

Knowledge, Attitudes, and Use of Artificial Intelligence Among Adult and Pediatric Hematologists in Türkiye: A National Cross-Sectional Survey

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Abstract

Background. Artificial intelligence (AI), including generative AI and large language models, is entering hematology practice and research, but real-world integration depends on clinicians' knowledge, attitudes, use, and governance rather than algorithm performance alone. Evidence specific to hematologists is scarce, and no national study in Türkiye has jointly assessed knowledge, clinical and research use, trust and governance, attitudes toward patients' AI use, and educational needs.

Methods. We conducted a national, cross-sectional, self-administered online survey (Google Forms), reported per the CHERRIES guideline. Practicing adult and pediatric hematologists were invited through the verified member e-mail list of the Turkish Society of Hematology (a closed survey) and surveyed from 15–30 May 2026 after ethics approval. The instrument covered seven domains (participant profile; awareness/knowledge; clinical use; research/writing use; trust–risk–ethics–governance; attitudes to patients' chatbot use; education and professional future). Categorical data are summarized as n(%) and ordinal items as median (IQR); groups were compared with non-parametric tests (effect sizes; Benjamini–Hochberg correction for exploratory analyses), with multivariable logistic and ordinal regression. Analyses used R.

Results. Of 639 invited members, 146 completed the survey (response rate 22.8%); 65.8% practiced adult hematology. Clinical AI use in the prior three months was reported by 87%, yet only 14% had received structured AI training. Generative AI for research/writing was used by 55.5%, of whom 81% had encountered fabricated references or incorrect information. Nearly half (48.6%) had entered patient data into non-approved public chatbots (8.2% identifiable), whereas only 4.8% reported a written institutional AI policy. Responsible-use norms were strong (90% endorsed verification; 73% endorsed declaring AI use), and few felt professionally threatened (8.2%). Educational need was high and internally consistent (Cronbach's $\alpha = 0.92$). Higher digital literacy was independently associated with AI use (adjusted OR 1.87 per point). Attitudes did not differ between adult and pediatric hematologists.

Conclusions. Hematologists have rapidly adopted AI while maintaining cautious, verification-oriented attitudes, but adoption is outpacing training and institutional governance. Hematology-specific policies, literacy-targeted training (especially safe generative-AI use), and supervised, institution-approved tools are needed for responsible integration.

INTRODUCTION

Artificial intelligence (AI), and especially generative AI built on large language models (LLMs), has moved rapidly from a research concept into routine clinical and academic workflows, spanning decision support, documentation, literature synthesis, and free-text generation [1, 2]. The same fluency that makes these tools useful also introduces distinct risks — plausible but fabricated content, unreliable output, and unclear accountability when such output informs clinical or scholarly decisions [3]. Because these tools are now directly accessible to individual physicians, their safe integration depends less on algorithmic performance alone than on how clinicians actually use and govern them.

Hematology is a particularly fertile and exposed setting. It is data-rich — generating high-dimensional information from blood and bone-marrow morphology, flow cytometry, cytogenetics, and next-generation sequencing — and AI has been proposed to augment morphologic classification, flow-cytometry and genomic interpretation, and prognostic modeling [4]. Yet uptake is mediated less by raw accuracy than by clinicians' knowledge and trust and by the availability of governance and training, with opacity, bias, and uncertain responsibility acting as barriers [5]. Generative AI widens these concerns from the clinic into research, scholarly writing, and the patient encounter, enlarging the range of considerations a practicing hematologist must manage.

Survey research has begun to map physicians' AI acceptance, readiness, and knowledge across health systems [6], but evidence specific to hematologists remains scarce [7], and documented gaps between physicians' interest in AI and their formal preparation — including in Türkiye — point to an unmet educational and governance agenda [8]. No national study has examined hematologists' knowledge, clinical and research use, trust and governance, patient-facing attitudes, and educational needs together. We therefore conducted a national cross-sectional survey of adult and pediatric hematologists in Türkiye — the founding project of the Artificial Intelligence Scientific Subcommittee (YZ-BAK) of the Turkish Society of Hematology — to provide the first national baseline on hematologists' AI knowledge, attitudes, and use, and to define what the responsible integration of this disruptive technology will require in training, governance, and tooling.

METHODS

Study design and reporting

This was a cross-sectional, self-administered web-based survey of practicing adult and pediatric hematologists in Türkiye. The study was designed and conducted by the Artificial Intelligence Scientific Subcommittee (Yapay Zekâ Bilimsel Alt Komitesi, YZ-BAK) of the Turkish Society of Hematology (Türk Hematoloji Derneği, THD) and constitutes the first project of the subcommittee. The survey was implemented on Google Forms (Google LLC, Mountain View, CA, USA). Because eligibility was restricted to identifiable, individually invited members of a defined sampling frame and the questionnaire was never publicly posted, the survey was a closed (members-only) survey rather than an open survey.

The study is reported in accordance with the Checklist for Reporting Results of Internet E-Surveys (CHERRIES) [9], and view, participation, and completion rates are described using American Association for Public Opinion Research (AAPOR) conventions where the relevant denominators are available. The full survey instrument (Additional file 1), the completed CHERRIES (Additional file 2) and STROBE (Additional file 3) checklists, and the statistical analysis plan (Additional file 4) are provided as additional files. The methodology follows the general approach used in comparable physician-facing surveys of artificial intelligence (AI) knowledge, attitudes, and use [8, 10].

Ethical approval and consent

The study protocol was approved by the Non-Interventional Clinical Research Ethics Committee of İstanbul Medipol University (approval number E-10840098-50.04-3372, dated 14 May 2026). The study was conducted in accordance with the principles of the Declaration of Helsinki. Participation was entirely voluntary, and participants could stop and exit the survey at any time without penalty.

The first item of the questionnaire served as a combined informed-consent and eligibility gate. Respondents were presented with a brief description of the study purpose, sponsor, expected completion time (approximately 10 minutes), the voluntary and anonymous nature of participation, a brief data-protection notice (referring to Türkiye's Personal Data Protection Law [KVKK], broadly analogous to the EU General Data Protection Regulation [GDPR]), and the instruction not to share any patient-, institution-, or person-identifying information in free-text fields. Informed consent was obtained electronically: respondents could proceed only by selecting the statement affirming that they were an adult or pediatric hematologist, had read the information provided, and voluntarily agreed to participate. Respondents who indicated that they were not hematologists or who declined to participate were excluded from all analyses. No personal identifiers were collected at any point, and responses were anonymous. Free-text fields included an explicit instruction to avoid identifying information.

Setting, population and recruitment

The target population comprised physicians actively involved in health care delivery as adult or pediatric hematologists in Türkiye. The sampling frame was the membership database of the Turkish Society of Hematology, which is the largest national registry of hematologists in the country. Recruitment was conducted exclusively through the verified e-mail addresses of THD-registered members. The invitation contained a direct link to the survey.

The survey was not publicly posted on any website or social-media channel, and no secondary distribution channel (e.g., open links, snowball forwarding, or public advertisement) was used; the study was therefore a closed survey directed only at the members of the defined frame. Invitations were delivered by individual e-mail to the adult and pediatric hematologists on the THD verified-member mailing list. Because the questionnaire was distributed only by individual e-mail, finer-grained CHERRIES denominators (unique site visitors and view rate) were not available from the platform; the number of members invited and the number who completed the survey are reported in the Results.

Sampling was by complete enumeration of the eligible membership frame (a census-style invitation rather than probability sampling of a larger population). No advertisement of the survey beyond the membership invitation was used.

Survey instrument and development

The questionnaire was developed by the YZ-BAK subcommittee to assess hematologists' AI knowledge, attitudes, and use. It was administered in Turkish. The instrument was organized into seven thematic

domains preceded by the consent/eligibility item:

- Domain A – Participant profile (A1–A6)
- Domain B – AI awareness and basic knowledge (B1–B4)
- Domain C – Clinical AI use (C0–C7)
- Domain D – Research and manuscript-writing generative-AI use (D1–D6)
- Domain E – Trust, risk, ethics and governance (E1–E5)
- Domain F – Attitudes to patients’ chatbot use (F1–F5)
- Domain G – Education needs and professional future (G1–G7)

The individual items within each domain are not described narratively here; the complete questionnaire, including the full wording of every item, all response options, and endpoint labels, is provided verbatim in both English and Turkish as Additional file 1.

In total the instrument comprised 41 answered items (one consent item plus 40 content items) together with one five-row matrix grid (item G1), corresponding to 45 response variables. Item formats were single-choice (radio), multiple-response (checkbox), 5-point Likert-type linear scales with the two endpoints labeled (e.g., 1 = strongly disagree ... 5 = strongly agree; 1 = very low ... 5 = very high), and two open-ended (free-text) items (G6 and G7). For the Likert-type items only the two endpoints were labeled; the midpoint was not labeled.

Conditional (branching) logic was implemented through textual skip instructions rather than automated branching: items C2–C4 were intended only for respondents reporting clinical AI use (C1 = yes), and items D2–D4 only for respondents reporting research/writing AI use (D1 = yes). Respondents answering “no” to C1 or D1 were instructed to skip the corresponding follow-up items.

The instrument was developed by the YZ-BAK subcommittee and was not formally pilot-tested, cognitively interviewed, or psychometrically validated before fielding; this is acknowledged as a limitation.

Survey administration and technical implementation

The survey was administered online via Google Forms. The estimated completion time was approximately 10 minutes. The survey was fielded from 15 May 2026 to 30 May 2026, following ethics approval on 14 May 2026.

Technical implementation followed the deployed Google Forms configuration. All items were mandatory (required) except those governed by the conditional logic described above; completeness was therefore enforced and item-missingness for mandatory items was minimal. Items and response options were presented in a fixed order (no randomization). Multiple submissions were prevented by enabling the “limit to one response” setting, which required Google account sign-in and thereby restricted each

respondent to a single submission; respondents' e-mail addresses and identities were not collected or stored, preserving anonymity. The questionnaire was presented across seven sequential sections (one domain per screen) with a section progress indicator, and respondents could navigate back to review and change their answers before final submission. No incentive was offered for participation, and a single invitation e-mail was sent with no reminders.

Data management and pre-specified handling decisions

Responses were exported from Google Forms to a spreadsheet and processed according to the codebook accompanying the instrument. The consent/eligibility filter was applied first: records indicating a non-hematologist or a refusal to participate were removed before any analysis. No personal identifiers were exported, and free-text responses were screened to ensure that no identifying content was retained.

The following analytic-handling decisions were pre-specified by the study team to reconcile minor formatting issues in the live instrument with the intended measurement model. These decisions are stated here and are reflected throughout the analysis:

- Item C6 (perceived risk of misdirection) is analyzed on the full sample. Although the item text references the C1 = yes condition, the item was configured as mandatory and was therefore completed by all respondents, including clinical non-users; it is consequently reported as a general AI risk-perception item across the entire sample.
- Conditional-item denominators are reported per subgroup: items C2–C4 are summarized only among clinical AI users (C1 = yes), and items D2–D4 only among research/writing AI users (D1 = yes). The applicable denominator is stated for every such estimate. Items legitimately skipped under the conditional logic are not treated as missing data.
- Multiple-response items (C3, D2, G2) are coded as binary indicator sets, with each option summarized as the percentage of responders within the appropriate denominator; item G2 is capped at two selections.
- “Other” response options carry no associated free-text field in the instrument and are reported as a single labeled category; a high frequency of “Other” responses is noted as a limitation where relevant.

Missing data are expected to be minimal because most items were mandatory; the analytic strategy is complete-case per item, with the analyzed denominator reported for each estimate, consistent with the Statistical Analysis Plan.

Statistical analysis

A detailed, pre-specified Statistical Analysis Plan was finalized before database lock; the analysis is summarized here. Categorical variables are summarized as counts and percentages, and ordinal/Likert-type variables as the median and interquartile range (IQR), with the mean and standard deviation reported secondarily and the full 1–5 distribution displayed as diverging stacked bar charts. Multiple-response items are summarized as ranked frequency tables within the correct denominator. Open-ended responses (G6, G7) were categorized into themes with the generative-AI (Gemini) feature integrated in Google Forms; the AI-generated categorization was reviewed and verified by the three authors by consensus, and an independent, reproducible keyword-based frequency analysis was performed as a cross-check. Theme frequencies are reported descriptively (a single response could contribute to more than one theme) and triangulated with the quantitative findings; given the AI-assisted categorization, themes are interpreted with caution.

Likert-type items are treated as ordinal throughout. Group comparisons use the Pearson χ^2 test (or Fisher's exact test when any expected cell count is below 5) for categorical-by-categorical comparisons, the Mann–Whitney U test for ordinal outcomes across two groups, and the Kruskal–Wallis test (with Dunn post-hoc tests and Holm adjustment) for ordinal outcomes across three or more groups. Associations between ordinal variables are assessed with the Spearman rank correlation, and ordered trends across ordinal groups with the Jonckheere–Terpstra test (or the Cochran–Armitage test for binary outcomes). Pre-specified primary subgroup contrasts (subspecialty, A1; and clinical AI user vs. non-user, C1) on key outcomes are treated as confirmatory; the remaining subgroup analyses are exploratory, with the false discovery rate controlled using the Benjamini–Hochberg procedure and confirmatory versus exploratory results clearly labeled.

A-priori conceptual subscales (perceived benefit; perceived risk/barrier; responsible-use/governance attitude; educational need; professional-future perception) are confirmed before use by examining internal consistency with Cronbach's α , with reverse-coding of opposing-valence items; items are reported individually if the subscale structure is not supported.

Pre-specified multivariable models estimate independent correlates of key outcomes: binary logistic regression for clinical AI use (C1), for research/manuscript-writing AI use (D1), and for any entry of patient data into non-approved public chatbots (C7, any entry vs. never), and proportional-odds ordinal logistic regression for a key attitudinal outcome (with the proportional-odds assumption examined and a linear-regression sensitivity model). Each model uses a parsimonious, pre-specified predictor set (subspecialty, years of experience, self-rated digital literacy, prior structured AI training, and institution type or institutional AI policy). To respect the achieved sample size, models were limited to approximately one predictor per ten outcome events; the clinical-use model was underpowered and is reported as exploratory. Adjusted odds ratios with 95% confidence intervals and multicollinearity (variance inflation factors) are reported.

Two-sided p values below 0.05 are considered statistically significant. No data are imputed, and all analyses are conducted on the achieved sample as collected. Analyses were performed in R (version

4.5.3), with figures using colorblind-safe, grayscale-readable palettes. The main text presents participant characteristics (**Table 1**), the multivariable models (**Table 2**), and four figures; complete item-level frequencies and summaries for every domain are provided in Additional file 5 (**Tables S1–S6**).

RESULTS

Participants

Of 639 invited adult and pediatric hematologists, 146 completed the survey (response rate 22.8%). Respondents represented both subspecialties (65.8% adult, 34.2% pediatric) and all career stages, with specialists and faculty predominating; full characteristics are given in **Table 1**. Self-rated clinical workload was high (median 4, IQR 4–5) and digital literacy moderate (median 3, IQR 3–4).

Table 1. Participant characteristics (N = 146)

Characteristic	Value
<i>Subspecialty</i>	
Adult hematology	96 (65.8)
Pediatric hematology	50 (34.2)
<i>Professional position</i>	
Fellowship trainee	17 (11.6)
Specialist	64 (43.8)
Faculty member	61 (41.8)
Other	4 (2.7)
<i>Institution type</i>	
Public university hospital	50 (34.2)
Training & research / city hospital	59 (40.4)
Foundation/private university hospital	20 (13.7)
State hospital (non-academic)	7 (4.8)
Private hospital / private practice	8 (5.5)
Other	2 (1.4)
<i>Years since specialization</i>	
0–3	35 (24.0)
3–5	31 (21.2)
5–10	29 (19.9)
>10	51 (34.9)
<i>Self-rating, median (IQR)</i>	
Clinical workload (1–5)	4 (4–5)
Digital literacy (1–5)	3 (3–4)

Categorical variables: n (%); self-ratings: median (IQR) on a 1–5 scale.

AI awareness and knowledge

Only 21 respondents (14.4%) had received any structured AI training. Familiarity with core concepts (AI/ML/DL/LLM) was modest (median 3, IQR 2–3; mean 2.62) and awareness of where AI could be

applied in hematology was moderate (median 3, IQR 2–4). The main sources of regular information were the workplace/colleagues (34.2%) and social media/podcasts (32.9%), with scientific articles or guidelines cited by only 17.1% (Additional file 5: **Table S1**).

Clinical use of AI

Non-work AI use in the previous three months was near-universal (91.8%), and 127 (87.0%) reported clinical/academic AI use. Among users, 40.9% used AI daily and 44.1% several times weekly ($\approx 85\%$ at least weekly). The most common purposes were literature summary/interpretation (81.1%), differential-diagnosis/decision support (60.6%), and drug-information/interaction checking (60.6%); hematology-specific image/morphology interpretation was least common (14.2%) (**Fig. 1**; Additional file 5: **Table S2**). Trust in clinical AI output was moderate (median 3, IQR 3–4). Respondents agreed that AI speeds clinical work (C5 median 4; 63.7% agreeing) while also acknowledging a risk of misdirection (C6 median 4; 55.5% agreeing). Regarding data handling, 51.4% never entered patient data into non-approved public chatbots, 40.4% did so only in anonymized form, and 8.2% sometimes entered identifiable personal or institutional information — i.e., 48.6% entered patient data of some kind (**Fig. 2**; Additional file 5: **Table S2**).

Generative AI in research and writing

Eighty-one respondents (55.5%) had used generative AI for research or manuscript writing. Among users, the commonest stages were language/style editing (75.3%), literature summarizing (66.7%), drafting/editing manuscript text (56.8%), and academic communication such as reviewer responses (50.6%); statistical/code assistance was used by 43.2% (Additional file 5: **Table S3**). A large majority of research users (81.2%) reported encountering fabricated references or incorrect information (“hallucinations”). Trust in AI output for research was moderate (D3 median 3), most endorsed declaring AI use (D5 median 5; 73.3% agreeing), and a majority perceived an added risk to scientific integrity (D6 median 4; 56.2% agreeing).

Trust, ethics, and governance

Responsible-use norms were strong: 89.7% agreed AI output must be independently verified before use (E1 median 5). Privacy and data-protection (KVKK) concern reduced use for a minority (E2 median 3; 38.4% agreeing), while medico-legal uncertainty was a barrier for most (E3 median 4; 65.1% agreeing). A written institutional AI policy was reported by only 4.8%, while 64.4% reported none and 30.8% were unaware (**Fig. 2**; Additional file 5: **Table S4**). For the preferred governance framework, the most common choice was physician discretion within institutional principles (39.0%), followed by fully free use (32.2%), with fewer endorsing only institutionally approved tools or restriction to non-clinical use (Additional file 5: **Table S4**).

Attitudes toward patients' use of AI

Patient-initiated chatbot queries were frequent: 41.1% encountered them 1–2 times weekly and 19.9% more often, while only 11.0% never did. Physicians were mostly neutral (54.1%) toward patient chatbot use, with more discouraging (22.6%) than encouraging (17.1%) it. Respondents were divided on benefit (F3 median 3; 33.6% agreeing it improves literacy/adherence) but largely concerned about harm (F4 median 4; 67.8% agreeing it raises anxiety/misdirection). Overall, 93.2% were open to an official, supervised patient-facing AI tool integrated into their clinic (49.3% as workload relief; 43.8% only under strict physician supervision) (Additional file 5: **Table S5**).

Educational needs and professional future

Educational need was uniformly high across all five topics (means 3.75–4.14 on a 1–5 scale; internal consistency $\alpha = 0.92$), greatest for academic AI use (G1e mean 4.14) and safe generative-AI use (G1d mean 3.99) (**Fig. 3**; Additional file 5: **Table S6**). Preferred training formats were evenly distributed across all options, with no single format dominating (Additional file 5: **Table S6**). Respondents were split on whether AI will meaningfully change the hematologist's role (G3 median 3; 47.9% agreeing), but few felt professionally threatened (G4 median 2; only 8.2% agreeing). Perceived institutional IT/EHR readiness for AI integration was low (17.8% yes, 45.2% no, 37.0% unsure).

Subgroup and multivariable analyses

Adult and pediatric hematologists did not differ significantly on any primary outcome (all $p > 0.05$), indicating consistent attitudes across subspecialties. Compared with users, non-users of clinical AI were more strongly deterred by privacy/KVKK concern (median 4 vs 3; $p = 0.013$, $r = 0.34$) and less convinced that AI will change the hematologist's role ($p = 0.016$). In multivariable models (**Table 2**), research/writing AI use was independently associated with higher digital literacy (adjusted OR 1.87 per point, 95% CI 1.21–2.89; $p = 0.005$) and inversely with >10 years' experience (OR 0.43, 0.20–0.90; $p = 0.025$). Endorsement of mandatory AI-use declaration increased with >10 years' experience (proportional-odds OR 4.20, 1.99–8.89; $p < 0.001$). Entering any patient data into public chatbots was not significantly associated with the modeled covariates (prior training borderline: OR 2.57, 0.90–7.32; $p = 0.078$). In an exploratory, underpowered model, clinical AI use rose with digital literacy (OR 5.26, 2.40–11.50; $p < 0.001$). All variance-inflation factors were <1.2. The a-priori risk-perception scale showed poor internal consistency ($\alpha = 0.49$) and its items are therefore reported individually.

Table 2. Multivariable models (adjusted)

Model / predictor	OR (95% CI)	p
<i>M2. Research/writing AI use (D1)</i>		
Adult subspecialty	0.68 (0.32–1.43)	0.305
Experience >10 y	0.43 (0.20–0.90)	0.025
Digital literacy (per point)	1.87 (1.21–2.89)	0.005
Prior AI training	1.78 (0.59–5.38)	0.307
Institutional AI policy	0.57 (0.10–3.19)	0.525
<i>M3. Any patient-data entry to public chatbots (C7)</i>		
Adult subspecialty	0.66 (0.32–1.35)	0.251
Experience >10 y	0.58 (0.28–1.18)	0.132
Digital literacy (per point)	1.15 (0.77–1.69)	0.497
Prior AI training	2.57 (0.90–7.32)	0.078
Institutional AI policy	1.58 (0.31–8.09)	0.582
<i>M4. AI use should be declared (D5; ordinal)</i>		
Adult subspecialty	1.33 (0.67–2.64)	0.419
Experience >10 y	4.20 (1.99–8.89)	<0.001
Digital literacy (per point)	1.23 (0.84–1.79)	0.293
Prior AI training	1.45 (0.54–3.88)	0.458
Institutional AI policy	1.03 (0.22–4.84)	0.966

Adjusted odds ratios (binary logistic for M2/M3; proportional-odds ordinal logistic for M4); each model adjusted for all listed covariates. M1 (clinical AI use) underpowered (19 non-users) and not tabled (see statistical analysis plan). All VIF < 1.2.

Open-ended responses (greatest opportunity and risk)

AI-assisted thematic categorization of the free-text items (n = 144 each), cross-checked by a reproducible keyword-based analysis, mirrored the closed-ended findings. The greatest opportunity was framed as efficiency and reduced workload (44%) and faster information/literature access (26%), followed by diagnostic support (12%) and research/writing support (12%). The greatest risk was dominated by misinformation/“hallucination” (51%), followed by misdiagnosis/wrong clinical decisions (11%) and patient-side misdirection or anxiety (10%); concerns about privacy (6%) and medico-legal liability (4%) were less frequent, and fear of job loss was essentially absent (1%). Hematologists thus

consistently characterized AI as an efficiency tool requiring supervision rather than an autonomous decision-maker.

The **Figure 4** summarizes the distribution of agreement-anchored attitudes.

DISCUSSION

In this national survey of 146 adult and pediatric hematologists in Türkiye — the first project of the Turkish Society of Hematology's AI Scientific Subcommittee — three patterns stand out. First, clinical AI use is already widespread (87%) but rests on a thin knowledge base: only 14% had received structured AI training and self-rated familiarity with core concepts was modest. Second, adoption coexists with strong responsible-use norms: 90% endorsed independent verification of AI output and 73% endorsed declaring AI use, while professional-threat perception was low. Third, and most actionable, a governance vacuum surrounds this activity — nearly half had entered patient data into non-approved public chatbots (8.2% identifiable), 81% of research users had encountered fabricated references, yet only 4.8% reported an institutional AI policy. Stated norms thus diverged sharply from reported behavior: near-universal endorsement of verification coexisted with the high rates of public-chatbot data entry and hallucination exposure noted above — a norm–practice gap that frames the interpretation below. Attitudes were remarkably consistent across adult and pediatric subspecialties.

Our 87% clinical and 92% overall three-month use rates exceed those of most earlier physician samples — the ~20% perceived utility and ~38% awareness in an early multinational survey [6], the modest use in national knowledge–attitude–practice surveys of mixed-specialty physicians [11–13], and the ~50% any-use with 27% clinical use reported among pediatric hospital providers in 2024 [14]. The direction of our findings nonetheless aligns with this literature and with systematic syntheses of ChatGPT in health care [15]: enthusiasm tempered by limited formal knowledge and concern about accuracy [6, 13, 16]. Two factors plausibly explain the higher magnitude — the mainstreaming of generative AI since those earlier studies and a self-selected, AI-interested respondent pool — so these rates are best read as an upper bound for engaged hematologists rather than the average clinician.

Generative AI is used most for literature and writing tasks mirrors a survey of genetic counselors, in which ChatGPT use (33.8%) clustered in writing and 82.2% flagged incorrect information as the dominant concern [17]; clinicians in a separate utility survey were likewise most comfortable with assistive, supervised roles and wary of fabricated content and bias [16]. Our data move this from a stated concern to a measured exposure: 81% of research users had already encountered fabricated references or incorrect information, operationalizing the integrity risks discussed for AI-assisted scholarship [18] and reinforcing our respondents' strong endorsement of disclosure.

Syntheses of medical-AI ethics and adoption barriers identify trust, accountability and clear governance — not raw performance — as the rate-limiting factors for clinical AI [2, 3, 5, 19, 20], and health-system surveys show institutional adoption still outpaced by implementation and oversight structures [21]. Our findings give this abstract gap a concrete, clinician-level magnitude: 48.6% had entered patient data into

non-approved public chatbots (8.2% in identifiable form) while only 4.8% reported any written institutional policy — a quantified norm–practice gap within a single specialty that, to our knowledge, has not previously been documented. On patient-facing AI, hematologists’ ambivalence — limited belief in benefit but substantial concern about anxiety and misdirection — parallels both the double-edged framing of oncology chatbots [22] and the mixture of trust and concern that patients themselves report toward health-care AI [23]. Within hematology, recognition of morphology, flow-cytometry and genomic interpretation as opportunities tracks the field’s technical trajectory [4], while the caution echoes an earlier hematologist readiness survey [7] and the responsibility/liability concerns of oncologists [10]; the uniformly high, internally consistent demand for training matches needs assessments in medical education, including Turkish data [8].

Three contributions distinguish this work. First, it is, to our knowledge, the first national, society-led survey to integrate clinical use, research-integrity exposure, patient-facing attitudes and governance for hematologists within a single instrument. Second, it quantifies two behaviors that prior attitude surveys leave implicit — the prevalence of patient-data entry into non-approved public chatbots (48.6%) and the real-world encounter rate of AI “hallucinations” among research users (81%) — and sets them against a near-absent institutional-policy base (4.8%). Third, it shows that these patterns are essentially uniform across adult and pediatric hematology, indicating a specialty-wide rather than subgroup-specific governance need.

The data point to a coherent profile: hematologists treat AI as an efficiency and information tool to be supervised, not an autonomous decision-maker — a reading reinforced by the open-ended responses, where efficiency dominated perceived opportunity and inaccuracy/“hallucination” dominated perceived risk, with negligible fear of replacement. The principal gap is therefore institutional rather than attitudinal. Three implications follow. (1) Governance: societies and institutions should provide clear, hematology-relevant policies on permissible tools and on patient-data handling, given that half of respondents already enter such data into public chatbots. (2) Training: structured education is both needed and wanted, with the highest demand for safe generative-AI use and academic applications; digital literacy was independently associated with use, suggesting literacy-targeted curricula could broaden equitable, competent adoption. (3) Tooling: the strong openness (93%) to an official, supervised patient-facing tool indicates a constructive path for institution-approved deployments that preserve clinician oversight.

Strengths include a national, society-led sampling frame restricted to verified hematologist members, comprehensive coverage of knowledge, clinical and research use, governance, patient-facing attitudes and education in a single instrument, CHERRIES-compliant reporting, and analysis with effect sizes, confidence intervals, multiplicity control and reliability checks. Limitations include the cross-sectional, self-report design (no causal inference; potential social-desirability and recall bias); a volunteer sample with a 22.8% response rate (146/639 invited), so non-response and self-selection likely over-represent AI-interested adopters and limit generalizability beyond responding THD members; a sample size that constrained multivariable modeling (the clinical-use model was underpowered and is reported as

exploratory); an investigator-developed instrument that was not formally validated or piloted; reliance on respondents' own definition of "anonymized" data; a risk-perception item set that did not form a reliable composite (reported individually); a proportional-odds assumption that could not be formally tested in this environment (a concurring linear sensitivity model is reported); and AI-assisted categorization of the open-ended responses (Gemini, verified by the three authors by consensus and cross-checked with a keyword-based analysis), which, although not independent double-coding with a formal agreement statistic, supported descriptive rather than formal qualitative reporting.

Conclusions

Turkish hematologists have rapidly adopted AI — including generative AI — in clinical and academic work, while holding cautious, verification-oriented attitudes and feeling little professional threat. Adoption, however, is outpacing both formal training and institutional governance: many enter patient data into non-approved chatbots, fabricated references are commonly encountered, and written AI policies are nearly absent. Closing this gap will require hematology-specific governance, literacy-targeted training (especially in safe generative-AI use), and supervised, institution-approved tools. As the inaugural output of a national society's AI subcommittee — and, to our knowledge, the first hematology-specific survey to integrate clinical use, research-integrity, patient-facing attitudes, and governance within a single instrument — these findings offer an actionable baseline for policy, education, and the responsible integration of AI into hematology practice.

List of abbreviations

AI: artificial intelligence; LLM: large language model; ML: machine learning; DL: deep learning; THD: Turkish Society of Hematology (Türk Hematoloji Derneği); YZ-BAK: Artificial Intelligence Scientific Subcommittee (Yapay Zekâ Bilimsel Alt Komitesi); CHERRIES: Checklist for Reporting Results of Internet E-Surveys; STROBE: Strengthening the Reporting of Observational Studies in Epidemiology; KVKK: Personal Data Protection Law (Kişisel Verilerin Korunması Kanunu), Türkiye's general data-protection law, broadly equivalent to the EU GDPR; GDPR: General Data Protection Regulation (European Union); IT: information technology; EHR: electronic health record; NGS: next-generation sequencing; IQR: interquartile range; OR: odds ratio; CI: confidence interval; FDR: false discovery rate; AAPOR: American Association for Public Opinion Research; ICMJE: International Committee of Medical Journal Editors.

Declarations

Ethics approval and consent to participate. Approved by the Non-Interventional Clinical Research Ethics Committee of İstanbul Medipol University (no. E-10840098-50.04-3372; 14 May 2026); conducted per the Declaration of Helsinki; electronic informed consent obtained; anonymous.

Consent for publication. Not applicable (no individual-level identifying data).

Availability of data and materials. The datasets generated and analysed during the current study are not publicly available because the free-text responses could compromise the anonymity of individual respondents, but the de-identified, screened dataset is available from the corresponding author on reasonable request. The full survey instrument is provided as Additional file 1.

Competing interests. The authors declare that they have no competing interests.

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Authors' contributions. All authors (OEÇ, HEG, ÖB), as members of the THD AI Scientific Subcommittee, contributed to the conception and design of the study and the survey instrument, to data interpretation, and to consensus verification of the qualitative theme categorization; OEÇ coordinated survey distribution and the statistical analysis and drafted the manuscript; all authors critically revised the manuscript and approved the final version.

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Use of generative AI. The generative-AI feature integrated in Google Forms was used to categorize free-text survey responses into themes, and generative-AI tools were used to assist with English-language editing of the manuscript. No AI tool is listed as an author; all AI-assisted outputs were reviewed and verified by the authors, who take full responsibility for the content and interpretations.

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Figures

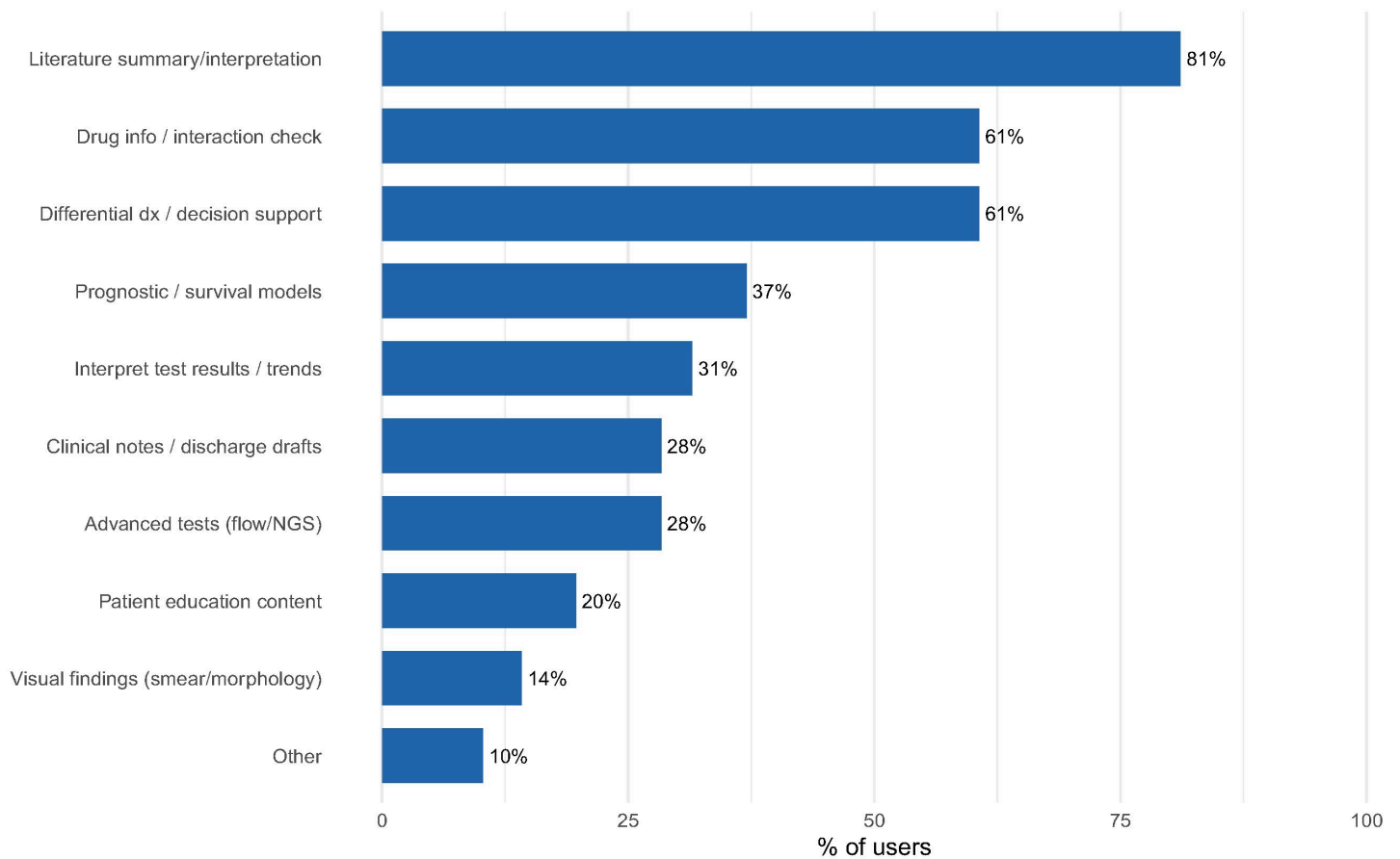


Figure 1

Clinical purposes of AI use among clinical AI users (n=127); multiple selections allowed.

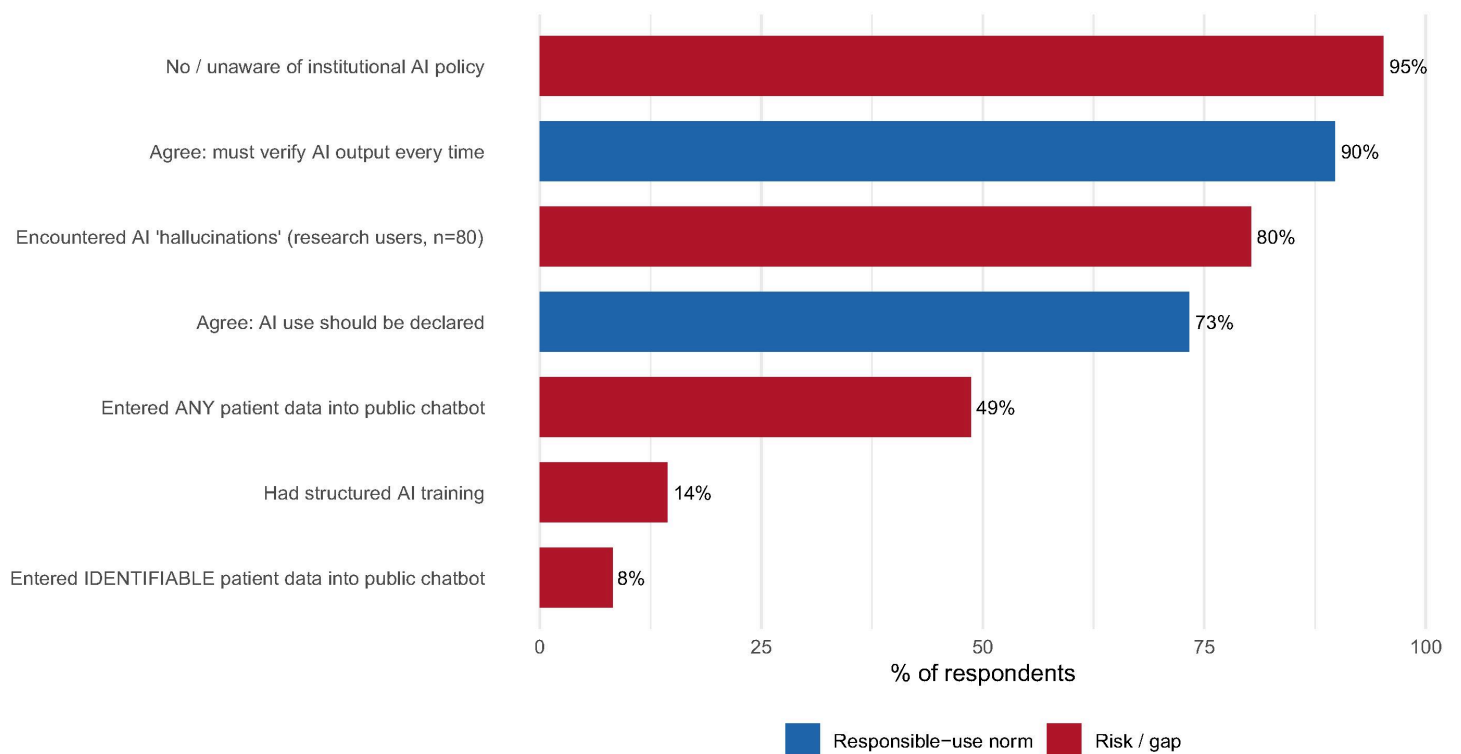


Figure 2

Governance, safety, and responsible-use indicators (denominators noted).

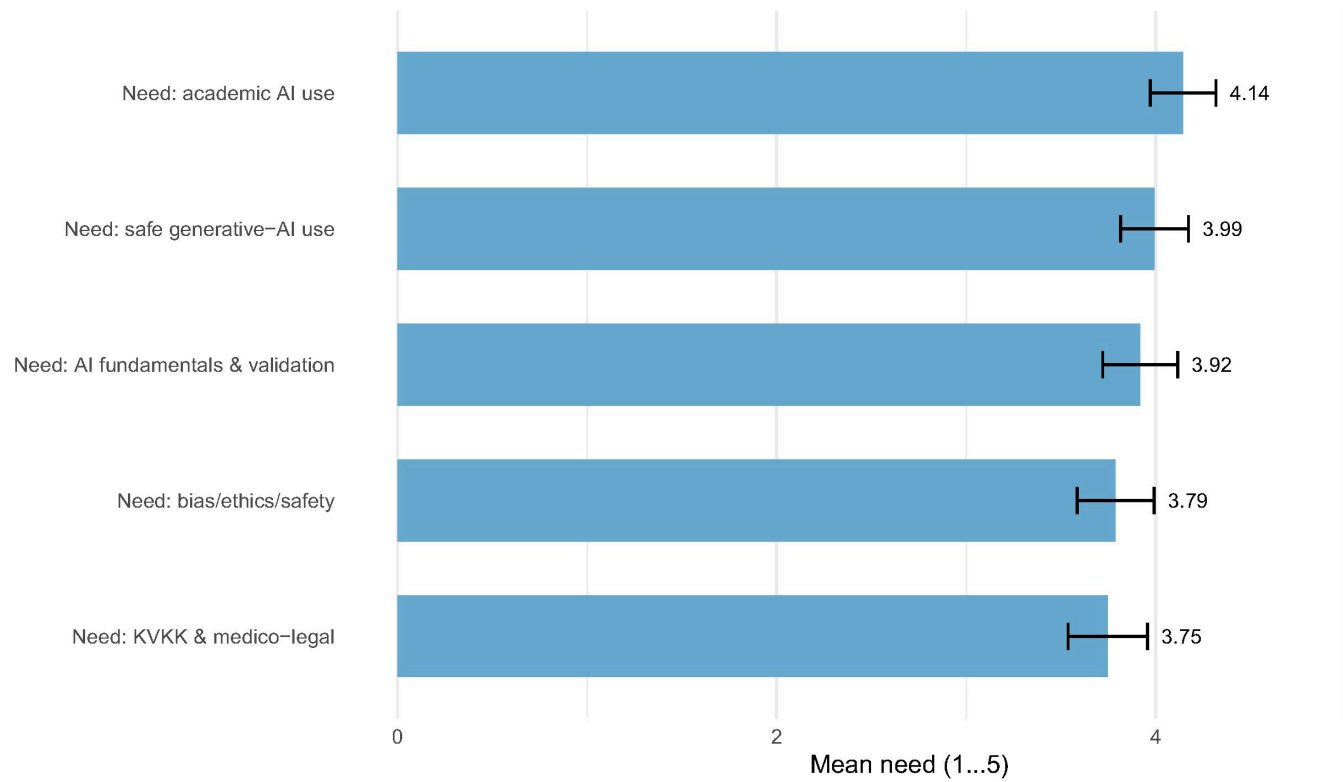


Figure 3

Perceived educational needs (G1a-e); mean (95% CI) on a 1–5 scale (Cronbach’s $\alpha=0.92$).

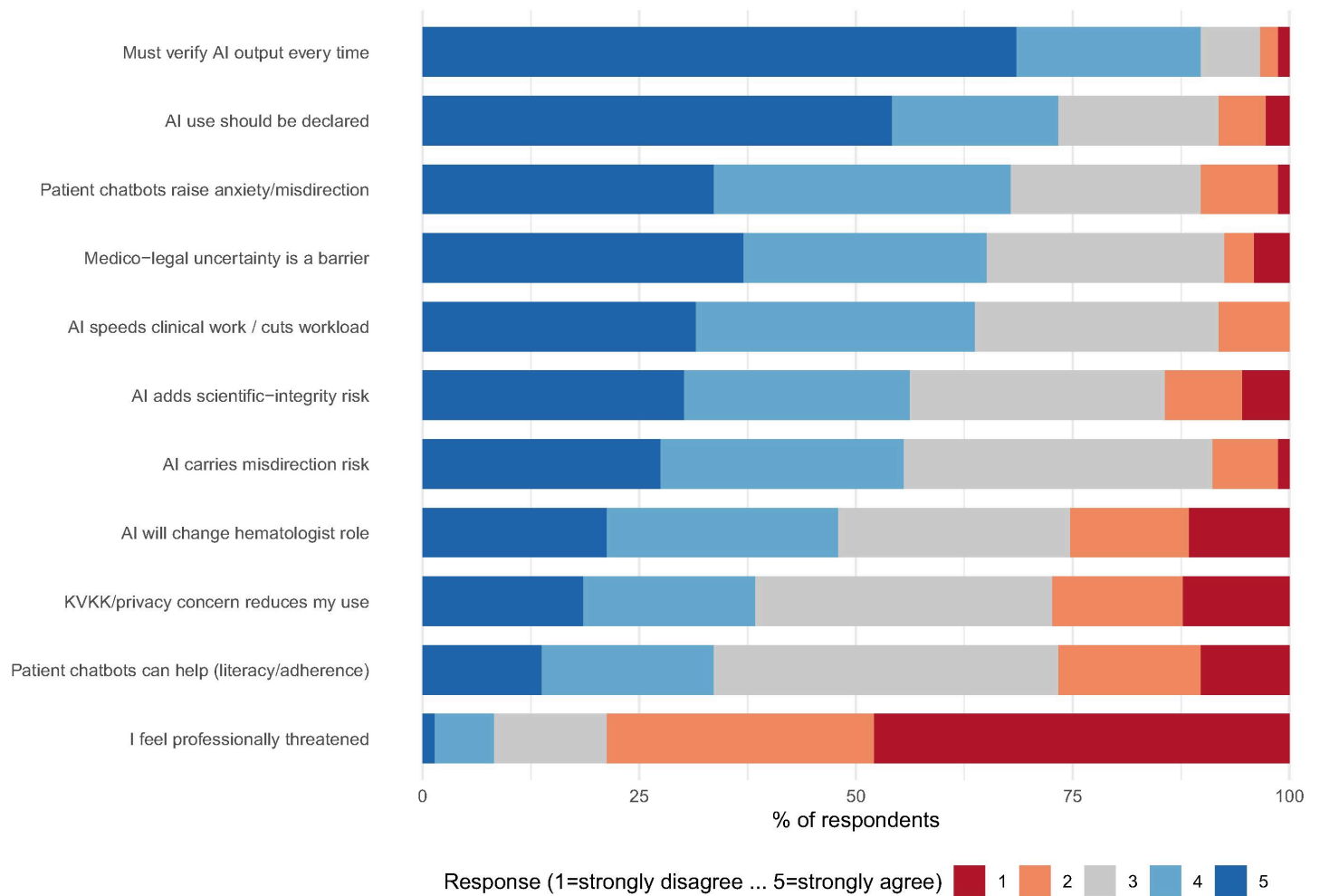


Figure 4

Distribution of agreement-anchored attitudes toward AI (11 items; 5-point Likert; N=146), ordered by percentage agreeing (4–5).

Supplementary Files

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