



Research Article

Disinformation in practice: Threats, actors, mechanisms, and constraints according to practitioners

How do the practitioners charged with fighting disinformation understand the problem they are meant to solve? We surveyed 106 French practitioners across military, government, regulatory, civil-society, and media organizations. These practitioners converge on an upstream, supply-side diagnosis (platforms and amplification structures, rather than public demand, drive the spread of disinformation) but describe a field blocked by weak coordination, scarce resources, and fear of censorship accusations. Their relationship to science adds to these constraints: while most practitioners trust peer-reviewed research, few engage with it directly. Nearly all expect disinformation to become a greater threat, and only 13% believe institutions will be able to contain it.

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Research questions

- How do counter-disinformation practitioners perceive the threat of disinformation, its trajectory, and those responsible for it?
- In the practitioners' view, why do people believe disinformation, and what makes it spread?
- What operational, legal, and ethical constraints hinder practitioners' actions?
- How do practitioners access and use scientific research, and how do their views compare with scientists'?

Essay summary

- Practitioners broadly share an upstream, supply-side diagnosis of disinformation, identifying platforms, algorithms, and organized actors as more important drivers of the problem than citizens' demand for false content.
- This shared diagnosis does not translate into effective action: practitioners report that governments call the fight against disinformation a priority but withhold the coordination, resources, clear mandates, and shared indicators an effective response requires.

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- Practitioners rank the fear of being accused of censorship among their top obstacles, yet most say they rarely or never face ethical dilemmas: what inhibits them is not moral conflict but the accusation they anticipate.
- Scientific research is trusted but rarely read firsthand. Most practitioners rely on press coverage and gray literature, leaving practice largely dependent on secondhand interpretations of the evidence base. The barriers they report are mainly organizational (lack of time, paywalled access, weak institutional incentives), and most read about disinformation in French while the literature is largely in English.
- Set against academics surveyed in 2022 (Altay, Berriche, Heuer, et al., 2023), practitioners agree on well-established drivers of belief in disinformation, such as confirmation bias and repetition, but judge its electoral impact larger and give less weight to institutional distrust. This comparison is descriptive, as the two surveys differ in instruments and timing.
- Nearly all practitioners expect disinformation to become a greater threat, and only 13% believe institutions will be able to contain it.
- Practitioners need research translated into their working language, shared measures of exposure and effects rather than activity counts, clearer coordination, and transparent safeguards that make legitimate intervention defensible.

Implications

The people who shape and carry out democracies' responses to disinformation are not scientists. They are civil servants, military officers, and regulators. Yet these practitioners remain largely unstudied. Recent surveys have mapped what scientists and experts think about misinformation (Altay, Berriche, Heuer, et al., 2023; Altay et al., 2025; Kruger et al., 2024), but not the practitioners who act on that knowledge.

We surveyed 106 French practitioners engaged in counter-disinformation work: senior figures such as members of the offices of the President and Prime Minister, officials in the ministries of Foreign Affairs and Health, military and intelligence officers, executives of independent regulators (such as the audiovisual regulator ARCOM and the telecommunications regulator ARCEP), and journalists specialized in fighting disinformation (see Appendix A for sampling and inclusion criteria). This study documents how counter-disinformation practitioners in a national setting understand the threat and identifies where institutional responses risk falling short of the evidence they claim to rely on.

This article uses “disinformation” as French practitioners and institutions do: as an umbrella term, broader and more heterogeneous than researchers' usage (Wardle & Derakhshan, 2017), routinely extended to misinformation, malinformation, and information manipulation at large (Darcy, 2026a, pp. 7–10; Appendix H). Even within the French field, the term's meaning follows each institution's mandate: security institutions (the armed forces, the Foreign Affairs Ministry, and VIGINUM, the government service against foreign digital interference) work with the narrower lens of foreign information manipulation and interference (FIMI), while journalists and educators confront the broader spectrum. We therefore imposed no definition on respondents.

By “counter-disinformation practitioners” we mean people who, by virtue of their position, hold responsibility for preventing, monitoring, analyzing, regulating, or responding to disinformation in this broad sense (see Methods). What unites them is functional rather than conceptual—a mandate within the response system, exercised under institutional or organizational constraints, not a shared profession, toolkit, or definition of the problem. Whether their understandings converge is therefore an empirical question, and the findings show that there is convergence on the diagnosis but divergence on obstacles and research use.

Research and practice form two communities, with distinct incentives, vocabularies, and timelines (Caplan, 1979; Weiss, 1979). In neighboring fields such as advertising and crisis communication, practitioners act on implicit theories that develop largely independently of academic findings (Claeys & Opgenhaffen, 2016; Kover, 1995; Nyilasy & Reid, 2009). Because knowledge translation must be tailored to the receiving community's beliefs and constraints (Oliver et al., 2014; Ward et al., 2009), documenting what practitioners believe, read, and face is a prerequisite for any research-to-practice effort.

Most of the practitioners we surveyed were trained in the social sciences and communication studies and report little formal research training, a sample profile oriented toward institutional analysis and operational response rather than research production or consumption (see Methods and Appendix A). This background plausibly leads them to frame the problem in terms of cases, discourse, and institutions more than quantitative data.

Practitioners share an upstream, supply-side understanding of the disinformation problem: they trace the problem to the production and amplification of false content and give little weight to the public's demand for such content (see Finding 2 below). Nine in ten rate social media platform owners as a major threat to the information environment, while ordinary citizens come last by a wide margin. The same supply-side logic shapes how they explain the spread of disinformation: large majorities attribute that spread to platform algorithms and to mass distribution by producers and platforms, whereas the idea that the public actively seeks out such content divides them.

In a descriptive comparison with about 150 academic scientists surveyed by Altay, Berriche, Heuer, et al. (2023), practitioners agree on well-established drivers of belief in disinformation but differ on contested questions. They rate the electoral impact of misinformation far higher and give less weight to institutional distrust, which scientists treat as central to vulnerability (see Finding 6 and Appendix C). This points to a selective diagnosis. By overweighting supply-side factors and individual credulity while underweighting the social and institutional conditions that make misleading claims persuasive, the field risks designing interventions that miss the deeper drivers of the problem.

This common diagnosis is not matched by a shared capacity to act. Practitioners report facing numerous concrete obstacles (Finding 3). The leading obstacle, which three in four respondents rate as serious, is a gap between rhetoric and action, and the complaint comes from inside the state. Officials, officers, and regulators report that counter-disinformation is proclaimed a priority without the resources, coordination, and indicators it requires. Most of these obstacles are structural. Institutions are asked to respond to a politically sensitive threat under fragmented authority, ambiguous mandates, and uncertain legitimacy, conditions under which even a shared diagnosis fails to produce action.

A further obstacle concerns knowledge itself. The research that could broaden this selective diagnosis rarely reaches practitioners directly (Finding 4). The issue is engagement, not trust in science. Seven in ten respondents trust peer-reviewed research to guide their decisions, yet only about a third keep up with it, relying instead on the press and gray literature. Language sustains the pattern, since nearly all read about disinformation primarily in French, a language in which far less of the literature is available.

The main barriers to scientific engagement are organizational. Lack of time, limited access to publications, and weak institutional incentives all rank above low perceived applicability, the language barrier, and methodological difficulty, though self-reports may understate the last two (Finding 4). Perceived applicability and the language barrier both vary sharply by role (Appendix D). Research is trusted in principle but consumed through intermediaries, which could create gaps between what practitioners believe the evidence shows and what it actually supports.

Whether this selective, supply-side diagnosis reflects incomplete uptake of the evidence or limits in the evidence itself can be partly answered item by item. The first reading, incomplete uptake, holds on the two divergences noted above, where current evidence does not support the practitioner position. On elections, the best available evidence finds little sign that misinformation decides outcomes (Allcott & Gentzkow, 2017; Budak et al., 2024; Eady et al., 2023). On trust, comparative research treats institutional

trust as central to vulnerability (Ejaz et al., 2025; Humprecht et al., 2020), and low institutional trust is widely recognized as making people more receptive to misinformation, even by researchers who disagree about misinformation's societal effects (Altay & Mercier, 2026; Tay et al., 2026). This makes practitioners' low ranking of institutional distrust all the more notable. The second reading, limits in the evidence, is also plausible: a literature that is largely Anglophone, platform-centric, and focused on average population effects may say less about the targeted foreign operations many respondents confront. Exploratory analyses do not settle the question: respondents who engage most with research find it neither more nor less applicable than those who rarely do (all $|p| \leq .18$; Appendix I).

A third reading ties the other two together and may help explain the supply-side diagnosis (Finding 2), though our data cannot test it. Institutions tend to diagnose the problem in terms of what they can measure. Disinformation's effects are hard to measure, and prevention that works leaves no trace, since success means the expected harm never happens. So, institutions count what they can see instead—the attempts they detect, mostly online. That focus on the digital, upstream side steers action toward the reactive policies whose results they can show. Acting at this level makes the technology-centered diagnosis look right, so it confirms itself. This dynamic is well documented in public administration. When measurable objectives stand in for hard-to-measure goals, indicators come to define the activity they monitor (Bevan & Hood, 2006; Campbell, 1979), and counter-disinformation is unusually exposed: its ultimate goal (an information environment citizens can trust) is among the hardest outcomes to measure, while its operational objectives (campaigns detected, content removed) are easier to count. Even impact metrics sit upstream of the harms that justify the policy, since institutions reach for engagement counts and declared beliefs, yet likes are not beliefs, and beliefs are not actions (Altay, Berriche, & Acerbi, 2023; Budak et al., 2024). Research faces the same constraint, since its evidence concentrates where data are accessible. The supply-side convergence of practitioners and scientists may therefore partly reflect shared observability limits rather than independent assessments.

None of this is inevitable, and each reading points to its own remedy. Incomplete uptake calls for translating what already exists more than for new studies: rapid briefs, short syntheses, and permanent brokerage roles that connect existing research to training, doctrine, and operational decisions in practitioners' working language. Limits in the evidence call for the reverse flow, carrying practitioners' operational questions back into research agendas. The measurement loop calls for measuring the outcomes that matter rather than the activity that is easiest to count.

Respondents do not experience these challenges uniformly. Educational background is the most consistent source of variation, especially in perceived obstacles to action (Appendix D). Research engagement and censorship fear also vary by role, with fear of censorship accusations highest among normative, regulatory, and public-protection roles and lowest among cybersecurity practitioners. Mandates and objectives diverge, too. Practitioners face different threats, use different tools, and define success differently.

Our findings have implications for institutions, researchers, and the infrastructure between them. We focus on how the response system could work better (its coordination, its evidence base, and the links between them) rather than on which interventions work, a question that existing reviews and guides already cover (Appendix J).

For institutions, coordination should accommodate the diversity across roles rather than flatten it. A single framework that assumes all practitioners see the problem alike would serve some roles and be distrusted by others. A limited set of common indicators (exposure, incident response, coordination quality, effects), embedded in clear mandates and auditable safeguards, would be a way out of this measurement loop.

For researchers, this diversity of mandates means there is no single standard for "fighting disinformation." Success for an educator (accurate beliefs) may mean nothing for a regulator (compliance) or an officer (attribution). The evidence base is just as fragmented. Psychology and communication study

corrections, literacy, and inoculation (Ecker et al., 2022); security, intelligence, and computer science study attribution and deterrence; some problems, like evaluating institutional responses, fall to no field at all.

The infrastructure between them could translate research into different products for different professions (a legal memo, a threat report, a classroom resource) rather than one brief for all. One speculative arrangement would combine measurement and knowledge translation in a standing observatory of the information environment, building the indicators current instruments miss and deploying the knowledge translation mechanisms the evidence-use literature has tested; its precedents, mechanisms, and design risks are in Appendix J.

This is pressing because practitioners expect deterioration (Finding 5). Nearly all foresee more foreign interference and more false content in users' feeds over the next three to five years, and most expect declining trust in media, science, and institutions. Yet, only one in eight believes the response will be sufficient, and practitioners see no trajectory that closes the gap under current arrangements.

These findings have limitations. The sample is non-random, France-centered, state-weighted, and thin in some sectors; a dedicated comparison found no public-private differences on the substantive questions, though low precision means this is not evidence of equivalence (Appendix D). Recruitment ran partly through defense and security networks, possibly tilting the sample toward foreign-threat and supply-side framings. All measures are self-reports of what practitioners believe, read, and face, not what they do, and with no imposed definition, answers may reflect heterogeneous understandings of "disinformation," which we treat as part of the object of study but which limit comparability. Subgroup analyses are exploratory, resting on uneven group sizes and variable response rates (Appendix A). The scientist comparison is likewise descriptive rather than confirmatory, because it sets side by side two surveys with different designs (different instruments, response scales, languages, populations, and fielding periods), so item-level contrasts should be read as indicative only (Appendix C). Respondents mandated to counter disinformation may overstate its prevalence or severity. Yet, because they select detection instruments, draft regulations, and decide when to intervene, their perceptions are consequential.

The French setting, however, is not only a limitation. As a European Union (EU) and North Atlantic Treaty Organization (NATO) member, France is covered by the Digital Services Act (DSA), into which the Code of Practice on Disinformation was integrated in 2025, and has built one of Europe's most institutionalized counter-disinformation apparatuses (e.g., VIGINUM and a national strategy adopted in 2026), making it both a leading case and, increasingly, a reference point for partners (Darcy, 2026a, pp. 101–106; Appendix H). At the same time, it concentrates features common to many democracies—fragmented responsibility, strong security salience, and uneven access to an overwhelmingly Anglophone literature—so its lessons are unlikely to be France's alone. Replication across national settings would clarify which patterns are specific to France and which reflect structural features of democratic counter-disinformation more broadly.

Findings

Finding 1: Practitioners treat disinformation as a first-order societal threat, on par with democratic decline and climate change, and attribute broad macro-political effects to it.

Nearly all respondents (96%) rate disinformation as an important or very important societal problem. Most place it at roughly the same level as democratic decline (69%), climate change (62%), and armed conflict (57%), rather than clearly above them (Figure G1). Practitioners also attribute broad consequences to disinformation: large majorities view foreign campaigns as a major threat to democracy

(90%) and believe disinformation sustains Russian support for the war in Ukraine (87%), fuels vaccine hesitancy (81%), enables voter manipulation (80%), and erodes trust in the state (78%; Figure G2). Although existing research has found limited and context-dependent evidence for misinformation effects on voting behavior (Allcott & Gentzkow, 2017; Budak et al., 2024; Eady et al., 2023), 83% agree that a disinformation campaign can decisively change an election result. Agreement is somewhat lower on the specific case of Trump's 2016 election (71%), which suggests that practitioners see disinformation as a greater threat in the abstract than in a concrete case. This threat assessment is anchored in direct experience: a majority of respondents (57%) report that their institution has already been directly targeted by disinformation, while 21% do not know, suggesting that even organizations engaged in counter-disinformation cannot always tell whether they have been targeted (Figure A1).

Finding 2: Practitioners share an upstream, supply-side diagnosis: they locate responsibility in platforms and amplification structures, explain belief through cognitive and algorithmic mechanisms, and give less weight to institutional distrust than scientists do.

Threat attribution is concentrated on actors who shape the information environment. Nine in ten practitioners rate social media platform owners as a major threat, and nearly three in ten name them the single greatest threat (Figure 1). Foreign governments rank next (69%), followed by private media (63%) and domestic politicians (57%). Ordinary citizens are rarely treated as major drivers (18%). As in the International Panel on the Information Environment's survey of 412 researchers (IPIE, 2024), which used the same actor list and scale, platform owners rank first and ordinary citizens and journalists last. Practitioners, however, are more alarmed about platform owners (91% vs. 64%) and private media, and they rank foreign actors above domestic politicians (69% vs. 57%), whereas researchers did the reverse (50% vs. 56%).

Beliefs about how disinformation spreads follow the same logic. Large majorities agree that platform algorithms strongly influence political opinions (85%) and that producers and platforms distribute misleading content on a massive scale (76%; Figure G3). The idea that the public actively seeks out such content divides the sample nearly in half (39% agree, 43% disagree). On belief drivers, the most prominent explanations are confirmation bias and selective exposure (90%) and algorithmic promotion (84%), followed by emotional reactions, repetition, and identity-based motivations (Figure 2).² Both were closed lists with a limited set of options, so neither covers every possible explanation.

A notable result is the relatively modest place of institutional distrust, which the academic literature often treats as a central condition of vulnerability (Ejaz et al., 2025; Humprecht et al., 2020). In short, practitioners frame disinformation as a supply-side problem, driven by infrastructure and amplification acting on cognitive vulnerabilities, and give less weight to audience demand.

² As worded in the survey, confirmation bias and selective exposure is a way of handling information ("one avoids contrary information and prefers information favorable to oneself") that can serve any prior belief. Political or identity-based motivation is a reason for wanting a conclusion ("one believes what reinforces one's side or one's identity"), which may or may not work through that mechanism. Altay, Berriche, Heuer, et al. (2023) also keep them separate, and here the two ratings correlate only moderately (Spearman $\rho = .47$, $n = 99$).

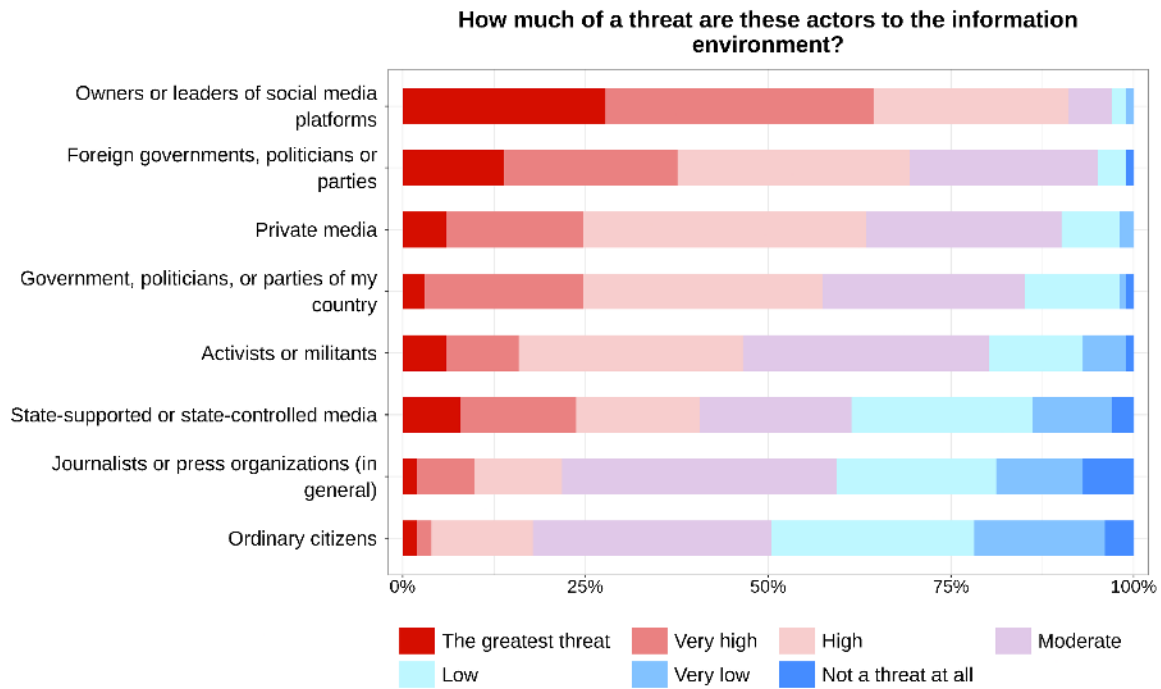


Figure 1. Perceived threats to the information environment by actor type (% , N = 101).

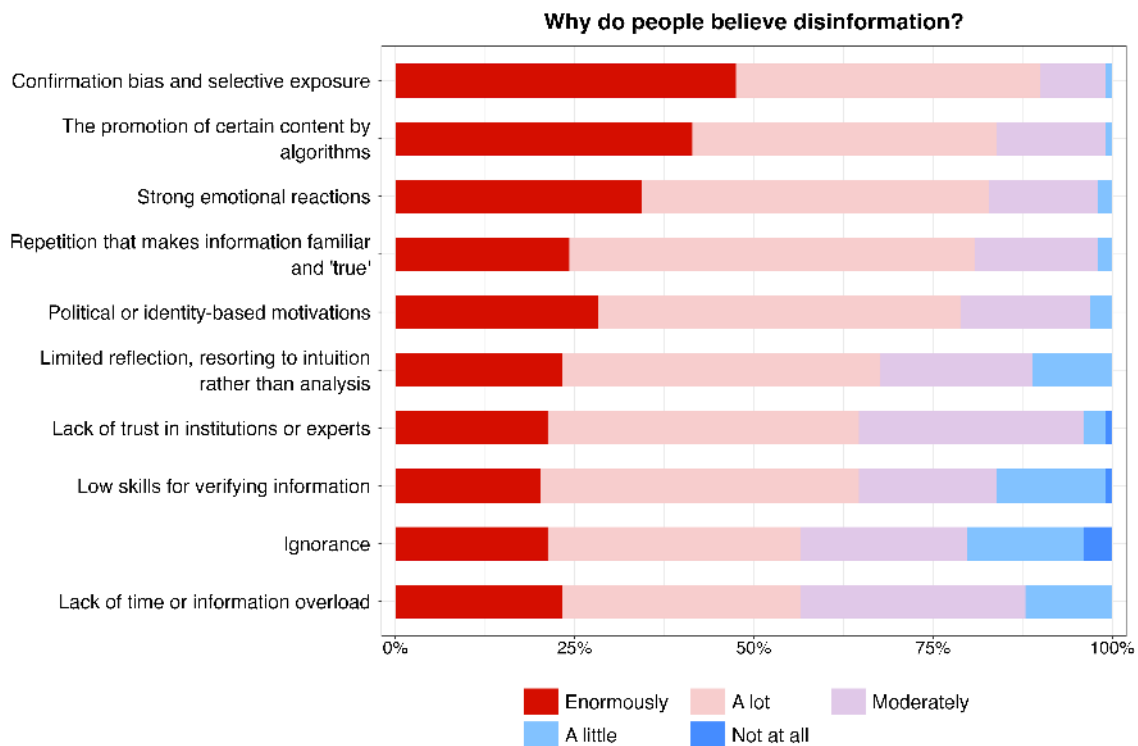


Figure 2. Beliefs about why people believe disinformation (% , N = 99).

Finding 3: The top obstacles to fighting disinformation are a rhetoric-action gap, reactive policies, and platform power, compounded by anticipatory fear of censorship accusations.

The most important obstacle, rated very or extremely important by three in four practitioners (76%), is that counter-disinformation is proclaimed a political priority while concrete action remains insufficient (Figure 3). The next most cited obstacles are reactive policies that lag behind new tactics (71%) and the influence strategies of large digital companies (70%). Structural constraints compound the picture, each cited by a majority of respondents (52–65%): insufficient budgets and staff, administrative slowness, the lack of operational tools and shared indicators, unclear roles and coordination with no lead actor, and difficulty attracting and retaining specialists. Fear of censorship accusations also ranks high (63%), yet only one in five practitioners (21%) reports encountering actual ethical dilemmas often in daily work, while more than six in ten (62%) encounter them rarely or never. The constraint appears largely anticipatory. What inhibits practitioners is mainly the prospect of being accused of overreach.

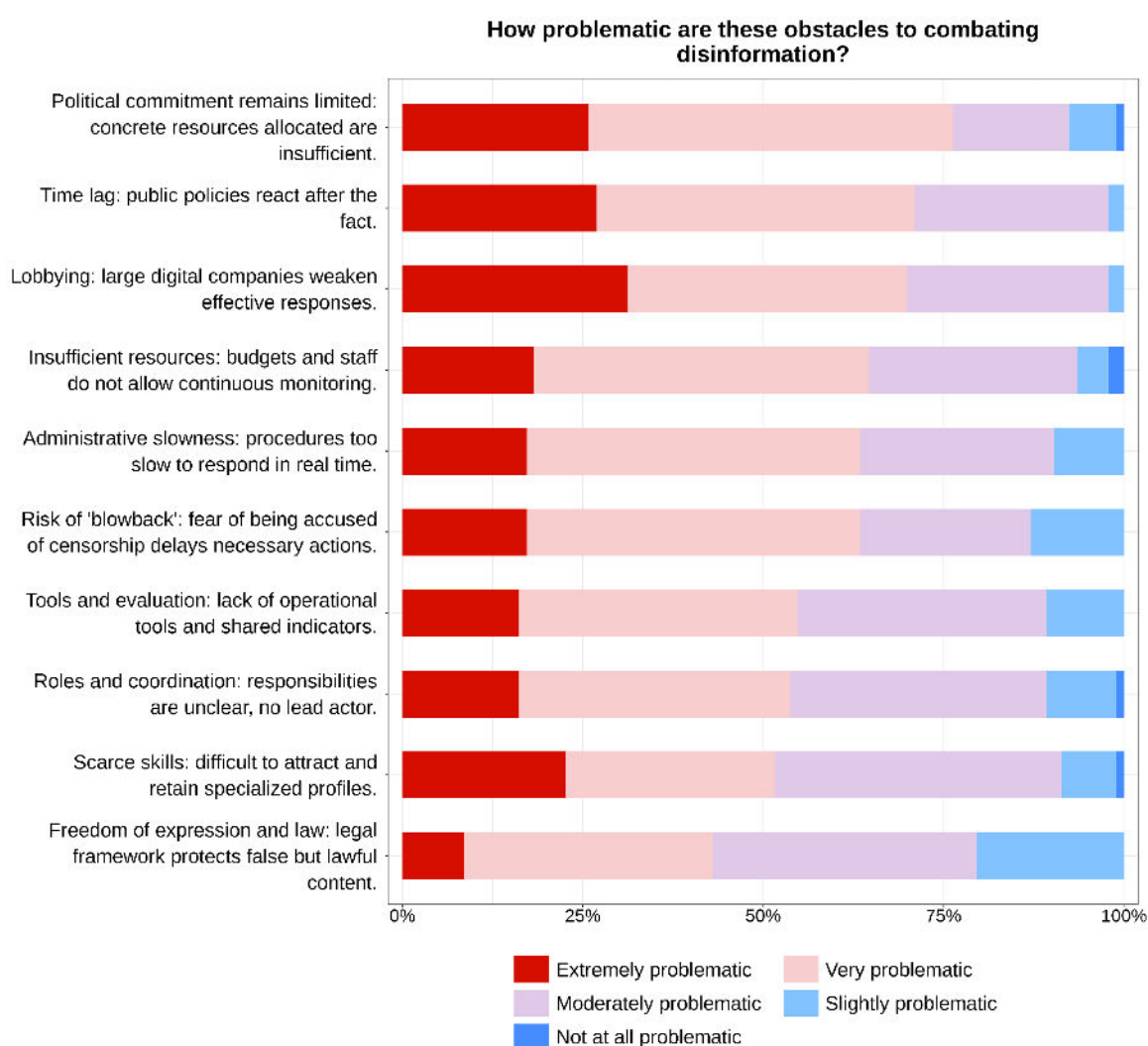


Figure 3. Obstacles to combating disinformation (% , N = 93).

Finding 4: Practitioners trust scientific research but rarely engage with it directly.

Nearly three in four practitioners (71%) say they trust peer-reviewed research to guide their decisions, but only about a third (36%) report keeping up with recent academic work (Figure 4). Nearly all (88%) read about disinformation primarily in French, a language in which far less of the scientific literature is available. The most frequent sources are the press and gray literature, with scientific articles secondary (Appendix G, Figure G4). The barriers are organizational: lack of time, limited access to publications, and weak institutional incentives all rank above methodological difficulty or skepticism (Figure 5).

Because these items ask respondents to judge their own competence, they may be affected by social desirability: admitting difficulty with methods or scientific English is more face-threatening than citing lack of time or access. The ranking should therefore be read with caution, and the 45% reporting methodological difficulty as a likely lower bound. The French setting may reinforce this under-reporting. French administrative elites are selected and legitimized through extensive, formalized general knowledge rather than specialized expertise (Mangset, 2017), and only 4% of our respondents have a research background (they hold or are preparing a doctorate, or work in higher education or research), so many may not recognize what they miss when reading a study. Two features temper this concern, however: answers were anonymous, and respondents readily gave other potentially face-threatening answers, admitting low engagement with research and reliance on French-language sources.

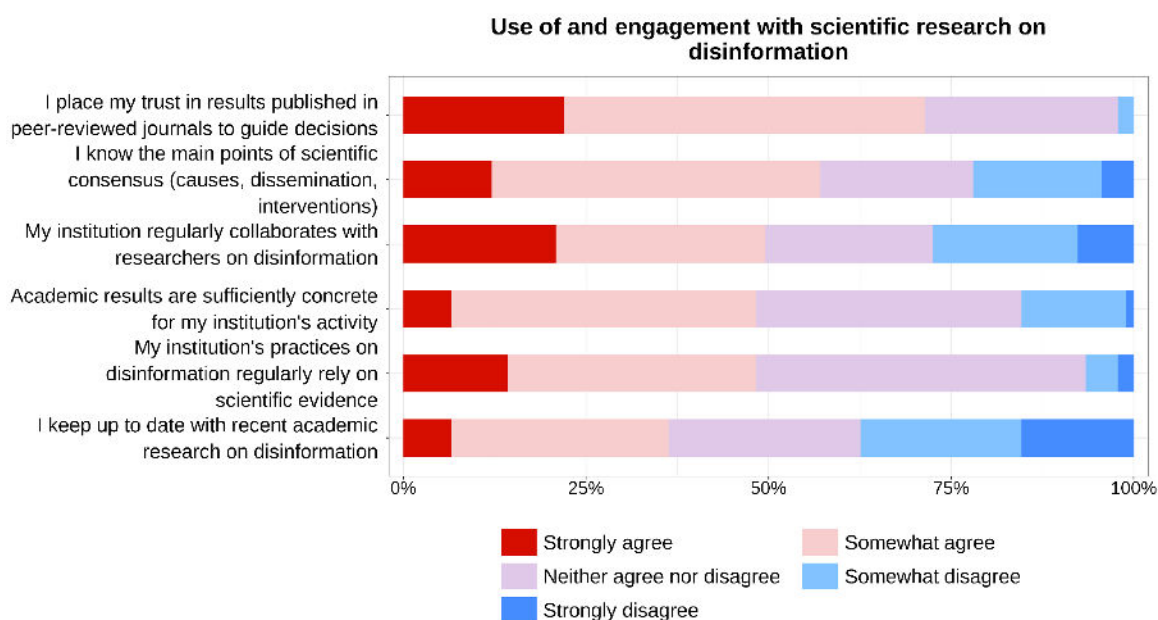


Figure 4. Engagement with scientific research (% , N = 91).

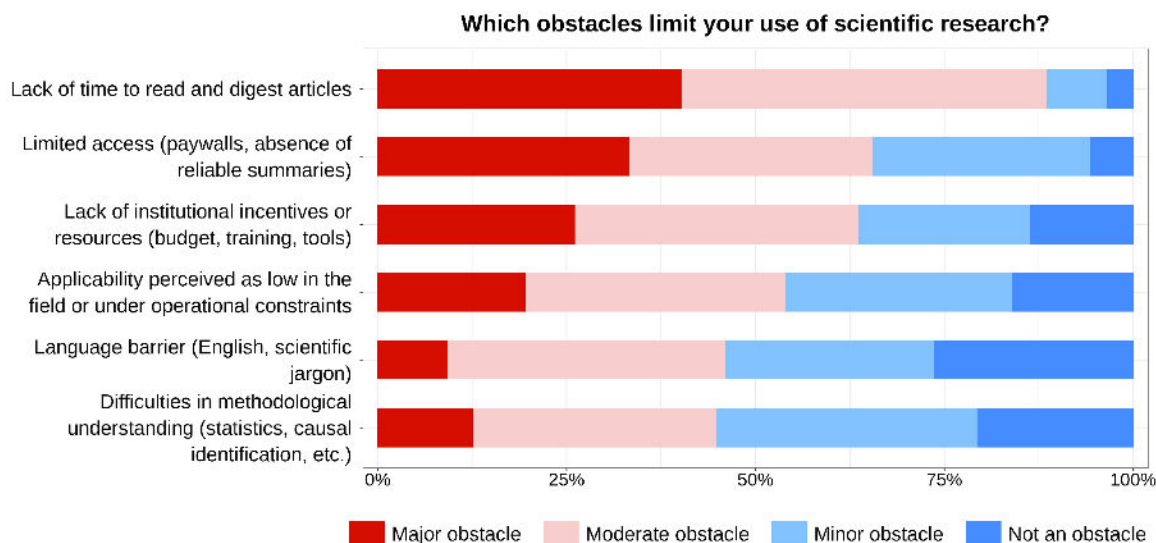


Figure 5. Obstacles to using scientific research (% , N = 87–88).

Finding 5: Practitioners expect the threat to worsen and do not believe institutional capacity will keep pace.

Nearly all respondents anticipate increases in foreign interference (96%) and in false or manipulated content in ordinary users' feeds (93%) over the next three to five years (Figure 6). Large majorities also expect declining trust in media, science, and institutions (83%). On the response side, six in ten (60%) think state capacity will increase, but only one in eight (13%) believes future capacity will be sufficient, while more than two in three (69%) judge that outcome unlikely.

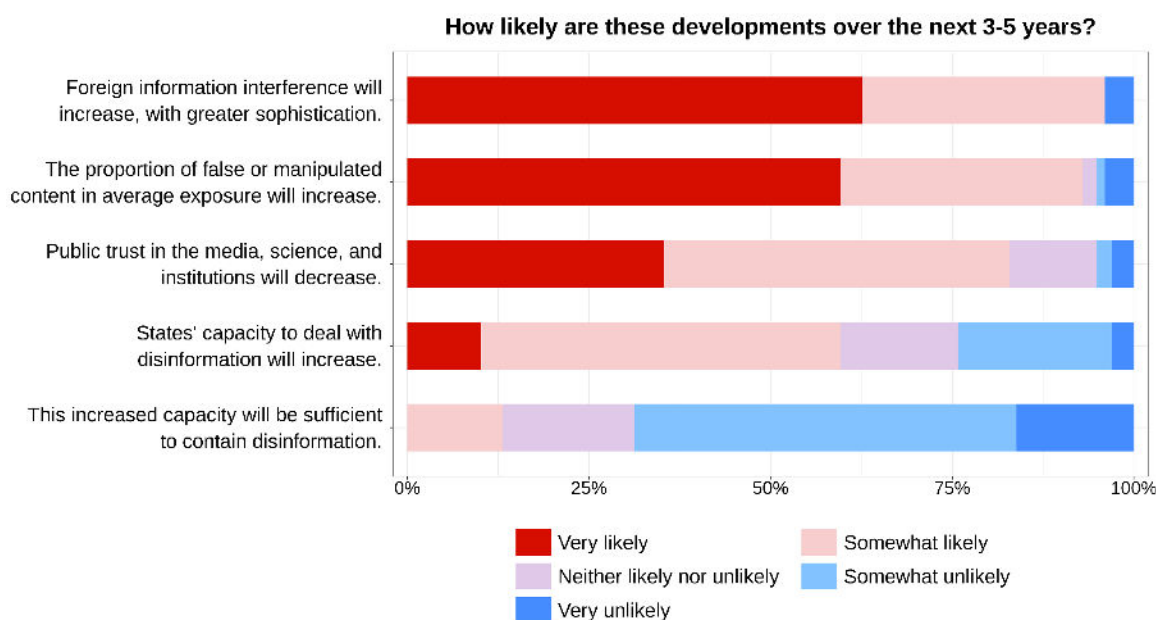


Figure 6. Expected developments over the next 3–5 years (% , N = 99).

Finding 6: Respondents converge on the diagnosis but diverge on obstacles and research use, with educational background the most consistent source of variation, and their views sometimes differ from scientists'.

Variation within the sample was assessed with linear mixed-effects models across three grouping variables (organizational type, educational background, and practitioner role; 60 omnibus tests, Appendix D). One effect survived multiple-testing correction: perceived obstacles to action varied by educational background (raw $p < .001$, adjusted $p = .007$, $\eta^2_p = .23$). Respondents trained in computer and data sciences ($n = 11$) rated obstacles as less severe overall (block mean 3.19 vs. 3.71–3.95 in the other fields; lower on nine of the ten items), while the ranking of obstacles did not differ detectably (group $\times$ item interaction, $p = .587$). Ranked by the variance of subgroup means, variation was strongest for obstacles to action and barriers to using scientific research, and weakest for perceived impact and expected future developments. The subgroup patterns are exploratory, given the study's precision limits (Appendix B). A dedicated comparison of public-sector and private respondents found no detectable difference in the substantive diagnosis (Appendix D).

We also compared respondents' answers with those of about 150 academic scientists surveyed by Altay, Berriche, Heuer, et al. (2023), on six closely matched items (see Appendix C). Because the two surveys differed in instruments, response scales, language, populations, and timing (fielded in 2022 and in 2025–2026, on either side of the 2024 U.S. election), the comparison is descriptive. The two groups give similar ratings to well-established mechanisms (confirmation bias, repetition) and diverge sharply on the role of disinformation in the 2016 U.S. election, which practitioners rate far higher ($d = 0.89$), and on lack of trust in institutions, which scientists rate higher ($d = -0.46$). Convergence thus concentrates on well-established psychological mechanisms. On contested items, practitioners favor explanations centered on individual credulity and campaign power, while scientists give more weight to the structural conditions that make audiences receptive, such as eroded institutional trust. The full item-by-item comparison and its caveats are in Appendix C.

Methods

The target population comprised practitioners holding official responsibility for preventing, monitoring, analyzing, regulating, or responding to misleading, manipulated, or hostile informational content. Academic researchers were excluded by design; their beliefs have been documented elsewhere (Altay, Berriche, Heuer, et al., 2023). No sampling frame exists for “disinformation practitioners” in France, so we maximized coverage through organizational charts, conferences, interagency initiatives, practitioner networks, and snowball referrals. The sample should not be interpreted as a random draw. Consistent with the institutional usage described above, the questionnaire did not impose a definition of disinformation; items used the term as it circulates among French practitioners.

Recruitment proceeded in two waves (September 2025–February 2026). Wave 1 contacted practitioners directly within state institutions and major non-governmental organizations ($n = 85$, 80%); Wave 2 disseminated an anonymous Qualtrics link through practitioner association channels ($n = 21$, 20%; see Appendix E for wave composition). Of 123 consented responses, 106 met inclusion criteria (see Appendix A for full details).

The resulting sample is skewed toward state institutions: one third of respondents work in military or intelligence services, 29% in regulatory or normative bodies, and 21% in senior government or political offices, while private-sector and media actors are comparatively limited (7% from private for-profit organizations, 6% from private non-profits, and 4% from journalism or media; Appendix A, Figure A1). Educational backgrounds are mostly (61%) in the social sciences and communication or media studies,

with smaller shares from computer and data sciences, the humanities, and the natural sciences (Figure A1). Only 4% are doctoral students, doctorate holders, academics, or researchers, and only 16% report formal training drawing on research on disinformation. This profile describes a sample oriented toward institutional analysis, communication, and operational response rather than toward research production, and should be kept in mind when interpreting the findings.

The questionnaire (92 items, in French) was closed-ended, apart from optional “Other (please specify)” fields in some blocks and one open question on ethical dilemmas. Respondents rated each statement in a predefined list separately on a labeled scale. Several blocks reuse, in French translation, items from existing expert surveys whose results serve as benchmarks for comparison. The threat block (Figure 1) reproduces the actor list and seven-point scale of the 2024 IPIE expert survey (IPIE, 2024). The belief drivers (Figure 2) take up the list of Altay, Berriche, Heuer, et al. (2023) to allow comparison with scientists; to shorten the survey, their identity, partisanship, and motivated-reasoning items were merged into one. Items on the 2016 U.S. election, opposing views online, fact-checking, and algorithms are adapted from the same survey (Appendix C). The research obstacles (Figure 5), which have no equivalent in these surveys, cover the barriers to evidence use most often reported for policymakers (time, access, skills, relevance, and institutional resources; Oliver et al., 2014), plus language. Full wording in French and English is in the codebook provided with the replication materials.

To maximize available information given heterogeneous missingness patterns, analyses rely on pairwise deletion, using all available data for each analysis rather than excluding participants with any missing value (Enders, 2010; Little & Rubin, 2019). Full methodology is detailed in Appendix A. Throughout the findings, percentages aggregate the highest response categories; item-level means and standard deviations on the original response scales are reported in Appendix F.

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Authorship

G. D. and S. A. designed the study and wrote the paper. G. D. collected and analyzed the data. G. D. is the corresponding author (gregoire.darcy@protonmail.com).

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Competing interests

The authors declare no competing interests.

Ethics

This study received ethical approval from the University of Zurich PhF Ethics Committee (ethics approval No. 24.02.13). All participants provided informed consent before taking part in the study. No demographic variables were collected beyond current professional role, institutional affiliation, and educational background. No personal identifiers, gender, age, or ethnicity data were recorded.

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Data availability

All materials needed to replicate this study are available via the Harvard Dataverse:
<https://doi.org/10.7910/DVN/2HDLCA>

Appendix A: Participants, sampling, and methods

Target population

The target population comprised practitioners who, by virtue of an official position in a public-sector, private-sector, or non-profit organization, hold responsibility for preventing, monitoring, analyzing, regulating, or responding to false, misleading, manipulated, or hostile informational content circulating in public communication channels. Eligibility required either (i) an explicit institutional mandate in communication or counter-influence; normative frameworks, regulation, or public policy; detection, monitoring, and analysis; public protection, journalism, or education; or cybersecurity and technical protection, including coordination and partnership functions within institutions formally tasked with counter-disinformation, or (ii) demonstrable functional responsibility for disinformation response within a broader portfolio (e.g., officers overseeing operations targeted by hostile influence campaigns, or senior communications staff supporting high-level political principals confronted with recurrent misinformation episodes).

Academic researchers were excluded by design. Their beliefs and policy preferences have been documented in prior surveys, notably by Altay and colleagues; the present study instead focuses on field actors who make and implement decisions under administrative, political, legal, and, in some settings, security constraints.

Sampling strategy

A probabilistic sampling design was not feasible because no comprehensive institutional mapping of “disinformation practitioners” exists in France. Mandates are distributed across organizations, job titles are heterogeneous, and responsibilities are often embedded within broader roles, preventing construction of a complete sampling frame. We therefore implemented an identification strategy aimed at maximizing coverage of the reachable practitioner ecosystem. Eligible participants were identified using public organizational charts and official documents, participation in conferences and working groups, interagency initiatives, professional networks and prior contacts, and snowball referrals. Because inclusion depended on identification, institutional authorization, and willingness to participate, the sample should not be interpreted as a random draw from the universe of all French practitioners working on disinformation.

Recruitment and data collection

Recruitment and data collection proceeded in two waves, from September 2025 to February 2026. In Wave 1, identified practitioners were contacted directly by email and, when feasible, in person, including ministerial cabinets and agencies formally mandated to counter foreign information manipulation such as intelligence services or VIGINUM (the French government service for vigilance and protection against foreign digital interference). Given heterogeneous confidentiality and authorization constraints (especially in defense and intelligence settings), a single standardized administration mode could not be imposed. Depending on institutional rules, respondents completed the questionnaire either with a researcher present in person, or autonomously via a secure link, with the research team reachable at any time for clarification. After applying inclusion criteria (valid consent and confirmed professional role), Wave 1 contributed 80% of the analytical sample.

Wave 2 was implemented to improve coverage of practitioner segments that remained underrepresented after direct outreach, particularly private for-profit and private non-profit

organizations. An anonymous Qualtrics link was therefore disseminated through two targeted channels: a professional community dedicated to media and digital literacy education and a newsletter circulated within a professional network of people engaged in counter-disinformation, coordinated by a member of the French armed forces. After applying the same inclusion criteria, this pathway contributed the remaining 20% of the final sample.

Sample composition

The final analytical sample ($N = 106$) spans six organizational types: military and intelligence services (33%), regulatory and normative bodies (29%), senior government and political offices (21%), private for-profit organizations (7%), private non-profit organizations (6%), and journalism and media (4%). Detailed institutional composition is described in the main text.

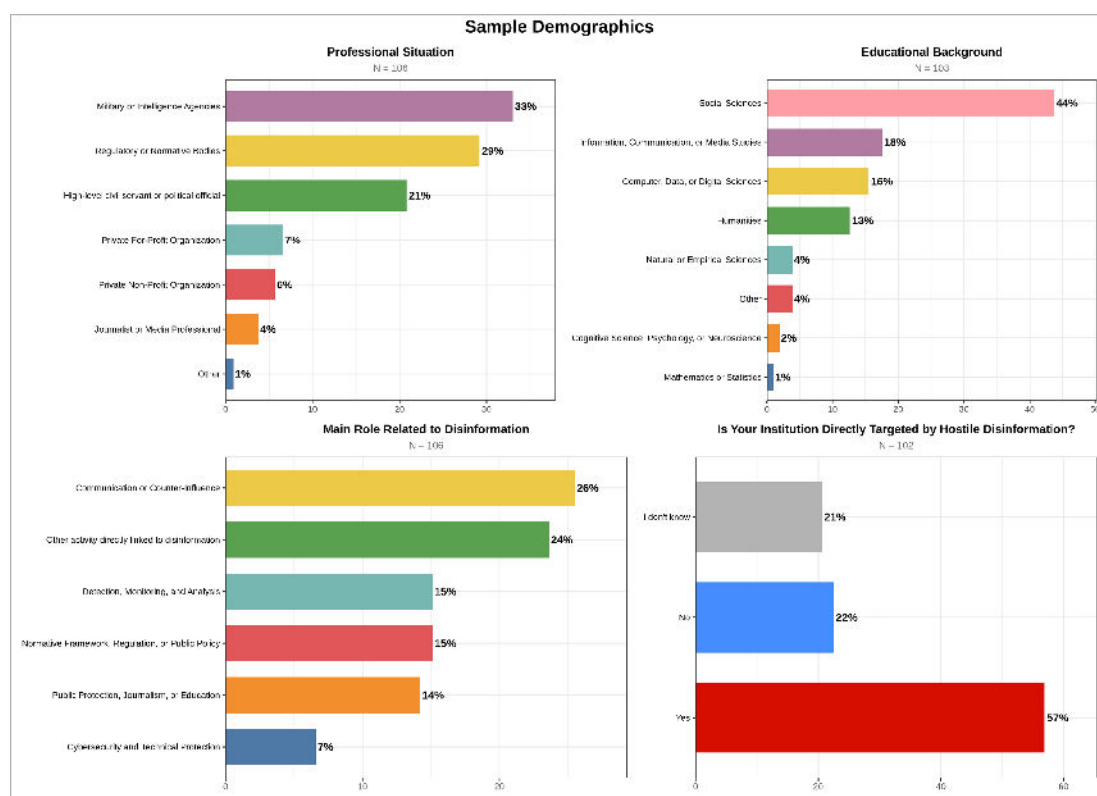


Figure A1. Sample composition and exposure to disinformation (% , N varies by panel: 102–106). Professional situation, educational background, main professional role, and whether respondents' institutions had been directly targeted by disinformation. Waves 1 and 2 combined.

The survey recorded no personal identifiers, so individual respondents cannot be identified from their answers. To preserve confidentiality, particularly for diplomats, members of presidential or ministerial cabinets, secret-service agencies, or the military, we collected no demographic data beyond professional role, type of organization, and educational background (no gender, age, or ethnicity). This also motivated certain category constructions (e.g., grouping “military and military agencies and secret services” or “diplomacy with high administration and politicians”) to prevent any possibility of re-identification from cross-tabulated data, which is a common practice for studies dealing with members of intelligence agencies.

Inclusion criteria and analytic sample

The survey received 123 consented responses. We excluded 17 cases that did not complete the initial demographic block (i.e., did not answer the professional-role screening question, Q7). Of these, 71% ($n = 12$) dropped out immediately after consent (survey progress = 5%), and one completed most of the survey (78 of 92 items) and provided demographic information but did not answer the screening item (Q7). Four additional cases reached intermediate progress (33–95%) but did not provide a valid professional-role response. Exclusions were disproportionately drawn from later recruitment batches, which may reflect cohort-specific response-rate variation. Among the five excluded cases with partial demographic data, three reported a sector (non-profit, $n = 1$; other, $n = 2$) and two reported only their educational background, suggesting that attrition was not concentrated in a single sector. The remaining 12 provided no demographic information. We treated completion of the professional-role item as a minimal completeness filter for inclusion in the analytic sample. By contrast, no respondent selected the screening option stating that their main activity was unrelated to disinformation, so no participant had to be excluded on that ground. This is informative in itself because it suggests that the targeted recruitment strategy reached the intended practitioner population rather than attracting a visible tail of topic-interested outsiders. The analytic sample therefore consists of $N = 106$ respondents.

Missing-data treatment

Given the small and specialized population, analyses rely on pairwise deletion, or available-case analysis, which retains all valid responses for each item rather than discarding an entire respondent because of a single missing value. In expert samples, listwise deletion may inadvertently privilege participants with greater time or institutional latitude to complete every question, thereby introducing sectoral distortions. Item-level denominators consequently vary across blocks: perceived impact (Q9, $N = 101$ – 102), reasons for belief (Q12, $N = 99$), mechanisms of spread (Q13, $N = 96$), obstacles (Q16, $N = 93$), research engagement (Q22, $N = 91$), and research obstacles (Q23, $N = 87$ – 88). Within most blocks, all items share the same denominator, meaning that missingness is block-level rather than item-level. The partial exceptions are Q8 (relative importance, $N = 101$ – 102), Q9 (perceived impact, $N = 101$ – 102), and Q23 (research obstacles), where minor item-level variation occurs; for Q23, the first five items each have $N = 87$ while the sixth has $N = 88$, a discrepancy of a single respondent that does not materially affect estimates. For all other multi-item blocks (Q10, Q12, Q13, Q15, Q16, Q19, Q22), pairwise and listwise deletion yield identical point estimates because respondents who answered any item within a block answered all items in that block.

To assess whether missingness was related to respondent characteristics, we conducted 48 χ^2 tests of independence crossing the 16 closed-ended question blocks with three grouping variables (organizational sector Q3, educational background Q5, and professional role Q7). After Benjamini–Hochberg correction (Benjamini & Hochberg, 1995), only one test reached significance (Q8 missingness $\times$ educational background, $p_{BH} < .001$), driven entirely by a single respondent in the mathematics/statistics category ($n = 1$, 100% missingness)—a cell-size artifact rather than a substantive pattern. Five tests were significant before correction: Q8 $\times$ Q5 ($\chi^2 = 35.27$, $df = 7$, $p < .001$), Q2 $\times$ Q5 ($\chi^2 = 20.88$, $df = 7$, $p = .004$), Q22 $\times$ Q5 ($\chi^2 = 16.67$, $df = 7$, $p = .020$), Q8 $\times$ Q7 ($\chi^2 = 13.06$, $df = 5$, $p = .023$), and Q16 $\times$ Q5 ($\chi^2 = 15.31$, $df = 7$, $p = .032$). All five involved minimum expected cell counts below 5, which inflates the χ^2 statistic and makes the asymptotic approximation unreliable; Fisher exact tests returned non-significant p-values for three of the five. These uncorrected associations are concentrated in Q5 (educational background) and trace back to very small subgroups (mathematics/statistics $n = 1$, natural sciences $n = 4$, cognitive science $n = 2$), where a single missing respondent can produce a large percentage shift. Although no robust evidence of a

missing-completely-at-random (MCAR) violation was found, the educational-background dimension warrants interpretive caution for blocks with higher missingness rates (Q16, Q22, Q23).

At the block level, representative tests confirm the absence of large-scale sectoral confounding: for example, a χ^2 test of Q23 (the final question) missingness by sector is non-significant ($\chi^2 = 8.30$, $df = 6$, $p = .217$). Missingness in Q23 is nonetheless uneven in absolute terms across organizational sectors: it is highest in private non-profit organizations (50.0%, 3 of 6) and private for-profit organizations (28.6%, 2 of 7), and lower in military/intelligence services (8.6%, 3 of 35) and among journalists (0%, 0 of 4). Under listwise deletion, these differences would mechanically remove disproportionate shares of certain sectors and bias aggregate estimates. Pairwise deletion preserves information from earlier sections while making variation in denominators explicit.

Appendix B: Statistical precision and detection limits

Sample size was determined by feasibility rather than by a priori power calculation: no comprehensive sampling frame exists for French counter-disinformation practitioners, and recruitment depended on institutional authorization, security clearance, and willingness to participate. The analytic sample of $N = 106$ was the maximum achievable under these constraints. We report minimum detectable effect sizes (MDEs) and precision limits to help readers gauge what the study can and cannot resolve.

At $\alpha = .05$ (two-tailed) and 80% power, the minimum detectable effect sizes (MDEs) are as follows:

- Aggregate analyses ($N = 106$): MDE $d = 0.27$ for one-sample comparisons against scale midpoints. The study can reliably detect small-to-medium deviations from neutrality in the full sample, but effects below $d = 0.27$ may go undetected.
- Practitioner–scientist comparison ($n \approx 100$ practitioners, 143 scientists): MDE $d = 0.37$. Three of the four divergences that remain after correction (absolute $d = 0.46$ to 0.89) exceed this threshold; the fourth ($d = 0.35$) falls slightly below it and should be read with corresponding caution. Subgroup comparisons between the three largest groups (military/intelligence $n = 35$, regulatory $n = 31$, government $n = 22$): MDE $d \approx 0.69$ to 0.78 , depending on the pair. Because the MDE for a two-group comparison is approximately $2.8 \times \sqrt{1/n_1 + 1/n_2}$ at these error rates, each pairwise contrast has its own detection limit: $d \approx 0.69$ for military/intelligence versus regulatory (35 vs. 31), $d \approx 0.76$ for military/intelligence versus government (35 vs. 22), and $d \approx 0.78$ for regulatory versus government (31 vs. 22). In other words, even between the best-represented sectors, only large differences (roughly three-quarters of a standard deviation) were reliably detectable; the comparisons involving the government group are the least sensitive. For the smallest subgroups (for-profit $n = 7$, non-profit $n = 6$, cybersecurity $n = 6$): MDE $d \approx 1.56$, meaning that only very large differences could have been detected. The 59 non-significant heterogeneity tests (of 60) should therefore be interpreted as reflecting insufficient precision to detect moderate heterogeneity, not as evidence of its absence. Accordingly, where the main text describes respondents as “converging,” convergence is a descriptive statement: uniformly high endorsement and low dispersion of subgroup means (Appendix D2), not statistically demonstrated homogeneity.

These detection limits confirm that the study has adequate precision for aggregate-level comparisons and the practitioner–scientist contrast, but limited precision for subgroup heterogeneity, consistent with the descriptive framing of the scientist comparison (Appendix C) and the exploratory framing adopted in Finding 6 and Appendix D.

Appendix C: Practitioners vs. scientists—Full comparison

We compared French practitioners' responses with the scientist sample from Altay, Berriche, Heuer, et al. (2023; hereafter Altay et al.). Given differences in instruments, response scales, survey language, populations, and timing between the two studies, we treat this comparison as descriptive and exploratory rather than confirmatory. Because the two instruments were not identical, we restricted the comparison to six items with close conceptual matching. Four additional items were excluded because the constructs do not align closely enough: "political or identity-based motivations" conflates Altay et al.'s separate identity, partisanship, and motivated-reasoning items; "low skills for verifying information" does not map cleanly onto "lack of digital or media literacy"; our platform-algorithm item is narrower than Altay et al.'s general social-media item; and our fact-check item differs in framing from Altay et al.'s intervention-effectiveness measure. Because the Altay et al. survey used 7-point scales while ours used 5-point scales, scientist responses were linearly rescaled to a 1–5 range using the formula: $1 + ((x - 1) \times 4/6)$ (Colman et al., 1997). One item required reverse-coding: Altay et al. asked whether people encounter more opposing viewpoints online than offline, whereas our instrument asked the logical inverse (offline than online); we reverse-coded the Altay et al. mean ($6 - M$ on the rescaled 1–5 scale) so that higher scores on both instruments indicate stronger endorsement of offline exposure. Effect sizes are Cohen's d with 95% confidence intervals (CIs); p -values are two-tailed independent-samples t -tests corrected using the Benjamini–Hochberg (BH) procedure at $\alpha = .05$ across the six admissible tests. Altay et al. report a final analytic sample of $N = 150$; the publicly released dataset contains 148 cases, of which 143 satisfy a strict completeness criterion (Qualtrics Progress = 100 and Finished = 1), and we use this $n = 143$ subset for all cross-study comparisons reported below. As a sensitivity check, applying the BH correction across all ten mapped items (including the four excluded for construct mismatch, all of which show small, non-significant differences, absolute $d \leq 0.22$) leaves the same four items below the corrected .05 threshold (largest adjusted $p = .018$).

Four caveats apply. First, wording is not strictly equivalent across instruments: most notably, our 2016-election item asks whether disinformation played an "important role," whereas Altay et al.'s asks whether it played a "decisive role in determining the outcome," a stricter claim; the belief-driver block also uses intensity anchors in French while Altay et al. used agreement anchors in English, a difference that linear rescaling cannot remove. Second, for the reverse-coded item, disagreement with the online-exposure statement is not strictly equivalent to agreement with its inverse, and acquiescence bias operates in opposite directions across the two framings; the $d = 0.76$ reported for item 3 below is therefore best read as an upper bound. Third, the surveys were fielded roughly three years apart (2022 vs. September 2025–February 2026), an interval spanning the 2024 U.S. election and new evidence on electoral effects (Budak et al., 2024); responses to the 2016 item in particular may have shifted in both populations. Fourth, because academic researchers were excluded from our sample by design, the practitioner–scientist contrasts cannot be attributed to professional status alone; they may equally reflect the instrument, population, and timing differences noted above. These caveats reinforce the descriptive reading of the contrasts reported below.

C1. Items showing differences that remain after multiple-testing correction

1. Disinformation played an important role in Trump's 2016 election (Mechanisms/impact)

Practitioners: $M = 3.98$, $SD = 0.98$, $n = 102$.

Scientists: $M = 2.98$, $SD = 1.21$, $n = 143$.

Cohen's $d = 0.89$ [95% CI: 0.63, 1.16] (large), adjusted $p < .001$.

Practitioners rated the role of disinformation in the 2016 U.S. election substantially higher. This may reflect practitioners' operational experience tracking campaign attribution and high-stakes electoral interference, versus scientists' awareness of the weak causal evidence linking disinformation exposure to voting behavior; the wording asymmetry ("important" vs. "decisive") and the timing gap between the surveys also plausibly contribute to the size of this contrast.

2. Lack of trust in institutions or experts (Belief drivers)

Practitioners: $M = 3.81$, $SD = 0.84$, $n = 99$.

Scientists: $M = 4.18$, $SD = 0.77$, $n = 143$.

Cohen's $d = -0.46$ [95% CI: -0.72 , -0.20] (medium), adjusted $p = .001$.

Scientists place more weight ($d = -0.46$) on institutional distrust as a driver of belief in disinformation. This aligns with the academic literature emphasizing trust as foundational to susceptibility (Ejaz et al., 2025; Humprecht et al., 2020). Practitioners, embedded within institutions, may underestimate the role that their own organizations' legitimacy deficits play in sustaining demand for disinformation.

3. People encounter opposing views more often offline than online (Mechanisms/impact)

Practitioners: $M = 3.20$, $SD = 1.12$, $n = 96$.

Scientists (reverse-coded): $M = 2.42$, $SD = 0.95$, $n = 143$.

Cohen's $d = 0.76$ [95% CI: 0.50, 1.03] (medium-to-large), adjusted $p < .001$.

After reverse-coding to align item direction (Altay et al. ask whether people encounter opposing views more often online than offline; our survey asks whether they encounter them more often offline than online), practitioners endorse the offline-exposure proposition substantially more than scientists. Practitioners' daily focus on online platform monitoring may lead them to overweight the digital environment and correspondingly see offline counter-exposure as relatively greater, whereas scientists, drawing on population-level evidence showing echo chambers are empirically overstated, give a more tempered assessment.

4. Limited reflection, reliance on intuition rather than analysis (Belief drivers)

Practitioners: $M = 3.80$, $SD = 0.93$, $n = 99$.

Scientists: $M = 3.46$, $SD = 0.98$, $n = 143$.

Cohen's $d = 0.35$ [95% CI: 0.09, 0.61] (small), adjusted $p = .011$.

Practitioners place somewhat more weight on cognitive laziness as a driver of belief. This may reflect a residual deficit-model framing among practitioners: a tendency to attribute disinformation belief to individual cognitive shortcomings rather than structural or contextual factors.

C2. Items showing no reliable difference after correction

Two items showed no reliable difference after BH correction (both adjusted $p > .05$):

- **Confirmation bias and selective exposure:**
Practitioners: $M = 4.36$, $SD = 0.69$; Scientists: $M = 4.19$, $SD = 0.74$; $d = 0.24$ [95% CI: $-0.02, 0.49$], adjusted $p = .082$.
- **Repetition that makes information familiar and 'true':**
Practitioners: $M = 4.03$, $SD = 0.71$; Scientists: $M = 3.96$, $SD = 0.81$; $d = 0.09$ [95% CI: $-0.17, 0.35$], adjusted $p = .478$.

C3. Summary

Of the six admissible items, four showed differences that remain after BH correction. The two largest effects were in opposing directions: practitioners attribute far more weight to the Trump-election item ($d = 0.89$) and to offline exposure exceeding online exposure ($d = 0.76$, after reverse-coding), while scientists place more weight on institutional distrust ($d = -0.46$). Practitioners also rate limited reflection higher ($d = 0.35$). The two remaining items (confirmation bias and repetition) showed no reliable difference, suggesting shared ground on core cognitive mechanisms. Overall, the comparison reveals selective divergence on politically salient and epistemically contested items, set against a baseline of agreement on well-established psychological drivers. An alternative reading is that divergence merely tracks residual wording mismatch; the institutional-distrust item, which is closely matched across instruments yet shows a clear difference ($d = -0.46$), argues against wording asymmetry as a full explanation, although it cannot be ruled out for the 2016-election and opposing-views items.

Appendix D: Heterogeneity analysis

This appendix reports the full results of heterogeneity analyses across three grouping variables: professional role (Q7, 6 categories), educational background (Q5, 4 categories), and organizational type (Q3, 3–5 categories). Groups with ≤ 5 respondents were excluded from subgroup models. Several remaining subgroups are very small (Private For-Profit $n = 7$, Private Non-Profit $n = 6$, Cybersecurity/Technical $n = 6$ in the analyses); means for these groups are reported for completeness but should be interpreted with extreme caution given the wide confidence intervals that small samples entail. For each question block, we estimated one linear mixed-effects model per grouping variable using the formula $\text{response} \sim \text{group} \times \text{item} + (1 \mid \text{respondent})$, where item indexes survey items within the block as a fixed effect and the random intercept accounts for repeated measures. Models were fitted with restricted maximum likelihood (REML) via lme4 (Bates et al., 2015); p-values use the Satterthwaite approximation from lmerTest (Kuznetsova et al., 2017).

Although the outcome variables are ordinal Likert items, we chose linear mixed-effects regression (LMER) over cumulative link mixed models (CLMM) for interpretability: LMER coefficients directly estimate mean differences on the response scale, which are more communicable to the practitioner audience than log-odds ratios. With mostly 5-point scales and approximately symmetric response distributions, linear approximation to ordinal data introduces minimal bias (Norman, 2010).

Note on multiple testing: With 10 question blocks and 3 grouping variables, we fitted 30 LMER models, each yielding two omnibus F-tests (group main effect and group $\times$ item interaction), for a total of 60 tests. All 60 p-values were corrected simultaneously using the Benjamini–Hochberg (BH) procedure at $\alpha = .05$. This 60-test family is corrected separately from the scientist comparison in Appendix C. Only one effect survives correction: Obstacles $\times$ Educational Background ($F(3, 78) = 7.89, p_{\text{raw}} < .001, p_{\text{adj}} = .007, \eta^2_p = .23, 95\% \text{ CI } [.07, .36]$). The remaining effects reported below should be treated as hypothesis-generating rather than confirmatory. All p-values below are uncorrected (p_{raw}).

D.1 Linear mixed-effects models: full results

Significant main effects of group:

Obstacles $\times$ Educational Background: $F(3, 78) = 7.89, p < .001$ ***
 Research Obstacles $\times$ Professional Role: $F(5, 82) = 3.79, p = .004$ **
 Research Obstacles $\times$ Educational Background: $F(3, 73) = 4.63, p = .005$ **
 Research Obstacles $\times$ Organization Type: $F(2, 72) = 5.47, p = .006$ **
 Mechanisms $\times$ Educational Background: $F(3, 474) = 3.87, p = .009$ **
 Impact $\times$ Educational Background: $F(3, 85) = 3.78, p = .013$ *
 Mechanisms $\times$ Professional Role: $F(5, 90) = 2.64, p = .028$ *
 Use of Research $\times$ Professional Role: $F(5, 85) = 2.47, p = .039$ *
 Relative Importance $\times$ Organization Type: $F(4, 90) = 3.41, p = .012$ *

Note: Denominator degrees of freedom are Satterthwaite approximations. They approach the residual df rather than the number of respondents when the random-intercept variance is estimated near zero, as in the Mechanisms $\times$ Educational Background model ($df_2 = 474$).

Significant interaction effects (group $\times$ item):

Threat Perception $\times$ Organization Type: $F(28, 637) = 1.90, p = .004$ **
 Reasons for Belief $\times$ Organization Type: $F(27, 765) = 1.96, p = .003$ **
 Threat Perception $\times$ Educational Background: $F(21, 588) = 1.73, p = .023$ *

Impact × Educational Background: $F(21, 594) = 1.57, p = .0497 *$

Relative Importance × Professional Role: $F(30, 552) = 1.50, p = .044 *$

D2. Items with highest between-group disagreement

By organizational type (Q3)—top 5 items ranked by variance of group means:

1. Limited reflection, intuition rather than analysis (variance = 0.33, range = 1.18, $k = 4$ groups)
2. Problem comes mainly from demand (public actively seeks content) (variance = 0.31, range = 1.07)
3. Activists or militants [threat] (variance = 0.31, range = 1.28, $k = 5$)
4. Gray literature or popularization (variance = 0.29, range = 1.16)
5. Foreign governments, politicians or parties [threat] (variance = 0.25, range = 1.15, $k = 5$)

By educational background (Q5)—top 5:

1. Journalists or press organizations [threat] (variance = 0.38, range = 1.40, $k = 4$)
2. Activists or militants [threat] (variance = 0.31, range = 1.30)
3. Applicability perceived as low (variance = 0.30, range = 1.27)
4. Insufficient resources (budgets and staff) (variance = 0.28, range = 1.14)
5. Disinformation played an important role in Trump's 2016 election (variance = 0.27, range = 1.20)

By professional role (Q7)—top 5:

1. Applicability perceived as low (variance = 0.38, range = 1.58, $k = 6$)
2. Language barrier (English, scientific jargon) (variance = 0.26, range = 1.46)
3. Fear of being accused of censorship (variance = 0.24, range = 1.33)
4. People encounter opposing opinions more often offline than online (variance = 0.23, range = 1.23)
5. State-supported or state-controlled media [threat] (variance = 0.23, range = 1.33)

D3. Detailed group means for highest-disagreement items

By organizational type (Q3):

Limited reflection, intuition rather than analysis:

Military/Intelligence: 4.18 ($n = 33$)

Normative/Regulatory: 3.96 ($n = 28$)

High-level civil servants/politicians: 3.19 ($n = 21$)

Private For-Profit: 3.00 ($n = 7$)

Activists or militants [threat]:

Private For-Profit: 5.14 ($n = 7$)

Military/Intelligence: 4.88 ($n = 33$)

Normative/Regulatory: 4.29 ($n = 28$)

Private Non-Profit: 4.00 ($n = 6$)

High-level civil servants/politicians: 3.86 ($n = 22$)

Foreign governments, politicians or parties [threat]:

Private For-Profit: 6.00 ($n = 7$)

Private Non-Profit: 5.83 ($n = 6$)

High-level civil servants/politicians: 5.18 ($n = 22$)

Normative/Regulatory: 5.11 ($n = 28$)

Military/Intelligence: 4.85 ($n = 33$)

By educational background (Q5):

Journalists or press organizations [threat]:

Humanities: 4.54 ($n = 13$)

Information/Communication/Media: 3.72 ($n = 18$)

Social Sciences: 3.35 ($n = 43$)

Computer/Data/Digital: 3.14 ($n = 14$)

Disinformation played an important role in Trump's 2016 election:

Computer/Data/Digital: 4.43 ($n = 14$)

Information/Communication/Media: 4.17 ($n = 18$)

Social Sciences: 4.14 ($n = 44$)

Humanities: 3.23 ($n = 13$)

Applicability perceived as low:

Information/Communication/Media: 2.87 ($n = 15$)

Social Sciences: 2.56 ($n = 39$)

Humanities: 2.50 ($n = 12$)

Computer/Data/Digital: 1.60 ($n = 10$)

By professional role (Q7):

Applicability perceived as low:

Other activity: 2.91 ($n = 23$)

Communication/Counter-Influence: 2.85 ($n = 20$)

Public Protection/Journalism/Education: 2.79 ($n = 14$)

Detection/Monitoring/Analysis: 2.42 ($n = 12$)

Normative/Regulatory/Policy: 2.00 ($n = 12$)

Cybersecurity/Technical: 1.33 ($n = 6$)

Language barrier (English, scientific jargon):

Public Protection/Journalism/Education: 2.71 ($n = 14$)

Communication/Counter-Influence: 2.48 ($n = 21$)

Other activity: 2.41 ($n = 22$)

Detection/Monitoring/Analysis: 2.33 ($n = 12$)

Cybersecurity/Technical: 2.17 ($n = 6$)

Normative/Regulatory/Policy: 1.25 ($n = 12$)

Fear of being accused of censorship:

Normative/Regulatory/Policy: 4.17 ($n = 12$)

Public Protection/Journalism/Education: 4.07 ($n = 15$)

Detection/Monitoring/Analysis: 3.79 ($n = 14$)

Communication/Counter-Influence: 3.57 ($n = 23$)

Other activity: 3.43 ($n = 23$)

Cybersecurity/Technical: 2.83 ($n = 6$)

D4. Summary of heterogeneity patterns

Dimensions with most heterogeneity: Research obstacles (significant across all three grouping variables), obstacles to combating disinformation (strongest single effect, by educational background), threat perception (significant interactions by organization and educational background), and mechanisms of disinformation (by educational background and role).

Dimensions with least heterogeneity: Impact assessment (non-significant by role, $p = .887$, and by organization, $p = .668$), future developments (non-significant by role, $p = .725$), and information-source preferences (non-significant by educational background, $p = .455$, and role, $p = .181$).

Respondents converge on the diagnosis (what causes disinformation, what its consequences are) but diverge on operational constraints (which obstacles matter, how accessible research is, what role censorship fear plays). This pattern is consistent with the diagnosis-capacity mismatch described in the main text: the shared upstream model does not translate into uniform experience of institutional constraints. Educational background is associated with how severe practitioners judge obstacles to action, the only effect that survives correction; perceived barriers to using research varied with professional role, educational background, and organizational type before correction ($p = .004$ – $.006$), but not after (adjusted $p = .058$ – $.061$).

D5. Heatmaps: deviations from item means

The following heatmaps display each group's deviation from the item mean, disaggregated by the three grouping variables (organizational type, educational background, and professional role). The item-level role heatmaps (D6–D33) show the five specific roles; respondents in the “other activity” category are not shown.

Cross-tabulations of grouping variables

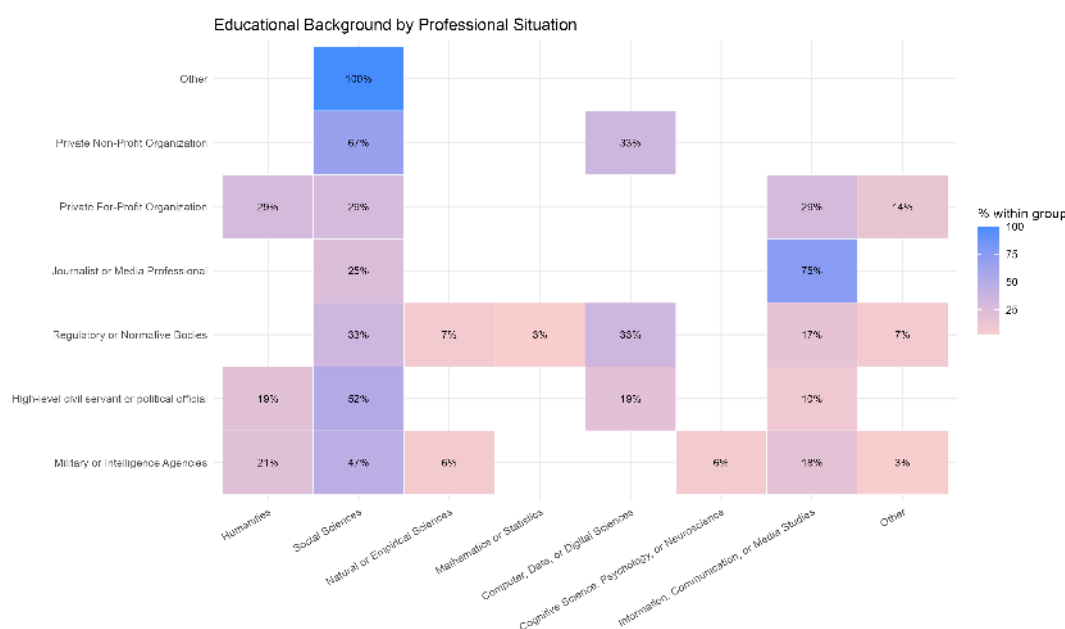


Figure D1. Cross-tabulations of grouping variables: organization type by educational background (N = 103). Cells show row percentages (% within each organization type).

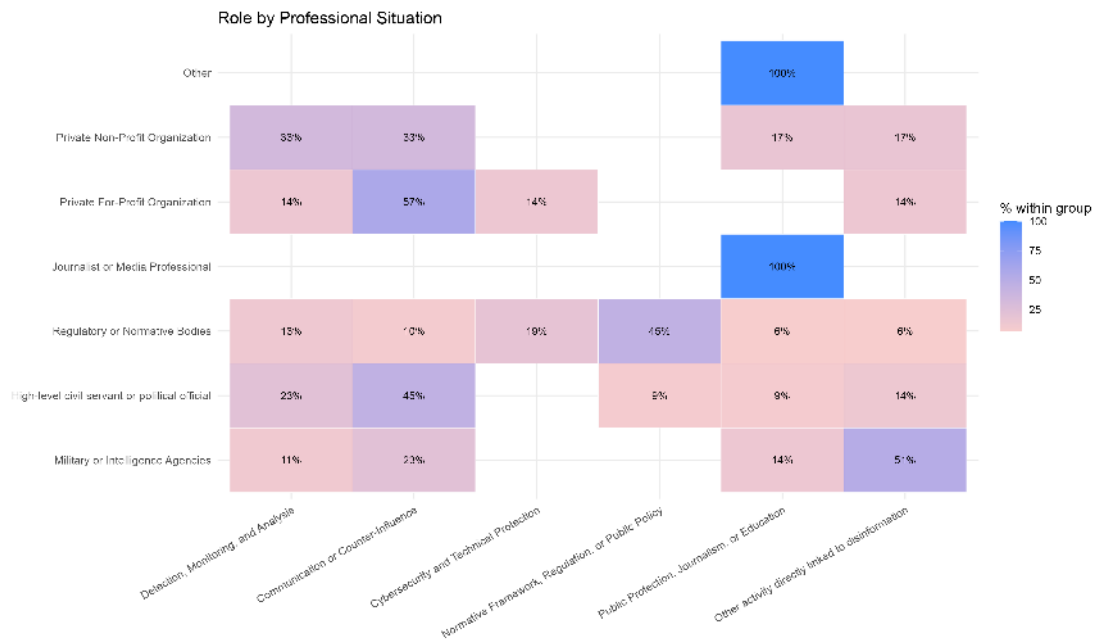


Figure D2. Cross-tabulations of grouping variables: organization type by professional role (N = 106). Cells show row percentages (% within each organization type).

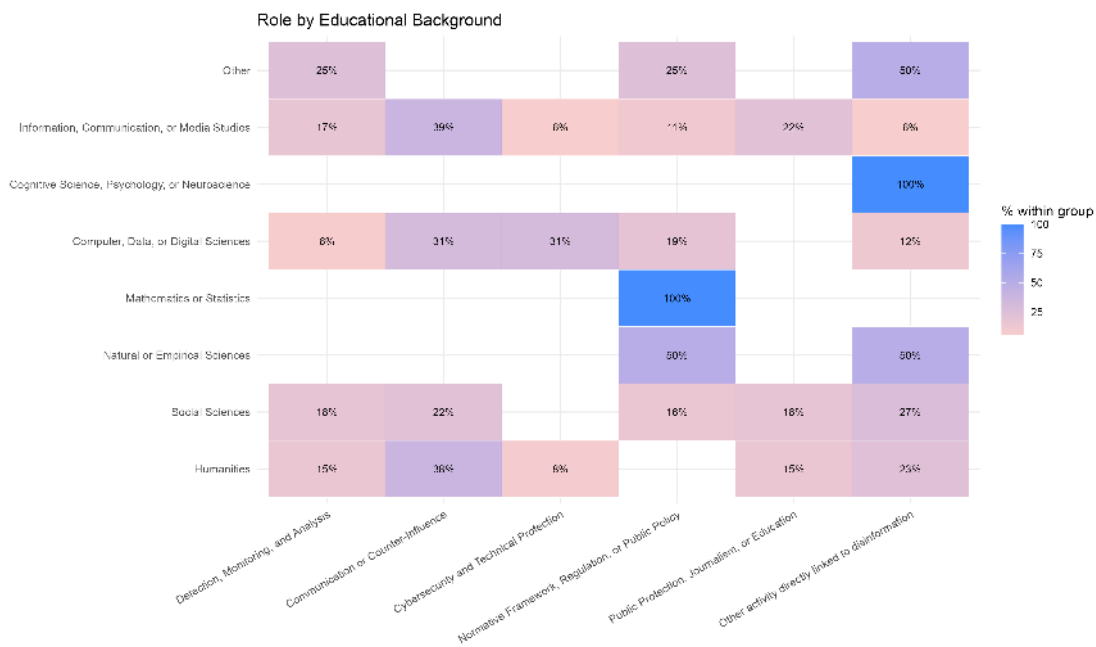


Figure D3. Cross-tabulations of grouping variables: educational background by professional role (N = 103). Cells show row percentages (% within each educational background).

Perceived threats

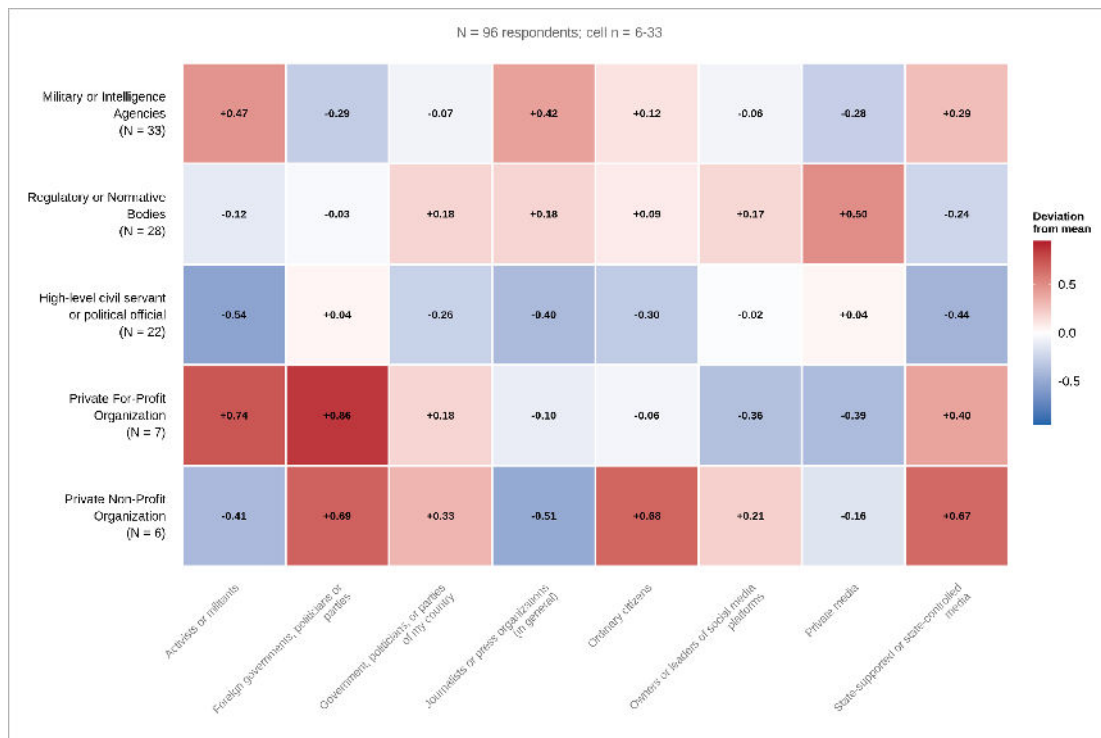


Figure D4. Perceived threats by organization type (N = 96). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.



Figure D5. Perceived threats by educational background (N = 88). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.



Figure D6. Perceived threats by professional role (N = 77). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

Perceived impact

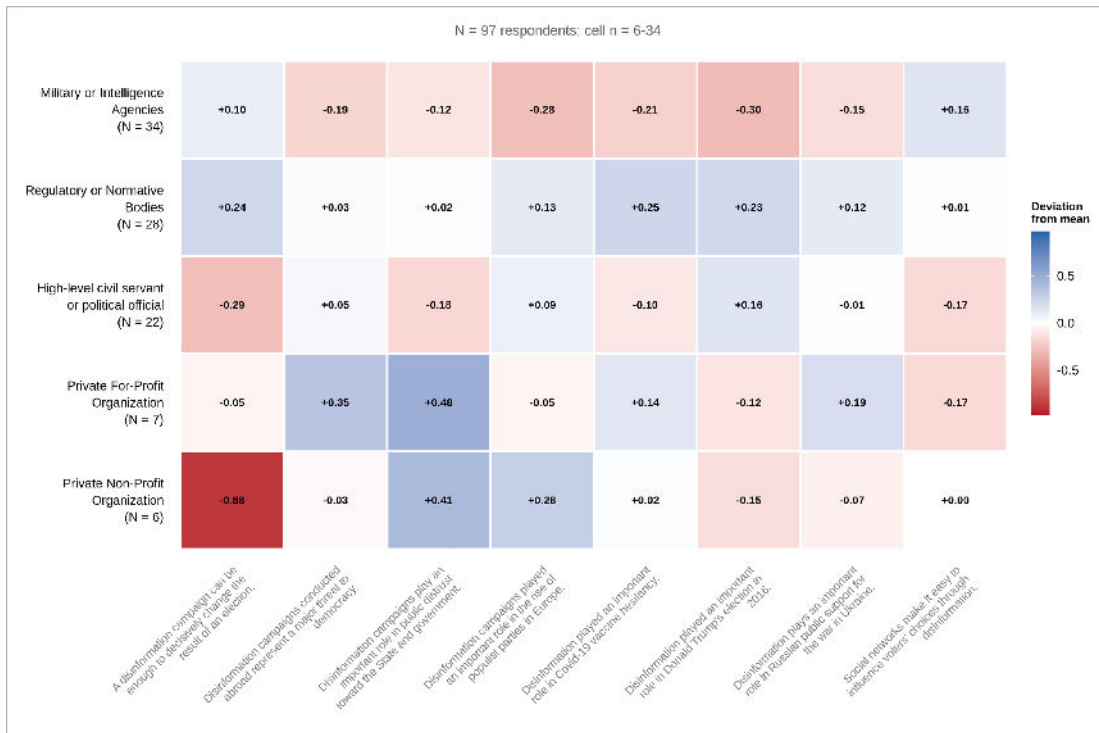


Figure D7. Perceived impact by organization type (N = 97). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

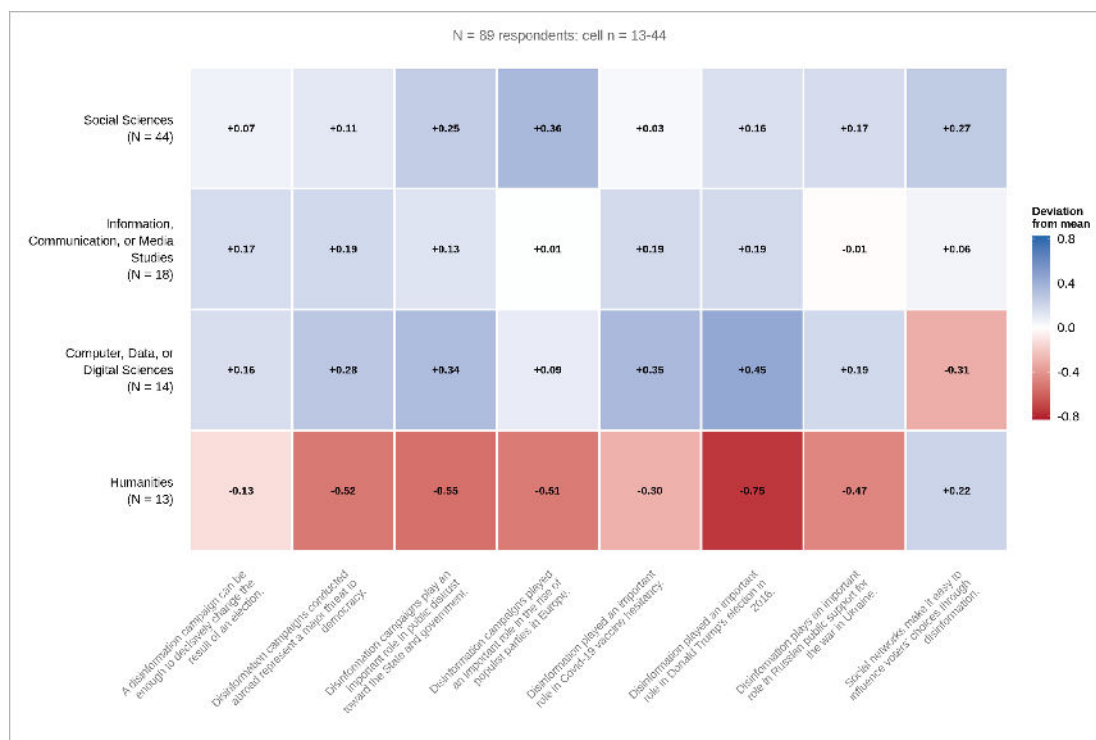


Figure D8. Perceived impact by educational background (N = 89). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.



Figure D9. Perceived impact by professional role (N = 77). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

Relative importance



Figure D10. Relative importance by organization type (N = 95). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.



Figure D11. Relative importance by educational background (N = 88). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

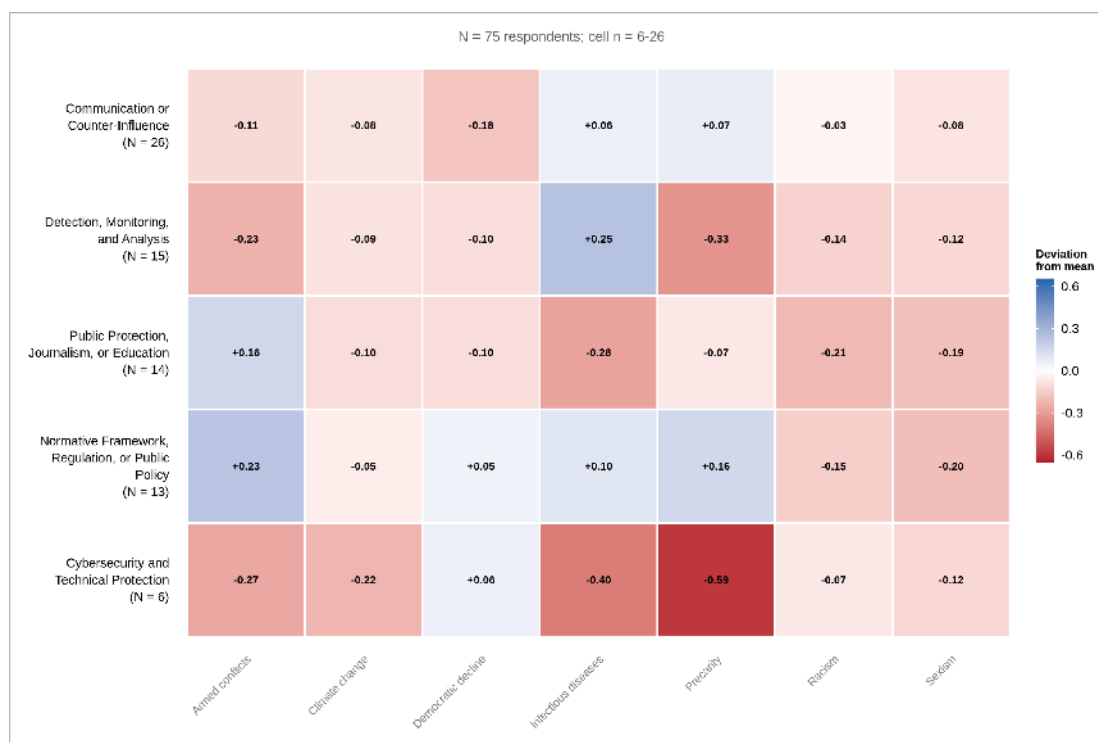


Figure D12. Relative importance by professional role (N = 75). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

Reasons for belief

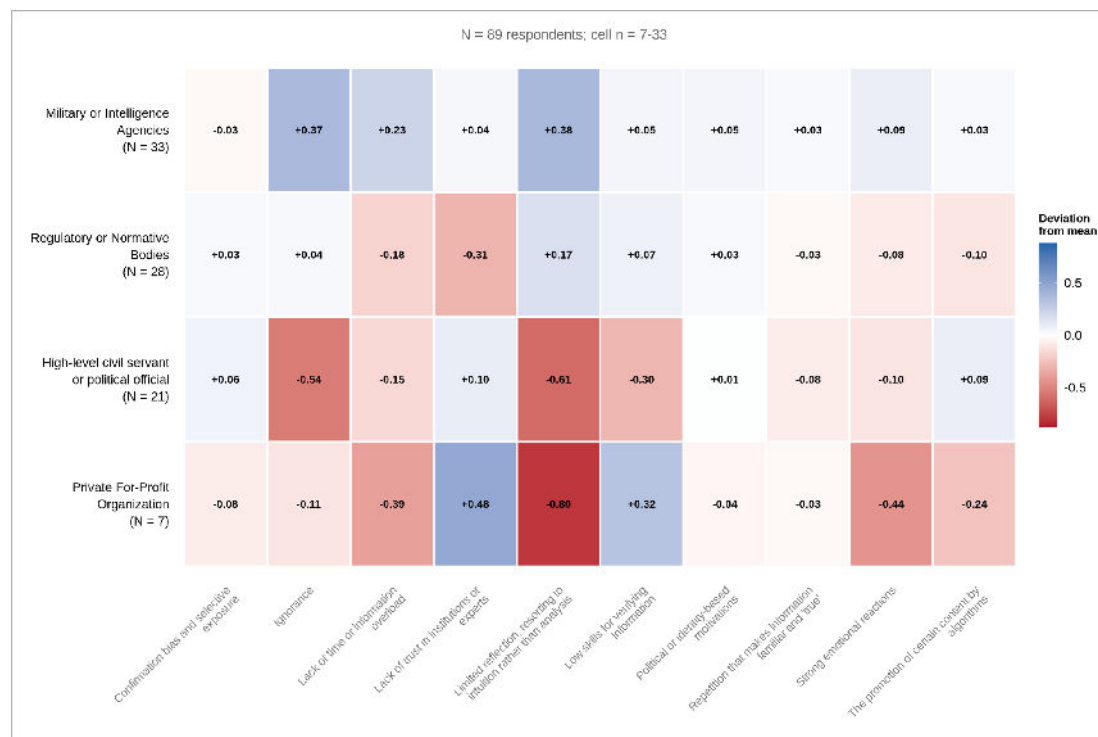


Figure D13. Reasons for belief by organization type (N = 89). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

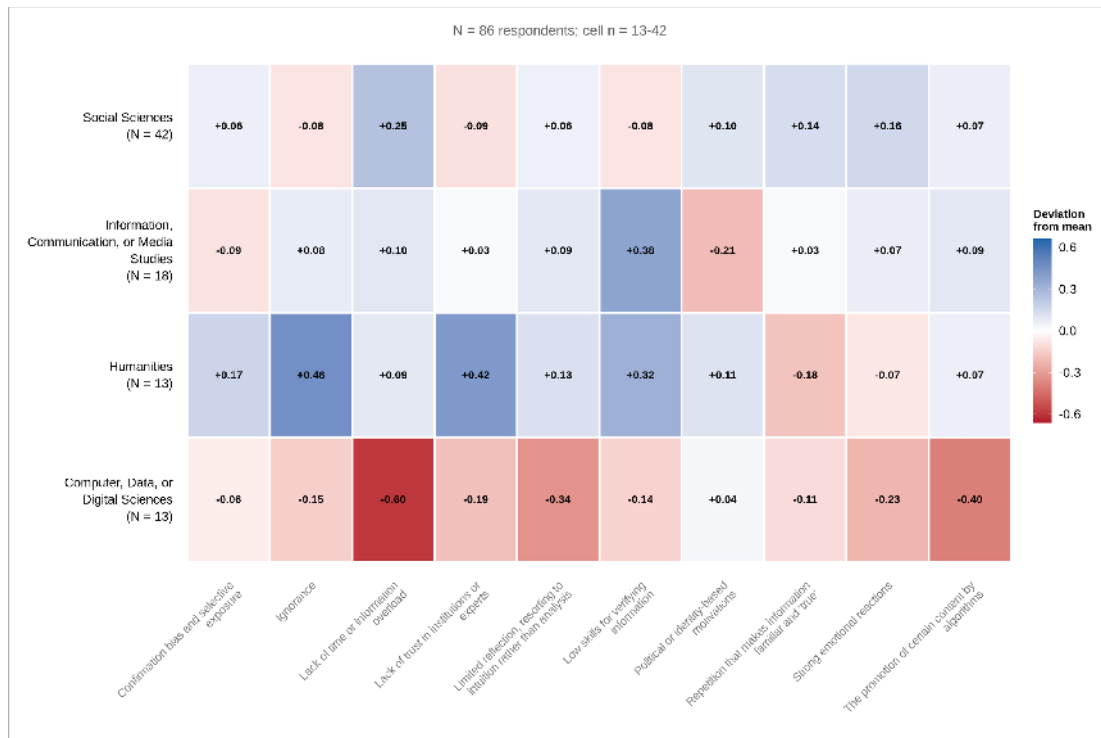


Figure D14. Reasons for belief by educational background (N = 86). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

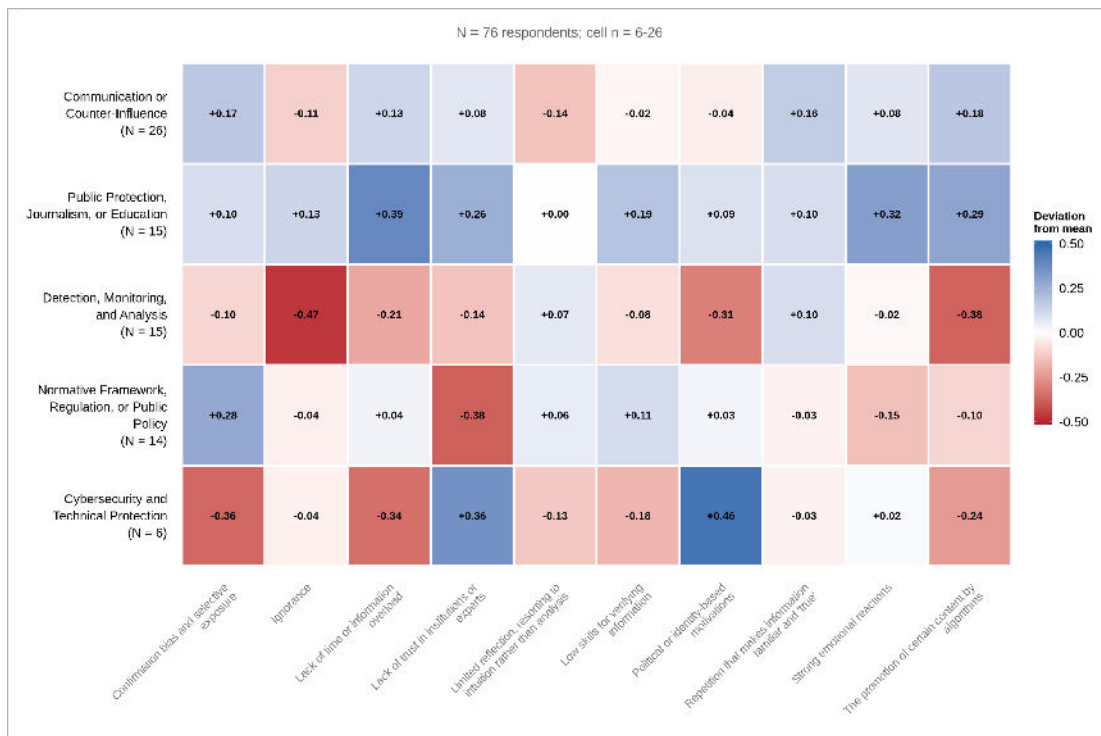


Figure D15. Reasons for belief by professional role (N = 76). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

Mechanisms



Figure D16. Mechanisms by organization type (N = 86). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

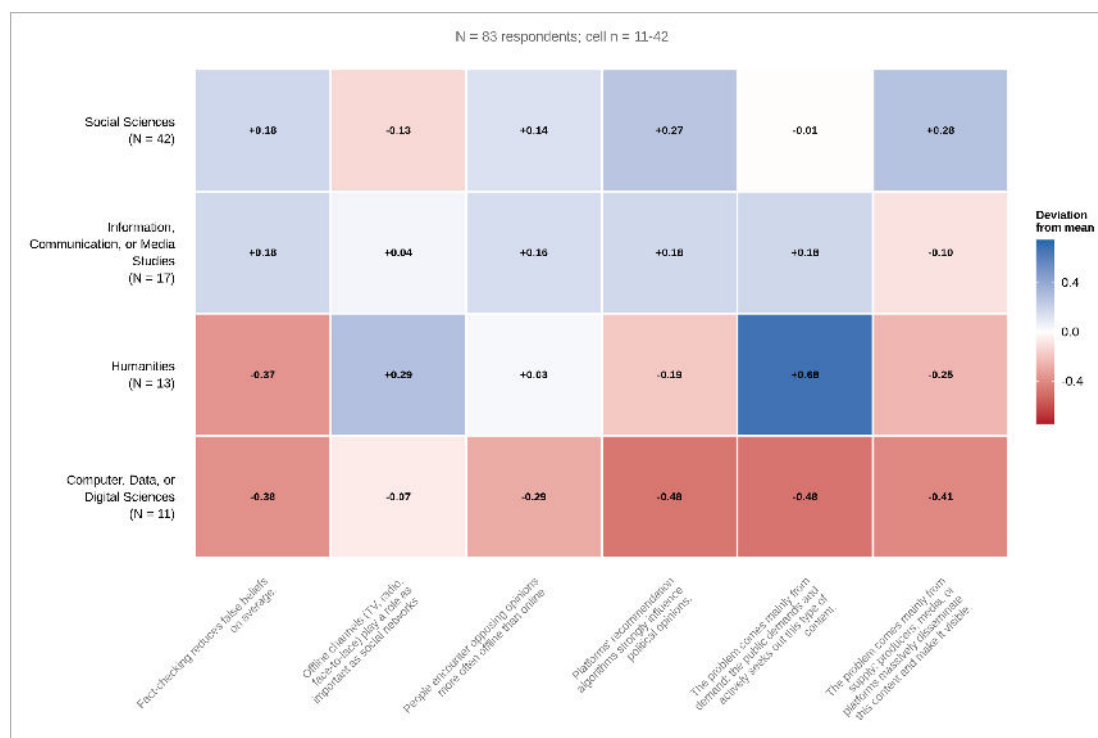


Figure D17. Mechanisms by educational background (N = 83). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

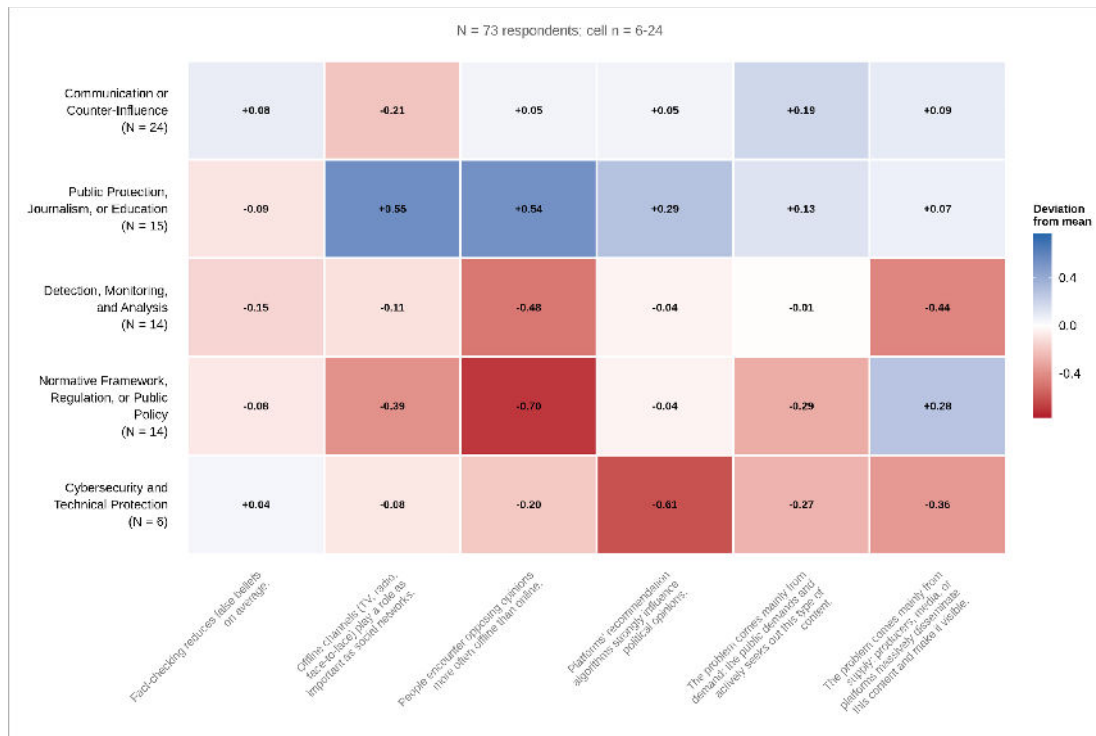


Figure D18. Mechanisms by professional role (N = 73). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

Obstacles

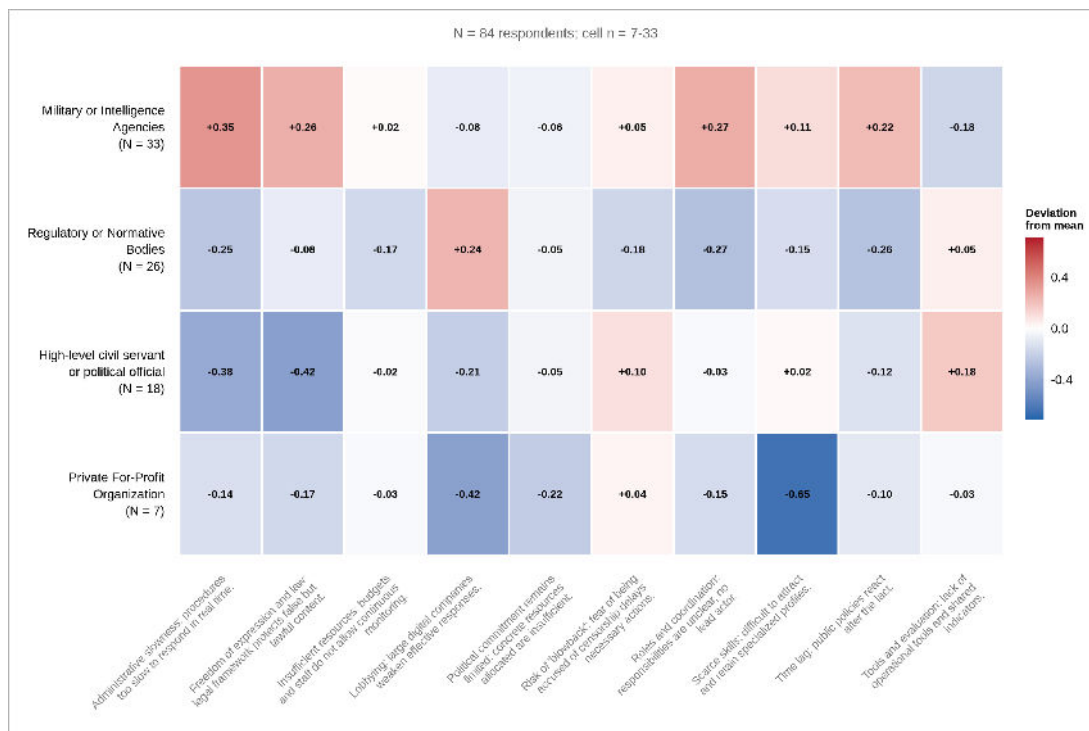


Figure D19. Obstacles by organization type (N = 84). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

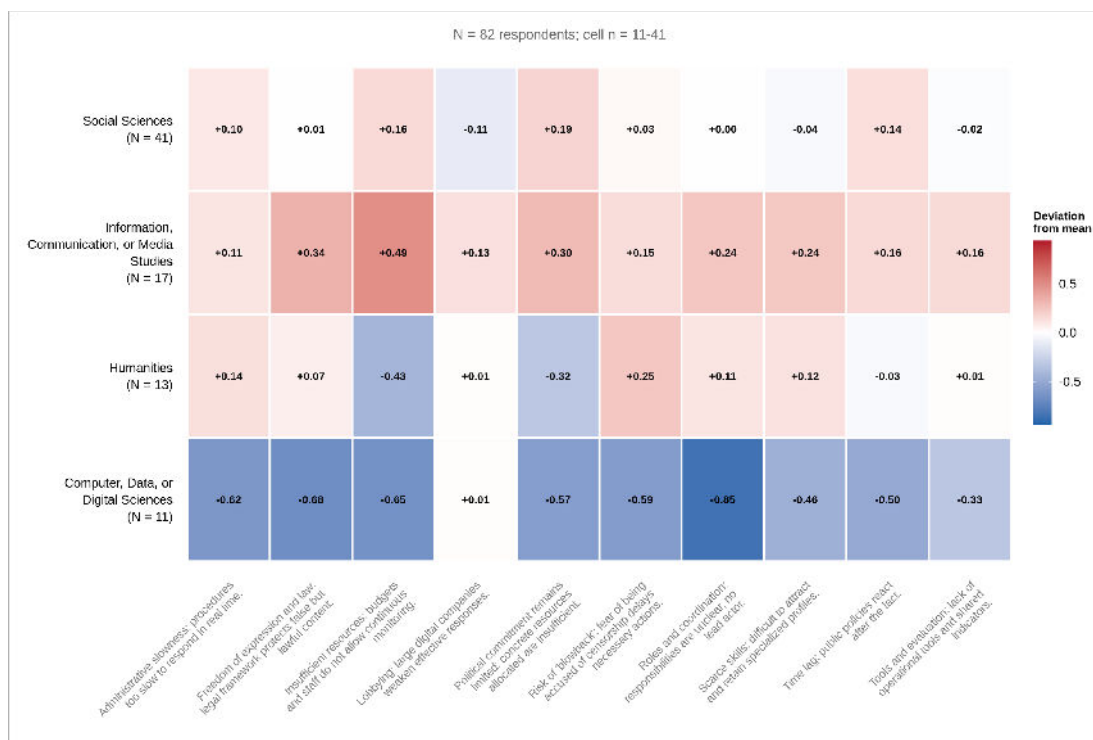


Figure D20. Obstacles by educational background (N = 82). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

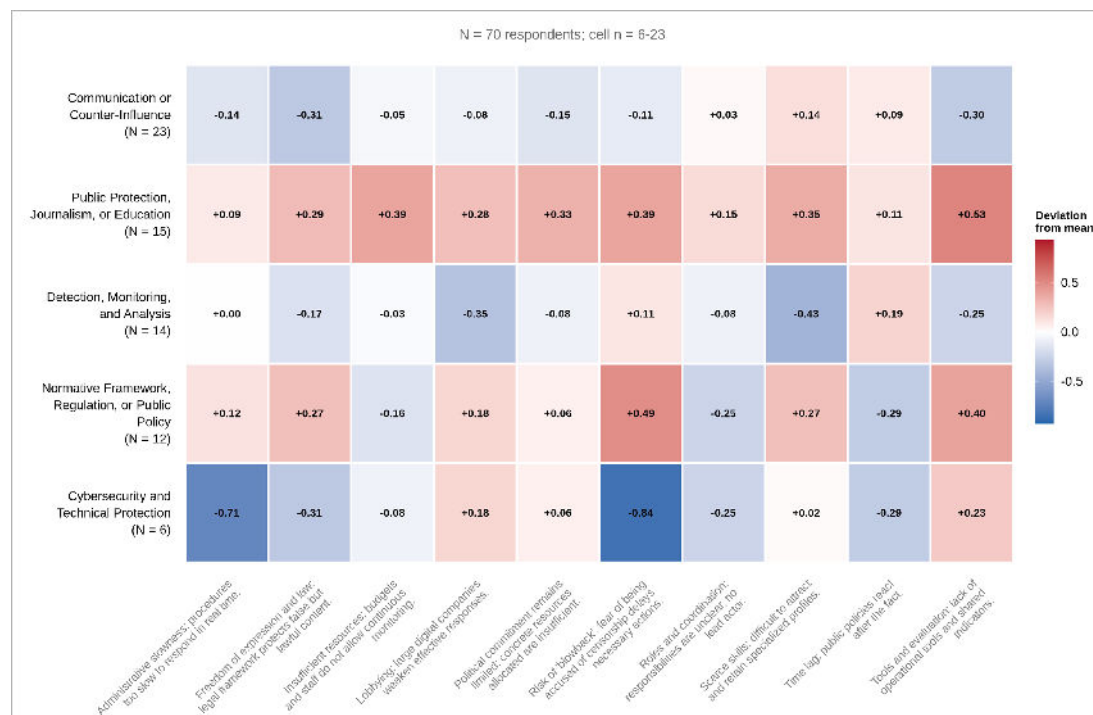


Figure D21. Obstacles by professional role (N = 70). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

Research obstacles

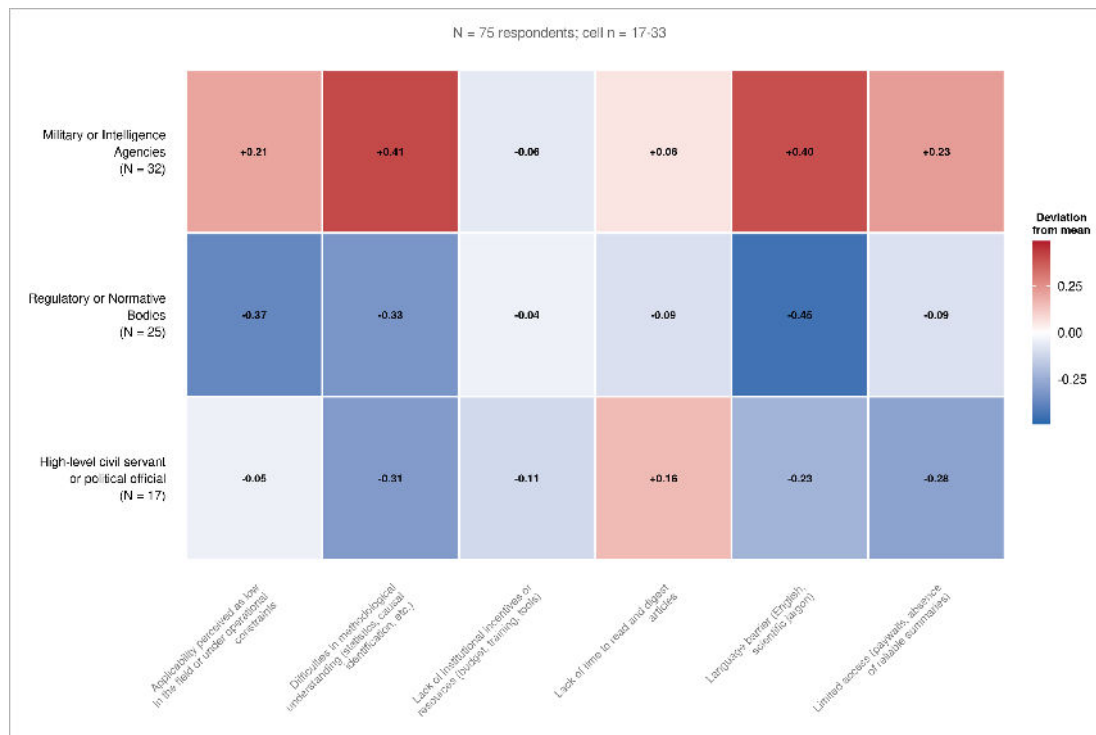


Figure D22. Research obstacles by organization type (N = 75). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

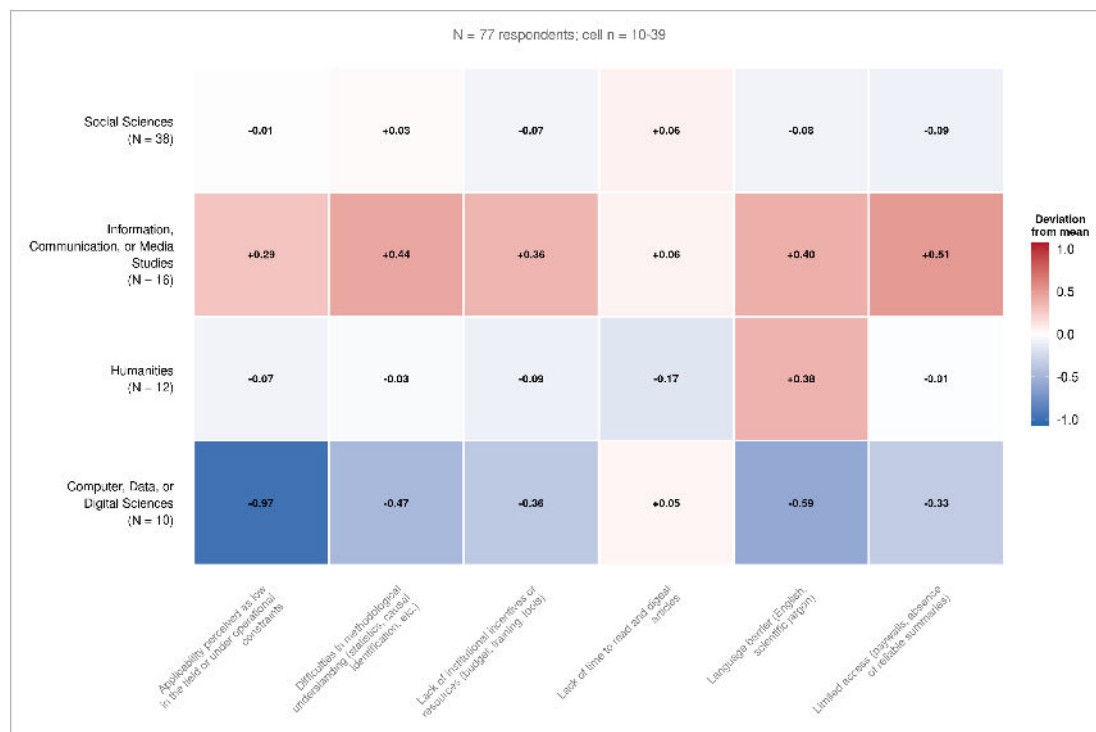


Figure D23. Research obstacles by educational background (N = 77). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.



Figure D24. Research obstacles by professional role (N = 65). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

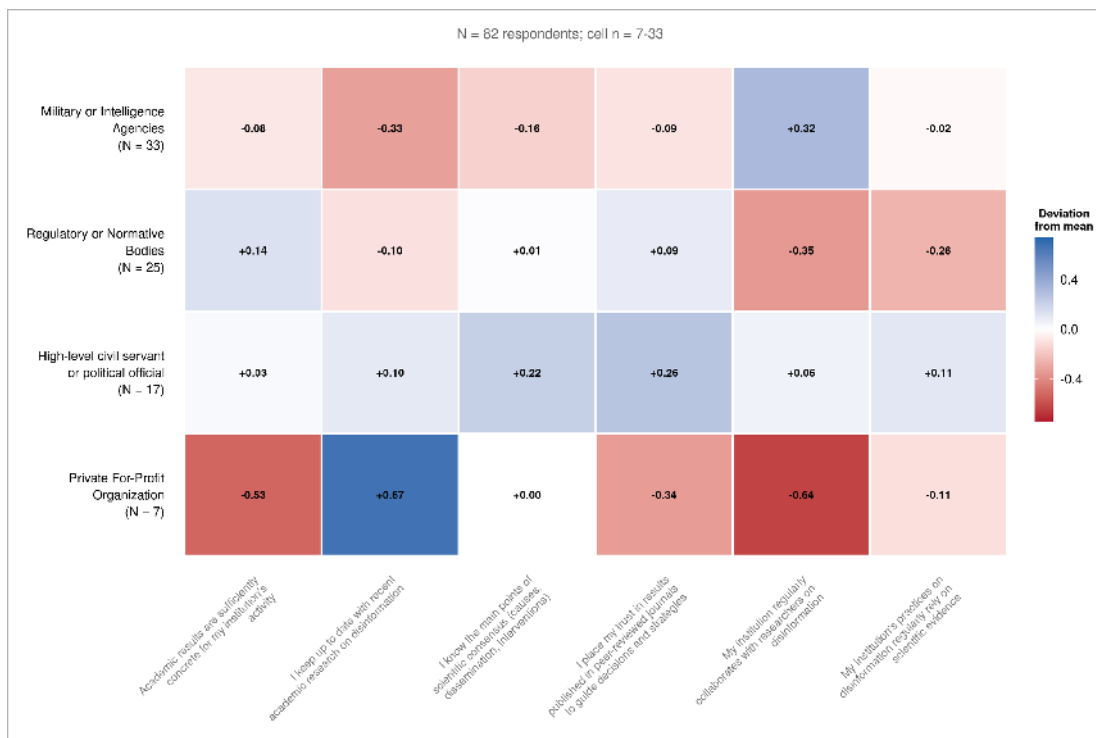


Figure D25. Research use by organization type (N = 82). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

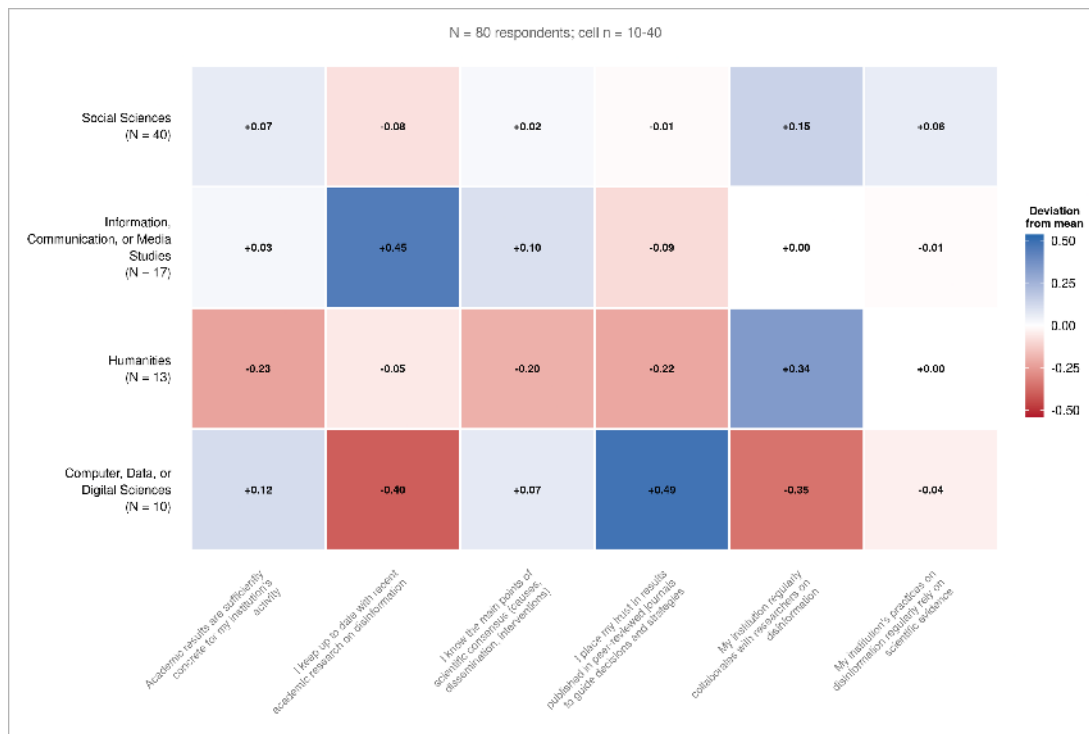


Figure D26. Research use by educational background (N = 80). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

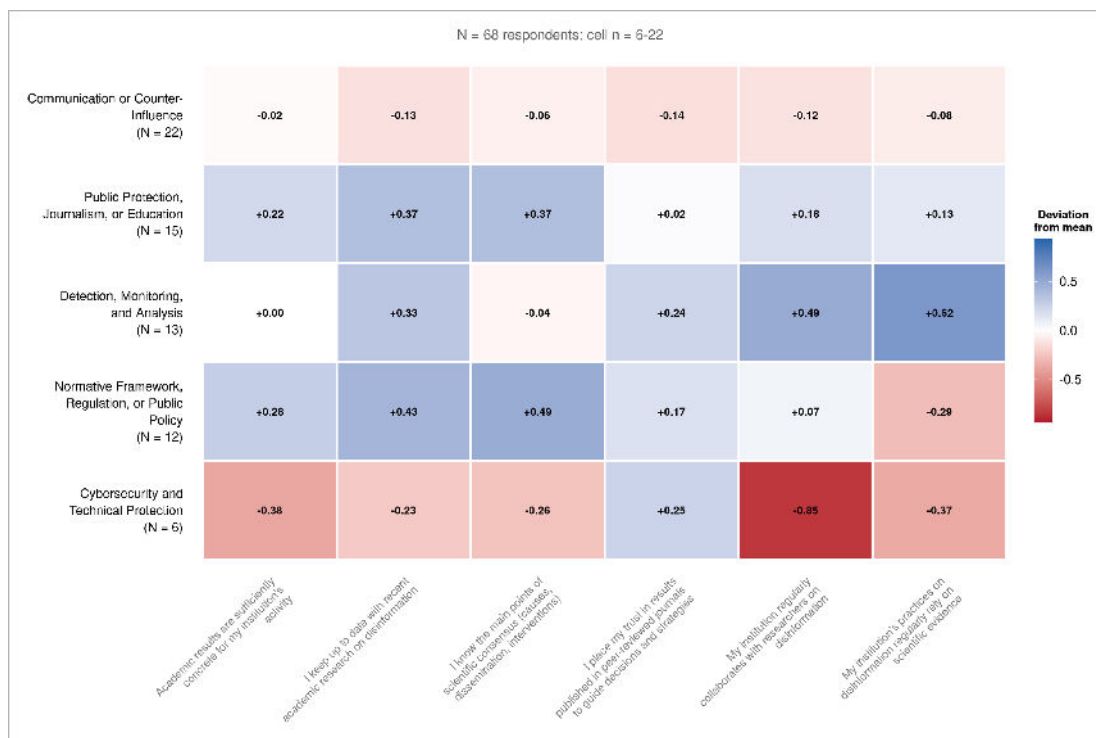


Figure D27. Research use by professional role (N = 68). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

Information sources

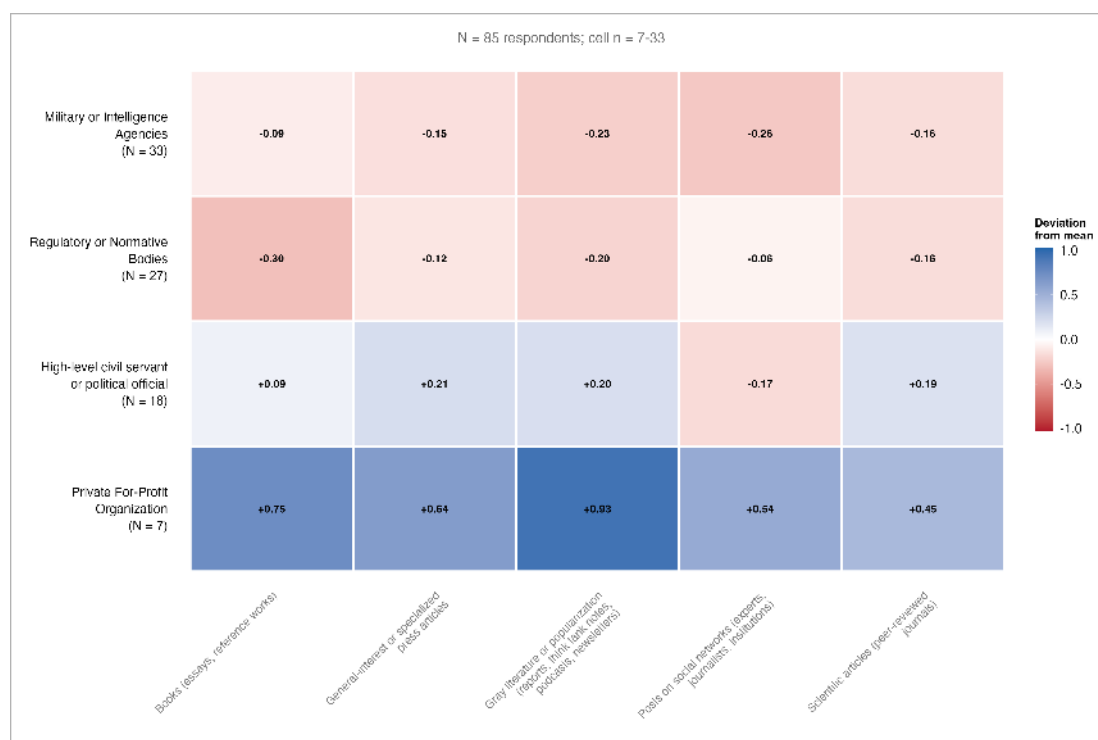


Figure D28. Information sources by organization type (N = 85). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

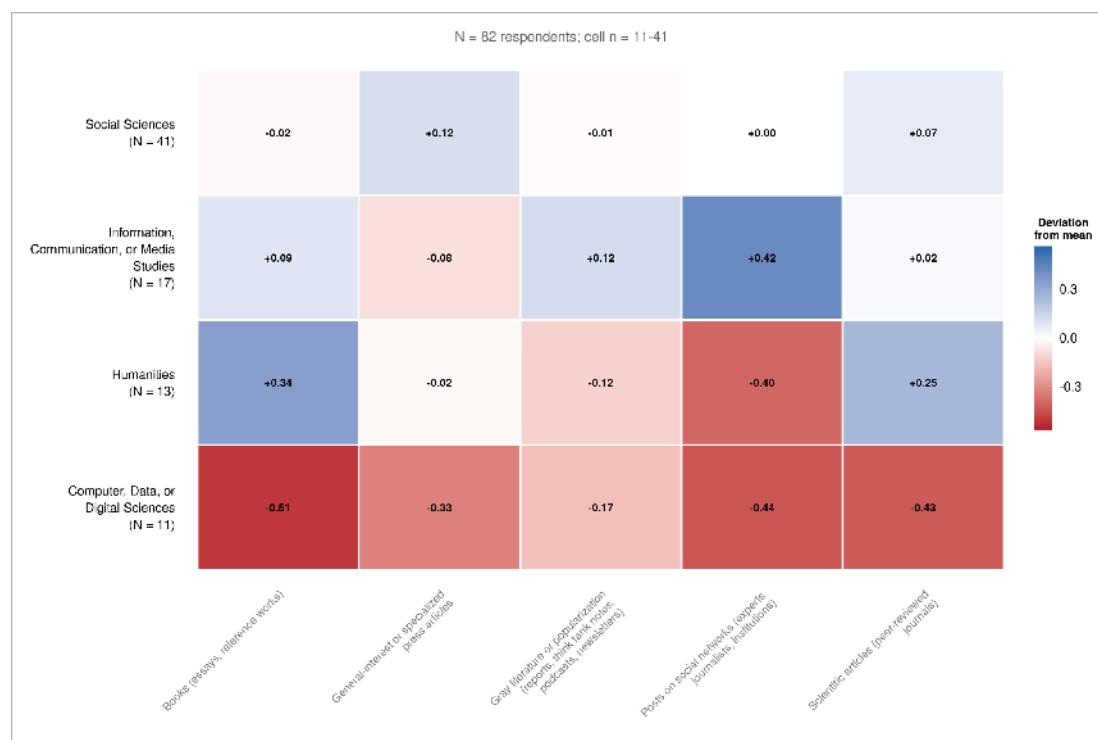


Figure D29. Information sources by educational background (N = 82). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

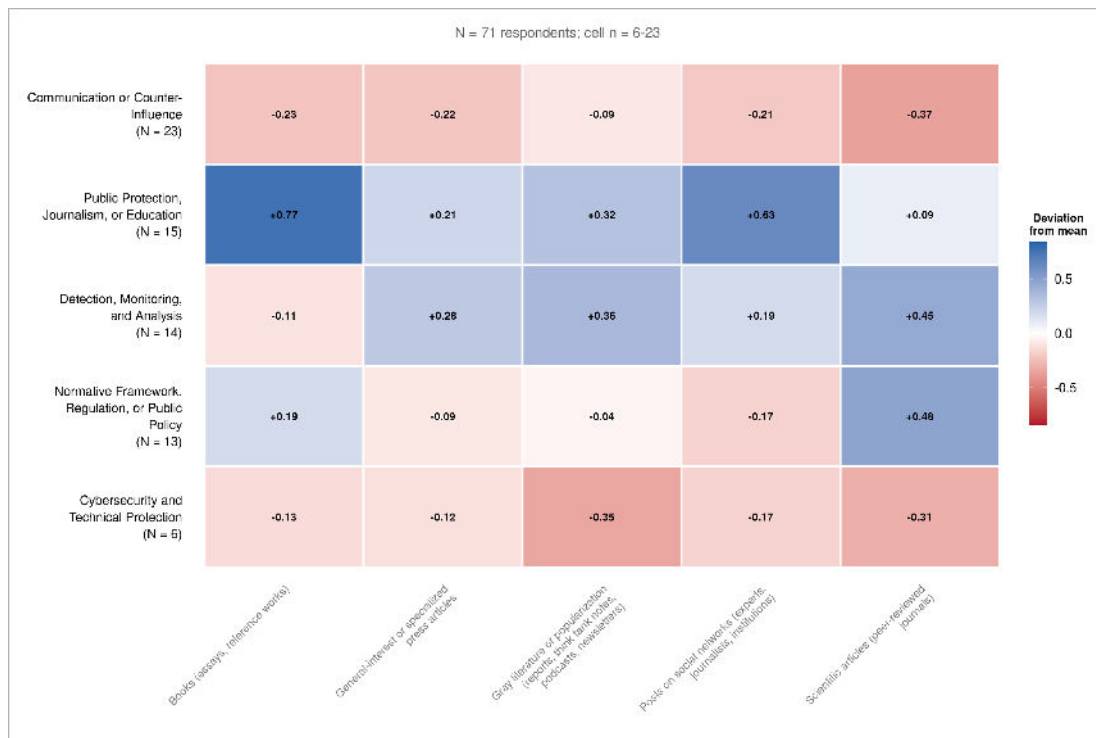


Figure D30. Information sources by professional role (N = 71). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

Expected evolution

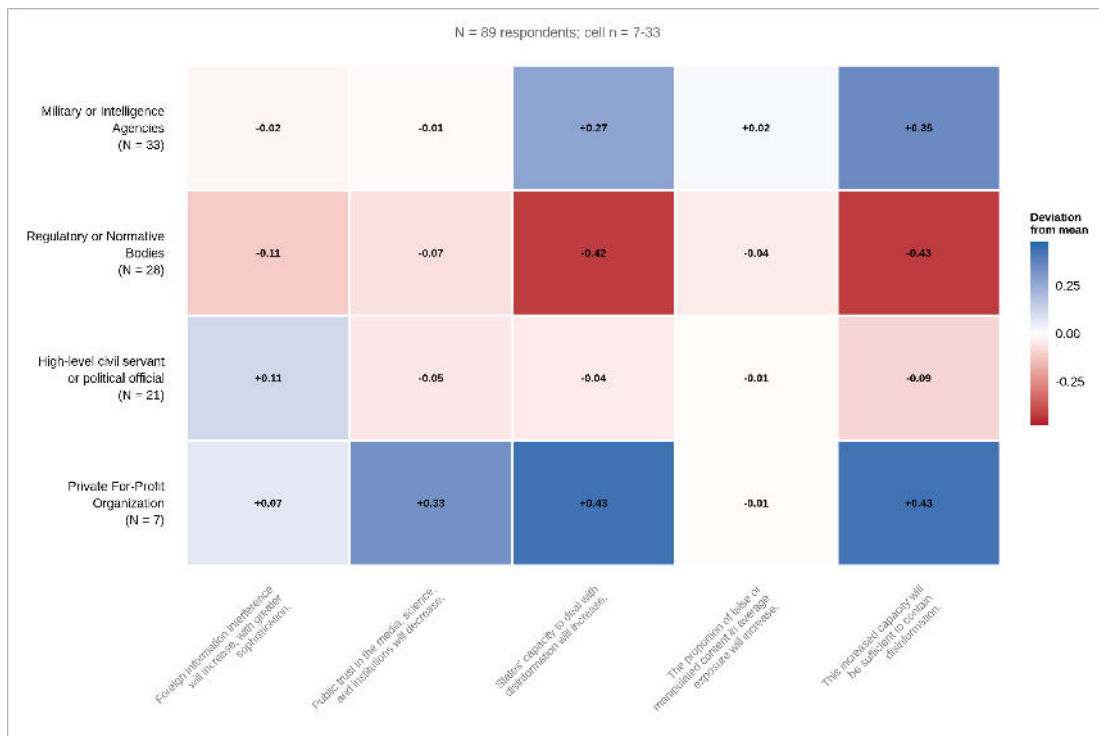


Figure D31. Expected evolution by organization type (N = 89). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

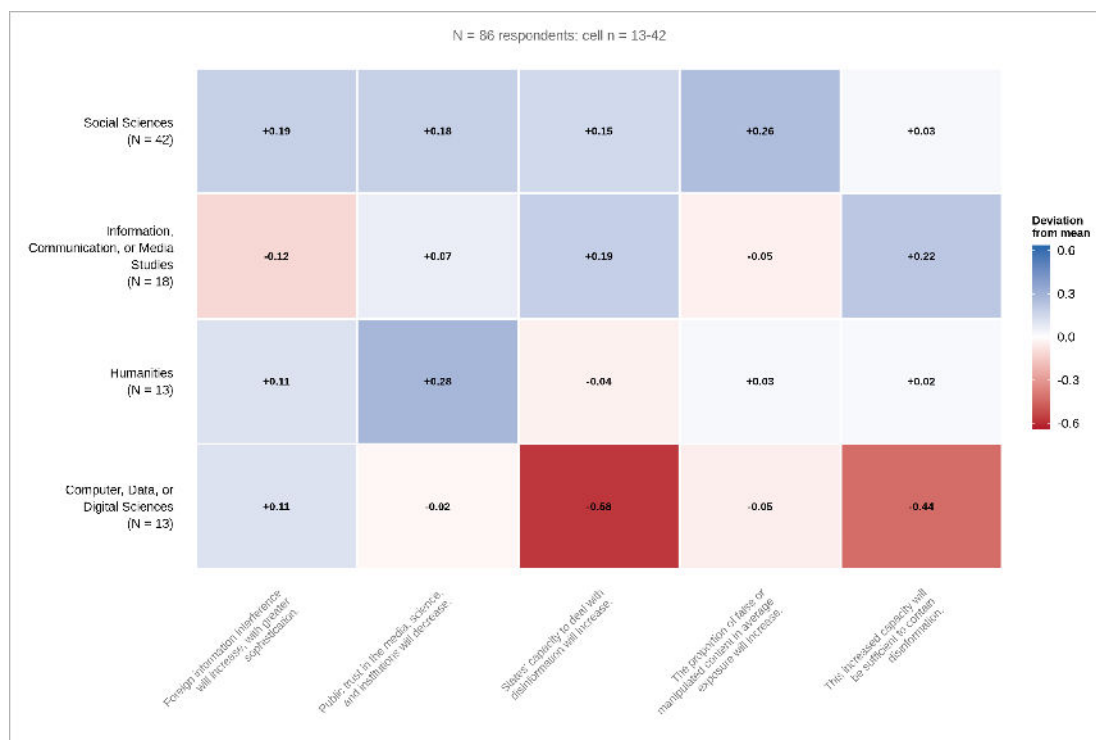


Figure D32. Expected evolution by educational background (N = 86). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

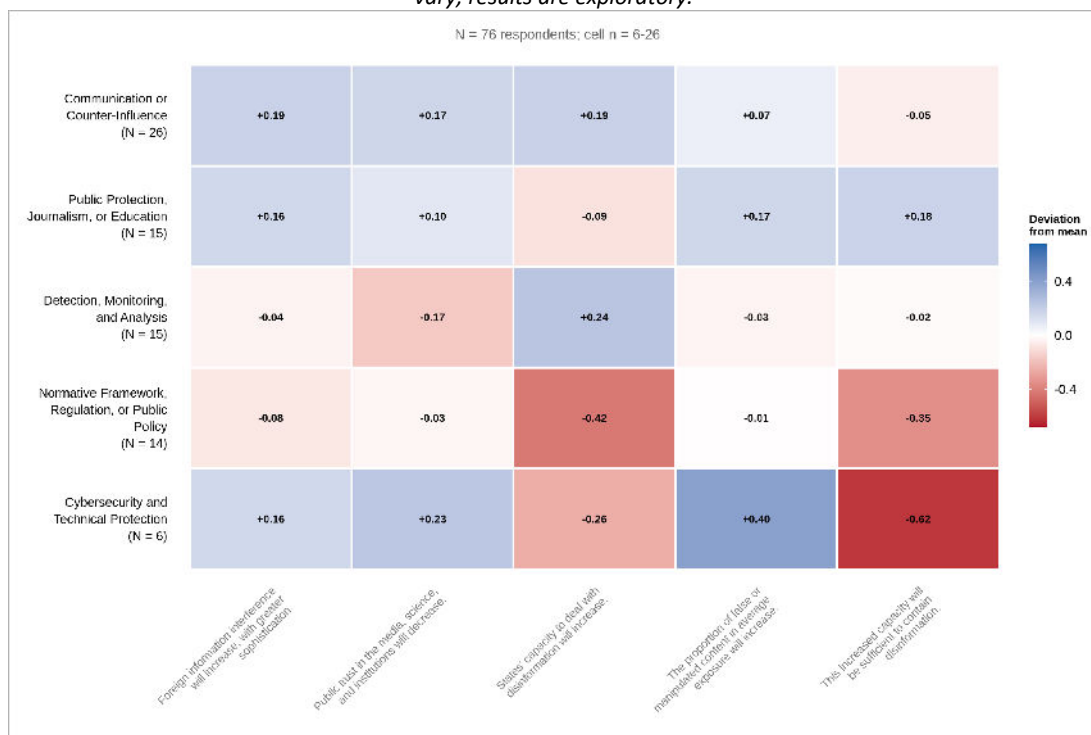


Figure D33. Expected evolution by professional role (N = 76). Cells show deviations from the item mean. Subgroup Ns vary; results are exploratory.

D.6 Public versus private organizations

To assess whether the underrepresentation of non-state actors affects the aggregate results, we compared respondents from public-sector institutions (military or military-affiliated institutions, senior government and central administration, independent regulatory authorities; Q3 categories 1–3, $n = 88$) and respondents from private and non-state organizations (journalism and media, private for-profit, private non-profit; Q3 categories 4–6, $n = 17$). One respondent reporting an “other” affiliation was excluded. For each of the ten question blocks, we estimated a linear mixed-effects model with the same structure as in D.1 (response $\sim$ group $\times$ item, random intercept per respondent, REML), with the public/private indicator as the grouping variable. These models were fitted in R with lme4 (Bates et al., 2015); inference uses Wald chi-square tests with sum-to-zero contrasts, so the group test reflects a main effect averaged across items. The resulting 20 p-values (10 blocks $\times$ group main effect and group $\times$ item interaction) were corrected with the Benjamini–Hochberg procedure as one family. Given the size of the private group, item-level contrasts have a minimum detectable effect of $d \approx 0.74$ ($\alpha = .05$, 80% power); non-significant results should accordingly be read as an absence of detectable differences, not as evidence that no differences exist.

One effect survived correction: a group main effect on information sources (Q19; Wald $\chi^2 = 9.41$, $df = 1$, $p_{\text{raw}} = .002$, $p_{\text{adj}} = .043$). Private and non-state respondents reported more frequent use of most information channels, with the largest item-level contrasts on posts on social networks (public $M = 3.00$ vs. private $M = 4.00$, $d = -0.87$), gray literature (3.23 vs. 4.00, $d = -0.68$), and books (2.85 vs. 3.60, $d = -0.66$). Two interactions approached but did not reach the corrected threshold (both $p_{\text{adj}} = .063$): perceived threats (Q10; $\chi^2 = 18.90$, $df = 7$), where public respondents rated journalists and press organizations as a greater threat ($d = 0.55$) while private respondents rated foreign governments higher ($d = -0.54$), and research engagement (Q22; $\chi^2 = 15.21$, $df = 5$), where the gap concentrated on keeping up to date with recent academic research (2.75 vs. 3.67, $d = -0.80$). All remaining tests were non-significant, including every group main effect on the substantive blocks: relative importance, perceived impact, perceived threats, reasons for belief, mechanisms of spread, obstacles, research obstacles, and expected developments.

In sum, public and private respondents in this sample do not detectably differ in their substantive diagnosis of the disinformation problem; the detectable differences concern information practices.

Appendix E: Wave composition

Before exclusion, the dataset contains 93 Wave 1 cases and 30 Wave 2 cases. After applying the analytic inclusion rule used in the paper—valid consent and a valid response to the professional-role item (Q7, the final question of the demographic block)—the final sample includes 85 respondents in Wave 1 and 21 in Wave 2.

The two waves differ in organizational composition. Wave 1 is concentrated in military/intelligence (36.5%), regulation/normative bodies (31.8%), and government/high administration (20.0%), with smaller shares from private for-profit organizations (5.9%), private non-profits (3.5%), and journalism/media (2.4%). Wave 2 is more heterogeneous: government/high administration (23.8%), military/intelligence (19.0%), and regulation/normative bodies (19.0%) remain important, but private non-profits (14.3%), journalism/media (9.5%), private for-profit organizations (9.5%), and other (4.8%) are more represented.

The clearest compositional differences are that Wave 1 includes more military/intelligence respondents (+17.4 percentage points) and more regulation/normative respondents (+12.7 points), whereas Wave 2 includes broader representation from non-state and residual categories. The wave variable therefore reflects not only timing, but also meaningful differences in the kinds of respondents reached in each wave.

Thus, any apparent “wave effect” is difficult to interpret because the two waves differ substantially in composition. Wave membership is therefore not separable from the types of practitioners reached in each recruitment phase. A model using wave as a predictor would mix recruitment-channel differences with genuine differences between respondent groups, and the smaller Wave 2 sample limits reliable within-sector comparisons. For this reason, we report wave composition descriptively rather than estimating statistical wave effects. Future studies with more balanced recruitment across sectors, or with weighting procedures, would be better able to distinguish recruitment effects from population differences.

Appendix F: Item-level descriptive statistics

This appendix reports item-level means and standard deviations (SDs) on the original response scales, alongside the aggregated percentages used in the main text and figures, so that the distributions behind the top-category summaries are fully transparent. Aggregation follows the convention of the figures: the two highest categories for 5-point scales, the three highest for the 7-point threat block (Q10, “high” or higher), and the two highest for the 4-point research-obstacles block (Q23, “moderate” or “major” obstacle). For Q8, the percentage shown is the share answering “about as important,” with “I don’t know” responses included in the denominator; Q8 means and SDs are computed on the 1–3 scale excluding “I don’t know.” Denominators vary by block under pairwise deletion (see Appendix A).

Q8. Relative importance of disinformation vs. other societal problems (1 = Less important; 2 = About as important; 3 = More important; 4 = I don’t know [excluded from mean/SD])

Table F1. *Relative importance of disinformation compared with other societal problems: item means, standard deviations, and share answering “about as important.”*

Item	N	M	SD	% high
Climate change	98 (102)	1.89	0.59	62
Racism	99 (102)	2.07	0.66	55
Sexism	99 (102)	2.12	0.69	50
Armed conflicts	99 (102)	1.77	0.60	57
Precarity	97 (101)	1.93	0.73	46
Democratic decline	98 (102)	2.10	0.53	69
Infectious diseases	97 (102)	1.90	0.77	38

Q9. Perceived impact of disinformation (1 = Strongly disagree ... 5 = Strongly agree)

Table F2. *Perceived impact of disinformation: item means, standard deviations, and percentage agreeing.*

Item	N	M	SD	% high
A disinformation campaign can decisively change an election result	101	4.05	1.06	83
Foreign disinformation campaigns are a major threat to democracy	102	4.36	0.87	90
Disinformation played an important role in Trump’s 2016 election	102	3.98	0.98	71
Disinformation plays an important role in Russian support for the war in Ukraine	102	4.24	0.85	87
Disinformation played an important role in the rise of populist parties in Europe	102	4.05	1.03	80
Disinformation played an important role in Covid-19 vaccine hesitancy	102	4.15	1.03	81
Social networks make it easy to influence voters’ choices	102	4.17	0.91	80
Disinformation plays an important role in distrust toward the State	102	4.09	1.02	78

Q10. Perceived threats to the information environment (1 = Not a threat at all; 2 = Very low; 3 = Low; 4 = Moderate; 5 = High; 6 = Very high; 7 = The greatest threat)

Table F3. Perceived threats to the information environment by actor type: item means, standard deviations, and percentage rating “high” or higher.

Item	N	M	SD	% high
Private media	101	4.82	1.08	63
Owners or leaders of social media platforms	101	5.79	1.04	91
Government, politicians, or parties of my country	101	4.67	1.13	57
Activists or militants	101	4.41	1.24	47
Ordinary citizens	101	3.49	1.22	18
Foreign governments, politicians or parties	101	5.14	1.17	69
State-supported or state-controlled media	101	4.17	1.57	41
Journalists or press organizations	101	3.67	1.36	22

Q12. Reasons why people believe disinformation (1 = Not at all; 2 = A little; 3 = Moderately; 4 = A lot; 5 = Enormously)

Table F4. Reasons why people believe disinformation: item means, standard deviations, and percentage answering “a lot” or “enormously.”

Item	N	M	SD	% high
Ignorance	99	3.54	1.12	57
Political or identity-based motivations	99	4.04	0.77	79
Confirmation bias and selective exposure	99	4.36	0.69	90
Limited reflection, intuition rather than analysis	99	3.80	0.93	68
Strong emotional reactions	99	4.15	0.75	83
Repetition that makes information familiar and ‘true’	99	4.03	0.71	81
Lack of time or information overload	99	3.68	0.97	57
Promotion of certain content by algorithms	99	4.24	0.74	84
Lack of trust in institutions or experts	99	3.81	0.84	65
Low skills for verifying information	99	3.68	1.00	65

Q13. Beliefs about how disinformation spreads (1 = Strongly disagree ... 5 = Strongly agree)

Table F5. Beliefs about how disinformation spreads: item means, standard deviations, and percentage agreeing.

Item	N	M	SD	% high
People encounter opposing opinions more often offline than online	96	3.20	1.12	45
Fact-checking reduces false beliefs on average	96	3.29	1.06	53
Problem comes mainly from demand (public actively seeks content)	96	2.94	1.15	39
Problem comes mainly from supply (massive dissemination)	96	3.86	1.00	76
Offline channels play a role as important as social networks	96	3.25	1.12	48
Recommendation algorithms strongly influence political opinions	96	4.11	0.84	85

Q15. Expected developments (next 3–5 years) (1 = Very unlikely ... 5 = Very likely)**Table F6.** Expected developments over the next 3–5 years: item means, standard deviations, and percentage rating “somewhat likely” or “very likely.”

Item	N	M	SD	% high
States’ capacity to deal with disinformation will increase	99	3.42	1.03	60
Increased capacity will be sufficient to contain disinformation	99	2.28	0.89	13
Foreign interference will increase, with greater sophistication	99	4.51	0.86	96
Proportion of false or manipulated content will increase	99	4.43	0.92	93
Public trust in media, science, and institutions will decrease	99	4.10	0.91	83

Q16. Obstacles to combating disinformation (1 = Not at all problematic ... 5 = Extremely problematic)**Table F7.** Obstacles to combating disinformation: item means, standard deviations, and percentage rating “very” or “extremely problematic.”

Item	N	M	SD	% high
Insufficient resources (budgets and staff)	93	3.74	0.88	65
Unclear roles and coordination, no lead actor	93	3.58	0.91	54
Legal framework protects false but lawful content	93	3.31	0.90	43
Administrative slowness	93	3.71	0.87	63
Political commitment limited, concrete resources insufficient	93	3.94	0.88	76
Lobbying by large digital companies	93	3.99	0.83	70
Scarce skills, difficult to retain specialists	93	3.65	0.95	52
Fear of being accused of censorship	93	3.68	0.91	63
Lack of operational tools and shared indicators	93	3.60	0.89	55
Public policies react after the fact	93	3.96	0.79	71

Q19. Information sources on disinformation (1 = Never; 2 = Rarely; 3 = Sometimes; 4 = Often; 5 = Very often)

Table F8. Information sources on disinformation: item means, standard deviations, and percentage answering “often” or “very often.”

Item	N	M	SD	% high
Books	94	2.97	1.17	31
Scientific articles (peer-reviewed)	94	2.98	1.32	41
Press articles	94	3.79	0.93	65
Gray literature or popularization	94	3.35	1.15	50
Posts on social networks	94	3.17	1.20	39

Q22. Engagement with scientific research (1 = Strongly disagree ... 5 = Strongly agree)**Table F9.** Engagement with scientific research: item means, standard deviations, and percentage agreeing.

Item	N	M	SD	% high
I keep up to date with recent academic research	91	2.90	1.18	36
I know the main points of scientific consensus	91	3.43	1.06	57
I trust peer-reviewed results to guide decisions	91	3.91	0.75	71
Academic results sufficiently concrete for my institution	91	3.38	0.85	48
My institution’s practices regularly rely on scientific evidence	91	3.54	0.87	48
My institution regularly collaborates with researchers	91	3.35	1.23	49

Q23. Obstacles to using scientific research (1 = Not an obstacle; 2 = Minor obstacle; 3 = Moderate obstacle; 4 = Major obstacle)**Table F10.** Obstacles to using scientific research: item means, standard deviations, and percentage rating “moderate” or “major obstacle.”

Item	N	M	SD	% high
Lack of time to read and digest articles	87	3.25	0.75	89
Language barrier (English, scientific jargon)	87	2.29	0.96	46
Limited access (paywalls, no reliable summaries)	87	2.93	0.93	66
Difficulties in methodological understanding	87	2.37	0.95	45
Applicability perceived as low	87	2.57	0.98	54
Lack of institutional incentives or resources	88	2.76	0.99	64

Note: For Q8, N is shown as “basis for mean/SD (n including ‘I don’t know’).” “% high” follows each block’s rule stated above.

Appendix G: Additional descriptive figures

This appendix collects descriptive figures whose results are reported in full in the main text: the relative importance of disinformation (Finding 1), its perceived impacts (Finding 1), beliefs about how it spreads (Finding 2), and the information sources practitioners use (Finding 4). The problems against which disinformation is compared here (Figure G1) are not mutually exclusive: disinformation can interact with them, exploiting issues such as climate change or feeding democratic decline.

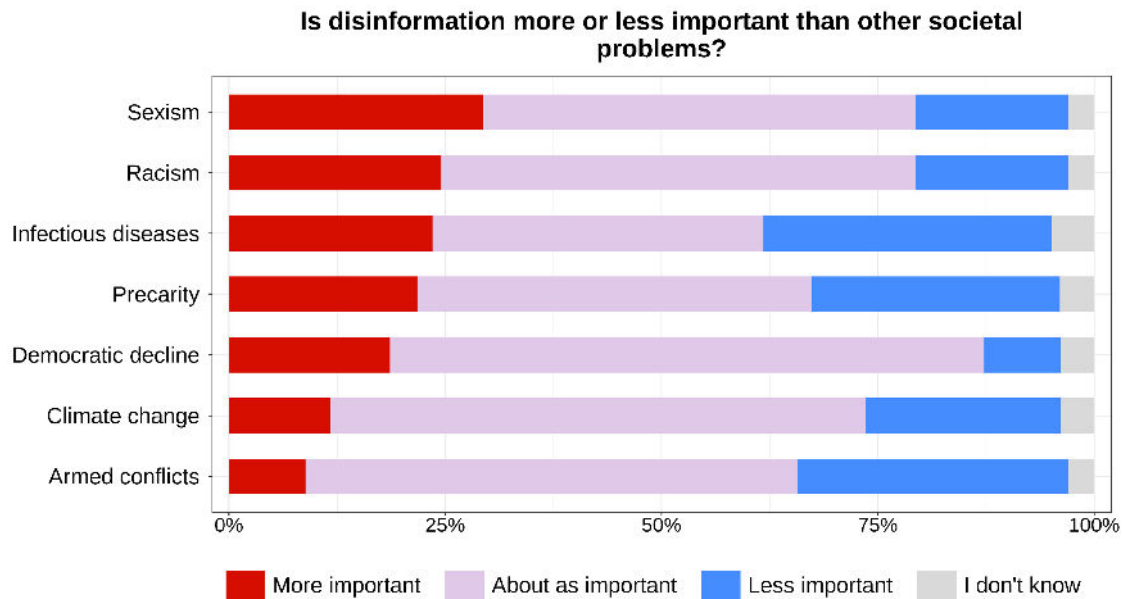


Figure G1. Relative importance of disinformation compared with other societal problems (% , N = 101–102).

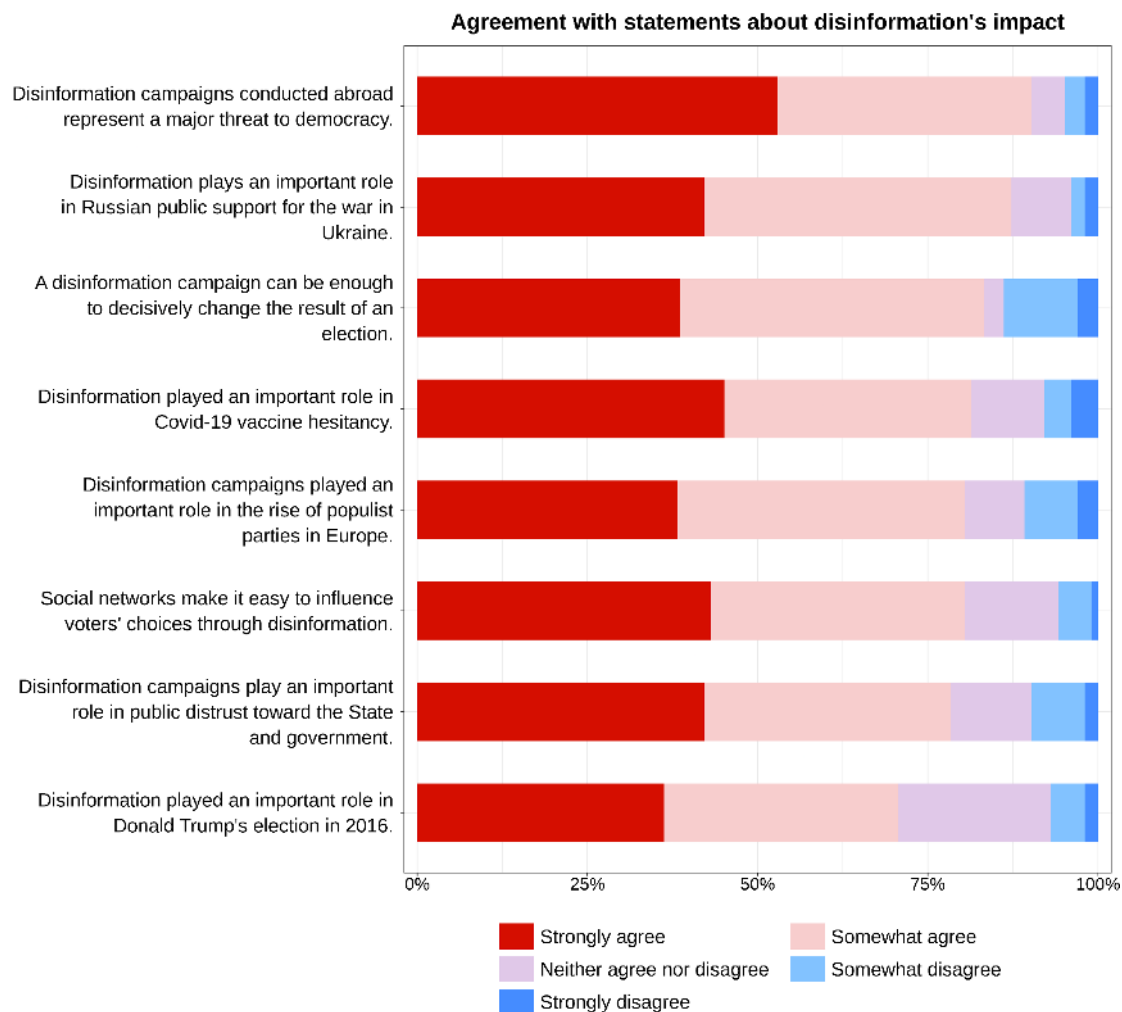


Figure G2. Perceived societal and political impacts of disinformation (% , N = 101–102).

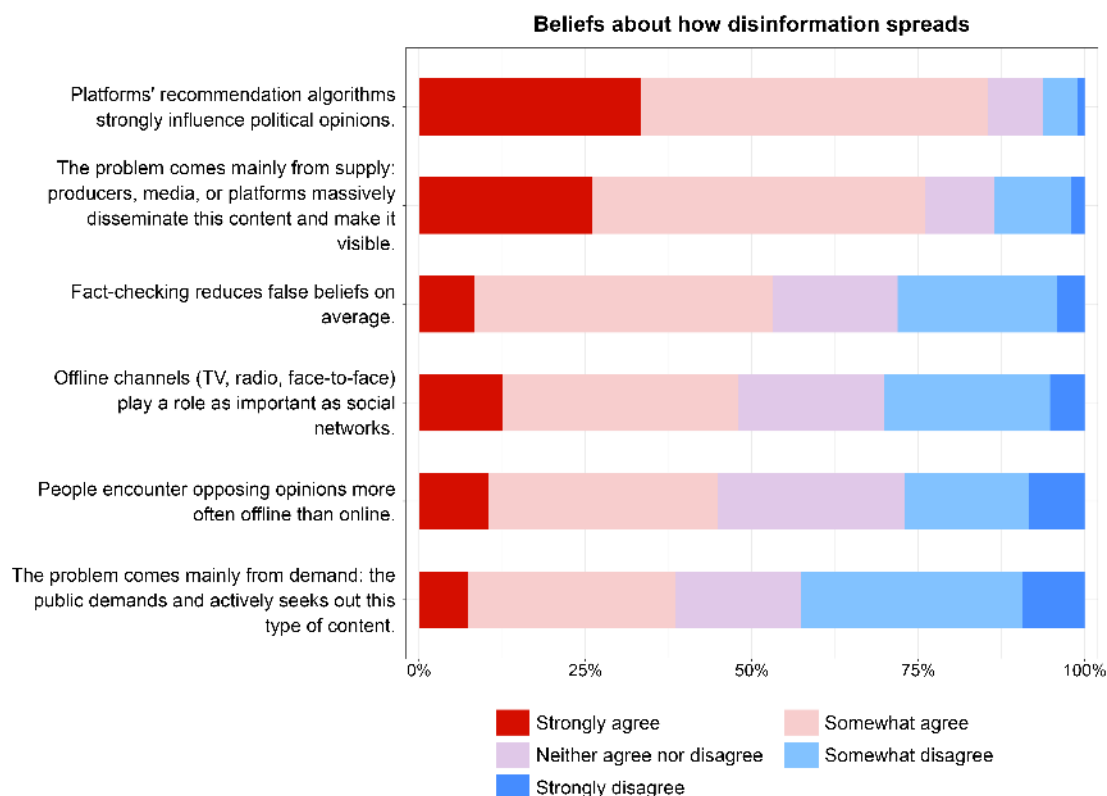


Figure G3. Beliefs about how disinformation spreads (% , N = 96).

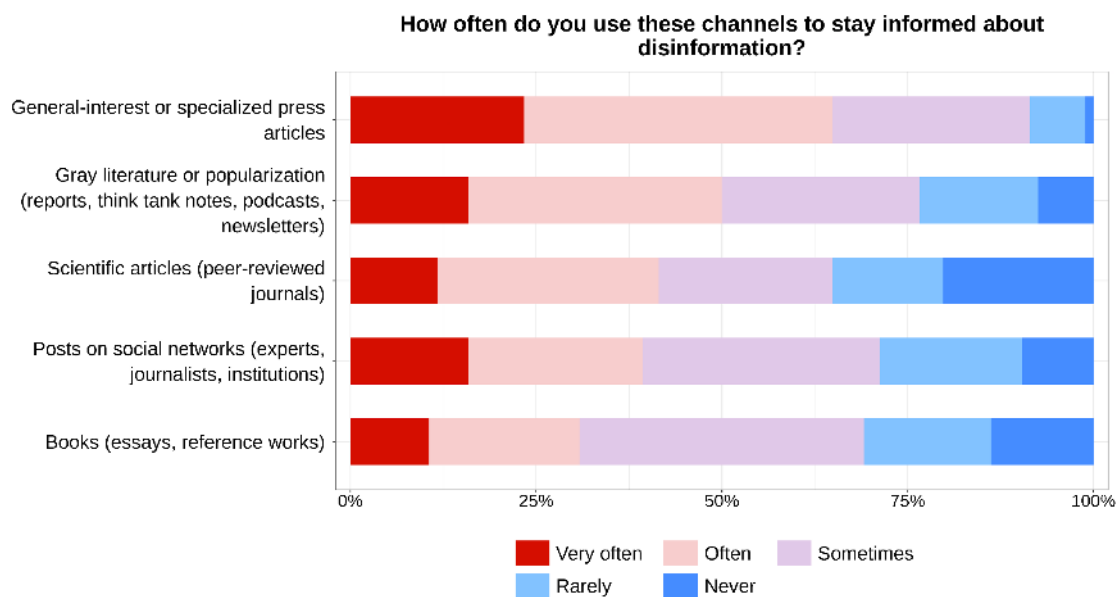


Figure G4. Information sources used to stay informed about disinformation (% , N = 94).

Appendix H: The French counter-disinformation context

Terminology in institutional usage. In French public documents, “*désinformation*” commonly functions as an umbrella term. While scholarship distinguishes disinformation (false, deliberately harmful), misinformation (false, shared in good faith), and malinformation (accurate, weaponized to harm) (Wardle & Derakhshan, 2017), institutional texts routinely use “disinformation” for the whole spectrum of information manipulation (e.g., Assemblée nationale, 2025), and the European Commission’s Code of Practice on Disinformation, though formally defining disinformation narrowly, in practice covers phenomena from foreign interference to political propaganda (Darcy, 2026a, pp. 7–10).

Legal instruments. French law has never created a general offense of disinformation; it proceeds through scattered provisions sanctioning specific harmful uses of falsehood (Darcy, 2026a, ch. 5). The 1881 press law (Article 27) penalizes false news published in bad faith and liable to disturb public peace; the electoral code targets false electoral news and bans commercial advertising for propaganda purposes. The 2018 law against the manipulation of information added a fast-track judicial procedure (Article L. 163-2 of the electoral code) against manifestly false or misleading information disseminated massively and deliberately during electoral periods; the Constitutional Council upheld the procedure while narrowing its scope, and to our knowledge the procedure has been used only once (2019, rejected). The May 2024 law on securing and regulating the digital space (SREN law) repealed several provisions of the 2018 law and aligned French law with the European Union (EU) Digital Services Act (DSA), shifting the center of gravity of platform regulation to the European level.

Institutional apparatus. The national strategy against information manipulation, adopted in February 2026 under the Secrétariat général de la défense et de la sécurité nationale (SGDSN), after the present survey’s fieldwork was completed, organizes French action around four pillars: societal resilience; regulation of platforms and generative artificial intelligence (AI) services; operational capacity against foreign digital interference; and allied action for a free, open, and secure information space (SGDSN, 2026). VIGINUM (Vigilance et protection contre les ingérences numériques étrangères), a service created in 2021 and attached to the SGDSN, is mandated not to counter disinformation in general but to detect and characterize foreign digital interference: campaigns involving a foreign actor and the artificial, massive, and deliberate dissemination of manifestly inaccurate or misleading content liable to harm the fundamental interests of the nation. A February 2026 decree extended its analytical scope to search engines and online interfaces and added public-information missions. Without coercive powers, it publishes reports on characterized campaigns (e.g., “Portal Kombat,” “Matriochka”). The Foreign Ministry created a monitoring and strategic-communication sub-directorate in 2022 and launched “French Response” in September 2025, an offensive debunking account on X that combines fact-restoration with rapid, platform-native ripostes. An active fact-checking and media-literacy sector completes the landscape.

Independent regulators. The Autorité de régulation de la communication audiovisuelle et numérique (ARCOM), the audiovisual and digital communication regulator, is the authority most directly concerned with disinformation: it supervises broadcasters, enforces platforms’ duty to cooperate against information manipulation under the 2018 law, and acts as France’s lead Digital Services Coordinator under the DSA. The Autorité de régulation des communications électroniques, des postes et de la distribution de la presse (ARCEP), the telecommunications regulator, shapes the infrastructure of the information environment: it enforces net neutrality, regulates the distribution of the press (a pluralism issue) and, since the 2024 SREN law, oversees cloud services and data-intermediation providers, with a doctrine

extending openness principles to devices, platforms, and generative AI. The Commission nationale de l'informatique et des libertés (CNIL), the data-protection authority, intervenes where disinformation meets personal data, notably political microtargeting and profiling. Executives of such independent authorities are part of the surveyed population (see Methods).

International dimension. France's response is embedded in EU platform governance (DSA, Code of Practice) and North Atlantic Treaty Organization (NATO) strategic-communication frameworks. VIGINUM cooperates most closely with its German and Swedish counterparts and the European External Action Service (EEAS) StratCom division, receives requests for advice from European and non-European states, and is developing a training academy on information-manipulation detection (Sénat, 2024; SGDSN, 2026). The framing that dominates French public administration (detecting and documenting attributable foreign operations rather than regulating disinformation in general) exemplifies the security-centered orientation discussed in the main text (Darcy, 2026a, pp. 103–104).

Information environment. According to the Reuters Institute's Digital News Report, trust in news is low (29%, against a 37% global average) and has not recovered, though France's relative position has risen as trust fell faster elsewhere (Antheaume, 2026). Interest in news is similarly low (36%), and about a third of the public (37%) avoids it. The market is strained: leading broadcasters and large publishers are cutting costs and freezing journalist recruitment as advertising falls, even as a subscriber-funded segment grows (Mediapart, Le Monde, Le Figaro). Some conservative media have become more overtly partisan than in the past (Antheaume, 2026). The March 2026 local elections were hit by a disinformation campaign using sites built to imitate local news outlets (Antheaume, 2026). Majorities believe owners (66%) and politicians (64%) shape coverage (Antheaume, 2026). Yet this low trust coexists with comparatively strong press freedom (France ranks 25th of 180 on the Reporters Without Borders index, score 76.68).

Institutional and political environment. Comparative research places institutional trust at the center of disinformation susceptibility (Ejaz et al., 2025; Humprecht et al., 2020), and in France trust runs low across institutions, politics, and everyday life. The political setting is unstable: five prime ministers have served in a single presidential term, and the far right and far left draw the youngest voters (Antheaume, 2026). Political trust keeps falling: in the 2026 Centre de recherches politiques de Sciences Po (CEVIPOF) barometer, trust in the President dropped to 18% (from 23% a year earlier), half of respondents (51%) see nothing to be proud of in the democratic system, more than in Italy (40%), Germany (34%), or the UK (32%), and the perception of politicians as corrupt is widespread (CEVIPOF, 2026). Perceived integrity has fallen in step: France's score on Transparency International's Corruption Perceptions Index dropped to 66 of 100 in 2025, its lowest under the current methodology, though France stays in the cleaner half of countries (Transparency International, 2026). The deficit is long-standing: for decades the French have trusted their fellow citizens, public authorities, and markets less than comparable democracies, a self-reinforcing "society of distrust" rooted in a statist, corporatist model (Algan & Cahuc, 2007). The French also underestimate how trustworthy others are and trust less than actual cooperation warrants (Darcy et al., 2026), and polarization in the National Assembly has risen sharply (Algan et al., 2025). Institutional, political, and interpersonal distrust thus converge on the very condition the literature places at the center of susceptibility, and that the practitioners surveyed weight comparatively lightly (Finding 2).

Appendix I: Research engagement and perceived applicability

This appendix tests whether practitioners who engage more with the academic literature find it less applicable to their operational contexts: if engagement bred disillusion, perceived applicability should be lower among respondents who consume research most. We correlated two consumption measures (keeping up with recent academic research, Q22; frequency of reading scientific articles, Q19) with five attitude and obstacle measures (trust in peer-reviewed results and perceived concreteness, Q22; perceived low applicability, methodological difficulty, and language barrier as obstacles, Q23), using Spearman correlations with Benjamini–Hochberg correction across the ten tests.

None of the associations is statistically significant (all absolute $p \leq .18$; smallest raw $p = .093$; all adjusted $p \geq .78$). Descriptively, frequent readers of scientific articles (categories 4–5, $n = 39$) and rare readers (categories 1–2, $n = 33$) are nearly indistinguishable: 46% versus 47% find academic results sufficiently concrete for their institution’s activity, and 58% versus 55% rate low applicability as a moderate or major obstacle; only trust trends higher among frequent readers (77% versus 63%, not significant).

Table 11. Spearman correlations between research consumption and trust, perceived applicability, and reported obstacles ($n = 87–91$), with raw and Benjamini–Hochberg-corrected p -values.

Consumption measure	Outcome	n	ρ	p (raw)	p (BH)
Frequency of reading scientific articles	Trust in peer-reviewed results	91	.18	.093	.784
Frequency of reading scientific articles	Methodological difficulty (obstacle)	87	–.12	.283	.784
Keeps up with recent academic research	Trust in peer-reviewed results	91	.11	.319	.784
Keeps up with recent academic research	Low perceived applicability (obstacle)	87	.09	.389	.784
Frequency of reading scientific articles	Results sufficiently concrete for institution	91	.08	.469	.784
Frequency of reading scientific articles	Language barrier (obstacle)	87	–.06	.570	.784
Keeps up with recent academic research	Language barrier (obstacle)	87	.05	.677	.784
Frequency of reading scientific articles	Low perceived applicability (obstacle)	87	.04	.700	.784
Keeps up with recent academic research	Results sufficiently concrete for institution	91	.04	.706	.784
Keeps up with recent academic research	Methodological difficulty (obstacle)	87	.01	.925	.925

These results are exploratory. At these sample sizes ($n = 87–91$), correlations below approximately $p = .30$ are not reliably detectable, and the design is cross-sectional: respondents who found research inapplicable may have stopped reading it, which would mask a negative association. Within these limits, the data show no sign that engagement breeds disillusion, nor that exposure alone improves perceived applicability. Analysis scripts and full results are provided with the replication materials.

Appendix J: An illustrative evidence infrastructure

The main text mentions, as one option in the French context, a standing observatory of the information environment. This appendix sketches such a body and weighs the case for and against it; the diagnosis it builds on is France's, and we cannot yet be sure it holds in other countries. Since our fieldwork, the United Kingdom has announced a National Centre for Information Defence, whose mandate, powers, and resources remain unspecified (Burnham, 2026). As announced, it would detect, attribute, and disrupt hostile-state campaigns, close to VIGINUM's remit; the measurement and translation functions sketched below could complement it. It is not a policy program: reviews of what works already exist in English (Altay, 2026; Kozyreva et al., 2024), alongside evidence-based guides and briefs that distill, for decision-makers, what science says about the policies to pursue (e.g., Bateman & Jackson, 2024; Lewandowsky et al., 2020), including recently in French (e.g., Darcy et al., 2025; DITP & VIGINUM, 2026). Those resources say what to do; the question here is how the response system itself could work better.

Two of this study's findings give the proposal its shape, speculative though it remains. Practitioners lack shared measures: 55% rate the absence of common indicators a serious obstacle, and institutions count what is easy to count (campaigns detected, content removed), so the habit of watching only the supply side keeps confirming itself. A second gap runs alongside the first: practitioners trust research without reading it, with 71% trusting peer-reviewed work, 36% keeping up with it, and 88% reading about disinformation in French while the evidence appears mainly in English. An observatory could supply what is missing on both counts: a unit to measure what current tools leave invisible, and a unit to translate existing research for those who act on it.

Its first task could be to get the institutions named here to agree on a handful of common indicators, and the precedents warn how hard that is. The European Monitoring Centre for Drugs and Drug Addiction (EMCDDA, now the European Union Drugs Agency, EUDA), the closest case of credible measurement in a politicized field, needed years to harmonize five indicators it could anchor partly in biological data; "exposure to disinformation" has no agreed definition.

Four kinds of work could fall to the measurement unit. It could begin with a recurring panel survey tracking what current tools miss: exposure, beliefs, trust, and how they shift over years. The Institut national de la statistique et des études économiques (INSEE) could field and hold it under statistical secrecy, releasing only anonymous aggregates, so that no state-linked body ever holds identified citizens' beliefs; the long series matters, since nearly all respondents expect the threat to worsen and only 13% expect the response to keep pace (Finding 5). It could add the supply-side measures current instruments miss: how many journalists cover local affairs in each territory, how news is financed, how trust in it evolves. It could also draw on the platform data that vetted researchers can now request under European Union (EU) regulation (Article 40 of the Digital Services Act, whose data-access mechanism became operational in 2025), using it to see how disinformation actually circulates: which accounts and networks amplify it, how fast, and to whom. That access could help, but it is granted project by project for a limited period, and platforms have restricted or withdrawn researcher access before, so a ten-year series cannot rest on it. Finally, it could test whether the interventions the field already funds actually work, running randomized or quasi-experimental trials of them (of a media-literacy campaign, say, or a fact-checking program) and standardized reviews after each major incident. One feature could cut across all four: demand-side measures (institutional trust, isolation) would appear in the same instrument, and on the same schedule, as the foreign-campaign counts. Because diagnoses tend to follow whatever the instruments measure, the instrument itself would have to correct the selective diagnosis of Finding 2.

The goal of the knowledge translation unit would be to bring existing research to the people who can act on it. The research they need largely exists; the trouble is that it reaches them in English, behind paywalls, in formats remote from the decisions they have to make. The evidence-use literature shows

both how to close that gap and why its effect sizes stay modest. Sending people research does little on its own: a large randomized trial, which sent evidence-based materials to hundreds of schools, changed neither teachers' use of research nor pupil outcomes (Lord et al., 2017); access helps mainly when it is paired with motivation and opportunity to use it (Langer et al., 2016). Both are present here: practitioners already trust research (71%) and seek operational answers, and the obstacles they report are practical ones of time, access, and incentive. A portal alone would go unused.

Instead, the unit could deliver four kinds of product. It could write, first, plain-language French syntheses, open access, summarizing what research says on the questions practitioners face repeatedly (does fact-checking work, how much exposure is there, do literacy programs transfer); none yet exists systematically in French, the language 88% of respondents read. It could tailor, second, role-specific products (a legal memo for the regulator, a threat note for the officer, a classroom resource for the educator), on a known schedule, with a channel carrying practitioners' questions back to researchers. It could assign, third, knowledge brokers selectively: a large randomized trial of knowledge brokering found brokers helpful only where research culture was weak (Dobbins et al., 2009), which in our sample points to the communication/counter-influence and public-protection roles that find research least applicable (Appendix D.3). And it could give, fourth, regular indicator feedback, which yields small gains (a median of 2.7 percentage points in the latest Cochrane review) that grow larger when the feedback compares performance to peers and comes with a concrete action plan (Ivers et al., 2026).

The same unit could also study translation itself. Research-policy initiatives almost never check whether they work (6% of some 2,300 in one census; Oliver et al., 2022); a unit that tracked its own uptake from the start could correct course early and produce some of the first systematic evidence on how translation works in this field.

The precedents show what could threaten such a body: in these institutions, survival is dictated mainly by funding. The endowed Education Endowment Foundation has run trials for over a decade, while the What Works Centre for Wellbeing closed in 2024 once its grants lapsed and no ministry owned its subject. The Stanford Internet Observatory's election work, which tracked false and misleading claims about the 2020 and 2022 elections, drew lawsuits, subpoenas, and congressional investigations that cost millions of dollars in legal fees; by mid-2024 its leadership had left and the election project had ended (Bond, 2024). Europe's media observatories, for their part, depend on renewable EU grants, which makes a long time-series hard to sustain. We can draw on these precedents to set three rules. Fund the body once (through an endowment or a multi-year statutory commitment) rather than renegotiate annually; give it public-law status, so that the state itself bears the legal defense; and say plainly what it will never do: no content flagging, no truth adjudication, no election-time operations, no data sharing with security services. That last rule speaks to a finding of this study: practitioners are inhibited less by the ethical dilemmas they actually face, which 21% encounter often, than by the censorship accusations they anticipate, which 63% rate a serious obstacle. A statute that made the accusation false could lower the cost of defending legitimate action and make unethical action both less likely and harder to carry out.

One of the main objections would be that the body merely duplicates what France already has: a detection service, a regulator that runs surveys, a European hub, and a statistical institute. Yet none is placed to pull these strands together. VIGINUM (Vigilance et protection contre les ingérences numériques étrangères) is intelligence-adjacent, so a panel of citizens' beliefs in its hands would not be trusted; the Autorité de régulation de la communication audiovisuelle et numérique (ARCOM) cannot credibly evaluate the policies it enforces; the European hub has no stable funding; INSEE commands the public's trust and the survey craft but holds no mandate over the information environment and performs no translation. More fundamentally, this very dispersion is the problem the body could address: each ministry treats "its own" disinformation (the Health Ministry vaccine falsehoods, the Interior Ministry electoral interference, Foreign Affairs and VIGINUM foreign campaigns, ARCOM platform compliance)

with its own instruments and definitions, so no one holds the shared picture and no institution leads (Darcy, 2026b). Respondents confirm it: 54% rate unclear responsibilities a serious obstacle.

One of the main vulnerabilities would be political, and it follows directly from that dispersion. The dominant story places the threat abroad. That story is convenient, because acting on causes at home, such as falling trust in institutions and a weakened local press, would implicate domestic choices (Darcy, 2026b); a government that gains from blaming outsiders has little incentive to fund the instrument that could correct it. Because that incentive is missing, the body could not arrive by decree; it could only be built in stages: first federate what already exists (a stable funding line for the existing hub, a recurring statistical-institute module, a small council commissioning evaluations), with the common indicators as the test, and institutionalize only if that work converges.

Two design risks would remain even then. Indicators that become targets get gamed (Bevan & Hood, 2006; Campbell, 1979), so the suite would have to rotate and carry its uncertainty openly; and because published measures of belief can be turned against the groups they describe, results should never be ranked by population group. Other questions stay open too: the body's resilience to political alternation, its independence, and the protection of the data it would hold. None of this makes the observatory a sure solution. It is one way, among others, of acting on what this study documents: a field asked to fight a phenomenon it cannot measure, with evidence it cannot read.