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Global Evolution of Artificial Intelligence Research in Diabetes: A Temporal Institutional Network Analysis

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Article

Keywords: artificial intelligence, diabetes, collaboration networks, interdisciplinarity, bibliometrics, digital medicine

Posted Date: November 24th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11680348/v1

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Additional Declarations: No competing interests reported.

Abstract

Artificial intelligence (AI) is used across diabetes prevention, screening, monitoring, and care, but the institutional collaborations that produce this work remain poorly mapped. We conducted a temporal institutional network analysis spanning nearly four decades, using 16,953 PubMed-indexed AI-related diabetes publications (1988–2025). The 67,973 unique institutional affiliations were classified into 13 disciplinary domains with a large language model, and collaboration networks were built across six periods. Institutions increased 4.5-fold and ties 14-fold, against a 1.5-fold increase in publications per period, yet only about 5% of institutions belonged to a single connected core by 2025. Collaboration became more interdisciplinary: single-domain communities fell from 65.6% to 42.5%, with clinical medicine as the principal hub. Geographic participation broadened, led by the Western Pacific region alongside the Euro-American backbone, and funding categories showed distinct collaboration structures. AI-related diabetes research is maturing rapidly into a clinically anchored and interdisciplinary translational ecosystem, while structural integration remains incomplete.

Introduction

Artificial intelligence (AI) is now used across diabetes research and care. Diabetes affects more than half a billion people worldwide (approximately 11% of adults), and its burden is projected to double by 2050, increasing demand on health-system capacity and capabilities to deliver earlier diagnosis, tighter glycemic control, and better prevention of complications and of associated conditions such as obesity, cancer, and mental health disorders (1). Advances in machine learning, computer vision, predictive analytics, clinical decision support, and digital health have expanded the role of AI across the diabetes continuum, from risk prediction and retinopathy screening to insulin dosing, complication surveillance, and population health (2, 3). The spread of electronic health records, continuous glucose monitoring, wearable sensors, and large biomedical datasets has accelerated this shift. AI-related diabetes research has grown in volume and scope, involving clinicians, public health researchers, informaticians, data scientists, engineers, and industry.

Publication growth, however, captures only part of how a field develops. Scientific progress depends on both publication volume and the structure of the collaborations that produce them. Fields develop through interactions among institutions, disciplines, regions, and funding systems that shape how knowledge is generated, shared, and translated. Collaboration structures show how technical work moves toward clinical practice and health policy, how interdisciplinary partnerships form, and how research priorities shift.

Previous bibliometric studies have described trends in AI-related diabetes publications, research topics, citation patterns, and country-level productivity (4–6). These analyses document rapid growth across areas such as diabetic retinopathy screening, glucose prediction, decision support, and digital therapeutics. Most, though, focus on publication volume, citation impact, keyword evolution, or author productivity. They rarely examine how universities and research centers, healthcare delivery

organizations (e.g., community health centers and hospitals), public health organizations, and companies, including pharmaceutical and medical technology firms, actually collaborate to advance this work, or how interdisciplinarity evolves and bridges traditionally siloed domains, from clinical medicine and its specialties (e.g., endocrinology) and complications-focused care through public health, biomedical and health informatics, and digital health, to engineering.

Institutional collaboration networks are suited to these questions (7–9). Institutions are relatively stable entities that link researchers, funders, infrastructure, and clinical practice. Thus, analyzing collaboration at the institutional level describes field-level development more directly than author- or publication-level analysis alone. Network methods characterize connectivity, interdisciplinarity, geographic diffusion, and the emergence of influential hubs, and can distinguish a field that remains concentrated within a few technical or specialty domains from one that is becoming more connected across domains (10–12). In the diabetes landscape, implementing AI typically requires coordinated contributions from clinical specialists, technical experts, health systems, public health agencies, and industry (13, 14). How this institutional collaboration has evolved over time, however, remains largely uncharacterized: existing analyses are mostly cross-sectional and publication-focused, leaving open whether AI-related diabetes research has become more interdisciplinary and clinically integrated or has remained concentrated within separate technical and specialty domains.

In this study, we conducted a global, temporal institutional network analysis of AI-related diabetes research published between 1988 and 2025. We sought to quantify growth and to describe how institutional collaboration has changed as AI has entered diabetes research and care.

Methods

Study design and data source

We conducted a temporal institutional network analysis of AI-related diabetes research using PubMed-indexed publications. PubMed was chosen for its broad biomedical coverage and structured affiliation metadata. The analytic unit was the institutional affiliation listed on each publication. Records were retrieved on 16 May 2026, with a hard publication ceiling of 31 December 2025 and therefore excluding papers published in 2026. Although the search covered publications from 1972 onward, the earliest record meeting all inclusion criteria was published in 1988; the analytic window therefore spans 1988–2025. Complete search queries are provided in Supplementary Methods S1. The study was reviewed by the Committee for the Protection of Human Subjects at The University of Texas Health Science Center at Houston and determined not to constitute human subjects research (HSC-SBMI-26-0950).

AI-related diabetes publications have grown exponentially over time; thus, uniform calendar intervals would place very few papers in the early decades and disproportionately many in recent years, distorting any comparison of collaboration structure across periods. To avoid this, period boundaries were defined on a logarithmic scale so that each period captured an approximately comparable number of

publications rather than an equal span of years. Boundaries were kept at whole-year units rather than arbitrary within-year cut-offs, so publication counts were approximately, though not exactly, balanced across periods (2,286–3,674 publications per period; coefficient of variation 22%). This segmentation yielded six periods, 1988–2015, 2016–2019, 2020–2021, 2022–2023, 2024, and 2025, in which the progressively narrower recent windows reflect the accelerating output of the field. These narrower recent windows also coincide with the COVID-19 pandemic and its aftermath, which reshaped institutional priorities and patient engagement with digital care, and with the rapid public diffusion of general-purpose AI tools from late 2022. Networks were constructed and analyzed independently within each period.

Screening and cohort development

Duplicate records and publications lacking usable affiliation data were removed. De-duplication was performed programmatically in the analysis pipeline: records were matched on PubMed identifier, and, where no identifier was present, on the combination of title and publication year. De-duplication and affiliation screening were applied to the pooled retrieval before period segmentation, so period boundaries were computed on the final analytic cohort and segment sizes reflect post-cleaning counts. Of 18,649 records retrieved across the two query blocks, 16,953 publications were retained (1988–2025). Of these, 4,197 carried at least one grant record and 12,756 had none. Cohort derivation and the analytic workflow are summarized in Supplementary Fig. S12.

Affiliation extraction and institutional unit definition

Each affiliation was taken exactly as written in the PubMed record (for example, a named department, hospital, university, or company). Different versions of the same institution's name, such as separate campuses, alternate spellings, or translations, were not manually combined into a single entry. Manual name cleaning would have made the analysis difficult to reproduce; the only automatic step applied was to exclude repeated entries for the same institution within a paper, so that one paper could not overstate the number of collaborations. One trade-off is that the same institution can occasionally appear under more than one name, which is addressed in the Discussion. In total, institutions were listed 73,779 times across all papers, representing 67,973 different affiliation names.

LLM-assisted institutional classification

To manage the complexity of affiliation extraction and to identify which disciplines contributed to each collaboration, each unique affiliation string was independently classified using a large language model (GPT-5-mini; OpenAI; used May 2026) instructed to assign exactly one institutional domain based on organizational identity rather than paper topic, with a confidence score between 0 and 1. The framework comprised 13 domains (Table 1). Strings scoring below 0.70 were flagged to a low-confidence review queue. Because affiliations often span multiple functions, assignments should be read as primary organizational anchors rather than exhaustive descriptions. Of 67,973 unique affiliations, 47,063 received

a specific domain label; 20,910 carry the “Other” label in the primary analysis so that every affiliation remained represented, comprising 1,660 assigned to Other by the model and 19,250 for which the classification request did not return a usable response. Classifier reliability was checked against an independent, blinded expert re-labeling of a random 100-affiliation sample (84% agreement; Cohen's κ = 0.81). The full schema, prompt, confidence framework and validation methods are in Supplementary Methods S2.

Table 1
Institutional domain classification framework used in the LLM-assisted analysis.

Institutional domain	Scope
Technical / AI / Informatics	Computer science, informatics, engineering, AI, data science, computational groups
Endocrinology / Diabetes	Endocrinology, diabetology, metabolism, diabetes specialty clinical groups
Ophthalmology / Vision	Ophthalmology, retina, optometry, vision science
Complications / Cardiometabolic / Nephrology / Neurology	Nephrology, cardiology, vascular medicine, neurology, renal/cardiometabolic medicine
Pediatrics / Maternal Health	Pediatrics, children's hospitals, obstetrics, gynecology, maternal-fetal medicine, gestational diabetes
General Clinical Medicine	General, internal, family, or primary care; broad clinical/hospital medicine
Public Health / Epidemiology	Public health, epidemiology, preventive medicine, population/community health, policy
Nutrition	Nutrition, dietetics, food science, clinical nutrition
Nursing / Diabetes Education	Nursing schools and practice, diabetes education
Behavioral / Psychological	Psychology, psychiatry, behavioral medicine, mental health
Exercise / Lifestyle	Exercise science, physical activity, sports and lifestyle medicine, wellness, rehabilitation
Industry / Digital Health / Device	Commercial, biotech, pharma, digital health, therapeutics, medical device organizations
Other	Affiliations not matching any predefined domain closely enough for a specific assignment

Network construction and institutional role assignment

For each period, an undirected institution–institution collaboration network was constructed from co-occurrence within publications: each node representing one institutional affiliation and each edge linking two institutions appearing on the same paper, weighted by the number of jointly authored publications

(15). Self-loops were excluded. We summarized the network structure using degree, weighted clustering, connected components, largest connected component share, and degree and betweenness centrality; betweenness, a path-based measure, was computed on the largest connected component, whereas all other measures used the full period network. Institutions were grouped into four participation tiers by degree centrality within the full period network, using within-period percentile cut-offs of the non-zero degree-centrality distribution: isolated (degree centrality of zero, i.e., no ties); limited-collaboration (below the 50th percentile); moderately collaborative (50th to below the 90th percentile); and highly collaborative (at or above the 90th percentile) (16). Because the tiers are based on degree rather than a path-based measure, isolates and institutions outside the largest connected component are still classified. Metric definitions are in Supplementary Methods S3. Analyses used Python 3.12 with Biopython 1.84, pandas 2.2.2, NetworkX 3.3, NumPy 2.1.1, matplotlib 3.9.2, seaborn 0.13.2, PyVis 0.3.2, pyarrow 17.0.0, and country-converter 1.2.0 (17–19).

Interdisciplinarity, geographic, and funding analyses

Interdisciplinarity was evaluated from the LLM-derived domains. For each connected component we counted the number and composition of domains represented, and examined three complementary layers: component-level domain diversity, pairwise domain co-occurrence within components, and exact three-domain combinations and their evolution. Because the clinical boundaries between endocrinology, complications-focused and cardiometabolic care, and maternal and pediatric diabetes are porous in practice, we repeated the component-level analysis with Endocrinology / Diabetes, Complications / Cardiometabolic / Nephrology / Neurology, and Pediatrics / Maternal Health merged into a single endocrine–cardiometabolic–maternal domain. Geographic analyses mapped each affiliation to a country (parsed from the affiliation text and standardized to a country name) and then to one of six World Health Organization (WHO) regions using a predefined country-to-region reference table. A country was resolved for 13,008 publications (76.7%), spanning 145 countries; regional publication and institutional counts were computed, together with publication-level co-occurrence between regions and between countries. A country could not be resolved for the remaining 23.3% of publications, in which the affiliation text as recorded did not yield an unambiguous country match. These publications were distributed across regions rather than concentrated in any one, so the limitation affects the precision of the regional counts more than their relative ordering. Funding analyses used PubMed grant metadata to assign each publication to one of three mutually exclusive categories (US federally funded, 2,939 publications; non-US or internationally funded, 1,258; and no grant listed, 12,756) and compared network characteristics, interdisciplinarity, geography, and domain-level collaboration across them.

Use of AI-assisted tools

The study concept and the analytic approach for exploring institutional collaboration were developed by the authors. AI-assisted tools were used to support the research, and the authors verified all outputs and take full responsibility for the accuracy and integrity of all data, analyses, and results, including the large

language model used for institutional-affiliation classification described above. A large language model (Claude Opus 4.8; Anthropic; used May 2026 – June 2026) assisted a portion of the literature review, with all sources independently verified by the authors. The original analysis code was written by the authors and refined with AI assistance; Claude Opus 4.8 (Anthropic) and OpenAI Codex (GPT-5.5; OpenAI) were used to help implement the analysis code and the associated software repository (used May 2026 – July 2026). This use follows current guidance on the acceptable use of AI in medical publication (20).

Results

Interpreting the collaboration networks. Throughout this section the AI-and-diabetes literature is represented as a collaboration network, in which each participating institution (author affiliation), such as an academic department, hospital, research center, or company, constitutes a node, and a collaborative tie (edge) is recorded whenever two institutions co-author a publication. Institutions connected directly or indirectly through such ties form a connected component: a set of institutions reachable from one another through chains of collaboration, the largest of which within a given period is termed the largest connected component.

Publication output, institutional participation, and network size

Between 1988 and 2025, publication output rose from 2,393 publications in 1988–2015 (the formative period) to 3,544 in 2025, peaking at 3,674 in 2022–2023 (Table 2); the first record listing more than one institution appeared in 2007 (see Discussion). Because 2022–2023 spans two calendar years, its annualized output of about 1,837 publications per year is below the 2025 figure. Across the six periods, publication counts and their shares of the 16,953-publication corpus were 2,393 (14.1%), 2,360 (13.9%), 2,696 (15.9%), 3,674 (21.7%), 2,286 (13.5%), and 3,544 (20.9%) (Table 2). Over the same interval, the number of distinct institutions (nodes) rose from 3,610 to 16,256, and collaborative ties (edges) from 3,788 to 54,301 (Fig. 1a; Table 2). Across the study period, institutions increased 4.5-fold and ties 14-fold, against a 1.5-fold increase in publications per period.

Table 2

Publication output, institutional participation, and collaboration network size by study period. Institution mentions denote the total number of institution–publication listings; nodes denote the distinct institutions that form the collaboration network, and edges the collaborative ties between them.

Period	Publications	Institution mentions	Nodes	Edges
1988–2015	2,393	3,681	3,610	3,788
2016–2019	2,360	11,466	11,158	439,972
2020–2021	2,696	12,671	12,194	42,862
2022–2023	3,674	17,929	17,051	65,180
2024	2,286	11,253	10,881	40,300
2025	3,544	16,779	16,256	54,301

Network cohesion and connected-component structure

Network cohesion was summarized by the number of collaborators of the typical institution (median degree) and the share of institutions within the largest connected component (Fig. 1b; Table 3). In 1988–2015 the median institution had no recurring collaborators (median degree 0); from 2016 onward the median institution was connected to five others (median degree 5). The weighted clustering coefficient ranged from 0.14 to 0.31 across periods. The largest connected component contained 20 institutions (0.6% of nodes) in 1988–2015 and 835 (5.1%) in 2025; in 2025 the 16,256 institutions formed 3,181 separate components (Table 3; Supplementary Table S8).

The 2016–2019 interval recorded 439,972 ties and an average degree of 78.9, both far above every other period (Table 3). Four conference-proceedings records in this interval each listed between 252 and 636 institutions; because every pair of co-listed institutions forms a tie, these four records alone account for approximately 414,000 of the period's 439,972 ties. The average degree and the largest-component share for this interval are inflated accordingly, whereas the median degree is little affected (5 with the records, 4 without). A sensitivity analysis excluding such records is provided in Supplementary Table S10.

Table 3

Network cohesion and largest connected component (LCC) metrics by study period. Average degree in 2016–2019 is inflated by four conference-proceedings records (see text).

Period	Nodes	Edges	Density	Avg degree	Median degree	Wtd clustering	LCC %
1988–2015	3,610	3,788	0.00058	2.10	0	0.135	0.6%
2016–2019	11,158	439,972	0.00707	78.86	5	0.300	5.7%
2020–2021	12,194	42,862	0.00058	7.03	5	0.181	1.4%
2022–2023	17,051	65,180	0.00045	7.65	5	0.153	2.0%
2024	10,881	40,300	0.00068	7.41	5	0.305	4.1%
2025	16,256	54,301	0.00041	6.68	5	0.226	5.1%

Institutional participation tiers and turnover over time

Within each period, institutions were grouped by degree centrality into four participation tiers (isolated, no ties; limited-collaboration; moderately collaborative; and highly collaborative) using the within-period percentile cut-offs defined in the Methods (Fig. 2b). Isolated institutions fell from 53.4% of institutions in 1988–2015 to 1.9% in 2025. Over the same interval, the limited-collaboration tier rose from 23.0% to 42.3%, the moderately collaborative tier from 17.8% to 44.3%, and the highly collaborative tier from 5.8% to 11.4% (Supplementary Table S7).

Institutional turnover was high in every transition (Fig. 2a). The number of new institutions entering the field between adjacent periods ranged from 10,310 to 16,426, whereas 66 to 625 institutions were active in both periods of a transition; new entrants outnumbered retained institutions by more than an order of magnitude in every transition. Among institutions active in consecutive periods, movement was predominantly toward more collaborative tiers: from 2020–2021 onward, 46 to 78 institutions per transition moved from the limited to the moderately collaborative tier and 48 to 54 from the moderately to the highly collaborative tier (Supplementary Table S3).

Domain diversity within collaboration communities

Each institution was assigned to one of thirteen disciplinary domains (Table 1), and each connected community was characterized by the number of distinct domains it contained; three or more domains was defined a priori as the threshold for multidomain collaboration (Fig. 3a). The share of single-domain communities fell from 65.6% in 1988–2015 to 42.5% in 2025, while the share spanning three or more domains rose from 2.5% to 19.5%. The mean number of domains per community rose from 0.85 to 1.70 (values below 1 reflect communities composed entirely of unclassified institutions, which contribute no

classified domain; e.g., 612 of 2,329 communities in 1988–2015), and the maximum within a single community from 5 to 12. From 2016 to 2024, the three-or-more-domain share remained between 19.5% and 22.4% (Supplementary Table S8). In a sensitivity analysis merging Endocrinology / Diabetes, Complications / Cardiometabolic / Nephrology / Neurology, and Pediatrics / Maternal Health into a single endocrine–cardiometabolic–maternal domain, the interdisciplinarity trend was unchanged: the single-domain share fell from 65.7% in 1988–2015 to 43.2% in 2025 (65.6% to 42.5% under the 13-domain framework), and the mean number of domains per community rose from 0.84 to 1.65 (0.85 to 1.70), the small downward shift following mechanically from the reduction in domain count from 13 to 11. The merged domain's collaborative footprint was, however, considerably larger than that of Endocrinology / Diabetes alone: in 2025 it was present in 38.9% of communities and comprised 2,816 institutions, against 17.9% and 1,135 for Endocrinology / Diabetes, approaching General Clinical Medicine (43.5%; 2,937 institutions).

Cross-domain co-occurrence and the position of clinical medicine

Across the full period, clinical medicine comprised the largest number of classified institutions (11,114), followed by technical/AI and informatics (10,633) and public health and epidemiology (5,166); a further 1,660 institutions were assigned to "Other" by the model and 19,250 returned no usable classification (Fig. 3b). Clinical medicine co-occurred with the widest range of partner domains: summed across all six periods, it shared collaboration communities most frequently with technical/AI and informatics (1,653 communities), public health and epidemiology (1,348), endocrinology and diabetes (1,121), and complications and cardiometabolic specialties (978) (Fig. 3c). Clinical medicine also had the most balanced partner profile: among two-domain collaborations, its most frequent single partner (technical/AI and informatics) accounted for 26.2% of its pairings, compared with 36.8% for the most concentrated domain, public health and epidemiology.

The clinical medicine–technical/AI interface was the most frequent cross-domain pairing in both 1988–2015 (44 communities) and 2025 (366 communities), and clinical medicine's interfaces with endocrinology, public health, complications specialties, ophthalmology, pediatrics, behavioral disciplines, and industry and device organizations also increased across periods (Supplementary Fig. S13). Among three-domain combinations, those that included clinical medicine were the most frequent and showed the steepest growth: clinical medicine with technical/AI and complications specialties rose from 3 communities in 1988–2015 to 39 in 2025, and clinical medicine with technical/AI and endocrinology from 2 to 29; every prominent three-domain combination included clinical medicine (Supplementary Fig. S6).

Geographic distribution and cross-regional collaboration

Publications were resolved to 145 countries and mapped to six World Health Organization (WHO) regions (Fig. 4a; Table 4). The Pan American Health Organization (PAHO) region led output in the first

three periods; the Western Pacific Region (WPRO) led from 2022–2023 onward, reaching 1,425 publications and 4,382 institutions in 2025, more than any other region (Table 4).

At the country level, the leading contributor shifted over the study period (Fig. 4b): the United States held the largest share of publications through 2022–2023, peaking at 26.4% in 2020–2021, after which China became the largest single contributor, rising from 25.7% in 2024 to 31.2% in 2025. Meanwhile, the US share declined from its 2020–2021 peak (26.4%) to 17.4% in 2025, so China's ascent reflected both its own rapid growth and a relative contraction in the US share rather than parallel expansion. The most frequent bilateral country pairings in 2025 were China–United States (56 co-authored publications), Canada–United States (36), India–United States (30), Australia–United States (28), and Germany–United States (28); at the regional level, the European Region (EURO)–PAHO pairing was the most frequent cross-regional collaboration in both 1988–2015 (14) and 2025 (148).

Table 4
Leading WHO region by publication count in each study period. Full regional rankings are in Supplementary Table S5.

Period	Leading region	Publications	Countries	Institutions
1988–2015	PAHO	422	12	616
2016–2019	PAHO	713	15	2,134
2020–2021	PAHO	888	18	2,738
2022–2023	WPRO	1,163	14	3,743
2024	WPRO	837	10	2,673
2025	WPRO	1,425	14	4,382

Collaboration structure by funding category

Each publication was classified from PubMed grant metadata as US federally funded, non-US or internationally funded, or without a listed grant (classification rules in Supplementary Methods S4) (Table 5). Most publications carried no listed grant (12,756; 51,751 affiliation mentions), followed by US federally funded (2,939) and non-US or internationally funded (1,258).

Averaged across periods, non-US or internationally funded research had the highest mean network density (0.0320), mean degree (21.57), and mean largest-component share (10.54%); US federally funded research had the highest share of communities spanning three or more domains (28.1%); research without a listed grant had the lowest values on these measures (mean density 0.0024; three-or-more-domain share 15.7%) (Table 5; Supplementary Fig. S14). As in the full network, the 2016–2019 interval inflates the mean density and mean degree of the non-US and no-grant groups, whereas the median degree was 5 to 6 in all three groups. In 2025, WPRO led internationally funded and no-grant output and PAHO led US federally funded output (Supplementary Table S6).

Table 5

Collaboration characteristics by funding category, aggregated across study periods. Mean 3 + field share denotes the mean proportion of components spanning three or more domains.

Funding category	Publications	Instit. mentions	Mean density	Mean degree	3 + field
US federally funded	2,939	14,924	0.0032	7.32	28.1%
Non-US / international	1,258	7,104	0.0320	21.57	23.0%
No grant listed	12,756	51,751	0.0024	20.39	15.7%

Discussion

In this temporal institutional network analysis of 16,953 AI-related diabetes publications, representing 67,973 unique institutional affiliations, spanning nearly four decades, the field expanded: participating institutions rose roughly 4.5-fold and collaborative ties 14-fold, far outpacing the 1.5-fold growth in publications per period. Expansion was therefore driven less by established groups publishing more than by the continual entry of new institutions. This growth, however, outpaced structural integration: even in 2025 only about 5% of institutions belonged to the single largest connected component, and collaboration remained spread across thousands of small, semi-independent communities rather than a unified core (16). Participation nonetheless became steadily more collaborative (the share of isolated institutions fell from more than half of the field to under 2%), consistent with the gradual consolidation of a stable collaborative core amid continual influx of newcomers.

The scale of that fragmentation invites a clinical reading. In 2025 the network comprised 3,181 separate components, and only 5.1% of institutions belonged to the largest of them. That degree of separation mirrors the technical siloing of diabetes care itself: continuous glucose monitors, automated insulin delivery systems, and electronic health records still largely exchange data in proprietary, non-interoperable formats, so the datasets on which multi-institutional AI work depends are themselves partitioned by vendor and by health system. On this reading, the structural fragmentation observed here is not only a geographic or academic phenomenon but also a downstream expression of the data standards that govern diabetes device and record ecosystems, and clinical translation is likely to remain correspondingly siloed until multi-institutional networks are built on open, vendor-neutral standards for device and record data.

Three patterns stand out: collaboration became substantially more interdisciplinary and clinically anchored; geographic participation broadened, with rising Asia-Pacific contributions layered onto a persistent Euro-American backbone; and distinct funding ecosystems were associated with different collaboration architectures. Although our descriptive design cannot establish causation, several factors plausibly contributed to this shift: the increasing accessibility of AI tools and platforms, open-source frameworks, pretrained models, and cloud computing, which lowered barriers to entry and broadened who could participate; accumulating clinical and regulatory evidence that drew clinical and specialty

institutions into the field; the expansion of digital-health data infrastructure; and funding and policy incentives favoring translational, multi-institutional work. Prior bibliometric analyses have charted the rapid growth and thematic breadth of AI in diabetes and its subfields (4–6, 22); our institutional-network analysis complements them by mapping the collaborative architecture that underlies that growth.

A central result was the sustained rise in interdisciplinarity (11, 12). The share of communities spanning three or more domains rose from 2.5% to 19.5% and the mean number of domains per community roughly doubled (0.85 to 1.70), and this breadth became a durable structural feature rather than a transient effect of a few large studies. Clinical medicine emerged as the principal hub, sharing collaboration communities with the widest range of partners and retaining the most balanced partner profile of any domain across the full period, with no single partner accounting for more than about a quarter of its pairings. Technical and AI work did not form a stand-alone enterprise; rather, technical expertise became embedded within progressively broader, clinically anchored structures. Several clinically relevant interfaces that were virtually absent early in the study, including ophthalmology, pediatrics, and industry and device partners, emerged consistently in later periods, indicating that expansion added new partnerships rather than displacing existing ones.

This pattern differs from a common account of AI in healthcare (3). Early accounts often treated technical development and clinical implementation as sequential and separate, with innovation originating in computational settings before eventual translation. These data suggest a different trajectory for diabetes: AI became embedded within clinically anchored networks early on, so the dominant structures are clinically centered collaborations that incorporate AI as one component of broader translational efforts. The growing prominence of complications-focused specialties, spanning nephrology, cardiometabolic medicine, neurology, and ophthalmology, suggests AI applications are extending beyond glucose management toward early detection, prevention, complication prediction, and disease management (2, 4, 5), while rising public health, behavioral, and lifestyle participation points to interest in prevention, implementation, and patient-centered care. This broad, clinically anchored footprint aligns with recent syntheses of AI in diabetes care, which position AI as an increasingly integral part of clinical workflows across the diabetes continuum (23).

The hub role of clinical medicine should not be read as implying a single translational pathway. AI applications in diabetes reach care by distinct routes. Screening and diagnostic applications, of which autonomous diabetic retinopathy screening is the clearest example, are distributed largely through primary care in partnership with technical teams and ophthalmology, and often do not involve the endocrinologist directly; the prominence of general clinical medicine as a hub, and the emergence of the ophthalmology interface in later periods, are consistent with that route. Therapeutic and device applications, including automated insulin delivery, closed-loop control, and predictive dosing algorithms, carry greater clinical risk and depend on sustained co-design among technical developers, industry device partners, and specialized adult and pediatric endocrine centers, which concentrates them within a narrower set of institutions. Because our design classifies institutions rather than applications, these

pathways cannot be separated empirically here; doing so would require topic-level classification of the publications themselves and is a natural extension of this work.

The rise of the Western Pacific region shows that recent growth is no longer concentrated in North America and Europe. Possible contributors include investment in biomedical AI, a large and growing diabetes burden (1), expanding digital health infrastructure, and rapid research-capacity building across several Asia-Pacific countries. Regional research output also broadly tracks regional disease burden: the Western Pacific and South-East Asia regions account for the largest absolute numbers of people with diabetes, which plausibly shapes both the clinical need and the data available for AI development. Output and integration, however, are not the same. China became the largest single contributor by 2025 (31.2% of the 3,544 publications in 2025), yet even its largest international collaboration, with the United States (56 co-authored publications), remained modest relative to its output, so higher productivity did not translate into proportional cross-border integration, a pattern seen in other fast-growing research systems (7, 24, 25). The concurrent decline in the US share did not reflect a contraction in US research: US-affiliated output continued to rise on an annualized basis (26), so the falling share is better read as dilution by faster-growing systems, principally China, than as a drop in US activity, and the incomplete, US-skewed PubMed grant metadata cannot attribute these country-level shifts to changes in funding. Longstanding Euro-American partnerships remained the dominant corridors throughout; the geography is best described as diversification layered onto an enduring backbone rather than a wholesale redistribution of leadership (10).

Funding environments were associated with different organizational models. Internationally funded studies tended toward more concentrated, tightly interconnected structures; US federally funded studies toward the strongest interdisciplinary integration (the highest share of communities spanning three or more domains, 28.1%); and studies with no listed grant, despite accounting for most output, toward lower structural integration. These associations should be read cautiously, since funding status may reflect study scale, priorities, reporting practices, publication types, and regional systems rather than any direct effect. PubMed grant metadata also disproportionately capture US federal (NIH) support and under-record non-US and industry funding, so these funding-category analyses are observational and hypothesis-generating. Still, the association between funding and interdisciplinarity is relevant, because many of the central challenges in diabetes (complications prediction, precision medicine, digital therapeutics, and implementation of AI-enabled care) require cross-disciplinary collaboration, and funding structures that reward such integration may support more connected translational ecosystems.

Several implications follow. First, the increasing clinical integration of AI argues for prioritizing multidisciplinary collaboration from the earliest stages of projects; implementation is likely to depend on algorithms together with sustained partnerships among clinicians, data scientists, health systems, and behavioral, public health, and industry partners. Diabetic retinopathy screening is the clearest clinical illustration: in autonomous AI for diabetic retinopathy screening, real-world adoption has depended on integration into care pathways and health systems, not on algorithm accuracy alone (27). The wider pattern behind that example is a gap between research activity and implementation: the volume of

published AI work in diabetes greatly exceeds the number of tools that reach routine care, and the collaboration structures described here are one determinant of which projects cross that threshold. Second, the translation of AI into diabetes care may depend less on the sheer volume of research than on sustained, interconnected collaboration among the institutions that produce it. This argues for mechanisms that convert expansion into connection (coordinated multi-institution consortia, shared data and evaluation infrastructure, and cross-institutional programs). Third, geographic diversification creates opportunities to strengthen international collaboration, which could improve the generalizability of AI systems and broaden participation. Finally, funders may shape collaborative ecosystems through the structures they support, and investment in interdisciplinary, multi-institutional work, together with capacity building for researchers and institutions able to work across clinical, technical, and implementation domains, may accelerate translation. A concrete mechanism follows from the funding pattern reported here: because federally funded work showed the highest interdisciplinary integration (28.1% of communities spanning three or more domains, against 15.7% for work with no listed grant), funders could require co-design at the point of award rather than encouraging it afterwards, for example by expecting co-principal investigators drawn from both technical (informatics and AI) and clinical (endocrinology and diabetes) domains from the outset, so that algorithm development and the clinical workflow it must enter are specified together. These implications hold even as the AI engines themselves advance rapidly: continuing progress in foundation and generative models will keep expanding what is technically feasible, but our findings indicate that the binding constraint on clinical translation lies less in algorithmic capability than in the institutional integration, evaluation, and cross-disciplinary collaboration needed to deploy such tools safely, so faster model progress heightens, rather than lessens, the importance of the connected collaboration structures described here.

Several limitations apply. First, the analysis was limited to PubMed-indexed publications and may not capture all relevant work. In addition, PubMed recorded only the first author's affiliation for most records before 2014, so multi-institution ties are systematically under-captured in the 1988–2015 period: fewer than 1% of records published before 2013 list more than one institution, compared with about 90% from 2020 onward. The earliest period should therefore be read as a sparse baseline shaped by indexing practice rather than as a direct measure of collaboration at the time, and the magnitude of change between 1988–2015 and later periods is correspondingly overstated. Second, analyses were conducted at the institutional-affiliation level rather than the individual-investigator level, which can obscure author-level patterns, and exact affiliation strings were retained rather than deeply harmonized, so some institutional fragmentation persists; a light canonicalization (case/accent/punctuation normalization) merged under 1% of nodes and left the findings unchanged, and deeper name harmonization remains a direction for future work. Third, institutional domains were assigned with an LLM-assisted single-label framework; this introduces classification uncertainty, and 20,910 affiliations (30.8%) carry the Other label in the domain analyses, which bounds them. Most of these (19,250) are affiliations for which the classification request did not return a usable response rather than affiliations the model judged ambiguous; among affiliations that were classified successfully, only 44 fell below the 0.70 confidence threshold. Because that population includes large academic medical centers, re-running the incomplete

requests, and mapping any residual names through clinical heuristics such as MeSH terms or hospital registry databases, would be expected to strengthen rather than alter the clinical and endocrine representation reported here. The 13-domain framework also imposes boundaries that are porous in clinical practice — endocrinology is intrinsically cardiometabolic, and endocrinologists commonly lead gestational diabetes care and direct nutrition-focused therapy — so the apparent footprint of any single specialty domain depends on how the framework is drawn, as the merged-domain sensitivity analysis indicates. Domain assignment also reflects organizational naming conventions that vary by country — biomedical and health informatics units, for example, sit within public health faculties in some systems and within medicine or engineering in others. Fourth, collaboration structure does not measure scientific impact, quality, clinical relevance, or translational success. Finally, temporal analyses used predefined periods, and observed cohesion can be strongly influenced by episodic consortium-scale publications, as the 2016–2019 interval shows; alternative segmentation could yield somewhat different estimates.

AI-related diabetes research has moved from a relatively fragmented technical–clinical set of collaborations toward a geographically broader, clinically anchored, and increasingly interdisciplinary translational ecosystem. Clinical medicine emerged as the principal hub connecting technical, specialty, public health, and complications-focused domains, while expanding Asia-Pacific participation contributed to the globalization of the field. This maturation remains structurally incomplete, since collaboration is still distributed across many small communities rather than a single integrated core. These findings provide a systems-level view of how AI-related diabetes research has developed and may inform future strategies for collaboration, funding, capacity building, and translation of AI into diabetes care.

Declarations

Competing interests.

The authors declare no competing interests.

Author Contribution

U.P.S. conceived the study, designed the methodology, wrote the analysis code, retrieved and curated the data, performed the network analyses, prepared all figures and tables, and wrote the main manuscript text. X.J. co-conceived the study, contributed to the methodology, supervised the analysis, and critically revised the manuscript. A.M. and K.K. contributed to the interpretation of the findings and their clinical and policy implications, and critically revised the manuscript. N.S. and P.R.O. provided clinical interpretation of the collaboration structures, proposed the sensitivity analyses on domain boundaries and the funding implications, and critically revised the manuscript. A.B. contributed to the methodological framing and reporting of the analysis and critically revised the manuscript. All authors reviewed and approved the final manuscript and agree to be accountable for the work.

Acknowledgements.

The authors thank collaborating mentors for clinical and methodological guidance. This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. During the preparation of this work, the authors used Claude Opus 4.8 (Anthropic; used July 2026 – August 2026) to assist manuscript preparation by drafting and editing text from an author-defined blueprint and reference list. The authors reviewed and edited all text, checked it for accuracy, and take full responsibility for the content. Bibliographic references were compiled and verified by the authors using standard reference-management software and were not generated by AI. No AI tool is listed as an author.

Data Availability

The publications analysed in this study are PubMed bibliographic records retrieved through the NCBI E-utilities on 16 May 2026 using the two search queries reported in Supplementary Methods S1; PubMed records are publicly available from the National Library of Medicine (https://pubmed.ncbi.nlm.nih.gov/). All datasets generated during this study — the PubMed identifiers of the 16,953 publications in the analytic cohort with their study period and funding category, the large-language-model domain classification of the 67,973 unique affiliation strings with confidence scores, the 100-affiliation expert-labelled validation sample, the period-level institutional collaboration networks (GraphML) and network metrics, the institutional participation-tier assignments, the country- and WHO-region collaboration matrices, and the sensitivity analyses reported in Supplementary Tables S10 and S11 — are openly available in the repository “AI in Diabetes: Temporal Institutional Collaboration Trends (1988–2025)” on GitHub (https://github.com/druday/AI_in_Diabetes_Trends_1988_2025) and archived at Zenodo (https://doi.org/10.5281/zenodo.24089677). Summary data supporting each table and figure are also provided in the Supplementary Information.

Code availability.

Analysis code is available in the study repository.

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Figures

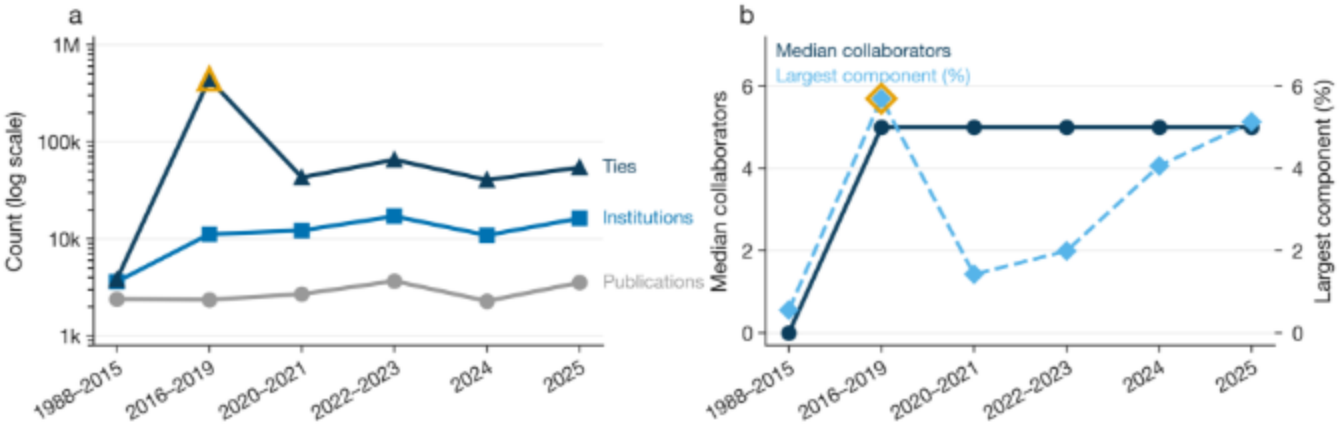

Figure 1

Growth and network cohesion, 1988–2025. *(a) Publications, distinct participating institutions (nodes), and collaborative ties (edges) by study period, on a logarithmic scale; the open marker denotes the 2016–2019 tie count, inflated by four conference-proceedings records (see text). (b) Median number of collaborators per institution (median degree, left axis) and the share of institutions in the largest connected component (right axis); the open marker denotes the outlier-affected 2016–2019 value. Underlying values are given in Tables 2 and 3. Figure generated using author-written code developed with AI assistance (Claude Opus 4.8, Anthropic; used July 2026 – August 2026); the authors verified all displayed data.*

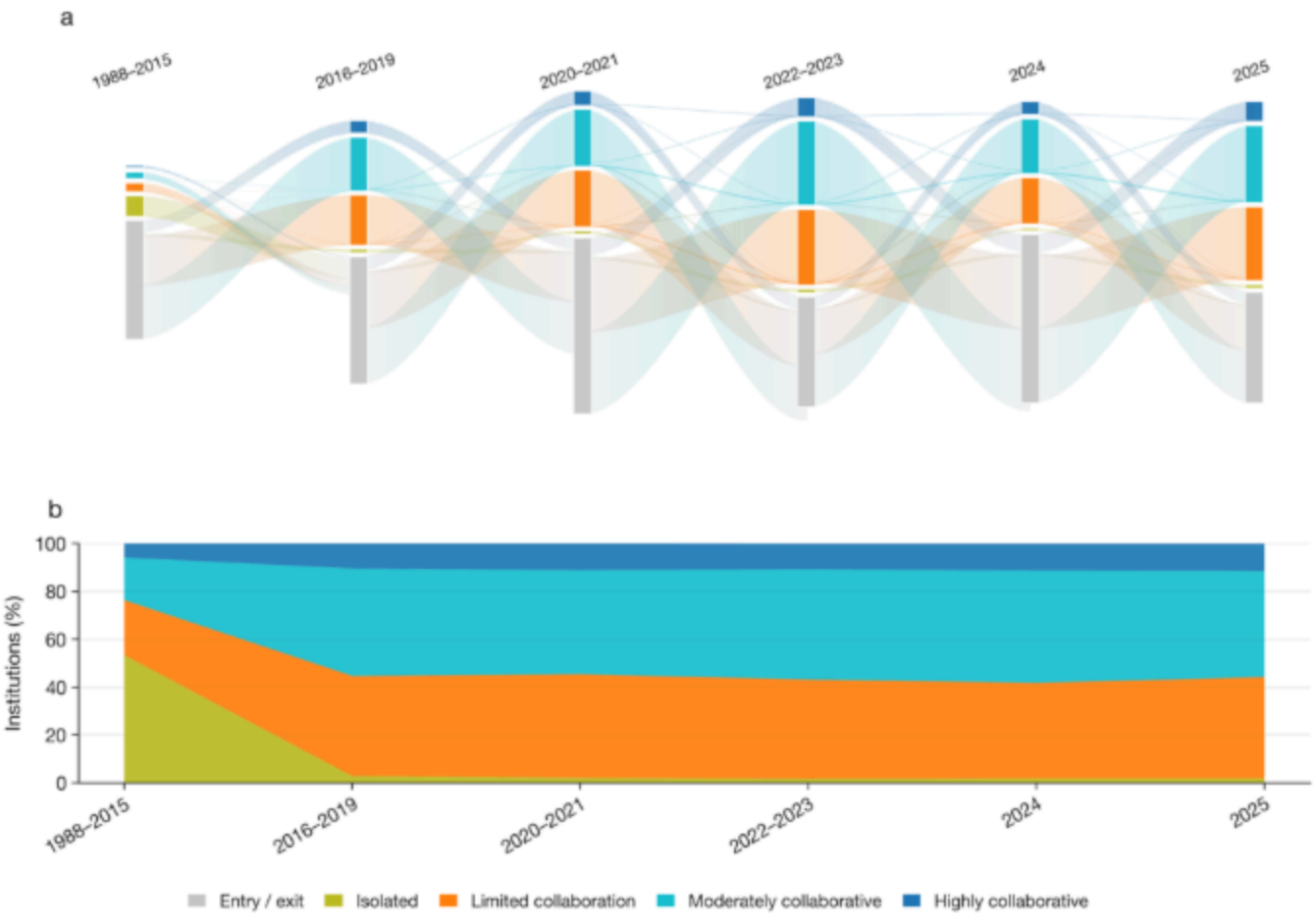

Figure 2

Institutional participation over time. *(a) Alluvial diagram of institutional transitions among participation tiers between consecutive periods; node height is proportional to the number of institutions in a tier, coloured ribbons trace institutions retained from the preceding period, and grey ribbons denote entry into and exit from the field (21). (b) Share of institutions in each participation tier (isolated, limited-collaboration, moderately collaborative, highly collaborative) by study period, shown on the same timeline. Per-period tier counts are in Supplementary Table S7. Figure generated using author-written code developed with AI assistance (Claude Opus 4.8, Anthropic; used July 2026 – August 2026); the authors verified all displayed data.*

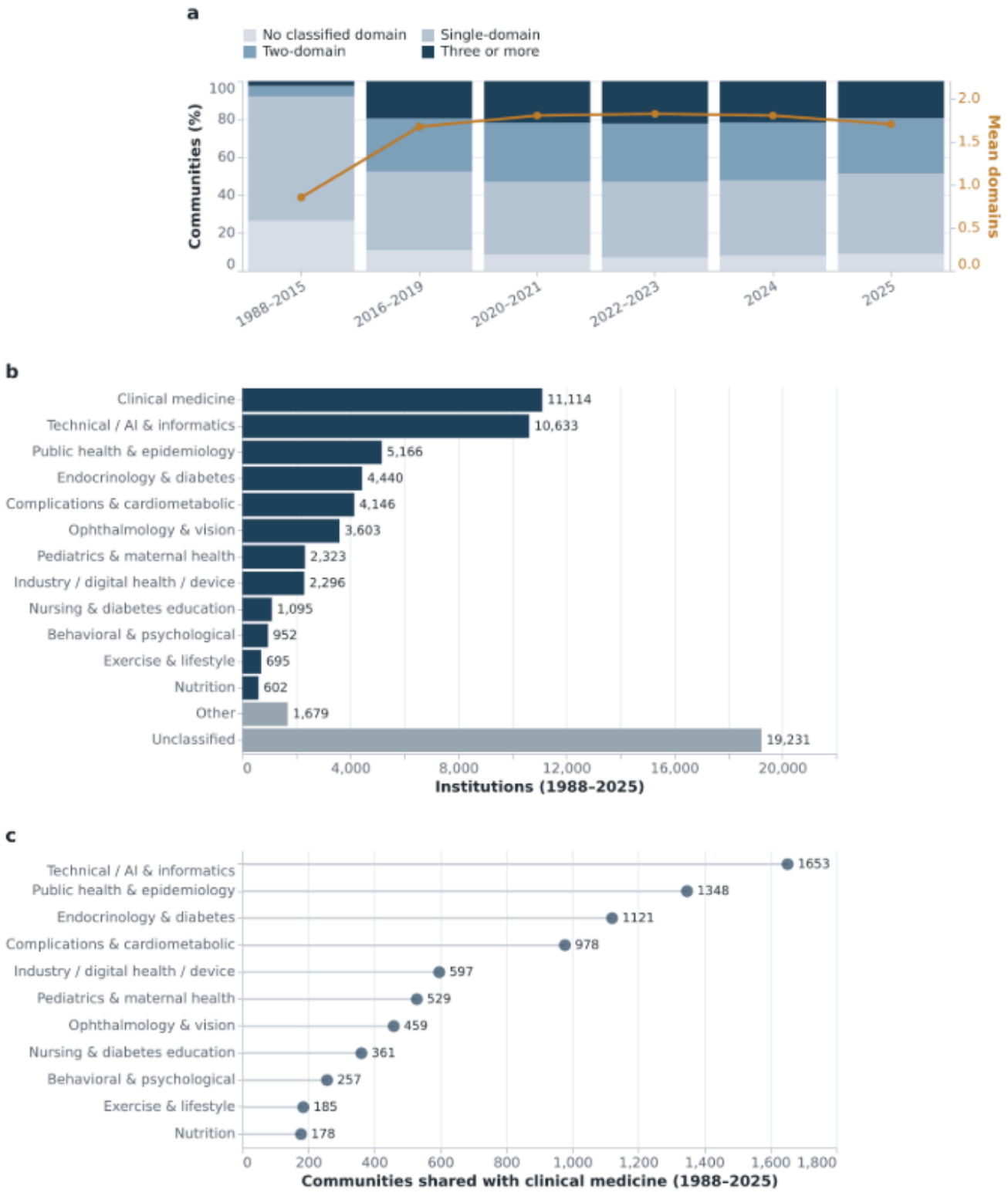

Figure 3

Interdisciplinary structure and the position of clinical medicine. *(a) Share of collaboration communities spanning one, two, or three or more domains, or with no classified domain, by study period, with the mean number of domains per community (line). (b) Number of unique institutions assigned to each disciplinary domain across the full period (1988–2025); institutions the model placed in "Other" or for which the classification request returned no usable response (labelled "Unclassified") are shown separately in grey;*

the bar labels reflect the classification snapshot used to draw the figure and differ by fewer than 20 institutions from the final totals given in Methods (1,660 and 19,250). (c) Number of collaboration communities each domain shared with clinical medicine, summed across the six study periods (1988–2025). Per-period interdisciplinarity metrics are in Supplementary Table S8; the full pairwise co-occurrence heatmap is Supplementary Fig. S5. Figure generated using author-written code developed with AI assistance (Claude Opus 4.8, Anthropic; used July 2026 – August 2026); the authors verified all displayed data.

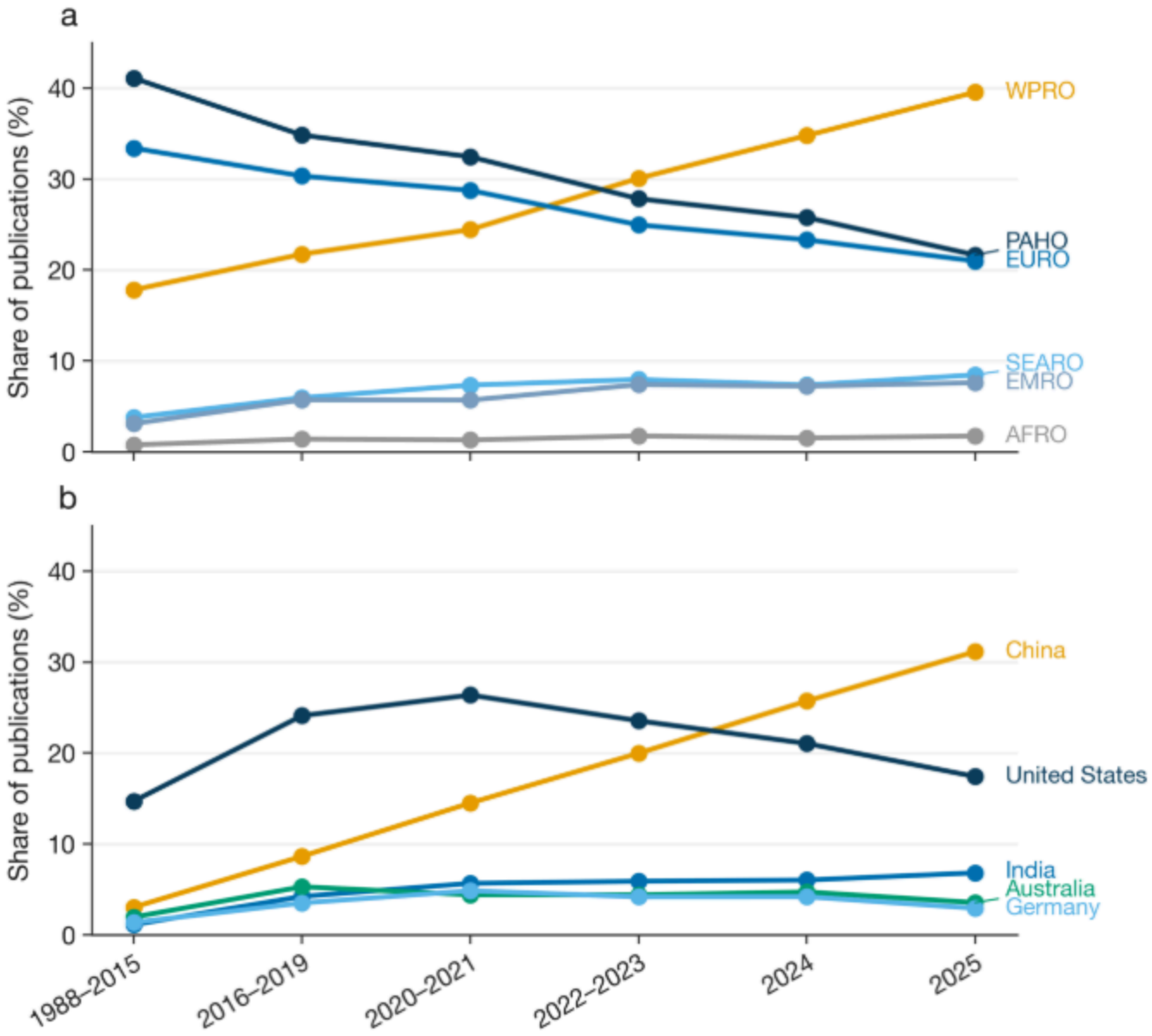

Figure 4

Geographic distribution of AI-and-diabetes research. *(a) Share of publications by WHO region and study period; the Western Pacific Region (WPRO) overtakes the Pan American Health Organization region (PAHO) from 2022–2023. (b) Share of publications from the leading countries by study period, on the same axes; China overtakes the United States from 2024. Full cross-region and country collaboration matrices*

(heatmaps) are provided in Supplementary Figs. S8 and S9. Figure generated using author-written code developed with AI assistance (Claude Opus 4.8, Anthropic; used July 2026 – August 2026); the authors verified all displayed data.

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