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Optimizing Survey Engagement: Factors Influencing Questionnaire Breakoff and Respondent Segmentation

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ABSTRACT: This study examines questionnaire breakoff – respondents' early survey discontinuation – and its implications for data quality in marketing research. Using telephone interviews with three independent random subsamples of Hungarian adults (n = 1040; 1028; 988), we applied K-means cluster analysis to segment respondents based on prior breakoff experiences and attitudes toward questionnaire characteristics. Chi-square, ANOVA, and Friedman tests identify the key drivers of discontinuation. Findings show that questionnaire length, perceived topic irrelevance, and poorly structured items significantly increase breakoff risk. Based on the results, three distinct respondent segments emerged – Discerning Evaluators, Experience Seekers, and Nonchalant Responders – each exhibiting different engagement preferences and tolerance thresholds. Trust in research, age, and educational attainment further shape breakoff propensities across segments. Practically, the results support segment-specific survey design strategies that optimize length, structure, and topic salience while incorporating trust-building elements. Conceptually, the study extends leverage–saliency theory by introducing a segmentation framework that accounts for heterogeneity in survey discontinuation risk and is adaptable to multinational research settings.

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1. Introduction

In recent decades, the pivotal role of data in organizational success has become evident (LaValle et al. 2011; Sundström 2019; Awan et al. 2021). Accurate and timely data underpin effective decision-making, innovation, and competitiveness, while suboptimal or incomplete data can lead to erroneous decisions and negatively affect long-term performance (Brynjolfsson et al. 2011; Fehrenbacher et al. 2023). In marketing research and related behavioral fields, surveys remain a core method of data collection; however, data quality is highly sensitive to survey errors such as missing responses, sampling issues, and measurement inaccuracies (Dillman et al. 2014; Hair et al. 2019). One particularly problematic form of error is survey breakoff, in which respondents abandon a questionnaire before completion (Barge–Gehlbach 2012). As a type of partial nonresponse, breakoff reduces data completeness, increases research costs, and can exacerbate nonresponse bias when discontinuers systematically differ from those who complete the survey, thereby distorting substantive conclusions (Daikeler et al. 2020; Becker 2023).

These challenges are particularly salient in marketing research, where survey-based data collection underpins critical managerial decision-making in areas such as customer experience management, brand performance tracking, and advertising effectiveness assessment. However, high breakoff rates undermine the reliability and applicability of survey insights, leading to misinterpretations of consumer preferences, satisfaction levels, and behavioral trends (Mittereder – West 2021). Thus, understanding why respondents discontinue surveys is essential for improving engagement, reducing data loss, and refining market intelligence.

Despite its importance, survey breakoff remains underexplored. As Kostyk et al. (2019) noted, most studies on survey participation were conducted before the rise of the internet and social media, which have significantly altered respondents' attention spans and digital behaviors. The fast-paced nature of contemporary life, characterized by digital distractions, multitasking, and chronic time pressure, warrants renewed attention to the drivers of survey breakoff. In Hungary, telephone and online surveys remain the two dominant data-collection modes, making it essential to understand breakoff patterns across both modes.

The available literature provides limited information on breakoff rates and their determinants, as research firms rarely publish such data. However, based on industry insights and previous studies, breakoff rates in telephone surveys typically range between 10% and 20% (Emery et al. 2023). A Hungarian research company also reports, in its online panel, that the share of respondents completing questionnaires reached 71% in 2024 (up from 58% in 2020, reflecting targeted improvements despite the broader decline in survey participation) (NRC 2025). Breakoff rates vary based on survey methodology, interview techniques, questionnaire length, respondent demographics, and topic relevance. Nonetheless, the specific influence of these factors, particularly across different survey modes (telephone vs. online), remains insufficiently explored.

To address these gaps, our study examines (1) the key drivers of survey breakoff and the questionnaire features that most disrupt respondents; (2) perceptions of optimal questionnaire length and the respondent segments that differ in this regard; and (3) differences between telephone and online surveys in breakoff patterns; and the role of trust in public opinion research in discontinuation.

The study is structured as follows: The next chapter examines data quality and key questionnaire design issues, followed by a description of the methodology and sample. We then present our analytical results, and finally, the discussion and conclusion sections interpret our findings and their practical implications.

2. Data quality and errors in questionnaire surveys

Questionnaire breakoff (mid-interview termination) is not only a methodological concern but also a strategic issue: high breakoff rates increase costs, reduce representativeness, and bias insights and campaign evaluations (Nunan et al. 2020).

The Total Survey Error (TSE) framework provides a comprehensive map of survey errors, distinguishing sampling from non-sampling errors (Groves – Lyberg 2010; see also Malhotra 2020). Although both matter, non-sampling components – coverage, nonresponse, measurement, and processing – often dominate total error in practice because they arise at multiple stages and are harder to standardize (Biemer – Lyberg 2003; Groves 2004). Managing non-sampling error is complex: sources are varied, sometimes unpredictable, and shaped by contextual and human factors (Groves 2004).

Within nonresponse, it is helpful to distinguish unit nonresponse (sampled individuals do not participate at all) from item/partial nonresponse (participants skip specific questions or terminate early). Breakoff belongs to the latter: the respondent initially cooperates but stops before completion (Yan – Curtin 2010; Reimers et al. 2022; Choumert-Nkolo et al. 2023; Dutwin et al. 2023). While total nonresponse is often treated as the more severe threat (Yan – Curtin 2010), breakoff can reduce cooperation in subsequent surveys and increase nonresponse (De Leeuw 2012; McGonagle 2013; Steinbrecher et al. 2014).

Prior research indicates interdependencies between nonresponse forms. Prior item and partial nonresponse increase the likelihood of subsequent unit nonresponse and breakoff in later survey waves (Loosveldt et al. 2002; McGonagle 2013). Some authors distinguish between "good" and "bad" breakoff: the former may screen out unmotivated respondents and reduce measurement noise, whereas the latter stems from preventable design flaws and should be minimized through careful questionnaire design (Stieger et al. 2007; O'Neil et al. 2003). From a design perspective, prevention should therefore prioritize eliminating these avoidable forms.

Why do respondents break off? Prior research typically distinguishes between researcher-controllable determinants of survey breakoff and contextual or individual-level influences. (Nancarrow et al. 2004). On the questionnaire side, recurrent triggers include length, topic salience, timing (e.g., near holidays), cognitive burden (complex wording, long lists, recall/calculation tasks), logical flow and routing, clarity/completeness of response options, sensitive content, and usability/presentation in online modes (De Leeuw 2012; Yan – Curtin 2010; Kmetty – Stefkovics 2021). Length is consistently linked to higher attrition; monotony and abrupt transitions can also act as "exit points" (McGonagle 2013; Daikeler et al. 2020; Sandelin 2022; Steinbrecher et al. 2014).

On the respondent side, breakoff likelihood co-varies with demographics and life-stage time pressure, psychographic traits and motivation, prior survey experience, and trust in research; interviewer behavior can also matter in interviewer-administered modes (Yan – Curtin 2010; Reimers et al. 2022; Bernhardt – Wunnava 2023). Although prior research highlights several correlates of survey breakoff, less attention has been paid to how these factors may operate differently across age groups. Given the acceleration of the digitalization of everyday life, it is reasonable to expect that tolerance for survey burden may differ across age cohorts, making age a theoretically relevant factor in investigating breakoff. Topic interest is a consistent driver of cooperation and persistence (Shropshire et al. 2009). In telephone contexts, participants who consent differ from refusers in terms of trust, attitudes toward surveys, and sociodemographic profiles (Malhotra – Simon 2017). Attitudes toward market research and data privacy further limit survey behavior (Grandcolas et al. 2003).

These heterogeneities align with leverage–saliency theory (LST): survey attributes differ in leverage (direction/strength of impact on participation) and saliency (perceived prominence). The same feature (e.g., length, sensitive item) can deter one segment and be tolerated by another, depending on what respondents notice and value (Groves et al. 2000). LST implies that one-size-fits-all design rules are suboptimal; instead, designs should balance burdens and benefits for distinct respondent segments.

The literature consistently recommends preventive design to reduce partial nonresponse and breakoff. Core practices include concise, unambiguous wording; coherent flow and routing; careful placement of sensitive modules (typically later); and rigorous pre-testing to identify friction points before fieldwork (Stieger et al. 2007; Albaum et al. 2011; De Leeuw 2012; Kmetty – Stefkovics 2021). In online modes, attention to device usability and visual presentation is equally critical.

Set against this background, our study contributes in three ways. First, we quantify the relative importance of disruption drivers reported by respondents, with particular attention to length and topic salience. Second, we test whether perceptions of ideal questionnaire length differ by mode (telephone vs online), addressing an open question in practice. Third, we explicitly model heterogeneity via K-means segmentation based on breakoff-related attitudes and experiences, and we examine links to demographics and trust in research. This segmentation lens complements existing nonresponse work by moving beyond mean effects to actionable respondent profiles (De Leeuw 2012; McGonagle 2013; Steinbrecher et al. 2014; Daikeler et al. 2020).

Finally, we articulate four hypotheses that flow directly from the reviewed papers and their tensions:

H1: The primary factor contributing to survey breakoff is questionnaire length

This expectation is grounded in prior findings identifying questionnaire length as a central burden and a key correlate of disengagement in fast-paced digital contexts.

H2: Respondents perceive the ideal length of online surveys to be slightly longer (+10–20%) but not substantially longer (+30% or more) than that of telephone surveys.

Earlier evidence indicates that respondents tolerate substantially longer online questionnaires than telephone interviews. For example, Klenovszki (2016) reports typical limits of approximately 15 minutes for telephone surveys and around 25 minutes for online surveys. Since then, the pace of everyday life and the volume of digital content have increased considerably. Building on this context and industry experience, we expect the difference in ideal length across modes to be more modest today. Accordingly, we hypothesize that respondents tolerate slightly longer online questionnaires, but not substantially longer ones, than telephone surveys.

H3: As respondents' age increases, the likelihood of breakoff decreases, and tolerance for longer questionnaires increases.

Everyday experience and industry practice suggest that age groups differ in how they manage time and digital attentional demands. We therefore expect systematic age-related differences in breakoff likelihood and tolerance. Industry evidence aligns with this expectation: NRC (2025) reports that while 10–15-

minute questionnaires remain broadly acceptable and 20–30-minute surveys are feasible with incentives, breakoff increases sharply beyond 30 minutes – driven primarily by markedly higher dropout among younger respondents compared with older ones. Age and education are therefore treated not as causal determinants but as proxies for life-stage constraints, digital exposure, and survey literacy, which prior research links to persistence and burden tolerance.

H4: Greater trust in public-opinion research is associated with lower breakoff rates and a preference for longer ideal questionnaire length.

Prior studies show that trust, survey attitudes, and previous positive experiences shape respondents' willingness to participate and their persistence in survey tasks (Yan – Curtin 2010; Reimers et al. 2022; Bernhardt – Wunnava 2023; Grandcolas et al. 2003). Building on this pattern, we expect higher trust to reduce the likelihood of breakoff and to increase tolerance for length.

This framework guides our empirical design and the interpretation of results. Specifically, if questionnaire length and topic salience are major drivers of attrition and their impact varies across respondent segments, then reducing breakoff requires both global design principles (clarity, logical flow, pre-testing) and segment-aware tailoring, while safeguarding data quality and external validity.

3. Methodology

We fielded an omnibus survey (i.e., a multi-topic survey where independent question modules from different clients are fielded within the same questionnaire) with a public-opinion research institute to address our research questions and test H1–H4. Fieldwork took place in Q2 2021 (subsample 1, n=1040, and 2, n=1028 in April, subsample 3, n=988 in June). In total, 3,056 Hungarian adults participated. The findings presented in this study are based on three separately conducted surveys, with no overlap in sampling. In all three cases, data were collected via telephone surveys conducted using random digit dialing (RDD) on mobile networks (any mobile phone user had an equal chance of being selected). This approach was chosen because of Hungary's high mobile phone penetration rate (exceeding 100%), which allows for broad population coverage. In contrast, due to the country's digital divide, online surveys in Hungary still face significant limitations in terms of representativeness, particularly among older individuals and those with lower levels of education. To maintain a balanced sample composition, fieldwork included soft demographic limits, used only as upper bounds. To address potential sampling bias, we applied weighting adjustments using population benchmarks from the Hungarian Central Statistical Office (Központi Statisztikai Hivatal, KSH). Weighting was based on the most recent census data, with adjustments for gender, age, education level, settlement type, and region to improve alignment with population benchmarks (Malhotra – Simon 2017). The weights were calculated using an iterative weighting procedure, a standard method in survey research to improve representativeness and reduce sampling bias (based on Malhotra, 2020). This approach ensured that the final weighted dataset more accurately reflected the target population. All results are based on the weighted data and are representative of the Hungarian adult population along these dimensions. Key distributions are as follows: gender (47% male, 53% female); age (18–29: 17%, 30–39: 16%, 40–49: 19%, 50–59: 16%, 60+: 32% (0.2% missing)); education (≤ primary: 24%, vocational/technical: 21%, secondary: 34%, higher education: 21% (0.1% missing)).

Our focal behavior, survey breakoff, was captured through recall: respondents indicated whether they had previously participated in telephone or online surveys (the two dominant modes in Hungary) and whether they had discontinued any such survey mid-way. Recall-based measures entail limitations (memory inaccuracies and potential social desirability), but they are widely used to study motivations and behavioral correlates in survey methodology (Yan – Curtin 2010; Reimers et al. 2022; Choumert-Nkolo et al. 2023; Dutwin et al. 2023). We measured whether respondents had ever discontinued a survey, rather than the frequency of such events, to minimize recall error; future studies could incorporate repeated-measures designs or paradata-based indicators of response behavior (e.g., item-level timestamps or observed breakoff points) to capture the intensity and dynamics of survey breakoff. In line with this tradition, our objective was not to estimate the absolute frequency of breakoff but to identify its drivers and associations, which cannot be directly observed in survey research and therefore require recall-based measurement to capture broader patterns. Accordingly, our analysis focused on determining which attitudinal and demographic characteristics exhibit significant associations with the likelihood of breakoff. To mitigate bias, we complemented recall items with structured follow-ups and triangulated insights with expert interviews (researchers, interviewers, and a frequent online panelist) and prior literature.

To operationalize ideal questionnaire length, respondents reported (a) a general tolerable duration and, in a separate item, (b) preferred durations for telephone and online modes. Trust in public-opinion surveys was measured on an ordered scale and linked to both breakoff history and preferred length.

Analytically, we first performed distribution checks (e.g., One-Sample Kolmogorov–Smirnov) and then used parametric or non-parametric tests as appropriate: chi-square tests for categorical associations; ANOVA or Kruskal–Wallis for group differences in continuous/ordered outcomes; Friedman tests for within-respondent rankings; and Mann–Whitney / Wilcoxon signed-rank tests for pairwise comparisons across modes or subsamples. Statistical significance was evaluated at $\alpha = 0.05$. In addition to bivariate tests, we employed an exploratory classification tree (CHAID) to identify irritation patterns most strongly associated with prior breakoff; implementation details and results are reported in the corresponding Results subsection.

To capture heterogeneity in perceptions and experiences, we conducted a K-means cluster analysis using the breakoff-related attitudes and disruptiveness ratings. The resulting segments were subsequently profiled in terms of demographics and trust in research to support interpretation and practical targeting. This segmentation complements mean-difference tests by revealing distinct respondent profiles associated with higher or lower attrition risk, consistent with the Leverage–Saliency perspective (Groves et al. 2000; Yan – Curtin 2010).

To ensure transparency, detailed distributions of the unweighted and weighted samples by key demographic variables are provided in the supplementary material.

4. Results

We first established respondents' prior survey experience to construct groups and test demographic differences. At contact, 42% reported that this was their first telephone survey and that they had never completed an online survey.[2] A further 7% were first-time telephone respondents but had previously taken online surveys. In contrast, 23% had only ever taken telephone surveys, and 28% had experience with both telephone and online surveys (0.3% gave no substantive answer).

Among those with any prior survey participation, 66% reported never breaking off a questionnaire. This proportion was 79% among telephone-only participants ($n = 705$), 61% among online-only participants ($n = 222$), and 55% among those experienced in both modes ($n = 846$). Group differences were statistically significant (chi-square $p \leq 0.05$; Cramer's $V = 0.365$).

When examining demographic differences, the following differences emerged. Patterns varied by age (chi-square $p \leq 0.05$; Cramer's $V = 0.211$). The highest share of first-time respondents occurred among people aged 60+ (48%). With age, telephone-only experience became more common (7% at ages 18–29 versus 35% at 60+). Online-only experience was concentrated among 18–29-year-olds (21%) versus 3–7% in older groups. Regular participation in both modes ranged from 31% to 37% under age 60, but only 14% at 60+. These findings reflect well-known communication habits: younger cohorts are more accessible online,

2 This high proportion reflects the characteristics of RDD-based telephone sampling, which reaches the general population randomly and therefore naturally includes many individuals with no prior survey experience. Because respondent panels represent only a limited share of the adult population, RDD sampling tends to yield a substantially higher proportion of first-time respondents than panel-based approaches.

while many older adults are less digitally active. Education also differentiated experience (chi-square $p \leq 0.05$; Cramer's V = 0.214). As education increased, first-time participation fell, and dual-mode experience rose. For example, 61% with at most primary education were first-time respondents versus 24% among university graduates; 11% with primary education had dual-mode experience versus 51% among graduates. Finally, the share who had never broken off a survey varied with age (Cramer's V = 0.108) and education (Cramer's V = 0.094; both $p \leq 0.05$): never-breakoff was less likely at younger ages and slightly more likely at higher education levels, consistent with expectations for H3. In addition, settlement type also showed a significant association with breakoff (Cramer's V = 0.156; $p \leq 0.001$), although this likely reflects underlying socio-demographic differences between urban and rural areas rather than settlement type itself.

4.1. Reasons for breaking off the questionnaire

The first subsample comprised 175 respondents who had previously discontinued a telephone or online survey. On average, they named 1.9 reasons. The most frequent reasons were excessive length (39%), lack of logical structure (36%), lack of topic interest (32%), personal reasons (25%), boredom (23%), and external interruptions (23%); 16% cited other reasons. A Friedman ranking test showed significant differences ($p \leq 0.05$), supporting H1 that length is the principal driver of breakoff.

External interruptions were more often mentioned by women than men (27% versus 16%), though this difference was not statistically significant. Age differences were more pronounced, with a significant age-related variation in the association between questionnaire length and breakoff (chi-square $p \leq 0.05$; Cramer's V = 0.387). At ages 18–29, 60% cited length versus 15% at 60+. Respondents under 50 were also more likely to label surveys as boring. These patterns reinforce the age-related component of H3: impatience and time constraints are more salient among younger adults.

4.2. Confounding factors in the questionnaire

To move beyond post hoc explanations and capture general irritants, the second subsample rated 11 questionnaire characteristics on a five-point disturbance scale. Internal consistency for the 11-item battery was adequate (Cronbach's alpha = 0.816), indicating a coherent construct. Table 1 reports the item means.

Uninteresting topics ranked as most disturbing (mean 3.34; 37% rated "very disturbing"), closely followed by non-native or unnatural wording (3.29). Complex or lengthy questions and response lists (3.15) and monotony in otherwise acceptable topics (3.08) also scored relatively high. Length, per se, was moderately disturbing (3.07). By contrast, the use of foreign or technical words was less problematic on average, and the opening placement of demographics was considered to be of relatively minimal disturbance. Formal versus informal addressing was of least concern overall, although 9% found informal style highly disturbing; 61% regarded both styles as acceptable.

Gender differences favored greater sensitivity among women: 8 of the 11 items showed higher disturbance means for women than men (ANOVA $p \leq 0.05$), notably for technical jargon, foreign words, length, and complex items. No item was rated as more disturbing by men. These results, together with Section 4.1, identify multiple design levers beyond length alone. See Table 1 for details.

Table 1. Factors that bother or would potentially bother participants

Confounding factors	Average (1-5)
Boring topic	3.34
Non-Hungarian wording	3.29
Complicated/long questions and answers	3.15
The topic itself is acceptable, but the questions are monotonous and boring	3.08
Length, much time to fill	3.07
There is no suitable answer for me	3.00
Use of foreign words	2.79
Use of technical words	2.61
The questionnaire begins with demographics, such as year of birth, and postal code	2.40
Informal register	1.73
Formal register	1.49

Source: authors.

To examine how irritation factors relate to survey breakoff, we first compared respondents who had ever broken off a questionnaire with those who had not using ANOVA and Mann–Whitney U tests. The results showed that respondents with prior breakoff experience were more sensitive to long questionnaires, boring topics, and situations where no suitable answer option was available ($p < 0.05$). To further explore which irritation patterns are more strongly associated with breakoff, we estimated an exploratory classification tree using the CHAID method. The dependent variable captured whether respondents had ever broken off a questionnaire (yes/no). The eleven irritation items (Table 1) were dichotomized (1–3 = low/no irritation, 4–5 = high irritation). Split selection was based on chi-square tests with Bonferroni-adjusted p-values ($\alpha = 0.05$), and prior probabilities were taken from the sample. The first and strongest splitter was boredom with the topic: respondents who reported high boredom were substantially more likely to have broken off the questionnaire than those who did not. Within this broad group, the tree next split on irritation with technical wording: those bothered by such wording showed an elevated likelihood of breakoff. Finally, among bored respondents who were not irritated by technical wording, breakoff was further differentiated by irritation with the lack of suitable answer options: those who felt no answer option had fit their opinion were more likely to have broken off a questionnaire. These patterns are consistent with the mean irritation levels reported in Table 1, in which boredom, complex wording, and inadequate answer options are among the highest-rated problems.

4.3. Ideal questionnaire length

We measured ideal questionnaire length in general and by mode. Mean preferred duration times were 8.44 minutes overall ($n = 953$), 8.33 for telephone ($n = 933$), and 8.49 for online ($n = 731$). Distributions were non-normal (one-sample Kolmogorov–Smirnov $p < 0.05$), so non-parametric tests were used. Mann–Whitney and Wilcoxon signed-rank tests indicated no significant differences between modes, implying that perceived tolerable length is not mode-dependent in this context. Therefore, H2 is rejected.

To increase power in subgroup analyses, we combined overall and telephone length into one variable. Age differences were statistically significant but substantively small (ANOVA homogeneity $p > 0.10$; F $p < 0.05$; eta squared = 0.07). Respondents aged 40–49 reported the shortest ideal length (mean about 7.7 minutes), followed by ages 30–39 and 18–29, while 50–59 and 60+ preferred slightly longer durations (about 8.4–8.8 minutes). These differences are consistent with time constraints among 40-49-year-olds but are too small to support age-based targeting. No gender significant differences emerged. A Kruskal–Wallis test showed a tendency for higher-educated respondents to prefer shorter surveys. However, the mean gap between the lowest and highest education categories was modest at 1.28 minutes and was not consistent across age strata. In practical terms, age- and education-related contrasts do not justify different target lengths.

4.4. Confidence in poll results

We assessed whether trust in public-opinion results relates to breakoff and ideal length. As expected, higher trust was associated with lower breakoff and longer ideal length (both $p < 0.05$). Breakoff rates nearly halved between those who did not trust polls and those who fully trusted them (46% versus 26%). Ideal length rose from 8.01 to 9.42 minutes across the same trust spectrum. These findings support H4. See Table 2 for the joint distribution of trust, breakoff experience, and ideal length.

Table 2. Level of trust in public opinion polls and ideal questionnaire length

How much do you trust the results of public opinion polls?	Have you ever broken off a questionnaire? (telephone or online) n=1142, row%		Ideal questionnaire length (minutes)
	Yes	No	
Do not trust them	46	54	8.01
Rather than trust them	36	64	8.10
Rather trust them	31	69	8.16
Trust them	26	74	9.42
Do not know/ do not want to answer	44	56	8.87

Source: authors.

Summary of hypothesis tests. H1 is accepted: length was the most commonly cited driver of breakoff (39%; Friedman $p \leq 0.05$). H2 is rejected: preferred length did not differ between telephone and online. H3 is partially accepted: age correlates with breakoff-relevant patterns, but tolerance for longer questionnaires did not increase with age in a practically meaningful way (ANOVA $p < 0.05$; eta squared = 0.07). H4 is accepted: higher trust was associated with lower breakoff (46% versus 26%, $p < 0.05$) and a longer ideal length (9.42 versus 8.01 minutes).

4.5. Cluster analysis – development of character profiles based on the individual confounding factors examined

To capture heterogeneity, we first applied K-means clustering to the original item ratings, focusing on tolerance for questionnaire length, perceived topic relevance, and response styles (items on formal vs. informal addressing were excluded). This analysis yielded three distinct clusters. To validate the robustness, we also ran K-means on the dimensions obtained from multidimensional scaling (MDS). The fit indices (Stress = 0.058; D.A.F. = 0.94; Tucker = 0.97) indicated that MDS adequately represented the inter-item structure. Cluster memberships were highly consistent across the two approaches (91%, 82%, and 100%), supporting the stability of the three-cluster solution. The three-cluster solution was retained based on interpretability, stability across specifications, and clear separation on key irritation dimensions. Differences across clusters on the disturbance items are reported in Table 3.

Table 3. Distinctions among scrutinized factors within identified clusters

In general, what bothers/annoys you about a questionnaire?	Discerning Evaluators (n=373) A	Experience Seekers (n=303) B	Nonchalant Responders (n=290) C
Length, too much time to fill out	3.6	3.9	1.5
Boring topic	4.1	4.1	1.7
The topic itself is acceptable, but the questions are monotonous and boring	3.7	3.7	1.7
Complicated/long questions and answers	3.9	3.5	1.7
The questionnaire begins with demographics, such as year of birth, and postal code	3.0	2.3	1.8
There is no suitable answer for me	3.8	3.1	2.0
Non-Hungarian wording	4.3	3.2	2.1
Use of technical words	4.0	1.7	1.8
Use of foreign words	4.1	1.8	2.1

Notes: Light gray shading: significantly different from the Discerning Evaluators segment ($p < 0.05$); Dark gray shading: significantly different from both the Discerning Evaluators and the Experience Seekers segments ($p < 0.05$). The deviation of individual averages in the examined clusters was analyzed with ANOVA.
Source: authors.

Discerning Evaluators (n = 373) display the most exacting quality standards. They are highly sensitive to wording quality, logic, and the completeness of response options, but are less affected by length than the other two groups. Experience Seekers (n = 303) prioritize the survey experience itself; boring topics and monotonous questions are particular pain points, and they show relatively low tolerance for long instruments. Nonchalant Responders (n = 290) have the lowest expectations and are least bothered by most features, including length.

Table 3 shows transparent gradients: compared with the other segments, Nonchalant Responders consistently rate topic boredom, monotony, length, complex items, early demographics, and wording issues as much less disturbing. Discerning Evaluators register the highest disturbance for non-native wording, technical and foreign words, and lack of suitable response options; Experience Seekers resemble Discerning Evaluators in topic boredom and monotony but show relatively less sensitivity to technical terminology.

The clusters were subsequently characterized demographically and geographically and analyzed with respect to behavioral differences. Table 4 summarizes these profiles and significant pairwise differences. Discerning Evaluators are more often women and appear more in middle-aged and older groups, with a concentration in Eastern Hungary. Experience Seekers skew younger and more highly educated and are overrepresented in Central Hungary, particularly Budapest. Nonchalant Responders have a mixed age distribution, tend to have medium or lower education levels, and are more prevalent in rural areas, small towns, and villages.

Table 4. Cluster profiles

Cluster profiles	Discerning Evaluators (n=373)	Experience Seekers (n=303)	Nonchalant Responders (n=290)
Male	*41%*	54%	58%
Female	59%	46%	42%
18-29	12%	29%	17% (b)
30-39	14%	23%	19%
40-49	21%	21%	20%
50-59	21%	12%	16%
60+	31%	***15%***	29%
Primary school or less	24%	***14%***	32%
Vocational school	22%	***11%***	31%
High school diploma	35%	40%	**25%**
University diploma	19%	34%	**12%**
West-Hungary	27%	23%	36%
Middle-Hungary	34%	54%	28%
East-Hungary	38%	***24%***	36%
Budapest	17%	36%	**8%**
The county seat, a city with county rights	23%	16%	19%
City	32%	29%	35%
Village, smaller town, homestead	28%	***20%***	39%
Average questionnaire length in minutes	7,71	7,63	**10,21**

Notes: Light gray shading: significantly different from the Discerning Evaluators segment ($p < 0.05$); Middle gray shading: significantly different from the Experience Seekers segment ($p < 0.05$); Dark gray shading: significantly different from the Nonchalant Responders segment ($p < 0.05$); Bold font: significantly different from both Discerning Evaluators and Experience Seekers ($p < 0.05$); Italic font: significantly different from both Experience Seekers and Nonchalant Responders ($p < 0.05$); Bold italic font: significantly different from both Discerning Evaluators and Nonchalant Responders ($p < 0.05$). The deviation of individual percentages within the clusters was examined using a Z-test.
Source: authors.

Experience also varied by cluster. Among respondents who had previously completed surveys, 75% were Experience Seekers, compared with 59% among Discerning Evaluators and 50% among Nonchalant Responders. Among those who had previously broken off a survey, Experience Seekers were again most common (39%), followed by Discerning Evaluators (36%) and Nonchalant Responders (21%). Preferred duration differed by cluster: Nonchalant Responders tolerated the longest instruments, with an average ideal of 10.2 minutes, whereas Experience Seekers and Discerning Evaluators preferred about 7.6 and 7.7 minutes, respectively. The Nonchalant Responders cluster reported a significantly longer average questionnaire length than both Discerning Evaluators and Experience Seekers.

Taken together, Tables 3 and 4 demonstrate that clusters differ systematically in sensitivities, behaviors, and socio-demographics. This heterogeneity explains why blanket rules are insufficient. For Discerning Evaluators, professional editing, clear logic, and complete response options are paramount; length is secondary. For Experience Seekers, topic selection and avoiding monotony are critical, with tighter time limits advisable. For Nonchalant Responders, moderate length is acceptable, but locally relevant content can improve engagement. These patterns provide actionable guidance for tailoring questionnaire profiles while controlling the principal breakoff risks.

To examine whether the three clusters differ in sociodemographic and behavioral characteristics beyond the irritation factors used for clustering, we estimated a multinomial logistic regression model. Cluster membership served as the dependent variable, with the Nonchalant Responders as the reference category. Predictors included gender, age, education, settlement type, region, subjective financial situation, prior breakoff experience, and preferred questionnaire length. A stepwise likelihood-ratio procedure was applied (entry criterion $p = 0.05$, removal criterion $p = 0.10$). Overall model fit was acceptable (model χ^2 $p < 0.001$; Nagelkerke $R^2 = 0.33$; deviance goodness-of-fit $p = 0.299$).

Relative to the Nonchalant Responders, several factors differentiated membership in the Discerning Evaluators cluster. Preference for a longer ideal questionnaire length was associated with a lower likelihood of belonging to this cluster ($B = -0.148$, $p < 0.001$, $Exp(B) = 0.863$). Education also played a role: respondents with vocational education were significantly less likely to belong to the Discerning Evaluators compared to those with higher education ($B = -1.256$, $p = 0.002$, $Exp(B) = 0.285$). A similar negative tendency was observed among respondents with primary education, although this association did not reach conventional levels of statistical significance ($B = -0.812$, $p = 0.065$, $Exp(B) = 0.444$). Other predictors showed no clear differentiation, although respondents aged 30–39 exhibited a marginally lower likelihood of belonging to the Discerning Evaluators cluster ($B = -0.778$, $p = 0.049$, $Exp(B) = 0.459$).

A comparable pattern emerged for the Experience Seekers cluster with respect to preferred questionnaire length: respondents who considered longer questionnaires acceptable were less likely to belong to this group ($B = -0.156$, $p < 0.001$, $Exp(B) = 0.856$). Education again proved to be a strong differentiating factor. Compared to respondents with a university degree, those with secondary education ($B = -1.081$, $p = 0.003$, $Exp(B) = 0.339$), vocational education ($B = -2.245$, $p < 0.001$, $Exp(B) = 0.106$), or primary education ($B = -1.552$, $p < 0.001$, $Exp(B) = 0.212$) were significantly less likely to belong to the Experience Seekers cluster. Age showed a clear positive association: respondents aged 18–29 were significantly more likely to belong to the Experience Seekers than to the reference group ($B = 1.213$, $p = 0.005$, $Exp(B) = 3.363$). Additional significant differences emerged for place of residence: living in Budapest ($B = 1.928$, $p < 0.001$, $Exp(B) = 6.874$) or in a small town ($B = 0.902$, $p = 0.012$, $Exp(B) = 2.464$) increased the likelihood of Experience Seeker membership. Regarding subjective financial situation, respondents reporting a medium (rather than good) financial position were more likely to belong to this cluster ($B = 0.740$, $p = 0.017$, $Exp(B) = 2.096$), while other categories showed no significant differences.

When directly comparing the Experience Seekers and Discerning Evaluators clusters, education again emerged as a key differentiator. Respondents without a university degree were significantly less likely to belong to the Experience Seekers relative to the Discerning Evaluators: this applied to those with secondary education ($B = -0.786$, $p = 0.005$, $Exp(B) = 0.456$), vocational education ($B = -0.989$, $p = 0.014$, $Exp(B) = 0.372$), and primary education ($B = -0.740$, $p = 0.042$, $Exp(B) = 0.477$). Age also strongly distinguished the two clusters, with respondents aged 18–29 ($B = 1.737$, $p < 0.001$, $Exp(B) = 5.680$) and 30–39 ($B = 0.772$, $p = 0.036$, $Exp(B) = 2.165$) being substantially more likely to belong to the Experience Seekers. Gender differences were also observed: men had a higher likelihood of Experience Seeker membership than women ($B = 0.677$, $p = 0.003$, $Exp(B) = 1.968$). With respect to settlement type, respondents living in Budapest ($B = 1.238$, $p < 0.001$, $Exp(B) = 3.447$) or in small towns ($B = 0.828$, $p = 0.008$, $Exp(B) = 2.288$) were more likely to belong to the Experience Seekers compared to the Discerning Evaluators.

5. Discussion

From a marketing management perspective, our findings translate directly into better survey practice. Managers routinely rely on questionnaires for assessing customer satisfaction, brand tracking, effectiveness, and pricing; accordingly, reducing breakoff improves the reliability and actionability of insights. The three respondent segments we identified – Discerning Evaluators, Experience Seekers, and Nonchalant Responders – offer a practical basis for tailoring instruments to segment-specific preferences. Such targeting, alongside attention to the major levers we document (length, topic salience, design quality, and trust), can reduce attrition, enhance data quality, and strengthen decision support.

Although we did not explicitly estimate breakoff rates by mode, our evidence and respondent narratives suggest that online questionnaires may be easier to abandon than telephone interviews. Respondents experienced in both modes also appear to be more critical and more frequent survey takers, an interaction that merits further study, especially as panel research expands, underscoring the importance of design vigilance online.

Consistent with prior work (Yan – Curtin 2010; Reimers et al. 2022), age and education are associated with item nonresponse: younger and more highly educated respondents are more likely to discontinue. This aligns with our expectation of decreasing breakoff with age and implies that studies targeting younger audiences should invest in engaging design elements, tighter pacing, and more explicit payoff cues.

We probed breakoff antecedents in two ways: reasons reported by confident respondents who had discontinued, and perceived disruptiveness of concrete questionnaire features. Consistent with prior work, multiple factors emerged as key drivers of breakoff, including survey length (Barge – Gehlbach 2011; Stefkovics 2022), topic relevance (Shropshire et al. 2009), and instrument quality – such as clarity, flow, and completeness (Yan – Curtin 2010; Albaum et al. 2011). While surveytainment is not yet common in Hungary and was not tested here, the literature indicates that it can offset the burden for specific groups; light-touch visual cues (e.g., emojis on mobile/web) may also help (Bosch – Revilla 2021). Looking ahead, AI offers opportunities to personalize item order, language, and examples to respondent profiles (Danó et al. 2025), potentially raising completion rates among younger cohorts.

Design guidance follows from these patterns. Concise wording, clear response options, and coherent routing improve data quality (De Leeuw 2012). Sensitive demographics should appear later (Biemer – Lyberg 2003), while the early placement of easy questions (Peytchev 2009) or high-interest topics (Plutowski – Zechmeister 2024) can build momentum and reduce early exits. Future work should quantify how question format and visual presentation trade off against completion time and measurement quality, and whether topic mixing produces interference effects.

In our context, the ideal survey length for the Hungarian population is roughly ten minutes. Length is especially consequential for younger and lower-educated segments, groups that are both harder to recruit and more attrition-prone, so parsimony is advisable. Cultural variation likely moderates these thresholds; cross-topic and cross-country comparisons of “optimal” durations remain a useful agenda. Device proliferation further motivates examining data quality by smartphone versus larger-screen completion.

Trust emerged as a pivotal correlate: respondents with greater trust in research were less likely to discontinue and more tolerant of longer questionnaires. Prior positive experiences appear to cultivate trust (Szeitl – Tóth 2020). Practically, transparency about objectives, procedures, privacy, and data use – paired with visible quality signals – can bolster credibility and reduce drop-off.

5.1. Positioning within Prior Research

Situating our results within prior survey research, we corroborate classic findings on length (Barge – Gehlbach 2011; Stefkovics 2022) and topic relevance (Shropshire et al. 2009) as determinants of engagement, and we echo evidence linking demographics to nonresponse (Yan – Curtin 2010). However, our results challenge the assumption that younger respondents uniformly prefer and better tolerate longer online surveys (Bosch – Revilla 2021): we observed no significant difference in preferred length by mode, implying that perceived burden is mode-invariant under typical conditions. Our segmentation further extends the literature (Plutowski – Zechmeister 2024; Kostyk et al. 2019) by offering refined, actionable profiles for design targeting.

5.2. Theoretical Contribution

The segmentation refines leverage–saliency theory (Groves et al. 2000) by demonstrating that salience and leverage cluster into stable respondent personas with distinct tolerance profiles for length, topic, and design features. Beyond feature-by-feature effects, a persona-based lens – bundling multiple attributes and preferences – provides a theoretically grounded explanation for heterogeneous engagement and an operational bridge to adaptive design. We also show that length tolerance is shaped not only by demographics (e.g., age) but by psychographics and prior experiences (notably, trust), enriching LST with an explicit credibility component.

5.3. International Relevance and Future Research Directions

Core breakoff mechanisms (length, salience, burden, motivation, trust) are likely universal, but thresholds vary culturally (Bosch – Revilla 2021; Daikeler et al. 2020; Sandelin 2022). As online panels and mobile surveys globalize, cross-cultural work should test mode-invariance of preferred length, sensitivity to question types, and responses to surveytainment across regions (e.g., Europe, North America, Asia). Applying our three-persona segmentation internationally can reveal whether the same clusters recur or whether culturally specific variants emerge, refining best practices for multinational marketing research. Future work should (i) validate these segments internationally; (ii) test AI-assisted adaptive designs; and (iii) examine device-specific effects for mobile-first surveys.

6. Conclusion

This study identifies the principal determinants of survey breakoff on both the questionnaire and respondent sides. On the questionnaire side, risks cluster around: (i) length; (ii) topic salience and timing, for example proximity to holidays; (iii) editing and wording quality, including clarity, logical flow, completeness of response options, and absence of errors; (iv) sensitive items; (v) presentation and usability in online modes; and (vi) selective use of engagement elements, often called surveytainment. On the respondent side, breakoff varies with demographics and life-stage time pressure, psychographic traits and motivation, prior survey experience, and trust in research. Together, these factors provide a concise design checklist for reducing attrition while safeguarding data quality.

Building on this synthesis, we propose cross-disciplinary best practices that are mode agnostic: keep instruments short and tightly scoped, ensure professional structure and coherent routing, and prioritize the respondent experience, including topic relevance, precise wording, and logical flow. Alignment with the target audience is essential, and rigorous pre-testing, with feedback integrated before fieldwork, remains the most cost-effective safeguard of quality.

A key practical contribution is our three-persona segmentation (Table 5), namely Discerning Evaluators, Experience Seekers, and Nonchalant Responders, which translates heterogeneous tolerance for length, topic, and design into actionable targeting. These profiles serve as design-oriented lenses rather than a priori targeting tools, highlighting how different respondent groups tend to engage with various questionnaire features. Practitioners can use these personas as design-oriented heuristics when tailoring instruments: concise and professionally edited questionnaires for Discerning Evaluators; innovative and engaging elements for Experience Seekers; and locally relevant, community-anchored content for Nonchalant Responders. Across segments, visible trust-building through transparent purpose, privacy assurances, and credible sponsorship can meaningfully reduce drop-off. For marketing applications such as customer satisfaction, brand tracking, ad testing, and pricing studies, these strategies improve completion and sharpen inference.

Table 5. Created personas

Persona	July	Adam	Peter
Cluster membership	Discerning Evaluators	Experience Seekers	Nonchalant Responders
Degree of criticality	Most critical	Moderately critical	Low expectations
Expectations	A well-edited and carefully worded questionnaire; length is less salient than quality and structure.	Boring topics and monotonous questions are annoying	Hardly any
Length of questionnaire	Secondary to wording quality and structural coherence	Long questionnaires quickly reduce engagement if the topic is not stimulating	Does not bother him at all
Gender	Woman	Man	Man
Age	50 years	28 years	42 years
Education	Higher education	Higher education	Secondary education
Residence	East-Hungary	Central Hungary (Budapest)	Smaller town
Questionnaire topic	Intellectual and professional topics, e.g., surveys on quality	Less common, innovative topics, e.g., design thinking, gamification	Region-specific research, e.g., measuring satisfaction with local services
Family status	Family with adult children	Lives in a relationship	Family with children
Job	Intellectual work, management position	Holds a managerial position	Employed in a local business
Hobbies	Reading, visiting cultural events	Travel, cultural events, and entertainment	Visiting local events, fishing

Source: authors.

Our findings point to several directions for future research. Methodologically, adaptive designs and AI-enabled personalization (e.g., dynamic ordering, language tuning) could optimize burden and engagement in real time, especially for younger cohorts. Recent work also shows that digital interfaces and AI-mediated interactions increasingly shape respondents' survey experiences (Danó et al. 2026), suggesting that future studies should examine how these emerging technologies may influence breakoff dynamics and engagement patterns. Cross-country studies should test cultural differences in survey length tolerance, question sensitivity, and engagement features. As mobile use grows, device-specific analyses can guide mobile-first design.

Several limitations temper interpretation. First, as the study relied on RDD-based telephone recruitment across multiple omnibus waves, precise AAPOR response rates are not available. As is common in commercial omnibus surveys, contact and cooperation rates are managed by the fieldwork agency and cannot be reconstructed ex post.

Second, data were collected in Hungary. While many mechanisms, such as length, salience, and trust, are likely general, thresholds and topic sensitivities may vary with cultural norms and media environments. Our sampling approach offers strong population coverage locally, but panel populations, increasingly common in practice, may exhibit different patterns, including higher trust, greater tolerance for length, and more critical evaluation of flaws.

Third, the breakoff measures rely on self-reported recall. Memory error and social desirability may bias reports of past participation and discontinuation. Future longitudinal or diary studies could reduce recall bias and validate the pathways we propose. Because recall captures whether breakoff occurred but not its frequency or intensity, future studies should incorporate measures of breakoff extent as well. Experimental or longitudinal designs could further clarify mechanisms and reduce reliance on retrospective reports.

Fourth, accurate interpretation assumes a baseline understanding of survey research among respondents. In rare cases, commercial interactions may be mistaken for research, which could contaminate recall, although this is unlikely to be widespread in our context.

Finally, the omnibus design implies that preceding modules on unrelated topics could have primed fatigue or interest in ways we cannot fully observe. Although such ordering effects reflect real-world survey ecosystems, experimental control over sequence would help isolate pure design impacts. The study is associative in nature and does not establish causality.

Despite these constraints, the core message is robust: keep surveys short, make them salient, signal quality, build trust, and tailor to segments. Doing so can help reduce breakoff, improve data quality, and strengthen the strategic value of survey-based insights.

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Declaration of interest

The authors declare no conflict of interest.

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Appendix

Table A1. Demographic Characteristics

		Unweighted %	Weighted %
Gender	Male	45	47
	Female	55	53
Age	18-29	11	17
	30-39	9	16
	40-49	17	20
	50-59	17	16
	60+	45	32
	Refuses to answer	1	0
Education	Primary school or less	11	24
	Vocational/technical	21	21
	Secondary	35	34
	Higher education	33	21
	Refuses to answer	1	0
Settlement type	Budapest	20	18
	County seat	18	20
	City	35	33
	Village	27	30
	Refuses to answer	1	0

		Unweighted %	Weighted %
Region	West-Hungary	29	30
	Central-Hungary	32	36
	East-Hungary	37	35
	Refuses to answer	2	0

Table A2. Questions asked in the surveys

Question		Answer options	Subsample
Have you ever participated in a telephone survey (i.e., a survey conducted by phone) and/or an online survey (i.e., a survey completed on an online platform)?		No, this is the first time I have responded to a survey Yes, telephone surveys only Yes, online surveys only Yes, both telephone and online surveys Don’t know / No answer	1, 2, 3
Have you ever discontinued a survey before completing it?		Yes, a telephone survey Yes, an online survey Yes, both No Don’t know / No answer	1, 2, 3 (If you have previously participated in a telephone or online survey)
Why did you discontinue this/ these survey(s)?	It was too long	Mentioned Not mentioned	1
	It was boring	Mentioned Not mentioned	1
	Something came up	Mentioned Not mentioned	1
	The questionnaire was illogical (questions, response options, errors)	Mentioned Not mentioned	1
	Because of personal or sensitive questions	Mentioned Not mentioned	1
	I did not like the topic	Mentioned Not mentioned	1
Why did you discontinue this/ these survey(s)?	Other, please specify:	Mentioned Not mentioned	1
	Don’t know / No answer	Mentioned Not mentioned	1
What do you consider to be the ideal questionnaire length (in minutes) in general?		Open-ended question	3

<table>
<tr><th colspan="2">Question</th><th>Answer options</th><th>Subsample</th></tr>
<tr><td colspan="2">What do you consider to be the ideal questionnaire length (in minutes) for a telephone survey?</td><td>Open-ended question</td><td>1</td></tr>
<tr><td colspan="2">What do you consider to be the ideal questionnaire length (in minutes) for an online survey?</td><td>Open-ended question</td><td>1</td></tr>
<tr><td rowspan="11">In general, what tends to bother or annoy you in a questionnaire?</td><td>The questionnaire is too long / takes too much time to complete</td><td></td><td>2</td></tr>
<tr><td>The topic is boring</td><td></td><td>2</td></tr>
<tr><td>The topic itself is fine, but the questions are monotonous or boring</td><td></td><td>2</td></tr>
<tr><td>The questions or response options are too complex or too long</td><td></td><td>2</td></tr>
<tr><td>The questionnaire starts with demographic questions (e.g., year of birth, postal code)</td><td></td><td>2</td></tr>
<tr><td>There is no response option that fits my opinion</td><td></td><td>2</td></tr>
<tr><td>Poor or awkward wording</td><td></td><td>2</td></tr>
<tr><td>Use of technical or professional terminology</td><td></td><td>2</td></tr>
<tr><td>Use of foreign words</td><td></td><td>2</td></tr>
<tr><td>Use of informal register (‘tutoiement’)</td><td></td><td>2</td></tr>
<tr><td>Use of formal register</td><td></td><td>2</td></tr>
<tr><td colspan="2">How much do you trust the results of public opinion surveys?</td><td></td><td>1, 2</td></tr>
</table>