engage with a human-voiced AI interviewer, 46% were AI adopters, 43% were neutral toward AI, and 11% were AI rejecters. This group's high proportion of adopters is unsurprising, given their generally favorable view of the technology. However, the substantial share of neutral respondents suggests that even those without a strong opinion about AI may be open to using it, particularly when the interaction is smooth and does not raise discomfort or concern. In such cases, their motivation to share their views may outweigh any reservations about the medium.

The 11% of willing respondents who were AI rejecters represent a small but significant group. This finding implies that some individuals, despite their broader skepticism or opposition to AI, are willing to interact with it under certain conditions. These individuals may not be fundamentally opposed to all AI applications or tolerate its use if the context is appropriate and the perceived benefits are clear.

Overall, the findings indicate that attitudes toward AI do not perfectly predict willingness to interact with a virtual interviewer. While most AI adopters are indeed more willing to engage, a subset remains reluctant. Conversely, some AI rejecters are willing to respond, suggesting a nuanced and context-dependent relationship between attitude and behavior. In short, while a positive view of AI increases the likelihood of

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engagement, other factors—such as the perceived importance of the survey, data security concerns, or preferred interaction styles—also play a meaningful role in shaping respondents' willingness.

4.3 Third research question

To examine the factors influencing respondents' willingness to engage with a virtual AI interviewer, we used eight statements designed to capture both positive and negative influences. The phrasing of the items naturally suggested a two-dimensional structure, and factor analysis was employed to validate this structure and explore underlying relationships. The results are presented in Table 2.

To assess the suitability of the data for factor analysis, we applied the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity. The KMO value was 0.84, exceeding the minimum threshold of 0.6, indicating high sampling adequacy. Bartlett's test returned a significant result ($p = 0.000$), confirming that the observed correlations among the variables were not random and that the data were appropriate for exploratory factor analysis.

Using the principal component method, we identified two factors that explained 67% of the total variance, well above the commonly accepted threshold of 60%, suggesting strong explanatory power. A Varimax rotation clarified the factor structure, with all factor loadings exceeding the 0.4 benchmark, indicating strong relationships between the observed variables and the underlying factors.

The analysis yielded two interpretable components: the first grouped variables that positively influence willingness to respond, while the second grouped those that act as barriers. Table 2 summarizes the results, including factor classification, Cronbach's Alpha, factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE). Each metric met or exceeded conventional standards, supporting the reliability and validity of the factor structure.

Table 2. Factors Influencing Willingness to Respond: Reliability, Internal Consistency, and Validity Metrics

Factors	Statements	Faktor-weight	CR & AVE values
Factor increasing willingness to respond	I would like to respond because it seems faster and more efficient.	*0.87*	*CR = 0.91*
Cronbach's Alpha = 0.88	I would like to respond because I enjoy trying new things.	*0.84*	*AVE = 0.71*
	I would like to respond because I'm curious and interested in what the experience will be like.	*0.83*	
	I would like to respond because I feel less judged by a machine than by a person.	*0.82*	
Factor reducing the willingness to respond	I'd be reluctant to respond because I don't trust technology at that level.	*0.81*	*CR = 0.84*
Cronbach's Alpha = 0.78	I'd be reluctant to respond because I believe robots are taking people's jobs.	*0.80*	*AVE = 0.58*
	I'd be reluctant to respond because I'm concerned about protecting my data.	*0.78*	
	I'd be reluctant to respond because I'd rather speak with a human.	*0.64*	

Source: Own analysis

The KMO test confirmed the adequacy of our sample size (Nkansah, 2018), while Cronbach's alpha (Vaske et al., 2017), composite reliability (CR), and average variance extracted (AVE) supported the internal consistency and convergent validity of our constructs (Raykov & Grayson, 2003; Santos & Cirillo, 2021). AVE values measure the proportion of variance captured by the construct relative to measurement error. Values above 0.7 are considered excellent, while values above 0.5 are acceptable. Although AVE ideally exceeds 0.5, a value as low as 0.4 may be accepted if the corresponding CR exceeds 0.6, thereby preserving convergent validity (Fornell & David, 1981). CR, which offers a less biased reliability estimate than Cronbach's alpha, is considered acceptable at 0.7 or higher. These metrics confirm the scale's appropriateness for our analysis and lend credibility to our interpretation of the data's underlying relationships.

Regarding factors that increased willingness to respond, respondents valued the speed and efficiency of AI-based surveys. Openness to novelty and curiosity also contributed positively, as did the perception that AI is less judgmental than a human interviewer. In contrast, a key factor that reduced willingness to respond was distrust in technology, particularly concerns about data security and fears of job displacement due to automation. While the lack of human interaction also had a negative effect, its influence was weaker than the other deterrents.

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Following the factor analysis, we conducted a cluster analysis to group respondents based on shared characteristics, ensuring that individuals with similar response patterns were assigned to the same cluster. A dendrogram was used to visualize the hierarchical relationships among respondents, ultimately supporting a three-cluster solution. We further evaluated these clusters by analyzing the number of individuals in each group and the within-cluster means and variances of the relevant variables. Special attention was given to ensure that standard deviations within clusters remained below 1, indicating internal consistency and homogeneity.

To identify significant differences between clusters, we analyzed variance (ANOVA), which confirmed that the clusters differed meaningfully in average scores. This ensured adequate heterogeneity between clusters. The cluster formation was based on positive and negative factors influencing respondents' willingness to engage in AI-based interviews. ANOVA was used to calculate the mean values of these factors within each cluster.

The results revealed three distinct clusters characterized by differing attitudes toward technology. We applied ANOVA and cross-tabulation analysis to explore further the relationships between these clusters and the key variables under study. The findings are summarized in Table 3.

Table 3. Characteristics of the Three Clusters Identified Through Factor and Cluster Analysis

			Open Sceptics (a)	Technology Sceptics (b)	Technology Friends (c)	*Evaluation of difference*
Variables included in the cluster analysis	N (respondents)		235	430	412	
	Factor increasing willingness to respond - factorweight		1.05	-1.00	0.44	*Sig*
	Factor reducing the willingness to respond - factorweight		0.84	0.31	-0.81	*Sig*
Variables not included in cluster analysis	Respondent	Man	30%	45% (a)	59% (a, b)	*Sig*
		Woman	70% (b, c)	55% (c)	41%	
		Average age	55 év (c)	52 év	45 év	*Sig*
	Region	West-Hungary	31%	27%	33%	*Not sig*
		Central-Hungary	31%	37%	36%	
		East-Hungary	38%	36%	31%	
	Settlement type	Budapest	8%	18% (a)	23% (a)	*Sig*
		County seat	19%	20%	20%	
		City	36%	33%	30%	
		Village	37% (b, c)	29%	27%	
	Occupation	Active	36%	47% (a)	60% (a, b)	*Sig*
		Non-active	64% (b, c)	53% (c)	40%	
	AI acceptance	AI Rejectors	11%	34% (b, c)	11%	*Sig*
		Neutral Towards AI	58% (c)	53%	47%	
		AI Adopters	31% (b)	13%	42% (a, b)	
	Average willingness to respond		2.94 (b)	1.47	3.41 (a, b)	*Sig*
	Used a virtual assistant	Yes	38%	43%	62% (a, b)	*Sig*
		No	61% (c)	55% (c)	38%	
	Chabot usage	Regular user	2%	3%	12% (a, b)	*Sig*
		Occasionally	9% (b)	5%	18% (a, b)	
		Tried but do not use	7%	12% (a)	19% (a, c)	
		Not tried	82% (c)	77% (c)	50%	
Original variables (average values)	I would like to respond because…	I'm curious and interested in what the experience will be like.	4.1 (b, c)	1.6	3.9 (b)	*Sig*
		it seems faster and more efficient.	3.7 (b, c)	1.3	3.2 (b)	*Sig*
		I feel less judged by a machine than by a person.	3.7 (b, c)	1.3	3.0 (b)	*Sig*
		I enjoy trying new things.	3.9 (b)	1.4	3.7 (b)	*Sig*
	I'd be reluctant to respond because…	I'm concerned about protecting my data.	3.9 (b, c)	3.6 (c)	2.1	*Sig*
		I believe robots are taking people's jobs.	4.3 (b, c)	4.1 (c)	2.3	*Sig*
		I don't trust technology at that level.	3.9 (c)	3.7 (c)	2.0	*Sig*
		I'd rather speak with a human.	4.6 (c)	4.6 (c)	3.3	*Sig*

a, b, c = Significantly higher compared to the indicated group
% values were tested for significant differences using the Z test ($p<0.05$)
For averages, significant differences were tested by ANOVA ($p<0.05$)

The analysis identified three distinct respondent clusters:

1) Open Sceptics – This group demonstrates a generally positive attitude toward technological innovation, as shown by the high factor weight (1.05) for variables that increase willingness to respond. However, they also express concern about technological risks (factor weight: 0.84). Demographically, they are typically older (average age: 55), predominantly female (70%), with a high proportion residing in rural areas (37%) and being inactive in the labor market (64%).

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Although 31% are AI adopters, this group reports below-average usage of virtual assistants and chatbots. Their willingness to respond is above average (mean: 2.94), indicating that human-like interaction, even through an AI, does not deter them. Communication and interpersonal engagement appear to be important to this cluster.

2) Technology Sceptics – Members of this cluster exhibit the lowest overall willingness to respond (mean: 1.47), driven more by risk aversion than by perceived benefits or curiosity. They express only moderate concern about technological risks and see limited advantages in AI-based interviews. The demographic profile closely matches the general sample, with an average age of 52 and a nearly even gender split. Nearly half are actively employed. While 34% are AI rejecters, this group has more experience with virtual assistants and chatbots than the Open Sceptics. However, they strongly prefer human interviewers and are unlikely to participate in AI-mediated surveys.
3) Technology Friends – This cluster holds a moderately positive view of AI, driven mainly by curiosity rather than the belief that AI is universally superior to humans. This is reflected in their moderate positive factor weight (0.44) for willingness-enhancing variables. Importantly, they are far less concerned about the risks of technology (negative factor weight: -0.81). Demographically, this is the youngest group (average age: 45), predominantly male (59%), with a high proportion of active employees (60%). They are also the most technologically engaged, with 42% identified as AI adopters, 62% using virtual assistants, and 50% having tried chatbots. Their average willingness to respond (mean: 3.41) is the highest among the clusters.

These three clusters reveal distinct patterns in attitudes toward technology and willingness to engage with AI-based survey methods. The findings underscore the importance of tailoring communication and outreach strategies to the varying levels of technological openness and risk sensitivity across different population segments.

5. Conclusion

The practical implementation of AI-based virtual interviewers in market research presents notable opportunities and significant challenges. While virtual interviewers offer clear advantages—scalability, cost-effectiveness, and improved efficiency—our findings underscore that broad societal acceptance remains a substantial barrier. Nearly half of the respondents (49%) expressed reluctance to engage with AI interviewers, pointing to an urgent need for trust-building initiatives and public education regarding the role and capabilities of AI.

As Huang and Rust (2020) have demonstrated, AI can automate routine tasks and improve the quality and speed of data collection, particularly in marketing research. Our study supports this view while emphasizing that public concerns remain prominent, especially regarding job displacement and data privacy. These findings echo the conclusions of Davenport et al. (2019), who highlighted ethical concerns and the lack of trust as major impediments to the widespread adoption of AI.

Additionally, our results show that prior experience with AI tools such as virtual assistants and chatbots significantly increases respondents' willingness to interact with AI-based interviewers. This supports Jarek and Mazurek's (2019) argument that familiarity with AI fosters acceptance. However, our data also reveal that even among AI adopters, a substantial minority remains hesitant to engage in AI-mediated interactions, suggesting that deeper societal concerns about the role of AI in human communication persist.

The cluster analysis further reveals pronounced demographic differences in AI acceptance. Younger, more technologically experienced respondents categorized as "Technology Friends" were notably more open to virtual interviewers. This aligns with the observations of Brynjolfsson and McAfee (2017), who noted that technological innovations often encounter resistance from less digitally literate segments of the population. These insights highlight the importance of targeted outreach and education to foster broader acceptance across diverse social groups.

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In this context, ethical and regulatory considerations become especially significant. Our findings affirm that individual concerns—particularly those related to data privacy, job security, and transparency—strongly influence public attitudes toward the adoption of AI. Risks such as algorithmic bias may lead to distortions in respondent selection or the interpretation of data. At the same time, the "black box" nature of many AI systems constrains transparency and limits the auditability of AI-driven decisions, a challenge also identified by Ma and Sun (2020). Regulatory frameworks have not yet fully adapted to these developments, often leaving market researchers without clear guidance regarding accountability and compliance. These challenges highlight the critical need for transparent, ethically grounded implementation of AI-based research tools. Although such systems offer the potential for greater efficiency and data quality, their successful integration depends on narrowing the gap between technological progress and societal trust.

Drawing from our empirical findings, several practical strategies may facilitate the effective deployment of AI-based virtual interviewers in market research. First, hybrid models incorporating human and AI interviewers could balance efficiency with interpersonal familiarity, thus increasing respondent comfort, particularly among those skeptical of full automation. Second, audience segmentation strategies, such as tailoring communication styles and system interfaces to suit varying levels of digital literacy or demographic characteristics, may enhance user acceptance. Personalized communication approaches, in particular, may benefit respondents with limited exposure to digital technologies.

Lessons from other AI-integrated fields—healthcare, education, human resources, and finance—offer valuable parallels. These sectors frequently encounter similar challenges, including concerns over data protection, algorithmic fairness, and public trust. As such, the challenges revealed in our study resonate more broadly, underscoring the necessity of aligning AI solutions with user expectations, legal standards, and cultural norms. Although AI-based interviewers promise scalability and operational efficiency, their long-term viability depends on embedding them within ethically robust, user-centered frameworks.

Finally, our findings regarding public acceptance of AI, attitudes toward human–technology interaction, and cluster-specific response tendencies may offer useful insights beyond the domain of market research. They could inform ongoing developments in other sectors where empirical research on public perception remains limited.

A key limitation of the present study is its focus on a single national context—Hungary. Future research should aim to include cross-national comparisons and examine respondents' innovation adoption profiles as potential explanatory variables.

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Conflict of interest:
The authors declare no conflict of interest.

References

Ali, M., & Abdel-Haq, M. K. (2021). Bibliographical analysis of artificial intelligence learning in higher education. In *Fostering communication and learning with underutilized technologies in higher education* (pp. 36–52). IGI Global. https://doi.org/10.4018/978-1-7998-4846-2.ch003

Arora, M., & Mittal, A. (2024). Employees' change in perception when artificial intelligence integrates with human resource management: A mediating role of AI-tech trust. *Benchmarking: An International Journal*, Advance online publication. https://doi.org/10.1108/bij-11-2023-0795

Arora, N., Chakraborty, I., & Nishimura, Y. (2025). AI–human hybrids for marketing research: Leveraging large language models (LLMs) as collaborators. *Journal of Marketing, 89*(2), 43–70. https://doi.org/10.1177/00222429241276529

Publisher name: Széchenyi István University
ISSN: 3058-1079 (Online)

Audeering. (2024, May 12). *[Company website]*. https://www.audeering.com

Awan, U., Shamim, S., Khan, Z., Zia, N. U., Shariq, S. M., & Khan, M. N. (2021). Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance. *Technological Forecasting and Social Change, 168*, 120766. https://doi.org/10.1016/j.techfore.2021.120766

Blau, I., & Shamir-Inbal, T. (2018). Digital technologies for promoting "student voice" and co-creating learning experience in an academic course. *Instructional Science, 46*(2), 315–336. https://doi.org/10.1007/s11251-017-9436-y

Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence. *Harvard Business Review*, 7, 3–11. https://tinyurl.com/5cnf3ur9

Chintalapati, S., & Pandey, S. K. (2021). Artificial intelligence in marketing: A systematic literature review. *International Journal of Market Research, 64*(1), 38–68. https://doi.org/10.1177/14707853211018428

Danyi, P., Iványi, T., & Veres, I. (2020). A turizmus jelene és várható változása a mesterséges intelligencia integrálásával, különösen a Z-generáció igényeire fókuszálva [Current and expected changes in tourism through the integration of artificial intelligence, with a focus on Generation Z's needs]. *Vezetéstudomány / Budapest Management Review, 51*(Special issue), 19–34. https://doi.org/10.14267/veztud.2020.ksz.03

Davenport, T. H., & Harris, J. G. (2007). *Competing on analytics: The new science of winning*. Harvard Business Press.

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2019). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science, 48*(1), 24–42. https://doi.org/10.1007/s11747-019-00696-0

Dempere, J., Modugu, K., Hesham, A., & Ramasamy, L. K. (2023). The impact of ChatGPT on higher education. *Frontiers in Education, 8*, Article 1206936. https://doi.org/10.3389/feduc.2023.1206936

dos Santos, P. M., & Cirillo, M. Â. (2021). Construction of the average variance extracted index for construct validation in structural equation models with adaptive regressions. *Communications in Statistics - Simulation and Computation, 52*(4), 1639–1650. https://doi.org/10.1080/03610918.2021.1888122

Fehrenbacher, D. D., Ghio, A., & Weisner, M. (2022). Advice utilization from predictive analytics tools: The trend is your friend. *European Accounting Review, 32*(3), 637–662. https://doi.org/10.1080/09638180.2022.2138934

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.2307/3151312

George, D. S. M., Sasikala, D. B., G., T., Sopna, D. P., Umamaheswari, D. M., & Dhinakaran, D. D. P. (2024). Role of artificial intelligence in marketing strategies and performance. *Migration Letters, 21*(S4), 1589–1599.

Goknil, A., Nguyen, P., Sen, S., Politaki, D., Niavis, H., Pedersen, K. J., Suyuthi, A., Anand, A., & Ziegenbein, A. (2023). A systematic review of data quality in CPS and IoT for Industry 4.0. *ACM Computing Surveys, 55*(14s), Article 3043, 1–38. https://doi.org/10.1145/3593043

Hell Energy. (2024). *Magyar világszenzáció* [Hungarian world sensation]. Hell Energy. Retrieved May 12, 2024, from https://www.hellenergy.com/magyar-vilagszenzacio/

Heryandi, A. (2020). Developing chatbot for academic record monitoring in higher education institution. *IOP Conference Series: Materials Science and Engineering, 879*(1), 012049. https://doi.org/10.1088/1757-899x/879/1/012049

Huang, M.-H., & Rust, R. T. (2020). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*(1), 30–50. https://doi.org/10.1007/s11747-020-00749-9

Indeemo. (2024). [Untitled webpage]. Retrieved May 15, 2024, from https://indeemo.com

Jarek, K., & Mazurek, G. (2019). Marketing and artificial intelligence. *Central European Business Review, 8*(2), 46–55. https://doi.org/10.18267/j.cebr.213

Kantar. (2024). AI-powered ad testing. *Kantar*. Retrieved May 12, 2024, from https://www.kantar.com/marketplace/solutions/ad-testing-and-development/ai-powered-ad-testing

Publisher name: Széchenyi István University
ISSN: 3058-1079 (Online)

Kulkov, I. (2021). Next-generation business models for artificial intelligence start-ups in the healthcare industry. *International Journal of Entrepreneurial Behavior & Research, 29*(4), 860–885. https://doi.org/10.1108/ijebr-04-2021-0304
Liu, Y., Chen, L., & Yao, Z. (2022). The application of artificial intelligence assistant to deep learning in teachers' teaching and students' learning processes. *Frontiers in Psychology, 13*, Article 929175. https://doi.org/10.3389/fpsyg.2022.929175
Ma, L., & Sun, B. (2020). Machine learning and AI in marketing – Connecting computing power to human insights. *International Journal of Research in Marketing, 37*(3), 481–504. https://doi.org/10.1016/j.ijresmar.2020.04.005
Mahendra, I., Ramadhan, A., Trisetyarso, A., Abdurachman, E., & Zarlis, M. (2022). Strategic information system planning in the Industry 4.0 era: A systematic literature review. In *Proceedings of the 2022 IEEE Creative Communication and Innovative Technology (ICCIT)* (Vol. 3, pp. 1–7). IEEE. https://doi.org/10.1109/iccit55355.2022.10119002
Megaro, A. (2023). Transparency in AI systems for value co-creation in healthcare. In *Big data and decision-making: Applications and uses in the public and private sector* (pp. 93–105). Emerald Publishing. https://doi.org/10.1108/978-1-80382-551-920231007
Mirwan, S. H., Ginny, P. L., Darwin, D., Ghazali, R., & Lenas, M. N. J. (2023). Using artificial intelligence (AI) in developing marketing strategies. *International Journal of Applied Research and Sustainable Sciences, 1*(3), 225–238. https://doi.org/10.59890/ijarss.v1i3.896
Mustak, M., Salminen, J., Plé, L., & Wirtz, J. (2021). Artificial intelligence in marketing: Topic modeling, scientometric analysis, and research agenda. *Journal of Business Research, 124*, 389–404. https://doi.org/10.1016/j.jbusres.2020.10.044
Nair, A. J., Manohar, S., & Mittal, A. (2024). AI-enabled FinTech for innovative sustainability: Promoting organizational sustainability practices in digital accounting and finance. *International Journal of Accounting & Information Management*. Advance online publication. https://doi.org/10.1108/ijaim-05-2024-0172
Neumann, M., Rauschenberger, M., & Schön, E.-M. (2023). "We need to talk about ChatGPT": The future of AI and higher education. In *2023 IEEE/ACM 5th International Workshop on Software Engineering Education for the Next Generation (SEENG)*. https://doi.org/10.1109/seeng59157.2023.00010
Niemi, H. (2021). AI in learning. *Journal of Pacific Rim Psychology, 15*, Article 183449092110381. https://doi.org/10.1177/18344909211038105
Nkansah, B. (2018). On the Kaiser-Meier-Olkin's measure of sampling adequacy. *Mathematical Theory and Modeling, 8*, 52–76.
Pollfish. (2024). *[No title]*. Retrieved May 12, 2024, from https://www.pollfish.com
Raykov, T., & Grayson, D. (2003). A test for change of composite reliability in scale development. *Multivariate Behavioral Research, 38*(2), 143–159. https://doi.org/10.1207/s15327906mbr3802_1
Rudolph, J., Tan, S., & Tan, S. (2023). War of the chatbots: Bard, Bing Chat, ChatGPT, Ernie and beyond. The new AI gold rush and its impact on higher education. *Journal of Applied Learning & Teaching, 6*(1), 364–389. https://doi.org/10.37074/jalt.2023.6.1.23
Sattu, R., Das, S., & Jena, L. K. (2024). Should I adopt AI during talent acquisition? Evidence from HR professionals of Indian IT organisations. *Journal of Organizational Effectiveness: People and Performance*. Advance online publication. https://doi.org/10.1108/joepp-05-2023-0186
Shao, J., Lou, Z., Wang, C., Mao, J., & Ye, A. (2021). The impact of artificial intelligence (AI) finance on financing constraints of non-SOE firms in emerging markets. *International Journal of Emerging Markets, 17*(4), 930–944. https://doi.org/10.1108/ijoem-02-2021-0299
Simay, A. E., Wei, Y., & Gáti, M. (2021). *Mesterséges intelligencia és marketing kapcsolatának rövid szakirodalmi áttekintése* [A brief literature review of the relationship between artificial intelligence and marketing]. In A. Mitev, T. Csordás, D. Horváth, & K. Boros (Eds.), *Post-traumatic marketing: Virtuality and reality – Proceedings of the EMOK 2021 International Conference* (pp. 204–211). Corvinus University of Budapest.
Soul Machines. (2024). *[No title]*. Retrieved September 23, 2024, from http://www.soulmachines.com

Publisher name: Széchenyi István University
ISSN: 3058-1079 (Online)

 Vol. 13, No. 1, pp. 32-46, 2025

Storeinsider. (2024). *Hogyan tud kóstolni a mesterséges intelligencia?* [How can artificial intelligence taste?]. Retrieved May 12, 2024, from https://tinyurl.com/5n8ur26w

Sundström, M. (2019). Climate of data-driven innovation within e-business retail actors. *FIIB Business Review, 8*(2), 79–87. https://doi.org/10.1177/2319714519845777

SurveyMonkey. (2024). *[No title]*. Retrieved May 12, 2024, from https://www.surveymonkey.com

Szűcs, K., Lázár, E., & Németh, P. (2023). *Marketingkutatás 4.0* [Marketing research 4.0]. Akadémiai Kiadó. https://doi.org/10.1556/9789634548546

Thakur, J., & Kushwaha, B. P. (2023). Artificial intelligence in marketing research and future research directions: Science mapping and research clustering using bibliometric analysis. *Global Business and Organizational Excellence, 43*(3), 139–155. Portico. https://doi.org/10.1002/joe.22233

Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine, 25*(1), 44–56. https://doi.org/10.1038/s41591-018-0300-7

Vaske, J. J., Beaman, J., & Sponarski, C. C. (2016). Rethinking internal consistency in Cronbach's alpha. *Leisure Sciences, 39*(2), 163–173. https://doi.org/10.1080/01490400.2015.1127189

West, J., & Bogers, M. (2013). Leveraging external sources of innovation: A review of research on open innovation. *Journal of Product Innovation Management, 31*(4), 814–831. https://doi.org/10.1111/jpim.12125

Zedginidze, S., & Berikashvili, L. (2023). Development of an enterprise marketing strategy. *Economics*, *(3–4)*, Article 163. https://doi.org/10.36962/ecs105/3-4/2023-163

Publisher name: Széchenyi István University
ISSN: 3058-1079 (Online)