administrative sciences

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Beyond Average AI Expectations: The Relative Prominence of Data Security and Privacy Concerns Among Entrepreneurs in 51 Economies

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Abstract

Entrepreneurs may differ both in how frequently they expect substantial business impacts from artificial intelligence (AI) and in which consequences they rate as high impact. Using the 2024 Global Entrepreneurship Monitor Adult Population Survey, this study compares five anticipated benefits and five challenges across 51 economies. National estimates are survey-weighted and averaged equally across economies. The operating-business owner-manager module provides the main evidence; a separate start-up module provides descriptive context. We compare high-impact prevalence with each item's position relative to a five-item domain benchmark. Among owner-managers, data security and privacy concerns stand 7.89 percentage points above the challenge benchmark on average, with a between-economy standard deviation of 6.23 points; the contrast is positive in 43 of 51 economies. Removing employee resistance from the benchmark preserves a similar national pattern. In contrast, a broader impact threshold changes some national profiles, and four-cell composition standardization is feasible in only 18 economies. By distinguishing absolute prevalence from within-domain position, the study identifies national response-profile differences that aggregate high-impact rates do not describe. For entrepreneurship support organizations, the findings suggest discussing specific anticipated consequences before designing assistance. The results concern reported expectations; national measurement equivalence and actual AI adoption were not assessed.

Keywords: artificial intelligence; entrepreneurship; anticipated business impacts; data security; privacy concerns; international comparison; Global Entrepreneurship Monitor

1. Introduction

Entrepreneurs must interpret potential consequences of artificial intelligence (AI) before deciding whether and how to implement it. Introducing AI may affect customer relationships, operations, products, revenues and the stewardship of business data. Research identifies opportunities throughout venture creation and development alongside organizational and social difficulties (Chalmers et al., 2021; Giuggioli & Pellegrini, 2023). A recent synthesis similarly documents the competing opportunities and constraints of generative AI in entrepreneurial activity (Lu et al., 2026). These studies examine AI's possible uses and consequences; the question considered here is which of those consequences business owners anticipate. The consequences they rate as high impact may differ even when their overall assessments of AI impacts are similar.

Technological expectations offer a perspective for examining these distinctions. The sociology of expectations considers how representations of technological futures, including

Check for updates

Received: 16 October 2026
Revised: 19 November 2026
Accepted: 20 November 2026
Published: 24 November 2026

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promises and concerns, can shape how new possibilities are understood (Borup et al., 2006). Such representations are socially situated rather than neutral forecasts (Brown & Michael, 2003). In entrepreneurship, digital technologies reshape both opportunities and uncertainty surrounding venture creation (Nambisan, 2017), while digital transformation opens heterogeneous pathways for value creation and capture (Nambisan et al., 2019). Anticipating greater operational efficiency is not the same as anticipating novel products; similarly, data-protection concerns differ from concerns about costs or employee resistance. These judgments may prompt different questions about preparation and experimentation even when overall enthusiasm is similar. Our analysis examines the distribution of anticipated consequences, leaving their subsequent effects on entrepreneurial decisions for future research.

International comparisons make this distinction consequential. A national population may rate many possible AI effects as high impact, creating the appearance of both strong expected gains and strong expected difficulties. Such aggregate intensity does not identify which consequences receive relatively more high-impact assessments. For example, privacy can have higher absolute prevalence in one economy but stand further above the other four challenges in another. The resulting profiles are relational: they describe the composition of reported expectations within the GEM's specified item set, rather than underlying concern free of survey or response constraints.

Earlier GEM evidence offers an important point of comparison. Crnogaj et al. (2026) analyze AI-related benefits and challenges among Slovenian entrepreneurs, while the Luxembourg GEM report presents country and European item profiles (GEM Luxembourg, 2025). The GEM Global Report discusses AI expectations within international entrepreneurship (GEM, 2025). Their identification of data security and privacy as a notable concern is therefore not a new finding of the present study. Our contribution is to estimate a common-respondent relative profile across 51 economies, show how much its national pattern depends on the five-item benchmark, and assess the effects of response differentiation, missingness and limited observable composition. Unlike studies of organizational AI adoption (Arroyabe et al., 2024), we analyze anticipated, not realized, business impacts.

We ask how the relative and absolute prevalence of expected AI benefits and challenges vary among the 51 participating entrepreneurial populations, focusing on the combined data security and privacy concerns item. Does its prominence reflect a consistent difference from other challenges, and to what extent are national patterns sensitive to response patterns and available composition measures? The distinction is motivated by the sociology of technological expectations: the anticipated content of technological change may differ even where aggregate expectations are similar (Borup et al., 2006). We describe the ten GEM impact items on comparable respondent sets, compare the focal item with each other challenge and examine selected sensitivity specifications. We neither infer a country's attitude towards AI nor attribute these reported expectations to adoption decisions.

2. Theoretical Framework

2.1. Expectations About Technological Consequences

An anticipated impact is a prospective judgment about what introducing AI could mean for one's business. It is neither an objective forecast nor necessarily a considered implementation plan. The expectations perspective makes these judgments relevant because technological futures can become reference points for present activity, although the survey does not test that process (Borup et al., 2006). Here the empirical object is the content of hypothetical business-impact assessments at the time of interview. No causal sequence from expectations to implementation is presumed.

AI can alter entrepreneurial opportunity recognition, operations and innovation, but its potential benefits are accompanied by organizational and informational risks (Chalmers et al., 2021; Giuggioli & Pellegrini, 2023; Obschonka & Audretsch, 2020). Recent work on generative AI likewise emphasizes that empowering effects can coexist with limitations that require entrepreneurial judgment (Lu et al., 2026). Digital entrepreneurship research distinguishes business model development from organizational challenges (Kraus et al., 2019), and innovation studies distinguish novel product development from operational applications (Haefner et al., 2021). These perspectives motivate item-specific expectations without implying that the GEM's questions directly measure the processes described in those studies. Expected revenue growth, for example, is neither observed performance nor a measure of the entrepreneur's intention to adopt AI.

Benefits and challenges should also remain distinguishable. Risk-perception research separates intuitive reactions from deliberative assessments, showing why a survey judgment should not automatically be treated as an objective risk estimate (Slovic & Peters, 2006). The present items cannot identify which process produced an answer. Nor are privacy and productivity opposite ends of one item: a respondent may envisage useful data-intensive applications while expecting substantial difficulty protecting the data involved. This is a substantive possibility, not an inference about observed individual co-occurrence from national averages. No bipolar attitude scale or paradox is presumed.

Research on organizational AI further illustrates why prospective judgments should not be reduced to a single evaluative attitude. Automation and augmentation create distinct, partly interdependent managerial tensions (Raisch & Krakowski, 2021), whereas adoption-readiness studies focus on organizational capabilities and implementation commitments (Jöhnk et al., 2021). The GEM items capture neither framework directly, but they distinguish several business referents: benefits involving customers, operations, innovation, compliance and revenue, and challenges involving data protection, implementation, employees, ethics and customer trust. This variety permits a more specific description of the changes entrepreneurs anticipate than a generalized optimism score. The items need not represent ten independent psychological constructs; similarly, the five-item domain average used below is a descriptive benchmark rather than a validated latent measure of optimism, risk concern or readiness.

Privacy and trust represent distinctive concerns. Privacy judgments can depend on context, uncertainty and how information is presented (Acquisti et al., 2015). Cross-national research predating current AI applications found variation in concerns about personal information, linked in different ways to culture, internet experience and regulatory environments (Milberg et al., 2000; Bellman et al., 2004). Those studies concerned consumers and information privacy, not owners' anticipated business impacts of AI; they support the relevance of context without establishing the source of the present contrasts. AI research also distinguishes trust in a technology from trust in deploying organizations (Glikson & Woolley, 2020; Hengstler et al., 2016), while algorithmic accountability raises ethical issues beyond privacy (Martin, 2019). These separate literatures help motivate a specific examination of privacy but do not identify the mechanisms operating in GEM respondents.

2.2. Intensity and Relative Prevalence Answer Different Questions

Domain intensity describes how frequently a national respondent population selects high impact across five specified benefits or challenges. Relative prevalence describes an item's high-impact share compared with that domain benchmark. Intensity concerns the extent of high-impact expectations across the item set; a profile concerns their composition. Distinguishing the two makes it possible to ask whether countries envisage a broadly similar set of consequences with different intensity or differentiate the consequences themselves.

A simple example illustrates the difference. If privacy receives 40% high-impact responses and the challenge-domain benchmark is 30%, its relative prevalence is +10 percentage points. In another economy, privacy might receive 50% high-impact responses against a 45% benchmark, producing a contrast of +5 points. Although privacy has higher absolute prevalence in the second economy, it stands further above the other challenges in the first. This distinction matters because equally intensive expectations need not describe the same anticipated transformation. A profile dominated by efficiency would suggest a different set of envisaged business applications from one in which innovation stands out; a profile emphasizing privacy would differ from one dominated by implementation costs. These examples concern the relative frequency of reported high impacts, not the seriousness of eventual harms, the amount of attention entrepreneurs allocate, or the behavioral responses that follow.

The contrast is relational: it can increase because the focal item's high-impact share rises, the other four items' shares decline, or both. Absolute response distributions are therefore needed alongside relative profiles. The benchmark also depends on which five challenges the GEM selected. Employee resistance, for example, may have a different practical meaning in a business with no working persons than in one employing a larger workforce. Moreover, because privacy enters its own five-item benchmark, its contrast is four-fifths of the difference from the mean of the other four items. Common within-domain respondents prevent the contrast from being assembled from inconsistent item denominators. Centering is consequently a transparent descriptive comparison, not a correction for all response styles or a new measurement theory. Its empirical value depends on the size and uncertainty of the observed differences and on whether they persist after plausible features of response patterns and business composition are examined.

2.3. International Interpretation and the Limits of Profile Comparison

National contexts may shape which technological consequences appear relevant. Business composition, digital exposure, public discussion, regulation and language can all influence how respondents understand the introduction of AI, although their effects are not estimated here. A national profile summarizes weighted judgments in a defined questionnaire-route population, rather than an attitude shared by all entrepreneurs in that economy. The distinction between expected impacts and implementation is also substantive: organizational readiness concerns capabilities and conditions relevant to AI adoption (Jöhnk et al., 2021), while the GEM questions ask about possible business consequences regardless of current adoption intentions. Similarly, the range of possibilities discussed in digital entrepreneurship research (Nambisan et al., 2019; Kraus et al., 2019) cannot be used to infer a national implementation trajectory from the reported profiles.

Cross-national survey research gives a further reason not to equate a reported profile with a cultural disposition. Harzing (2006) documents differences in response styles across countries and languages; Davidov et al. (2014) explain the need for measurement equivalence when comparing subjective constructs. Studies of information privacy also suggest that privacy concerns may depend on experience and national context (Milberg et al., 2000; Bellman et al., 2004), but they do not provide an invariant benchmark for AI-impact expectations. The common English GEM master establishes intended wording and coding, not equivalence of fielded translations or national survey implementation. The item-specific approach used here does not establish measurement invariance.

Subtracting a domain average cannot remove country-specific response thresholds, floor and ceiling constraints, differences in item interpretation or all manifestations of response style. The English master questionnaire presents privacy first among five challenges, leaving position effects as a further possible influence; equal weighting of countries does not

establish the equivalence of national-language questionnaires. An elevated relative privacy contrast is therefore best interpreted as a feature of reported expectations within GEM's five-item challenge set. It may be consistent with greater attention to data governance, but it cannot by itself identify regulatory burden, opposition to AI or lower technological readiness. Explaining where these differences originate, whether they persist and whether they guide entrepreneurial decisions requires additional evidence.

3. Materials and Methods

3.1. Data Source and Study Population

The 2024 GEM Adult Population Survey (APS) contains 167,575 records from 51 economies. The study retains respondents aged 18–64 with a finite positive WEIGHT_L and a new- or established-owner classification (TEA24STA = 2 or ESTBBUSO = 1). From 18,062 potentially eligible owners, 533 individuals simultaneously classified as early-stage and established owners (TEA24 = 1 and ESTBBUSO = 1) were excluded to prevent ambiguous status attribution. These 533 include the narrower overlap of 113 individuals meeting both new- and established-owner classifications; the groups are not additional exclusions. The resulting restricted frame contains 17,529 individuals (6389 new and 11,140 established owners). Questionnaire routing further limits the observed AI-impact samples (Table A2). The study population is therefore restricted to eligible new and established business owners aged 18–64 and does not encompass all forms of entrepreneurial activity captured by the GEM APS.

The operating-business owner-manager (OM) questionnaire is the primary analysis route; the start-up (SU) route is reported separately. Routes refer to the businesses described in the questionnaire rather than unambiguous venture stages. A same-business rule skips subsequent OM questions when the relevant business has already been described in SU. There are 320 respondents with valid answers in both modules, possibly for different businesses; the two modules are therefore neither independent samples nor a within-person stage comparison. Appendix A records the intended questionnaire rules, and Appendix B traces the retained owner frame through routing and response completeness.

3.2. Measures

The GEM questionnaire covers five anticipated AI benefits—customer personalization, productivity and efficiency, product and service innovation, risk management and compliance, and revenue growth—and five anticipated challenges: data security and privacy concerns, implementation costs, resistance among employees, ethical dilemmas, and customer resistance or mistrust. Each item records no (1), low (2) or high (3) impact; 'don't know', refusal and system-missing responses are excluded from the valid denominators. Critically, data security and privacy concerns form a single questionnaire item and cannot be disentangled. 'Privacy contrast' below is a short label for this combined item. The questions refer to potential consequences of introducing AI, not current adoption or realized performance. The English master presents challenges before benefits, but equivalence of fielded national translations has not been established (GEM, 2024a, 2024b; Appendix A).

3.3. Analytical Approach

We first calculate survey-weighted national distributions across the three response categories for each item, using the supplied individual weight (WEIGHT_L) within each economy. International summaries are arithmetic means of the 51 national estimates, giving economies equal rather than population-proportional weight. These statistics describe participating economies as comparable units; they do not estimate the proportion of all entrepreneurs worldwide selecting a given response. We retain the full ordinal distributions descriptively and use the prevalence of high-impact assessments (category 3) for compar-

isons of particular anticipated consequences. To distinguish the overall frequency of high-impact responses from the relative position of a specific impact, we calculate within-domain contrasts. For economy c and item j in domain d, let $p(c,j)$ be the weighted high-impact share and $B(c,d)$ the mean of the five within-domain high-impact shares. The percentage-point contrast is:

$$r(c,j) = 100 \times [p(c,j) - B(c,d)], B(c,d) = (1/5)\ \Sigma(k \in d)\ p(c,k).$$

Contrasts use identical respondents for all five items within a domain and therefore sum to zero within each national profile. For the combined data security and privacy item, a positive value means that more owner-managers rate this consequence as high impact than they do the five challenges on average. The contrast represents a relative prevalence, not a scale of concern, and can change because of the focal item, its comparator items or both. We consequently report absolute and relative estimates side by side and examine an alternative benchmark omitting the employee-resistance item.

We summarize the observed dispersion of national contrasts by their unweighted standard deviation; a noise-adjusted descriptive value subtracts the mean estimated national sampling variance from the observed variance. National sampling variances are approximated using fixed, normalized survey weights and respondent-level composite contrasts, thereby preserving covariance between answers from the same person. Pointwise normal intervals and Cochran's inverse-variance Q are approximate because complete national design information is unavailable. For the fixed 51-economy set, we also give an interval for the country-equal mean that propagates these estimated national variances, rather than assuming that the participating economies were randomly sampled from a global population of countries. The formulas and limitations are set out in Appendix B. Analyses were implemented and independently checked using Python 3.12.

3.4. Sample Support, Sensitivity and Comparability

Of 17,529 individuals in the restricted owner frame, 12,731 reached the reconstructed OM continuation route. Of these, 11,826 provided at least one valid AI-impact response and 10,264 completed all five challenges; 2467 (19.4%) failed to give a valid response to at least one challenge. Challenge-item missingness within the continuation route ranges from 10.5% to 12.3%, largely involving 'don't know' responses. Across the 50 economies with both complete and incomplete challenge responses (Thailand had no incomplete cases), the challenge-complete group had a lower proportion of women (−4.59 percentage points) and a higher proportion of respondents with postsecondary education (+8.10 points) than the incomplete group. These are descriptive selection differences, not a formal missing-data correction. The complete five-benefit OM and five-challenge SU samples contained 10,571 and 4345 respondents, respectively; the SU benefit-complete sample contained 4450. Each domain-complete group included all 51 economies. Table A2 and Appendix B provide the sample flow and further detail.

Our sensitivity analyses consider respondents who distinguished between the five binary challenge answers, a minimum national effective sample size, complete answers to all ten items, and a broader 'any impact' threshold (categories 2–3). We additionally compare the combined data security and privacy item with each challenge separately and recompute its centered contrast after removing employee resistance. National correlations with challenge intensity and an exploratory quadratic model describe, but do not remove, the contrast's algebraic constraints. Four-cell composition standardization is undertaken only where all subgroup support conditions hold. Appendix B identifies the 18 economies; subgroup sizes appear in Supplementary Table S1.

For the five challenge items, $H(i,j) = 1$ denotes high impact and $H(i,j) = 0$ denotes low/no impact among valid answers. A respondent is 'differentiating' when between

one and four of the five indicators are high; all five high or all five not high are binary-uniform, regardless of whether their original ordinal responses are identical. Let $d(c)$ be the national weighted share of differentiating respondents and $m(c)$ their weighted mean individual privacy contrast. Binary-uniform respondents contribute zero, so the national contrast satisfies the exact identity $R(c) = d(c) \times m(c)$. This decomposition separates the prevalence of within-domain differentiation from privacy's position among those who differentiate. Let $I(c)$ be overall challenge high-impact intensity as a fraction. The sharp feasible privacy-contrast bounds are $100 \times \max[-I(c), 4I(c) - 4]$ and $100 \times \min[4I(c), 1 - I(c)]$, respectively. Thus centering cannot make the contrast mathematically independent of intensity near its floor or ceiling.

Composition analyses distinguish new and established owners and zero versus positive counts on OMNOWJOB, an item that excludes owners but includes exclusive subcontractors and should not be described as a payroll-employee count. Each of four status-by-working-person cells requires at least 10 observations and Kish effective $n \geq 5$; only 18 economies qualify. Their common reference composition is the country-equal average of the four national weighted cell shares: established/positive 45.21%, established/zero 24.37%, new/positive 18.18%, and new/zero 12.25%. We compare raw and standardized estimates on these same economies. The calculations condition on the estimated common reference shares and cannot rule out other compositional differences (Appendix B).

4. Results

4.1. Patterns of Anticipated AI Benefits and Challenges

Table 1 indicates that anticipated AI impacts are not evenly distributed across business consequences. In the primary OM sample, productivity and efficiency are most often rated a high-impact benefit (41.9% across equally weighted economies), followed by product and service innovation (40.2%); risk management and compliance are least often rated high (34.6%). Among challenges, data security and privacy stand out (40.3%), while implementation costs and difficulties (34.3%) and especially employee resistance (26.2%) receive less frequent high-impact assessments. The privacy–employee resistance difference is approximately 14 percentage points. The substantive distinction is between different anticipated consequences, not between objectively measured technology benefits and harms.

Table 1. Country-equal distributions of anticipated impacts (%).

Dimension	OM No	OM Low	OM High	OM *n*	SU No	SU Low	SU High	SU *n*
Customer personalization	32.6	29.3	38.1	11,240	19.5	28.5	52.0	4792
Productivity and efficiency	30.2	27.8	41.9	11,331	18.1	28.0	53.9	4812
Product/service innovation	31.8	28.0	40.2	11,292	19.3	29.4	51.3	4798
Risk management/compliance	34.8	30.7	34.6	11,148	22.1	31.3	46.6	4705
Revenue/business growth	31.6	30.3	38.1	11,180	18.7	30.5	50.7	4772
Data security/privacy	31.8	27.8	40.3	11,394	21.2	31.6	47.2	4800
Costs/implementation	32.6	33.1	34.3	11,229	22.7	35.9	41.5	4783
Employee resistance	44.7	29.1	26.2	11,163	31.8	34.7	33.5	4736
Ethical dilemmas	40.8	29.1	30.2	11,165	31.0	33.7	35.3	4682
Customer resistance/mistrust	38.3	31.2	30.5	11,198	28.4	34.1	37.5	4713

Notes: Item-specific valid samples; every item covers 51 economies. WEIGHT_L is applied within countries, then country estimates are averaged equally. *n* is the unweighted total valid-response count, not an international weight. Percentages may not total 100 due to rounding. Codes 1/2/3 are no/low/high impact. SU denotes responses to the start-up AI-impact module among eligible new and established business owners, rather than a sample restricted to nascent entrepreneurs.

The supplementary SU module exhibits a broadly similar item ordering but higher observed high-impact shares, including 53.9% for productivity and 47.2% for privacy. This

descriptive difference cannot be attributed to venture stage because questionnaire routing and business referents differ. Across economies, mean high-impact prevalence for benefits and challenges is positively correlated ($r = 0.764$ in OM; $r = 0.730$ in SU). These ecological correlations may partly reflect country-level propensity to endorse high-impact categories and motivate the separate assessment of relative item profiles; they are not evidence that individual entrepreneurs simultaneously express both orientations.

4.2. Domain Intensity and Relative Impact Profiles

Table 2 reports high-impact prevalence and relative contrasts on identical domain-complete respondents; Table 1 instead retains all valid responses to each item individually. Among OM respondents completing all five benefits, productivity and efficiency stand +3.2 points and innovation +1.7 points above the five-item benefit benchmark. On the challenge-complete OM sample ($n = 10{,}264$), 39.7% rate data security and privacy concerns as high impact, against a challenge benchmark of 31.8%, giving a +7.89-point contrast. Employee resistance has a lower absolute prevalence of 26.4% and a −5.37-point contrast. This shared-denominator comparison separates a particular consequence's prominence from the general tendency to select high-impact answers.

Table 2. Common-sample absolute high-impact prevalence and relative profiles across 51 economies.

Dimension	OM High (%)	OM Relative (pp)	OM Country SD (pp)	SU High (%)	SU Relative (pp)
Customer personalization	38.1	−0.8	5.6	52.9	+1.0
Productivity and efficiency	42.1	+3.2	5.2	54.5	+2.7
Product/service innovation	40.6	+1.7	3.8	52.0	+0.2
Risk management/compliance	35.0	−4.0	5.8	47.7	−4.1
Revenue/business growth	38.9	0.0	5.4	52.0	+0.2
Data security/privacy	39.7	+7.9	6.2	47.2	+7.9
Costs/implementation	33.5	+1.7	6.1	41.7	+2.5
Employee resistance	26.4	−5.4	6.0	34.1	−5.1
Ethical dilemmas	29.3	−2.5	5.1	34.9	−4.4
Customer resistance/mistrust	30.0	−1.8	5.9	38.4	−0.8

Notes: High (%) and relative contrast (pp) use the same five-item domain-complete respondents within each economy. OM $n = 10{,}571$ for benefits and 10,264 for challenges; SU $n = 4450$ and 4345, respectively. Each economy enters international averages once. OM SD is the unweighted between-economy standard deviation of its relative contrasts. The item-specific valid samples in Table 1 differ and should not be subtracted from this table.

Figure 1 shows the extent to which country profiles depart from their overall domain benchmarks. Pale points are the 51 national OM estimates for each item; vertical jitter is for visibility only. Diamonds and circles are OM and restricted SU country-equal means. Positions describe high-impact prevalence relative to the five-item domain benchmark. The plotted point spread is country variation, not a confidence interval. Among OM benefits, national dispersion of the relative contrast ranges from 3.8 points for innovation to 5.8 for risk management; the largest challenge-domain dispersion is 6.23 points for the combined data security and privacy item. The supplementary SU module yields an average +7.9-point contrast for that item and −5.1 points for employee resistance, although its smaller effective national samples limit comparisons. Similar international averages can therefore mask different country-level configurations without revealing the causes of those configurations.

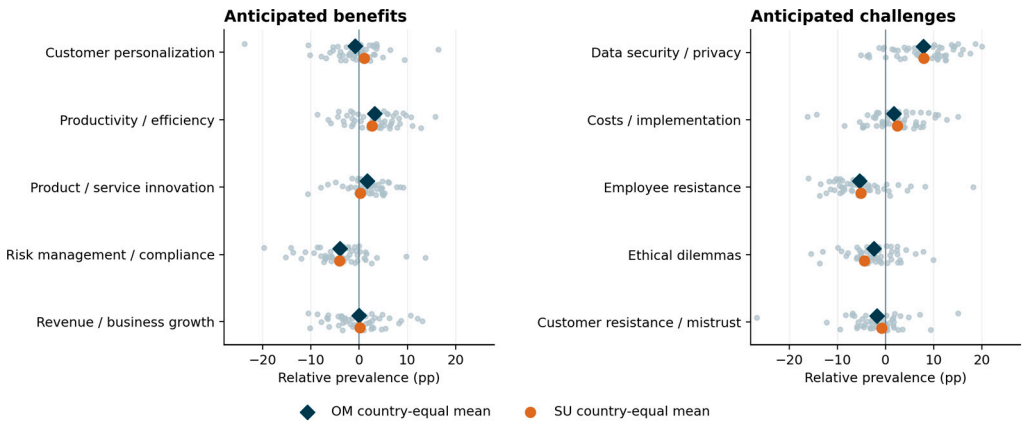


Figure 1. Relative item prevalence on complete-domain samples.

4.3. International Heterogeneity in the Data Security and Privacy Contrast

The country-equal OM data security and privacy contrast averages +7.89 percentage points across the fixed 51-economy set (approximate 95% sampling interval: 6.83–8.95 points). It is positive in 43 economies, while national contrasts range widely (tenth and ninetieth percentiles −0.54 and +15.07 points). The interval describes uncertainty in the mean for these participating economies under the stated approximation; it is not a confidence interval for all economies worldwide. Figure 2 displays the national contrasts against overall challenge-domain high-impact intensity.

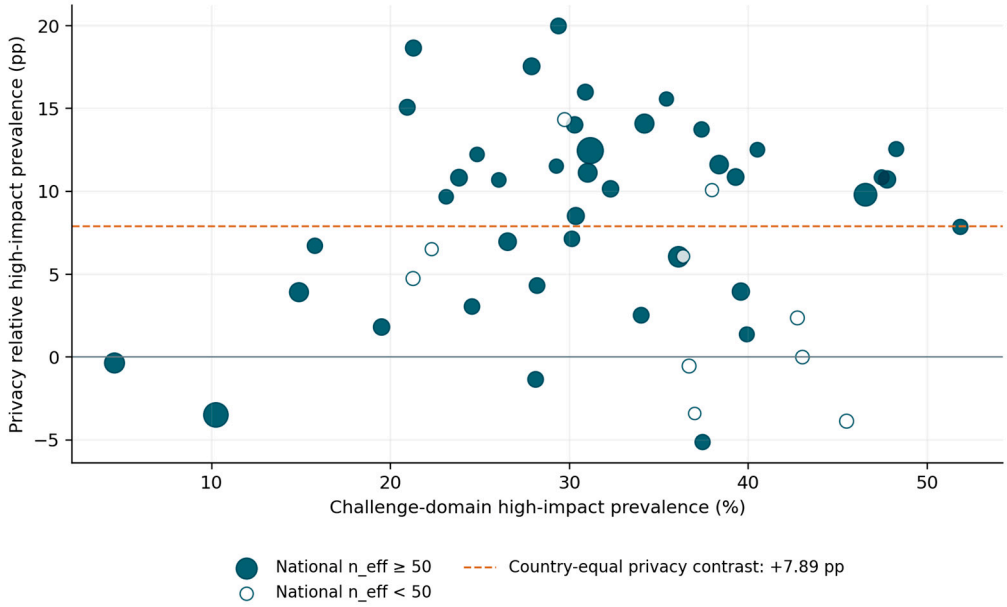


Figure 2. Relative prevalence of data security and privacy concerns and challenge-domain intensity in OM. **Notes:** Each point is one economy. The horizontal axis shows the mean high-impact prevalence across five challenges; the vertical axis shows the combined data security and privacy item's contrast against that benchmark on the same OM respondents. Bubble size represents Kish effective n; open markers identify economies with effective $n < 50$. The dashed line shows the country-equal mean. The relationship shown is at the economy level and should not be interpreted as an individual-level association.

The national contrast has little overall linear or monotone association with the domain high-impact intensity (Pearson r = 0.049; Spearman ρ = −0.004), but the relationship need not be linear. A descriptive quadratic fit accounts for 8.9% of the observed country variation.

Among respondents who differentiated between challenges, the association of conditional contrast with conditional intensity is negative (Pearson r = −0.370; Spearman ρ = −0.337). The five-item contrast is also bounded near zero when overall intensity approaches its floor or ceiling. Accordingly, the weak aggregate correlations do not establish independence from intensity or eliminate response-process differences.

The observed between-economy standard deviation is 6.23 points; subtracting the mean approximate national sampling variance yields a descriptive noise-adjusted value of 4.89. The inverse-variance heterogeneity diagnostic is $Q(50) = 476.3$ (approximate $p < 0.001$), but it is especially sensitive to Poland: excluding it reduces Q to 278.8 (49 df). The country-equal SD changes little in leave-one-economy-out checks (6.01–6.30), and remains substantial among economies with effective $n \geq 50$. These results document variation in the observed national estimates; neither Q nor the adjusted SD validates cross-national measurement equivalence. The supplementary SU module has a similar country-equal mean contrast (+7.90 points) but less precise national evidence.

4.4. Response Differentiation, Business Composition and Robustness

Within the challenge-complete OM sample, 48.6% of respondents were binary-uniform across the five challenge indicators: 8.6% rated every challenge high and 40.0% rated none high. The other 51.4% differentiated, a share ranging from 11.4% in South Korea to 89.2% in Germany (28.8% in Poland). This variation may reflect substantive views, sample composition or survey response processes. Among 5141 differentiating respondents, the country-equal mean conditional contrast is +16.04 points (Table 3). Its larger magnitude is partly mechanical: respondents with binary-uniform patterns contribute exactly zero, so excluding them increases nonzero national contrasts without changing their signs. The identity $R(c) = d(c) \times m(c)$ is a decomposition, not a correction for response style. The overall contrast correlates only weakly with the national differentiating share (r = 0.060), but this alone cannot establish comparable response processes across economies.

Table 3. Sensitivity of national privacy relative-prevalence contrasts in OM.

OM Analysis	G	*n*	Mean pp	Country SD	Adj. SD	Q (df)
Primary: high impact	51	10,264	7.89	6.23	4.89	476.3 (50)
Five-item differentiators	51	5141	16.04	13.49	11.19	374.2 (50)
Differentiators, n_eff ≥ 50	25	4281	15.60	11.49	10.45	261.0 (24)
Ten-item complete	51	9761	7.88	6.10	4.64	458.1 (50)
Primary, n_eff ≥ 50	41	9861	8.93	5.93	4.90	464.6 (40)
Any impact (2–3)	51	10,264	5.52	6.70	5.78	680.4 (50)
18-economy unadjusted	18	5753	10.00	6.04	5.39	90.3 (17)
18-economy standardized	18	5753	10.06	5.91	5.20	85.5 (17)

Notes: Countries are equally weighted in the reported means and SD; WEIGHT_L is used within economies. The primary contrast is centered on five high-impact challenges. The 'any impact' row changes the threshold to categories 2–3; other rows change respondent or economy subsets. Conditional contrasts among differentiators are mechanically larger because binary-uniform respondents contribute zero. Adj. SD is a descriptive sampling-noise adjustment and Q uses approximate inverse-variance weights; neither constitutes fully design-based inference. Additional benchmark checks and national estimates are reported in the text and Appendix C. Both 18-economy rows use the same 5753 OM challenge-complete respondents with valid working-person counts; only the four-cell composition weights change under standardization. Supplementary Table S1 reports the unweighted subgroup counts and Kish effective sample sizes.

The benchmark's composition matters because employee resistance may be less applicable to enterprises without working persons. Nevertheless, the combined data security and privacy item exceeds each other challenge for the same OM respondents: by +6.17 points relative to costs and implementation, +13.25 to employee resistance, +10.34 to ethical

dilemmas and +9.66 to customer resistance or mistrust. The corresponding differences are positive in 38, 45, 46 and 42 of the 51 economies. Removing employee resistance from the centered benchmark reduces the country-equal mean to +6.54 points (SD 5.65), but preserves strong national rank agreement with the original (Spearman $\rho = 0.968$; same sign in 49 economies). This is a useful benchmark check, not proof that the items have equal relevance in every business. Using a broader low-or-high impact threshold instead gives a +5.52-point mean, only moderate national rank agreement ($\rho = 0.709$), and three sign changes (Table 3). Robustness therefore depends on the definition of anticipated impact.

The ownership and staffing checks are more limited. Among 35 economies with supported working-person comparisons, businesses with positive counts rate employee resistance as high impact 6.10 points more often than those with zero counts, but their difference in the relative privacy contrast is small and uncertain (−1.08 points; country-based 95% interval −3.84 to 1.68). The established-minus-new owner contrast is similarly uncertain (+1.37 points; −0.65 to 3.38; 47 economies). Direct four-cell standardization for the 18 supported economies changes their mean from +10.00 to +10.06 points and their SD from 6.04 to 5.91. This cannot establish that composition is immaterial beyond the two coarse observed characteristics. Appendix B lists the supported economies, and Supplementary Table S1 provides their four-cell sample sizes.

For subgroup comparisons, WEIGHT_L-weighted estimates were calculated separately for each subgroup within each economy. Paired economy-level differences were formed (positive minus zero working-person counts, or established minus new ownership); both subgroups required Kish effective $n \geq 10$. For the G eligible economies (G = 35 and G = 47, respectively), the country-equal mean difference has a descriptive 95% Student's t interval: $\overline{d} \pm t(0.975, G - 1) \times s_d/\sqrt{G}$, where s_d is the sample standard deviation of the G national differences. These intervals depend on an economy-exchangeability assumption and omit full national survey-design features. Both intervals for the relative privacy contrast include zero, so they do not establish a directional subgroup difference. The employee-resistance high-impact difference for positive versus zero working-person counts is +6.10 percentage points (95% country-t interval +2.77 to +9.43); this remains a descriptive rather than a causal comparison.

5. Discussion

5.1. Empirical Contribution of the 51-Economy Comparison

The central result is not merely that data security and privacy concerns receive frequent high-impact assessments. Across the same respondents, their prevalence exceeds other anticipated challenges on average, yet their relative position varies considerably between participating economies. This variability is not captured by a country's overall frequency of high-impact answers. More importantly, it remains descriptively similar when employee resistance is removed from the benchmark, although a broader low-or-high impact threshold changes some national patterns. These qualifications identify both the value and the limits of comparing the configuration of anticipated consequences.

Relative to earlier GEM studies of Slovenia and Luxembourg, the article adds consistent denominators, an equal-economy international description, and explicit tests of benchmark composition and missingness. The theoretical connection is to the content of technological expectations (Brown & Michael, 2003; Borup et al., 2006): two populations may foresee comparably extensive AI-related change but emphasize different anticipated consequences. The present survey cannot determine why the configurations differ. In particular, the mechanically increased contrast among differentiators and the small 18-economy standardization change are qualifications of the descriptive evidence, not independent demonstrations of an underlying mechanism.

5.2. Conceptual Contribution to the Study of Expectations

This interpretation treats AI expectations as a differentiated set of anticipated business consequences rather than a single orientation towards technology. Productivity and innovation, for example, are distinct expected opportunities; data security and privacy, implementation costs and customer mistrust are distinct anticipated difficulties. Their national item profiles can differ even where domain-wide impact intensity is similar. Entrepreneurship and digital innovation research already distinguishes multiple pathways for technology-enabled value creation and adaptation (Nambisan, 2017; Nambisan et al., 2019; Haefner et al., 2021). Our contribution is therefore not a new psychometric scale, but a cross-national empirical demonstration of what is concealed when multiple possible consequences are summarized by a single average.

The sociology of expectations regards descriptions of technological futures as socially situated representations, not straightforward forecasts (Brown & Michael, 2003; Borup et al., 2006). The differing relative profiles suggest that the content of expected AI-induced change deserves as much attention as its aggregate intensity. Recent entrepreneurship research emphasizes both the potential and the trade-offs of AI (Lu et al., 2026; Fossen et al., 2024), but the GEM questions measure neither the processes that form those expectations nor their effects on subsequent decisions. The contrast is also conditional on the selection of five GEM challenge items; it should not be interpreted as an intrinsic national level of privacy concern.

Adoption research addresses the subsequent question of whether and how firms implement AI in the context of organizational capabilities and constraints (Arroyabe et al., 2024; Jöhnk et al., 2021). An important next step is therefore to examine whether particular expected consequences, rather than a single summary of enthusiasm or concern, are associated with readiness, experimentation, investment or eventual adoption. The present evidence helps define the anticipations to be followed in such research, without presuming that they cause those outcomes.

5.3. Implications and Alternative Interpretations

The findings suggest a practical starting point for public institutions and entrepreneurship support organizations. Rather than inferring needs from a generic measure of AI enthusiasm or reluctance, they can ask entrepreneurs which consequences they anticipate for their particular business and distinguish data-protection needs from implementation costs, employee adaptation and customer trust. Advisers and training providers could use this distinction to organize introductory AI-readiness conversations and tailor examples to each firm's activities. Entrepreneurship education research independently indicates that learning environments and individual characteristics interact (Kariv et al., 2025), supporting the general case for contextualized training rather than one uniform program. Neither study establishes that a particular intervention improves subsequent AI adoption.

For entrepreneurs considering AI, the profiles point to a useful sequence of questions: which business process might benefit, what information would AI systems need, and which safeguards or skills might that use require? Consultants supporting early ventures can discuss these issues alongside opportunities for partnerships and access to complementary resources. Recent work on start-up–incumbent collaborations highlights the opportunities and coordination challenges of such relationships (Giglio et al., 2025), although it does not examine the GEM expectations studied here. These uses of the findings are proposed applications of descriptive evidence, not evaluated policy recommendations.

Variation in the relative data security and privacy profile is consistent with the possibility that institutional contexts, business exposure and public discussion affect how consequences are anticipated. Prior information-privacy research finds contextual and

cross-national differences (Milberg et al., 2000; Bellman et al., 2004; Acquisti et al., 2015), but these studies largely concern consumers rather than owners' prospective business judgments. The unusually wide range of response differentiation across economies also warrants methodological care (Harzing, 2006; Davidov et al., 2014). Neither institutional explanation nor national measurement equivalence was tested here.

National contrasts should not be read as a ranking of technological readiness, regulatory strictness or entrepreneurial competitiveness. A positive relative value could arise from greater anticipated data-governance challenges, lower ratings of other challenges, or both. Similarly, a high-impact response need not signal rejection of AI: respondents may simultaneously expect improvements in productivity and innovation. The immediate scholarly implication is to distinguish the specific content of reported expectations from their intensity; explaining the origins and behavioral implications of those expectations requires further research.

6. Limitations and Conclusions

Several limitations concern comparability and selection. National-language translations, field implementation and cross-economy measurement equivalence were not independently verified. In the English master questionnaire, the combined data security and privacy item appears first among the five challenges; position effects remain possible. National differences in binary response differentiation may reflect both substantive judgments and survey processes. Complete-case respondents also differ observably from incomplete respondents, notably in gender and education, and missing answers may carry information about uncertainty. The analysis therefore describes the participating questionnaire-route samples rather than an invariant population-level construct.

The variance estimates assume fixed weights and independent respondent records; national sampling clusters, strata and full nonresponse adjustments could not be incorporated. The 51 economies are not a probability sample of countries worldwide, and the focal item was selected after exploratory inspection. Its contrast is sensitive to the chosen benchmark and response threshold, while composition standardization covers only two coarse characteristics and 18 economies. The data are cross-sectional and concern anticipated, rather than observed, adoption or business outcomes. These boundaries restrict generalization and causal interpretation without negating the descriptive comparisons.

The study documents differences between national owner-manager response profiles in both the overall prevalence of high-impact AI expectations and the relative position of specific anticipated consequences. Data security and privacy concerns exceed the five-challenge benchmark in 43 of the 51 participating economies; this pattern remains broadly similar when employee resistance is excluded. These profiles offer a more differentiated starting point for comparative research and context-sensitive entrepreneurship support than aggregate intensity alone. Their institutional origins and influence on actual adoption remain open empirical questions.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/admsci16120579/s1, Table S1. Four-cell sample support for direct standardization.

Funding: The Slovenian component of the Global Entrepreneurship Monitor (GEM) study was supported by SPIRIT Slovenia, Public Agency for Investments, Entrepreneurship and Internationalization; the Ministry of the Economy, Tourism and Sport of the Republic of Slovenia; and the Slovenian Research and Innovation Agency (ARIS). This work was also supported by ARIS research programme P5-0023, Entrepreneurship for Innovative Society. The funding sources had no involvement in the study design, data collection, analysis, interpretation, writing of the manuscript, or in the decision to submit the article for publication.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: This study uses individual-level data from the Global Entrepreneurship Monitor (GEM) 2024 Adult Population Survey, released on 20 February 2026. Access to these data is governed by the GEM Consortium, and the individual-level records cannot be redistributed by the author. The analytical procedures are documented in the Methods and Appendices A–C, with additional subgroup information provided in Supplementary Table S1. Analysis code and non-disclosive aggregate results are available from the author upon reasonable request. Reproduction of the analyses requires authorized access to the GEM individual-level data. Full national survey-design variables and fielded questionnaire translations were not available.

Acknowledgments: Although this work is based on data collected by the Global Entrepreneurship Monitor (GEM) consortium, responsibility for the analysis and interpretation rests solely with the author. During the preparation and revision of this manuscript, the author used OpenAI ChatGPT (GPT-5.6) for English-language editing and to assist with the development and checking of Python 3.12. code for statistical analyses. The author reviewed and verified the analytical procedures, numerical results and interpretations, critically edited AI-assisted content, and takes full responsibility for the final manuscript.

Conflicts of Interest: The author declares no conflicts of interest.

Appendix A. AI Impact Measures and Questionnaire Routing

Table A1. GEM APS 2024 AI-impact items and questionnaire identifiers.

Item	AI Impact Dimension	SU Question	OM Question
NEG1	Data security and privacy concerns	1DAI10	2DAI10
NEG2	Increased costs and implementation challenges	1DAI11	2DAI11
NEG3	Resistance among employees	1DAI12	2DAI12
NEG4	Ethical dilemmas in artificial intelligence decision-making	1DAI13	2DAI13
NEG5	Customer resistance or mistrust	1DAI14	2DAI14
POS1	Enhanced personalization for customers	1DAI15	2DAI15
POS2	Improved productivity and efficiency across operations	1DAI16	2DAI16
POS3	Innovative product and service development	1DAI17	2DAI17
POS4	Better risk management and compliance	1DAI18	2DAI18
POS5	Increased revenue and business growth	1DAI19	2DAI19

Source: GEM APS 2024 master questionnaire and question-by-question commentary (GEM, 2024a, 2024b). **Notes:** NEG1–NEG5 identify anticipated AI challenges, and POS1–POS5 identify anticipated benefits. The start-up (SU) and operating-business owner-manager (OM) modules use the same substantive item wording. Responses are coded as 1 = no impact, 2 = low impact, and 3 = high impact; 'don't know' (−1), refusal (−2), and system-missing values are excluded from valid-response denominators. Both modules present the five challenges before the five benefits, with data security and privacy appearing first among the challenges. The questions concern potential impacts of introducing AI into the respondent's business, rather than actual AI adoption or realized outcomes. No three-year forecast horizon is specified.

Questionnaire routing and comparability. The GEM APS 2024 questionnaire administers AI-impact questions through separate SU and OM modules, depending on respondents' entrepreneurial activities and business ownership. The questionnaire routing includes a same-business skip rule: where a business has already been covered in the SU module, the corresponding OM questions are not repeated for that business. Some respondents may nevertheless provide valid answers in both modules, potentially referring to different businesses. Consequently, the two modules represent distinct questionnaire-route populations and cannot be interpreted as independent samples of successive entrepreneurial development stages. The analysis therefore reports SU and OM results separately.

The English master questionnaire establishes the intended item wording, response categories, and routing rules. However, the available documentation does not establish equivalence of national-language translations or identical questionnaire implementation across all 51 participating economies. Cross-economy comparisons should therefore be interpreted as comparisons of reported AI-impact expectations within the GEM measurement framework, rather than as evidence of fully invariant underlying perceptions.

Appendix B. Additional Methodological Details and Robustness Checks

Sample selection and routing. Applying the 18–64 age restriction and finite positive WEIGHT_L retained 161,520 of 167,575 APS records. The new- or established-owner screen identified 18,062, and the overlapping early-stage/established exclusion removed 533 once (including the nested narrower overlap of 113), leaving 17,529. The progression through the separate OM questionnaire route and five-challenge completeness is given in Table A2. Counts describe reconstructed analytical filters, not national questionnaire response rates.

Table A2. Analytical sample progression and OM questionnaire route.

Sequential Selection Step	Retained *n*	Removed *n*
Original GEM APS records	167,575	—
Age 18–64; finite positive WEIGHT_L	161,520	6055
New or established ownership screen	18,062	143,458
Exclude overlapping early-stage/established owners	17,529	533
After same-business SU–OM skip	14,264	3265
After OM continuation screen	12,821	1443
After OM ownership screen	12,731	90
At least one valid OM AI item	11,826	905
All five OM challenge items valid	10,264	1562

Note: Exclusions are sequential. 'OM continuation' is reconstructed from recorded routing fields; missing items are not equivalent to nonresponse to the APS as a whole.

Missing responses and response patterns. Among the 12,731 OM continuation cases, 2467 are incomplete on at least one challenge item, with item-level invalidity of 10.50–12.32%. Across 50 economies allowing within-country comparisons, challenge-complete respondents have a 4.59-point lower female share, an 8.10-point higher postsecondary education share, and a 2.40-point higher established-owner share. These characteristic-specific comparisons do not assume missingness at random. Binary-uniform response patterns contribute exactly zero to the relative contrast, giving the identity $R(c) = d(c) \times m(c)$, where d is the weighted differentiating share and m the conditional contrast. Alternative thresholds and sample restrictions appear in Table 3; national patterns under the any-impact threshold agree only moderately (Spearman $\rho = 0.709$), with three sign changes.

Variance and standardization. Let $x_ci = 100[H_ci,privacy - (\Sigma_j\ H_cij)/5]$ and $q_ci = w_ci/\Sigma_i\ w_ci$. The country estimate $r_c = \Sigma_i\ q_ci\ x_ci$ has approximate variance $v_c = [n_c/(n_c - 1)]\ \Sigma_i\ q_ci^2(x_ci - r_c)^2$, yielding pointwise $r_c \pm 1.96\sqrt{v_c}$ intervals. For the fixed 51-economy set, mean $= (\Sigma_c\ r_c)/51$ and SE $= \sqrt{(\Sigma_c\ v_c)/51}$. Cochran's $Q = \Sigma_c\ (r_c - r_IV)^2/v_c$, where $r_IV = (\Sigma_c\ r_c/v_c)/(\Sigma_c\ 1/v_c)$. Kish effective $n = (\Sigma_i\ w_ci)^2/\Sigma_i\ w_ci^2$. This approximation assumes independent records and fixed weights; it omits clustering, stratification, weight estimation and selection. The fixed-set interval does not describe worldwide economy sampling.

The descriptive noise-adjusted between-economy standard deviation is $SD_adj = \sqrt{[\max(0, s^2 - (1/G)\Sigma_c\ v_c)]}$, where $s^2 = \Sigma_c(r_c - \bar{r})^2/(G - 1)$ is the observed sample variance of the G national contrasts and v_c is each economy's approximate sampling variance defined above. This adjustment removes the mean estimated national sampling

variance from the observed cross-economy variance, truncated at zero; it is not a fully survey-design-based measure of underlying heterogeneity.

Composition standardization. Four cells cross new/established ownership with zero/positive working-person counts. Within each supported economy, their weighted shares s_cg and contrasts r_cg are estimated after removing missing working-person counts. The reference share S_g is the equal-country average of s_cg across 18 economies, and r_c,std = Σ_g S_g r_cg. Its approximate conditional variance is Σ_g S_g^2v_cg, holding S_g fixed and omitting shared-target covariance. The supported economies are Armenia, Austria, Brazil, Chile, Ecuador, France, Guatemala, Hungary, India, Jordan, Norway, Oman, Slovenia, Spain, Sweden, Taiwan, Thailand and the United States. The four-cell sample counts and effective sizes appear in Supplementary Table S1.

Appendix C. Economy-Level Privacy Contrasts

Table A3 gives the unweighted and effective OM challenge-complete sample sizes, the relative data security and privacy contrast, its approximate pointwise 95% interval and the weighted share of respondents differentiating between the five challenges. The intervals communicate unequal national precision; they are not an evaluation of translation equivalence or a ranking of national attitudes.

Table A3. National OM support, combined data security and privacy contrast, and differentiation.

Economy	OM *n*	Effective *n*	Contrast (pp)	95% Approx. Interval (pp)	Differentiating (%)
Argentina	82	78.8	+7.85	[+0.17, +15.53]	73.3
Armenia	130	128.4	+1.81	[−2.92, +6.55]	38.1
Austria	315	294.0	+14.09	[+10.22, +17.95]	54.9
Belarus	49	42.8	+14.33	[+5.28, +23.38]	45.5
Bosnia and Herzegovina	85	84.6	+6.70	[+0.77, +12.63]	32.9
Brazil	177	174.2	+3.96	[−1.84, +9.75]	62.3
Canada	55	50.5	+15.58	[+4.49, +26.67]	65.0
Chile	257	172.1	+10.72	[+5.59, +15.84]	68.8
China	45	44.7	−0.54	[−11.16, +10.07]	68.8
Costa Rica	30	29.4	+10.07	[−0.24, +20.38]	39.8
Croatia	59	58.7	+10.68	[+0.80, +20.56]	50.3
Cyprus	130	129.3	+10.15	[+4.39, +15.90]	49.5
Ecuador	280	276.2	+11.12	[+7.57, +14.66]	44.5
Egypt	93	80.2	−5.14	[−14.36, +4.09]	75.1
Estonia	113	103.0	+15.07	[+9.19, +20.96]	35.6
France	263	250.9	+11.61	[+7.25, +15.98]	61.9
Germany	140	100.1	+2.53	[−5.93, +10.98]	89.2
Greece	203	190.8	+6.95	[+2.02, +11.88]	38.3
Guatemala	310	140.8	+10.86	[+4.64, +17.08]	63.3
Hungary	150	141.4	+10.82	[+5.96, +15.68]	40.1
India	226	91.4	+3.05	[−2.96, +9.06]	45.4
Israel	58	58.0	+9.67	[+3.17, +16.16]	22.5
Italy	95	90.5	+7.12	[+0.44, +13.81]	58.3
Jordan	107	99.2	−1.35	[−7.16, +4.46]	52.0
Kazakhstan	39	36.9	0.00	[−8.46, +8.45]	41.5
Latvia	134	125.4	+14.01	[+7.83, +20.19]	52.6
Lithuania	46	46.0	+4.74	[−2.74, +12.23]	34.6
Luxembourg	100	61.8	+12.51	[+3.51, +21.51]	56.3
Mexico	51	44.2	+2.37	[−6.83, +11.56]	55.5
Morocco	18	17.9	−3.41	[−21.70, +14.88]	60.8
Norway	132	113.1	+18.65	[+11.97, +25.34]	56.9
Oman	98	97.5	+19.99	[+13.49, +26.49]	38.3
Poland	1023	1023.0	−3.50	[−4.84, −2.15]	28.8
Puerto Rico	74	71.9	+12.55	[+6.03, +19.07]	51.3
Qatar	77	72.5	+1.37	[−7.41, +10.16]	62.8

Table A3. *Cont.*

Economy	OM *n*	Effective *n*	Contrast (pp)	95% Approx. Interval (pp)	Differentiating (%)
Romania	63	47.0	−3.87	[−13.99, +6.24]	50.8
Saudi Arabia	711	709.4	+9.79	[+6.83, +12.75]	73.7
Serbia	64	58.7	+12.22	[+2.93, +21.52]	52.6
Slovakia	51	50.5	+11.52	[+2.09, +20.95]	48.4
Slovenia	146	145.6	+17.55	[+11.65, +23.45]	57.2
South Korea	379	378.5	−0.36	[−1.84, +1.12]	11.4
Spain	2200	1372.1	+12.45	[+10.70, +14.21]	50.5
Sweden	153	103.2	+15.99	[+8.27, +23.72]	58.6
Switzerland	84	83.8	+13.74	[+5.80, +21.67]	71.7
Taiwan	179	160.5	+8.51	[+3.27, +13.74]	55.6
Thailand	291	290.7	+3.92	[+0.89, +6.94]	36.4
Ukraine	28	28.0	+6.50	[−4.93, +17.93]	35.8
United Arab Emirates	72	72.0	+10.84	[+2.23, +19.45]	66.9
United Kingdom	97	96.4	+4.32	[−2.65, +11.29]	47.3
United States	468	394.2	+6.05	[+2.70, +9.40]	53.3
Venezuela	34	30.9	+6.07	[−3.65, +15.79]	36.9

Note: Estimates use the five-challenge-complete OM sample. *n* is an unweighted count; effective *n* is the Kish unequal-weight size. The contrast is in percentage points relative to the five-challenge high-impact benchmark; differentiating (%) is survey-weighted within economy. Intervals are pointwise normal approximations under fixed weights and independent records. They omit national survey-design features and selection bias and should not be interpreted as country rankings. Kazakhstan's contrast rounds to 0.00 points.

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