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REVIEW

Global trends and hotspots in the learning curves of robotic-assisted surgery: a bibliometric and visualization analysis

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Abstract

In recent years, there has been a substantial increase in the number of research papers published in the field of robotic-assisted surgery (RAS). Nevertheless, systematic analyses focusing on the key hotspots associated with the learning curves (LCs) of RAS, global collaboration models, and future trends remain relatively limited. This study employed bibliometric methods to conduct a comprehensive search and analysis of papers on the LC of RAS published in the Web of Science Core Collection between 2005 and 2025. A visual analysis was performed across multiple dimensions, including countries, institutions, sources, and authors. The results revealed an upward trend in the number of publications, with a peak observed in 2024. The United States ranked first in terms of publication volume, while Yonsei University emerged as the most productive institution. Mottrie Alexandre contributed to the highest number of publications, and Dindo d received the highest number of citations. Frequently occurring keywords included “outcome”, “experience”, “minimally invasive surgery”, “revision”, and “laparoscopic surgery”. Clustering keywords were associated with “rectal cancer”, “en-y gastric bypass”, “transoral robotic surgery”, “spine surgery”, and “endometrial cancer”. Furthermore, the top five keywords with the strongest citation bursts were “laparoscopic radical prostatectomy”, “total mesorectal excision”, “da vinci”, “prostatectomy”, and “mrc clasicc trial”. This study offers valuable insights into the future development of this field and supports further exploration and innovation.

Keywords Robotic-assisted surgery · Learning curve · Bibliometric analysis · Visual analysis

Introduction

Robot-assisted surgery (RAS) represents a pivotal advancement in the surgical domain, showcasing substantial technical benefits across various specialties and progressively transforming conventional surgical practices. Since its inception in the 1990 s, RAS systems, exemplified by the Da Vinci platform, have markedly enhanced surgical precision and operational dexterity through key technologies, such as multi-articulated robotic arms, high-definition three-dimensional visualization, and tremor reduction [1, 2]. Presently, RAS has emerged as the preferred standard for complex procedures including pedicle screw placement, joint arthroplasty, robot-assisted radical prostatectomy (RARP), and robot-assisted partial nephrectomy (RAPN). In managing intricate anatomical configurations, RAS demonstrates superior adaptability and safety compared to traditional open and endoscopic techniques [3–5].

Research indicates that, following systematic training, the accuracy of novice surgeons markedly improves after performing approximately 50 robot-assisted spinal screw implantation procedures [6]. The learning curve (LC) for robot-assisted thyroid surgery typically ranges from 30 to 40 cases [7, 8]. For robot-assisted minimally invasive esophagectomy (RAMIE), the LC is relatively extended, ranging from 35 to 119 cases [9]. In robot-assisted radical prostatectomy (RARP), achieving proficiency in reducing positive surgical margins requires a LC of approximately 200 cases [10]. Furthermore, significant variations exist in the LCs among different robotic spinal systems, such as

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Mazor and ExcelsiusGPS [11], highlighting the substantial influence of technological advancements on learning costs.

Currently, there is no consensus on a standardized definition of the LC for RAS. Evaluation metrics utilized across studies vary and may include operation time, complication rates, or composite indicators, among others [12, 13]. Additionally, the high acquisition cost of robotic systems, coupled with extended operating room times during the LC phase, has yet to be adequately addressed through a well-defined economic evaluation model [14]. Research indicates that while robot-assisted fracture reduction significantly enhances accuracy, its prolonged LC may pose a barrier to its widespread adoption [15, 16].

Through bibliometric visualization analysis, it is possible to delve deeper into the core themes, methodological advancements, and clinical challenges associated with research on the LCs of RAS. Future investigations should prioritize strengthening multi-center collaborations, developing standardized assessment tools, and innovating training methodologies, thereby facilitating the safe dissemination and efficient utilization of robotic technologies in clinical practice [17–19].

Methods

Search strategy

Search date: April 7, 2025.

Data source: Web of Science (WOS) Core Collection Database.

Search method: TS = (("robotic surgery" OR" robot-assisted surgery "OR" da vinci system") AND ("learning curve "OR" skill acquisition"OR"operative time")).

Search time frame: 2005–2025.

Included document types: original research articles and review articles.

Exclusion criteria: meeting abstracts, conference proceedings, other publication types, and non-English literature.

A total of 2,865 articles were included in the analysis. The detailed search process is illustrated in Fig. 1.

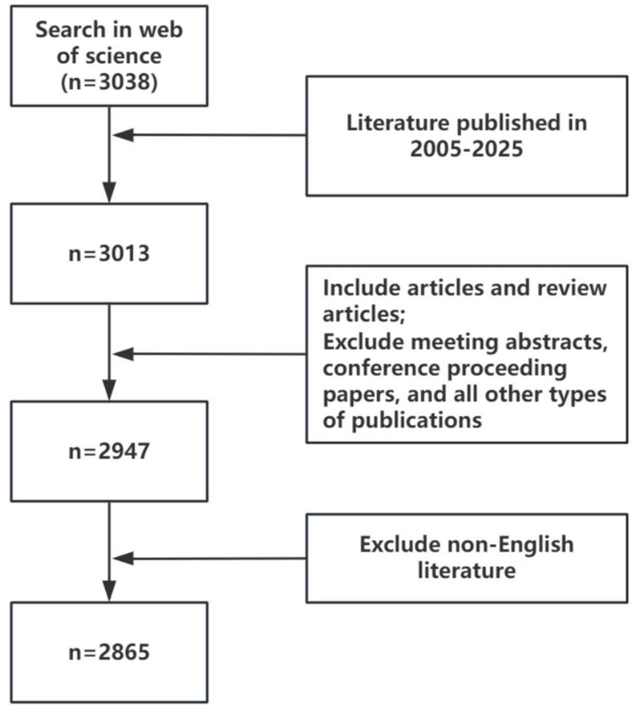

Fig. 1 Search process flowchart

Analytical tools

This bibliometric analysis utilized R software version 4.3.1 (with the Bibliometrix package), VOSviewer 1.6.19, and Citespace 6.4.R1 to examine collaboration networks among countries, institutions, and authors, analyze citation counts of papers and references, conduct co-occurrence and emergence analyses of keywords, perform cluster analysis of the included literature, and generate visualized maps.

Results

Using the Bibliometrix software package for analysis, the following results were obtained. This study encompassed a total of 464 publication sources, 2865 documents, with an average annual growth rate of publications at 10.74%. A total of 14,799 authors contributed to these documents, among whom 37 authored single-author papers. The international co-authorship ratio was 19.51%, and the average number of co-authors per document was 7.14. Additionally, there were 44,462 references cited, resulting in an average citation frequency of 20.14 per document. The number of published documents exhibited an overall increasing trend over time, reaching its peak in 2024, as illustrated in Fig. 2.

Annual publications

Country/Region

This study included a total of 84 countries or regions for analysis. Among the top ten countries in terms of publication output (as shown in Table 1), the United States, Italy, and China ranked first, second, and third, respectively. Specifically, the United States contributed 1,016 articles, accounting for 35.46% of the total; Italy published 467 articles, representing 16.3%; and China published 352 articles, comprising 12.29%. Regarding

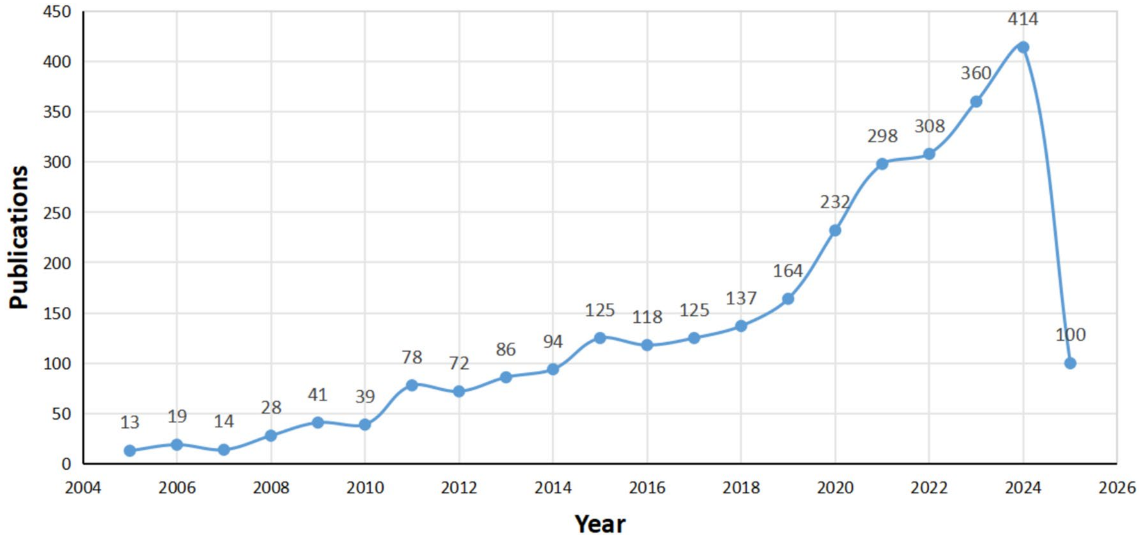

Fig. 2 Annual trend chart of published article volume

Table 1 Top 10 countries and institutions ranked by the number of published articles

Rank	Countries	Documents	Citations	Institutions	Documents	Citations
1	USA	1016	26,718	Yonsei University	70	2939
2	Italy	467	10,089	Cleveland Clinic	52	1760
3	China	352	4807	University of Illinois	49	1809
4	England	204	5517	Mayo Clinic	34	781
5	South Korea	190	5713	Catholic Sacred Heart University	34	551
6	France	186	3651	University of Pittsburgh	33	1332
7	Japan	181	1858	Sichuan University	30	410
8	Germany	138	2920	Korea University	27	984
9	Spain	102	1784	Saint Mary's Hospital Antwerp	27	784
10	Netherlands	98	2688	The Ohio State University	26	588

citation impact, the United States, Italy, and South Korea ranked first, second, and third, respectively. Overall, the United States demonstrated leadership not only in terms of publication volume but also in citation frequency, placing it at the forefront globally.

Figure 3A and 3B illustrates the distribution of co-authorship networks and citation networks across countries. As clearly evident from the figures, the United States exhibits highly robust collaborative ties with other nations and regions, occupying a central position within the global cooperation network. This underscores its leadership role and substantial influence in research areas pertinent to the subject matter.

Institutions

A total of 488 institutions contributed to the publication of these articles. Among the top ten institutions ranked by publication output (see Table 1), Yonsei University ranked first, accounting for 2.01% (n = 70) of the total publications. The Cleveland Clinic Foundation (n = 52) and the University of Illinois (n = 49) followed closely, ranking second and third, respectively. Notably, Yonsei University not only led in terms of publication volume but also demonstrated exceptional performance in citation frequency, establishing itself as an institution that excels in both publication and citation impact.

Figure 4A and 4B depicts the co-authorship and the citation networks among institutions. As illustrated in the figures, Yonsei University occupies a central position within the institutional collaboration network, forming robust collaborative ties with other institutions. This extensive collaborative capacity is one of the key factors contributing to its significant achievements in the research domain and provides substantial support for the efficient generation of high-quality publications.

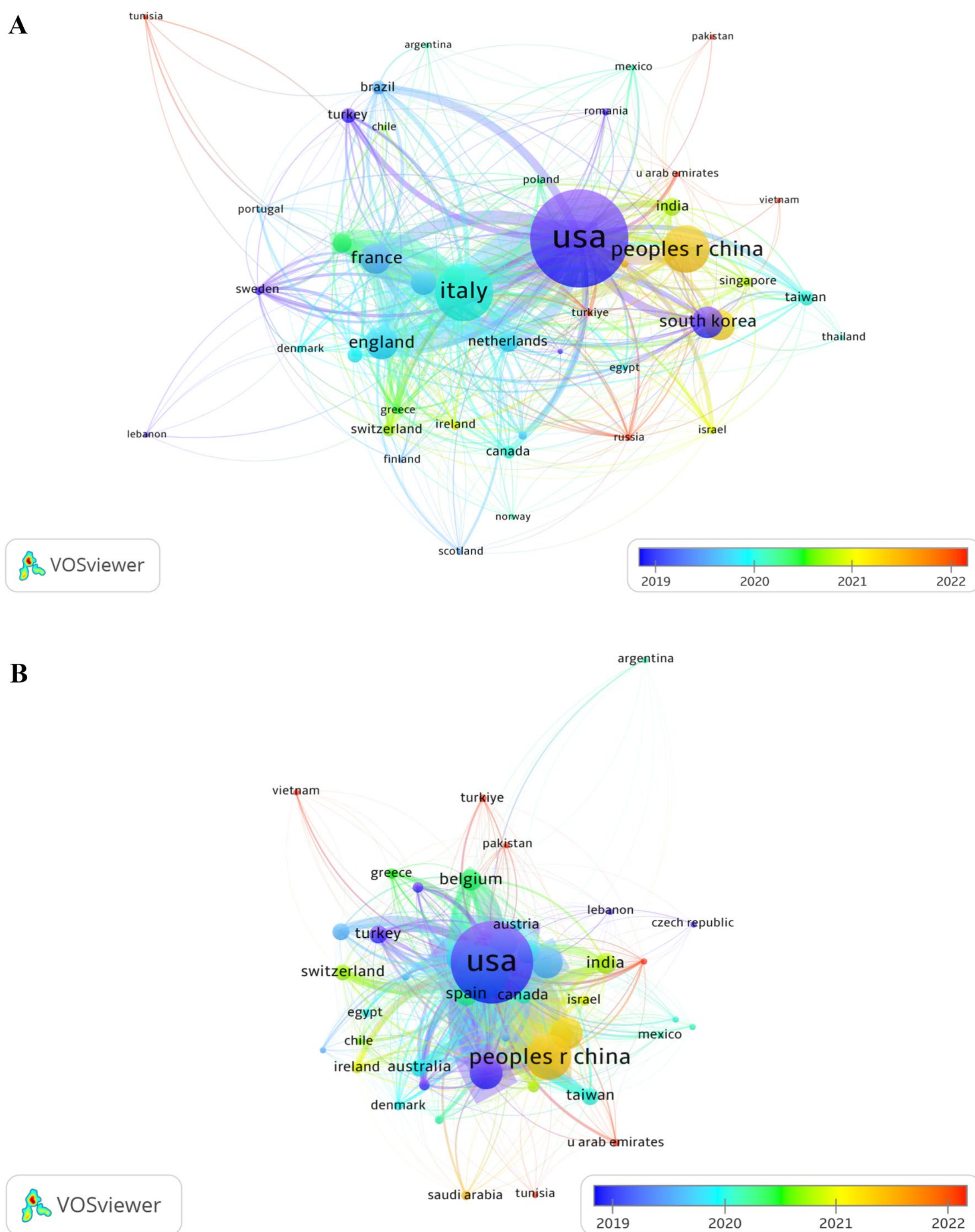

Fig. 3 **A** Network map of co-authored countries/regions, **B** Network map of citation countries/regions

Authors

A total of 278 authors contributed to the 3023 articles included in this study. Table 2 presents the top ten authors with the highest publication outputs. Among them, the three most prolific authors were Mottrie Alexandre (27 publications), Liu Rong (26 publications), and Coratti Andrea (20 publications). Notably, Gill Inderbir S demonstrated the highest citation frequency, with a total of 907 citations. This was closely followed by Dasgupta Prokar (870 citations)

Fig. 4 **A** Network map of co-authored institutions, **B** Network map of citation institutions

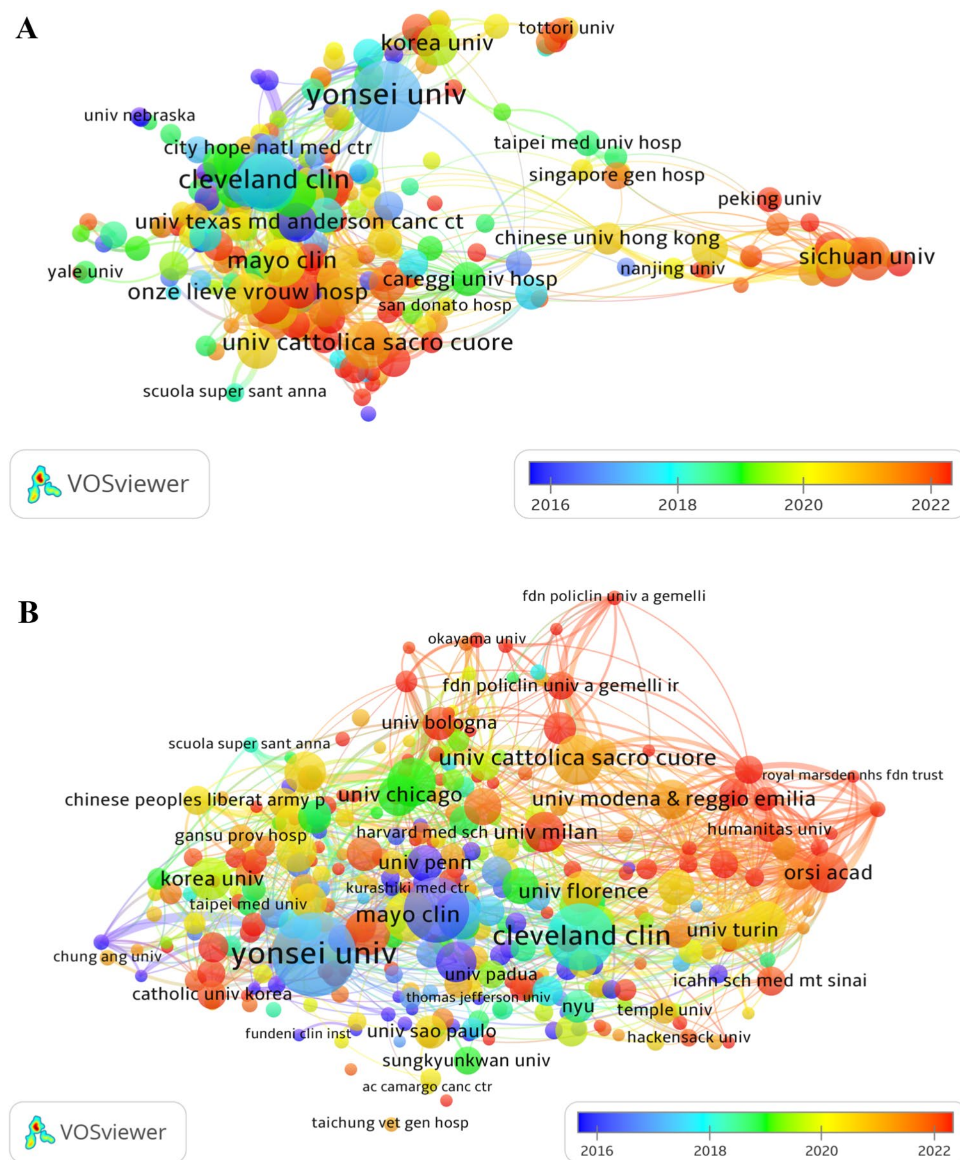

Table 2 Top 10 authors ranked by the number of published articles and citations

Rank	(Co-authored/Citation) Authors	Documents	Citations	Cited authors	Citations
1	Mottrie Alexandre	27	812	Dindo d	396
2	Liu Rong	26	472	Giulianotti Pc	376
3	Coratti Andrea	20	797	Park Js	245
4	Scambia Giovanni	20	378	Baik Sh	216
5	Hogg Melissa e	17	520	Clavien Pa	192
6	Dasgupta Prokar	16	870	d'Annibale a	188
7	Ceccarelli Graziano	15	412	Menon m	179
8	Gill Inderbir S	15	907	Bonjer Hj	163
9	Gundeti Mohan S	15	315	Jayne d	152
10	Kaouk Jihad	15	473	Ficarra v	142

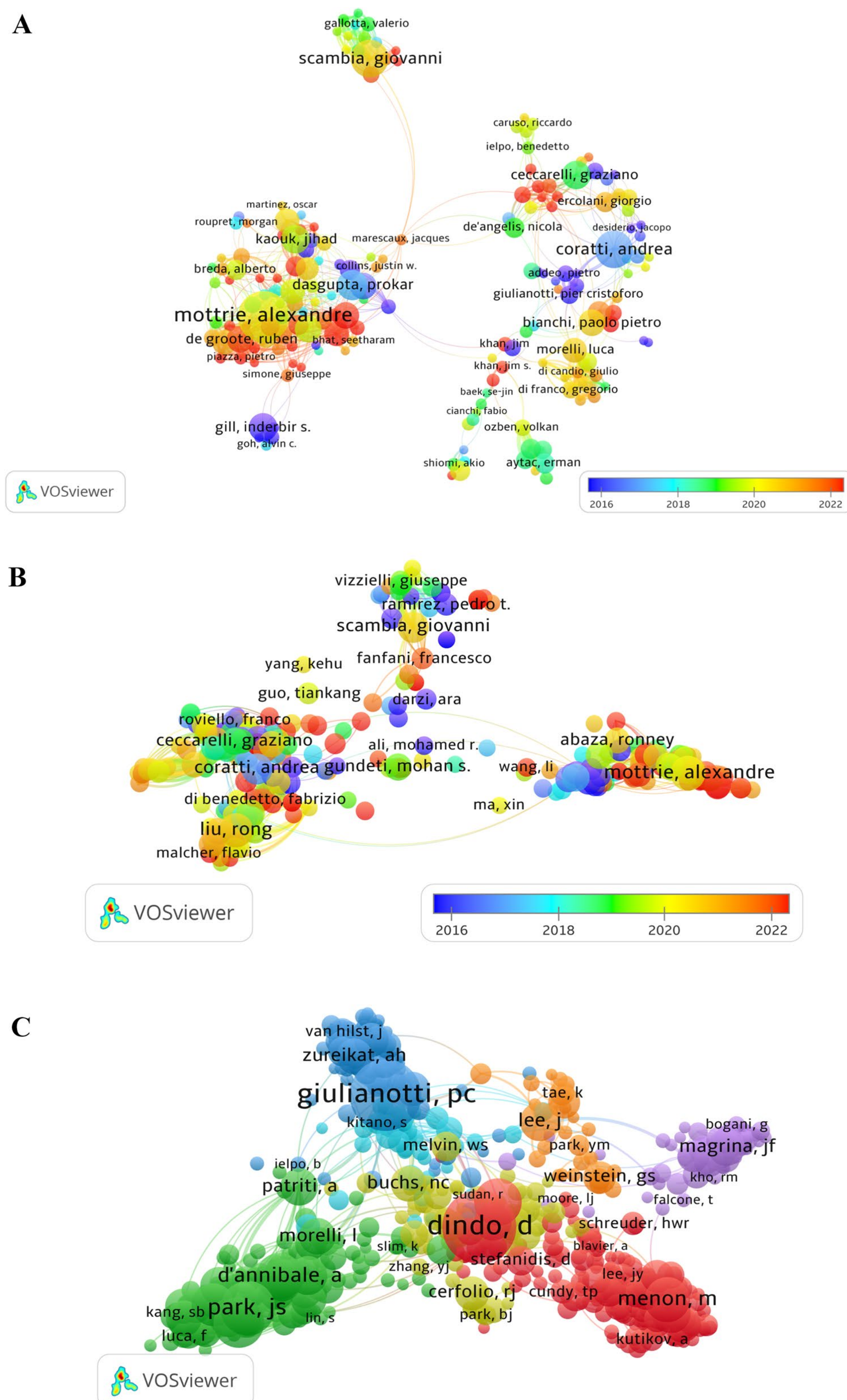

Fig. 5 **A** Network map of co-authored authors, **B** Network map of citation authors, **C** Network map of cited authors

and Hyung Woo Jin (860 citations). Figures 5A, 5B, and 5C depict the relationships among co-authors, citation contributors, and cited authors.

Sources

This study analyzed a total of 464 publication sources. Among these, the journal with the highest number of published articles was *Surgical Endoscopy and Other Interventional Techniques* (n = 241), followed by *Journal of Robotic Surgery* (n = 208) and *Asian Journal of Surgery* (n = 102). In terms of citation frequency, the top three journals were *Surgical Endoscopy and Other Interventional Techniques* (7972 citations), *European Urology* (4236 citations), and *Annals of Surgery* (1348 citations). Notably, *Surgical Endoscopy and Other Interventional Techniques* ranked first in total citations (7972 citations). Furthermore, *Journal of Robotic Surgery* exhibited the highest citation frequency among all journals, reaching a total of 8454 citations.

Figure 6A and 6B illustrates the network diagrams of citation sources and literature coupling sources, respectively. Furthermore, Table 3 presents a detailed overview of the top ten journals ranked by publication volume, including their respective publication counts and citation frequencies.

Keywords

Through the analysis of keyword co-occurrence networks, key research areas and emerging trends in the LC of RAS can be identified. Table 4 highlights the top 20 keywords ranked by their frequency of occurrence. Figure 7A presents a word cloud visualization for the top 50 keywords. After excluding terms directly associated with the core topic, such as"robotic surgery"and"learning curve", the high-frequency keywords primarily focus on topics including"outcome","experience","minimally invasive surgery","revision"and"laparoscopic surgery". Additionally, the table provides centrality measures for each keyword, reflecting its degree of association with other keywords. A higher centrality value indicates a closer relationship between the keyword and other research-related terms.

To systematically summarize the key themes and research hotspots in the LC of RAS, we conducted a cluster analysis of relevant keywords. This analysis provides researchers with a deeper understanding of critical issues and emerging trends in this field. As shown in Fig. 7B, the keywords were categorized into nine distinct clusters, forming a tightly interconnected network that demonstrates strong correlations among these terms. In recent years, the top five frequently occurring cluster keywords include"rectal cancer","en-y gastric bypass","transoral robotic surgery","spine surgery", and"endometrial cancer". These keywords reflect the primary focus areas of current research.

Keyword emergence analysis serves as a tool to identify keywords that have exhibited significant growth within a defined time period. This approach aids in elucidating the dynamic trends of research focal areas and frontier subjects, while also enabling the prediction of potential future research trajectories. According to the evaluation of emergence intensity, the five keywords with the highest emergence scores in the field of RAS LC research are “laparoscopic radical prostatectomy”(11.44), “total mesorectal excision”(10.24), “da vinci”(9.47), “prostatectomy”(9.25), and “mrc clasicc trial”(9.08). The values in parentheses denote the degree of emergence intensity. For additional information, please consult Fig. 7C.

Cited references

The prominence of cited references indicates that the referenced literature has attracted substantial attention from researchers during a defined period and may signify an emerging research focus or frontier. This study highlights the top 25 articles with the highest citation prominence associated with the LC in RAS. Among these, the article authored by Jayne D [20], published in *JAMA-J AM MED ASSOC* in 2017, demonstrates the strongest prominence (Strength = 34.85). Closely following are the works by Sheetz KH (Strength = 24.66) and Page MJ (Strength = 22.9) [21, 22]. For additional details, see Fig. 8. Jayne D et al. conducted a randomized clinical trial named ROLARR, concluding that for patients with rectal adenocarcinoma suitable for radical resection, robot-assisted laparoscopic surgery did not significantly reduce the risk of conversion to open surgery compared to traditional laparoscopic techniques. Furthermore, Sheetz KH et al., through a cohort analysis involving data from 169,404 patients across 73 hospitals, observed that between 2012 and 2018, the proportion of robot-assisted surgeries (RASs) among all general surgical procedures increased from 1.8% to 15.1%. In institutions implementing RAS programs, there was a rapid and widespread growth in its adoption, which coincided with a decline in the usage rate of conventional laparoscopic minimally invasive surgery.

Discussion

The development of proficiency in RAS adheres to a LC characterized by distinct phases. Surgeons typically undergo a phase of rapid skill acquisition during the initial 20–30 procedures; however, as their expertise accumulates, the pace of improvement gradually diminishes and stabilizes [23–27]. It is worth noting that there are significant disparities in both the duration and steepness of LCs across various

Fig. 6 **A** Network map of citation sources, **B** Network map of bibliographic coupling sources, **C** Network map of cited sources

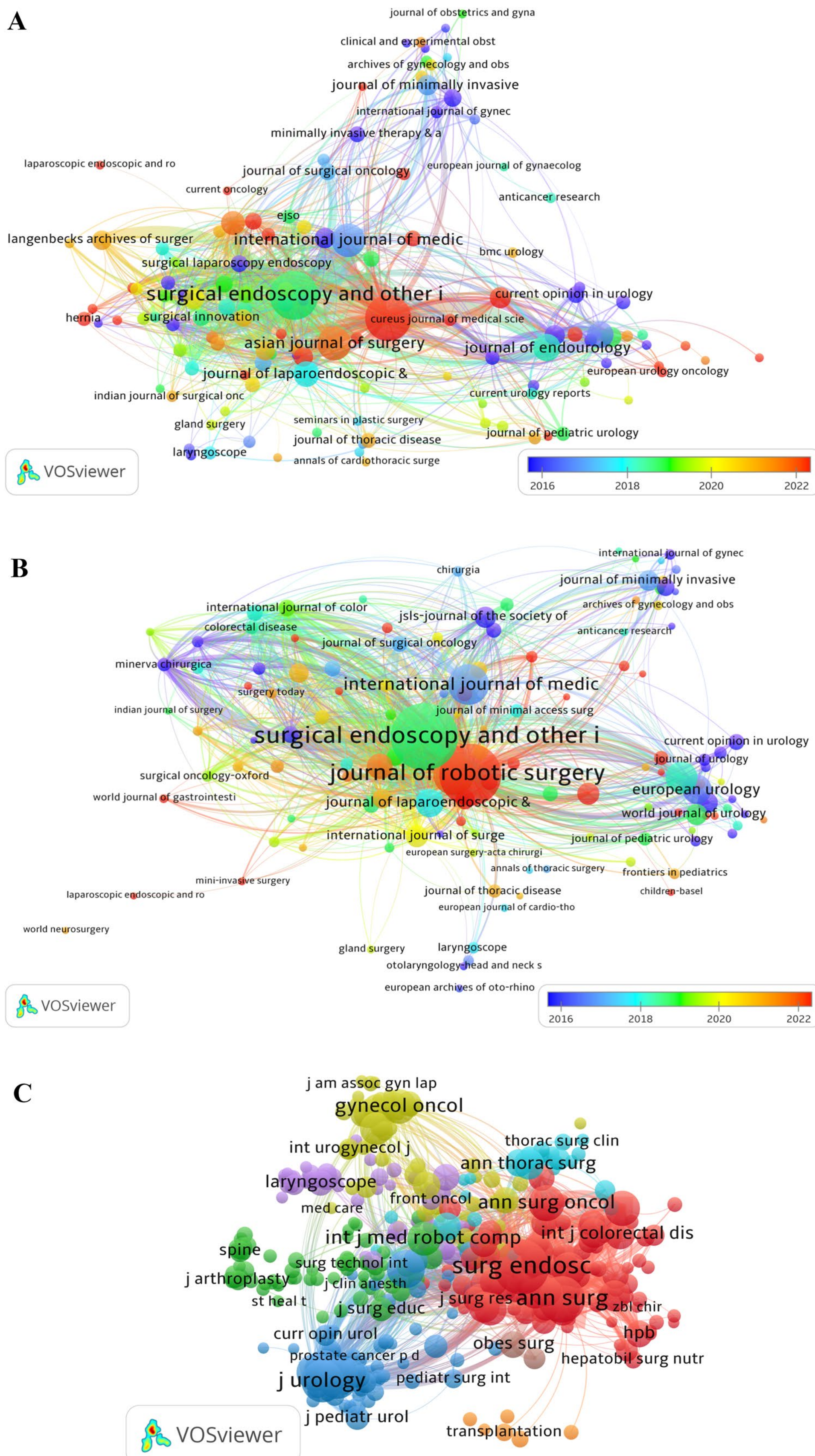

Table 3 Top 10 sources ranked by the number of documents and citations

Rank	Sources	Documents	Citations	Cited sources	Citations
1	Surgical Endoscopy And Other Interventional Techniques	241	7972	Surgical Endoscopy and Other Interventional Techniques	8454
2	Journal Of Robotic Surgery	208	1579	Surgical Endoscopy and Other Interventional Techniques	4308
3	Asian Journal Of Surgery	102	973	The Journal of Urology	3020
4	International Journal Of Medical Robotics And Computer Assisted Surgery	102	1728	The Journal of Urology	2729
5	Journal Of Endourology	66	1348	The Journal of Urology	2015
6	European Urology	59	4236	Urology	1958
7	Journal Of Laparoendoscopic & Advanced Surgical Techniques	55	970	Journal of Endourology	1953
8	Updates In Surgery	45	490	British Journal of Urology International	1734
9	Journal Of Clinical Medicine	36	289	British Journal of Urology International	1637
10	International Journal Of Surgery	35	505	British Journal of Urology International	1482

Table 4 Top 20 keywords with the highest frequency of occurrence

Rank	Keywords	Frequency	Centrality	Rank	Keywords	Frequency	Centrality
1	Robotic surgery	1483	0.03	11	cancer	224	0.04
2	Surgery	571	0.05	12	rectal cancer	214	0.01
3	Learning curve	553	0.05	13	total mesorectal excision	188	0.03
4	Outcome	518	0.03	14	robot-assisted surgery	156	0.06
5	Experience	373	0.04	15	management	154	0.07
6	Minimally invasive surgery	313	0.07	16	meta-analysis	147	0.02
7	Resection	285	0.05	17	impact	131	0.04
8	Learning curve	269	0.12	18	colorectal surgery	122	0.01
9	Laparoscopic surgery	259	0.04	19	short-term outcome	113	0.02
10	Complications	245	0.03	20	radical prostatectomy	108	0.04

surgical techniques. Complex surgeries often necessitate longer durations and larger case volumes to attain mastery [28–33]. Moreover, pivotal milestones, such as the initial attainment of skills, notable improvements in efficiency, and reductions in complication rates, provide essential reference points for the evaluation and enhancement of surgical training programs [34, 35].

Comparison of robotic platforms and cost considerations

A range of robotic systems serve as alternatives to the da Vinci platform, each offering unique trade-offs in terms of cost and performance [36]. The Hugo RAS system features modular designs tailored for soft tissue surgeries, achieving a 45–60% reduction in costs compared to conventional options [37]. In contrast, the Toumai system emphasizes high cost-effectiveness for single-port and multi-port surgeries, making it particularly suitable for resource-limited regions [38, 39]. The Versius system underscores its portability and lower consumable expenses, addressing general surgical requirements [40, 41]. Furthermore, the Senhance system incorporates cutting-edge technologies, such as haptic feedback and eye-tracking, facilitating hybrid laparoscopic–robotic procedures [42]. While these emerging platforms exhibit comparable efficacy in standard surgeries, they still lag behind the da Vinci system in handling complex cases [43]. Training costs and learning curves vary considerably across systems. Nevertheless, the integration of virtual reality (VR)-based training has demonstrated potential in reducing these expenditures. Long-term benefits of these robotic systems include decreased complication rates and shorter hospital stays, ultimately contributing to overall cost efficiency [44–48].

Key determinants shaping the LC in RAS

Surgical category: The characteristics of surgical procedures, encompassing anatomical regions and procedural complexity, exert a substantial influence on

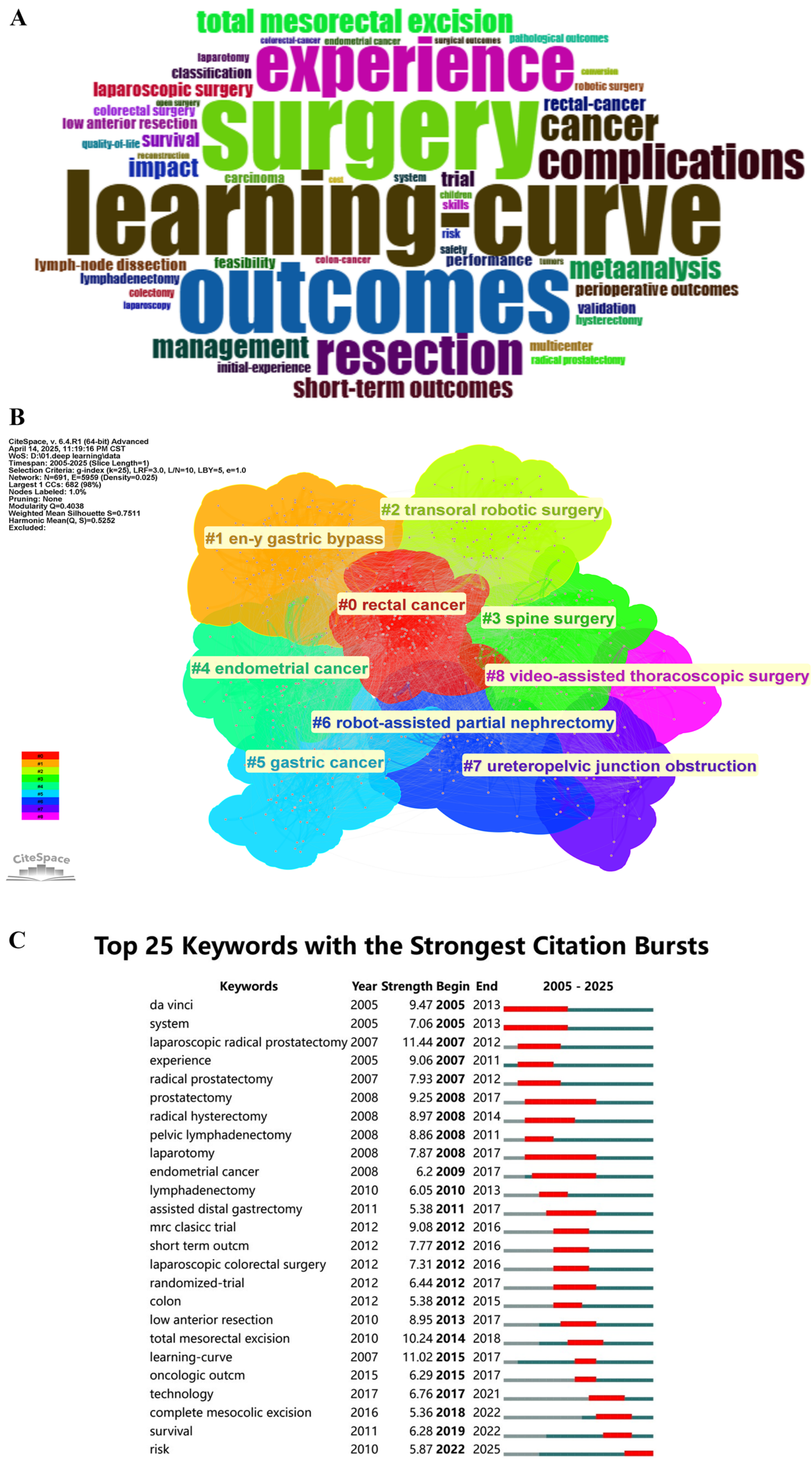

Fig. 7 **A** Word cloud of the top 50 most frequently keywords, **B** Network map of keyword clustering analysis, **C** Top 25 keywords with the strongest citation bursts

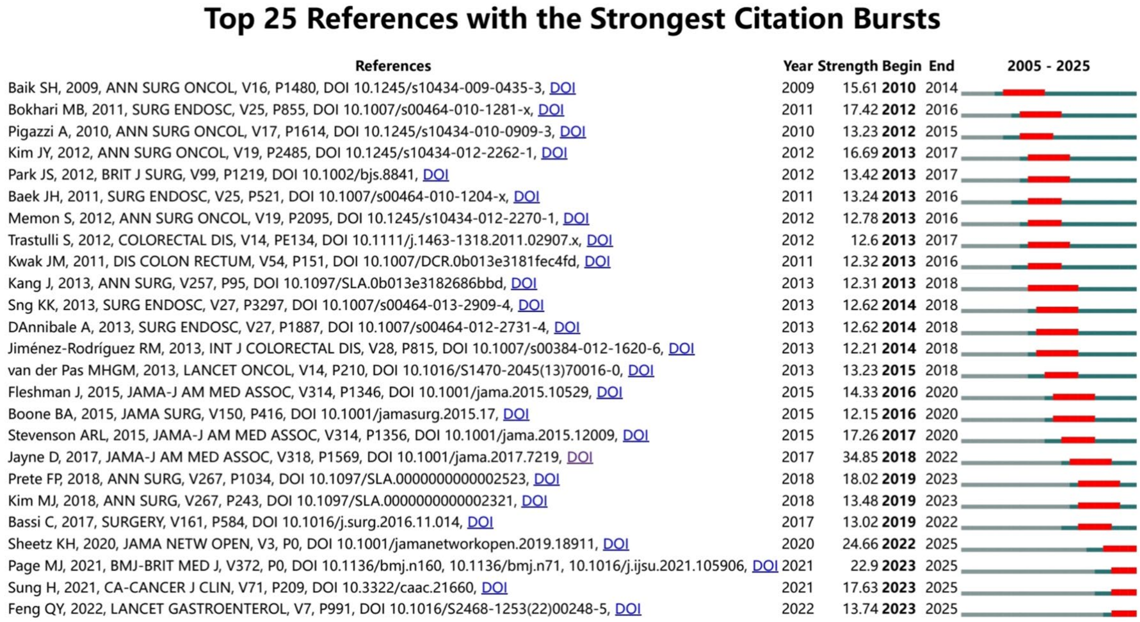

Fig. 8 Top 25 references with the strongest citation bursts

the LC. For instance, well-developed RASs, such as radical prostatectomies in urology and hysterectomies in gynecology, typically exhibit shorter LCs and are relatively easier to master [49, 50]. Conversely, highly complex surgeries, including cardiothoracic and head and neck procedures, are associated with steeper LCs and pose greater challenges for surgeons [51, 52].

Surgeon background: A surgeon's previous exposure to traditional open surgeries and minimally invasive laparoscopic techniques significantly impacts their ability to adapt to RAS [53]. Surgeons with extensive prior experience can more swiftly acclimate to the new methodologies, thereby effectively shortening the learning process [54].

Training approach: Comprehensive training frameworks, including structured courses, virtual simulation exercises, and mentorship from seasoned professionals, play a pivotal role in optimizing the LC [55, 56]. Simulation-based training is particularly beneficial, providing surgeons with repeated opportunities for practice to enhance technical proficiency and address a variety of surgical scenarios, thus accelerating skill development [57].

Hotspots and trends

Through bibliometric analysis, it has been identified that recent research emphases on the LC in RAS predominantly revolve around key domains, including surgical outcomes, surgical experience, minimally invasive approaches, revision surgeries, and laparoscopic techniques. With ongoing technological advancements and expanding clinical applications, future research is anticipated to progressively shift toward multi-center studies with larger cohorts. Furthermore, such investigations are expected to incorporate cutting-edge technologies, such as artificial intelligence and big data analytics, to optimize the LC and improve overall surgical efficacy [58, 59].

The importance and relevance of the research

Defining the characteristics and pivotal milestones of the LC in RASs can improve the design of surgical training programs and enhance the precision of assessment standards. Acknowledging the factors that shape this LC facilitates the development of customized training frameworks and optimizes the allocation of resources. Evaluating the LC contributes to more effective clinical scheduling, enhances the quality of surgical procedures, and ensures greater patient safety. This research establishes a robust theoretical basis and provides substantial empirical support for the advancement of RAS, thereby propelling the growth of the discipline. The utilization of bibliometric methods offers novel perspectives for medical research and promotes a more rigorous and systematic approach to scientific inquiry.

Research limitations

The majority of existing studies rely on single-center retrospective data, with a notable lack of multi-center prospective controlled trials to confirm the generalizability of the LC in RAS [60–62]. Approximately 40% of the literature does not adequately address the potential impact of case complexity on LC assessments, which may undermine the comprehensiveness and accuracy of the findings. Moreover, the bibliometric approach has limitations in deeply exploring the underlying mechanisms of the LC, as its focus is predominantly centered on RAS without fully examining its associations with patient outcomes and healthcare costs.

For instance, advanced surgical robots, such as the Versius system and ExcelsiusGPS222, have introduced innovative features like enhanced tactile feedback [63, 64]. These technological advancements are expected to significantly reshape the characteristics of the LC; however, research in this area remains insufficient [65, 66].

A visual analysis of the literature indicates that only 15% of studies explore the design of structured training pathways [67]. To enhance future efforts, it is crucial to develop a tiered training framework that integrates simulation-based exercises, clinical supervision, and competency certification [68, 69]. Furthermore, an artificial intelligence-powered real-time skill evaluation system should be developed to further improve training effectiveness and surgical quality [70, 71].

The data sources for this study may be subject to publication bias, potentially influencing the completeness and precision of the results. Additionally, the bibliometric method inherently has constraints in thoroughly analyzing the LC mechanism. Simultaneously, the current research scope primarily focuses on the LC of RAS, lacking a comprehensive investigation into its relationships with factors affecting patient outcomes and medical expenses.

Potential areas for future research

Integrating multidisciplinary perspectives to investigate the formation mechanisms and influencing factors of the LC in RAS, such as psychological assessments of surgeons'cognitive and emotional changes, as well as engineering improvements in surgical robot design [72]. Conduct personalized analyses of LCs by utilizing big data and machine learning methodologies to predict surgeons'skill progression and provide customized training suggestions [73]. Carry out long-term follow-up studies to evaluate surgical outcomes and professional development after the stabilization of the LC. Perform cost–benefit analyses to examine economic and social benefits at different stages, thereby supporting decision-makers [74, 75]. Foster the rational application and sustainable evolution of robot-assisted surgical techniques.

Recommendations for training programs

Through a comprehensive review of the literature discussed in this paper, several key recommendations are proposed to refine and enhance the robot-assisted surgery training program. The program's efficacy can be strengthened by implementing individualized training plans, advanced simulation-based exercises, structured mentorship frameworks, proficiency-driven assessment protocols, and strategic resource management [76–78]. Additionally, training content can be customized according to specific surgical specialties and trainee backgrounds through the integration of virtual reality simulations, phased mentorship interventions, objective performance evaluation metrics, and standardized curriculum design principles [79–82]. These strategies collectively aim to shorten the learning curve, improve the safety and efficiency of surgical procedures, and provide a robust foundation for future research endeavors.

Conclusion

Research on the LC in RASs holds considerable theoretical and practical importance. Through in-depth analysis and optimization of the LC, the quality of surgical training can be enhanced, clinical proficiency can be improved, and the development of the discipline can be promoted. However, current studies still encounter specific limitations. Looking ahead, it will be crucial to extend the research scope and innovate research methodologies to better address the challenges and seize the opportunities within the field of RASs.

Author contributions XZ: Conceptualised the study, led the research design, and was the principal investigator. XZ, JW, LC: Contributed signifcantly to the data collection and analysis, and played critical roles in interpreting the results. XZ, JW: Drafted the manuscript. HD: Reviewed the literature and revised the manuscript critically. XZ: Contributed to the study's methodology development and performed the statistical analysis. All authors approved the final version of the manuscript to be published. Each author agreed to be accountable for all aspects of the work, ensuring that questions related to the accuracy or integrity of any part of the work were appro-priately investigated and resolved.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no competing interests.

Human ethics and consent to participate declarations Not applicable.

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