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Towards clinical implementation of artificial intelligence in cancer care: Concept mapping analysis of provincial workshop findings

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ABSTRACT

Background: Artificial intelligence (AI) has rapidly garnered interest in healthcare, with research showing promise to improve quality, efficiency, and outcomes. Cancer care's multidisciplinary nature and high coordination demands are well positioned to benefit from AI. While attitudes in the uptake of evidence and toward the implementation of AI in medicine has been explored generally, literature remains scarce with specific regards to AI in cancer care. This study sought to understand how perspectives of both patients and professionals are essential for guiding responsible, effective implementation of evidence-based (EB) AI in cancer care.

Methods: We conducted a workshop at the 2024 British Columbia (BC) Cancer Summit (Vancouver, Canada). Discussions addressed three guiding questions: concerns, benefits, and priorities for AI in cancer care. Responses from 48 workshop participants (patients and families, AI/computer science/cancer researchers, clinicians and allied health professionals, information technology professionals, healthcare administrators) underwent structured conceptualization by concept mapping, leveraging multidimensional scaling and hierarchical cluster and subcluster analysis to produce visual and quantitative maps of stakeholder priorities.

Results: A total of 265 statements on perceived benefits, concerns, and priorities related to the implementation of AI in cancer care were generated from the workshop and underwent concept mapping. Two clusters were identified; Cluster 1 focused on “Challenges and Safeguards for AI Implementation,” and Cluster 2 focused on “Clinical Benefits and Efficiency Gains.” Subcluster analysis distinguished 8 thematic subclusters (4 per cluster). Both mean importance ($P < .001$) and feasibility ($P < .001$) ratings were significantly higher for Cluster 2. No differences were found between ratings by clinical and nonclinical professionals. Further go-zone analysis classified statements according to their relative superiority/inferiority in importance and feasibility compared to the overall average.

Conclusions: Stakeholder ratings were higher for statements describing clinical benefits and efficiency gains than for those describing challenges and safeguards for AI implementation in cancer care. Concept mapping analysis distinguished between workflow-aligned AI applications, perceived as ready for implementation, and system-level governance requirements requiring longer-term investment. Present findings provide a structured, stakeholder-informed framework for prioritizing and sequencing AI implementation efforts in cancer care, constituting a practical blueprint to catalyze meaningful progress.

MAIN MANUSCRIPT TEXT

BACKGROUND

Artificial intelligence (AI) may be best understood as the emulation of human intelligence and cognitive processes by computer systems[1]. Recently, AI technologies have been undergoing rapid and substantial growth, sparking major enhancements across systems and processes of virtually all industries[2,3]. In healthcare, AI likewise holds a prominent and promising role that has the potential to drastically improve care[4,5]. Virtually every medical specialty has been seeking to harness the benefits of AI in their practices, as seen by an ever-growing body of AI-related literature in recent times[6–9].

Oncology, the field dedicated to the care of patients affected by cancer, is a discipline marked by a high degree of interdisciplinary collaboration, coordination, and disease complexity. Indeed, specialties involved in cancer care include, but are not limited to, medical oncology, radiation oncology, surgical oncology, and supportive care. This is not to mention the various allied health professionals who are equally crucial members of oncologic care teams. Coordination between these parties is required to cater to patients suffering from cancer, who experience suffering not only at the physical level, but also psychosocially, often rippling into their families and surroundings. Given the complex, multidisciplinary care required to optimize patient outcomes in oncology, it may uniquely benefit from modern AI technologies.

A key aspect in the implementation of new paradigms and translation of new evidence (e.g. evidence-based [EB] AI) is to evaluate stakeholders' attitudes[10–12] and ascertain the acceptability and satisfaction[13–14] of the latest research findings about new services and technologies among all stakeholders including payers, providers and patients[15]. In the context of EB innovations and implementation, stakeholders are not limited to clinical end-users: they also include the knowledge creators (i.e. AI engineers) and AI knowledge brokers (implementation scientists)[16,17]. Adequate attention to the attitudes of all stakeholders has been shown to facilitate collaboration[16,17]. Conciliatory attitudes towards EB innovation and its resulting stakeholder participation should be encouraged, and be continued throughout the entire stages of research and implementation: such as in co-identification of AI research agenda, collaboration in research conduct and co-creation of new AI knowledge, and finally in co-selection of implementation strategies and implementation outcome indicators[16]. Otherwise, mere awareness of the latest worldwide research findings on cancer or other disease risk factors[18–19] and treatments[20], or even knowledge of locally grown and hence relevant science, has historically not automatically translated to knowledge uptake and the consequent meaningful improvements in healthcare, health or human development[21,22]. At best, it has caused fractional uptake after considerable translation delays exceeding a decade[23,24]. Past research, drawing on normalization process theory in implementation science, has demonstrated that conciliatory attitudes toward EB innovations, and hence improved evidence uptake, could occur through many means, including advanced participatory research powered by modern technologies[25], such as AI itself[26]. However, it is argued that collaboration in implementation research could also take place through the use of less fashionable methods, such as past research on the impact of asynchronous telemedicine to improve service demand by patients or to improve uptake by care suppliers of innovative computerized systems[20,27,28].

In this regard, scarce but otherwise valuable work has emerged which looks at patient and healthcare professionals' attitudes towards AI in medicine at large[29–34]. Yet, there lacks a dedicated effort specific to oncology to account for the field's unique intricacies, with one review study looking at patient attitudes toward AI in cancer care[35]. In this context, our group sought to conduct a participatory, collaborative and multi-step study of the attitudes of AI stakeholders, including AI engineers and developers as well as cancer patients and health professionals alike. In doing so, we focused on the implementation of AI tools and technologies in cancer care. Our project consisted of an interactive and collaborative workshop at a provincial cancer summit, followed by a mixed-method participatory data collection and analysis through concept mapping. The objective of the study was to provide insight into the entire stakeholders' and beneficiaries' perceived benefits, concerns, and priorities regarding the implementation of AI in cancer care. The goal of the study was to inform research priorities and guide future work on the selection of best AI implementation strategies and AI implementation outcome measures according to the needs of the cancer community.

METHODS

Study Context: BC Cancer Summit Workshop

The BC Cancer Summit is an annual oncology event in the Canadian province of British Columbia. It is hosted by BC Cancer, the province's comprehensive cancer control program, providing education, professional development, and relationship-building opportunities for oncology professionals from all cancer disciplines, in addition to patients, family members, community providers, researchers, and members of non-profit organizations[36,37]. On November 21, 2024, our team held an in-person workshop at the Summit, entitled "How Do You Want Predictive Artificial Intelligence Tools to Be Deployed at BC Cancer? An Interactive Session." The workshop addressed 3 guiding questions: (1) concerns regarding the integration of AI into cancer care, (2) perceived benefits of AI, and (3) priorities for AI implementation and research. The session combined a brief overview of relevant AI applications with small-group discussions, structured prioritization exercises, and a closing plenary to synthesize key themes.

Participants

Conduction of study activities was approved by the University of British Columbia (UBC) Research Ethics Board (H24–03306). The workshop was attended by 48 participants who consented to the collection of data for research purposes; this was almost all participants, besides a few who were intermittently present. The participants included patients with cancer, family members, AI and computer science researchers, cancer researchers, oncology specialists, family physicians, other allied health clinicians, information technology professionals, and individuals in administrative or leadership positions within the healthcare system. Further demographic information was not available due to the nature of integrating data collection into this summit event. For the purpose of this concept mapping study, workshop participants assumed the brainstorming part. As for the sorting and rating parts of concept mapping, an expert panel of 13 members was recruited through purposive sampling to ensure representation across key domains relevant to AI implementation in cancer care. Panel members were chosen to form a representative group on the topic of interest (i.e. AI in cancer care). All panel members were affiliated with academic or healthcare institutions, stemming from various and diverse backgrounds spanning clinical cancer patient care, implementation science, computer science, and health system administration. All participants (n = 13, 100%) were involved in cancer research. Of these, 31% (n = 4) had specific expertise in AI research and development, 54% (n = 7) were clinicians, 8% (n = 1) were health administrators and patient-experts each. The clinical participants had backgrounds spanning medical oncology, radiation oncology, primary care, nursing, cancer psychiatry, and cancer dietetics, ensuring comprehensive representation across cancer care specialties. All 13 experts provided valid sorts and ratings of importance and feasibility of concept mapping statements. For subgroup analysis purposes, participants were categorized as clinical (n = 7, 54%) or non-clinical (n = 6, 46%) based on their primary role. Clinical participants included those with direct patient care responsibilities across various cancer care specialties.

Concept Mapping Procedure

Concept mapping is a structured mixed-methods approach that integrates participant-generated ideas with quantitative multivariate analyses to produce interpretable visual representations of conceptual domains. It has been widely applied in healthcare and implementation research to organize stakeholder perspectives and inform planning[38–43]. In this study, concept mapping was performed following Trochim's sequential 6-stage framework: (1) preparation, (2) generation, (3) organization, (4) representation, (5) interpretation, and (6) utilization[39].

The first 2 stages, preparation and generation, were accomplished through the workshop, where statements pertaining to the implementation of AI in cancer care were generated by participants. Generated statements were subsequently deduplicated, order-randomized, and rephrased, after which they were subject to sorting and rating (stage 3). The 13-member panel performed sorting and rating on Qualtrics XM (Qualtrics LLC, Provo, UT, USA). Sorting involved grouping all statements into arbitrary groups "in a way that makes sense to [the person performing the sorting task]"[40]. Rating was done for each individual statement using a 5-point Likert scale for (1) importance and (2) feasibility[40]. Importance was rated on a scale from 1 (relatively unimportant) to 5 (extremely important), relative to other statements. Feasibility was defined as how easy it will be to implement a priority, actualize a benefit, or address a concern, rated on a scale from 1 (relatively unfeasible) to 5 (extremely feasible), relative to other statements. All operations, including statement processing and panel selection, were performed following established concept mapping documentation and literature to ensure validity[38-40,44-46].

Analysis

Importance and feasibility ratings were verified for completeness and organized into matrices for analysis. Multidimensional scaling (MDS) was applied to generate a two-dimensional representation of the statements. A co-occurrence matrix was constructed from participant sorting data by counting how frequently each pair of statements was sorted into the same pile across all participants, normalized by the number of participants. This co-occurrence matrix was converted to a distance matrix, and MDS was applied using a precomputed dissimilarity matrix with a random seed for reproducibility. This approach follows established concept mapping methodology where statement proximity reflects how often participants grouped statements together during the sorting phase[39]. Stress values were computed to evaluate the goodness-of-fit, with lower values indicating a more accurate representation of the original high–dimensional distances.

Hierarchical cluster analysis was performed on the MDS coordinates using Ward's method, which iteratively merges clusters to minimize within-cluster variance. Ward's method was selected for its ability to produce compact, interpretable clusters, which is particularly suitable for concept mapping where clear conceptual groupings are essential. The optimal number of clusters was determined using silhouette analysis and the elbow method, which examines cluster cohesion and separation to identify the most meaningful solution. Consistent with literature recommendations, clusters were labelled through a conceptual interpretive approach utilizing iterative review of statement content, mean ratings, and thematic density[47].

A secondary hierarchical cluster analysis was performed to identify subclusters within main clusters. This allows for further fine-grained conceptual distinctions. Subclustering was performed separately within each main cluster using Ward's method on the MDS coordinates of statements belonging to that cluster. The optimal number of subclusters was determined through visual inspection of dendrograms and consideration of conceptual coherence, resulting in 4 subclusters within each main cluster. Subclusters were labeled using the same interpretive approach and according to their position within the hierarchical structure (e.g. Subcluster 1.1, 1.2, 1.3, 1.4 within Cluster 1, and Subcluster 2.1, 2.2, 2.3, 2.4 within Cluster 2).

Likert ratings of importance and feasibility were analyzed at the statement, cluster, and subcluster levels. For individual statements, mean importance and feasibility scores, standard deviations, and response counts were calculated, and gap analyses were performed by subtracting feasibility from importance ratings. At the cluster level, aggregated means were computed, clusters were compared, and strategic priorities were identified based on observed patterns in importance and feasibility. At the subcluster level, mean importance and feasibility ratings were calculated for each of the 8 subclusters, enabling more nuanced comparisons of strategic priorities within the broader cluster structure. Pattern match analysis was conducted to examine the relationship between importance and feasibility ratings across subclusters, revealing distinct patterns that inform implementation strategies. Finally, we conducted subgroup analysis, comparing importance and feasibility ratings between clinical and nonclinical participants at both the cluster and subcluster levels. Comparative analyses were performed using the Mann–Whitney U test and Student's t-test with Cohen's d for effect size. Statistical significance was determined with *P* values less than .05.

Strategic prioritization was performed using a go-zone analysis framework, which maps subclusters into 4 quadrants based on their mean importance and feasibility ratings relative to overall means. This approach enables identification of: (1) priority subclusters (high importance, high feasibility) representing immediate implementation opportunities; (2) strategic subclusters (high importance, low feasibility) requiring research and development investment; (3) quick wins (low importance, high feasibility) suitable for rapid implementation; and (4) low priority subclusters (low importance, low feasibility) that may be deferred. The subcluster-level go-zone analysis provides more actionable insights than statement-level analysis by grouping related concepts and reducing complexity while maintaining granularity.

The analysis was implemented in Python (version 3.12, Python Software Foundation, Wilmington, DE), adapting the concept mapping methodology from Bar & Mentch[47] for Python implementation. The code and scripts used for this analysis are publicly available on GitHub (https://github.com/chhaviiiii/concept_mapping).

RESULTS

Workshop Outcomes

Following the 2-hour workshop, 48 participants together contributed to generating a total of 265 statements on the implementation of AI in cancer care. Of these, 87 statements (32.8%) pertained to concerns, 72 (27.2%) pertained to perceived benefits, and 106 (40.0%) pertained to research priority, with respect to the 3 workshop discussion questions.

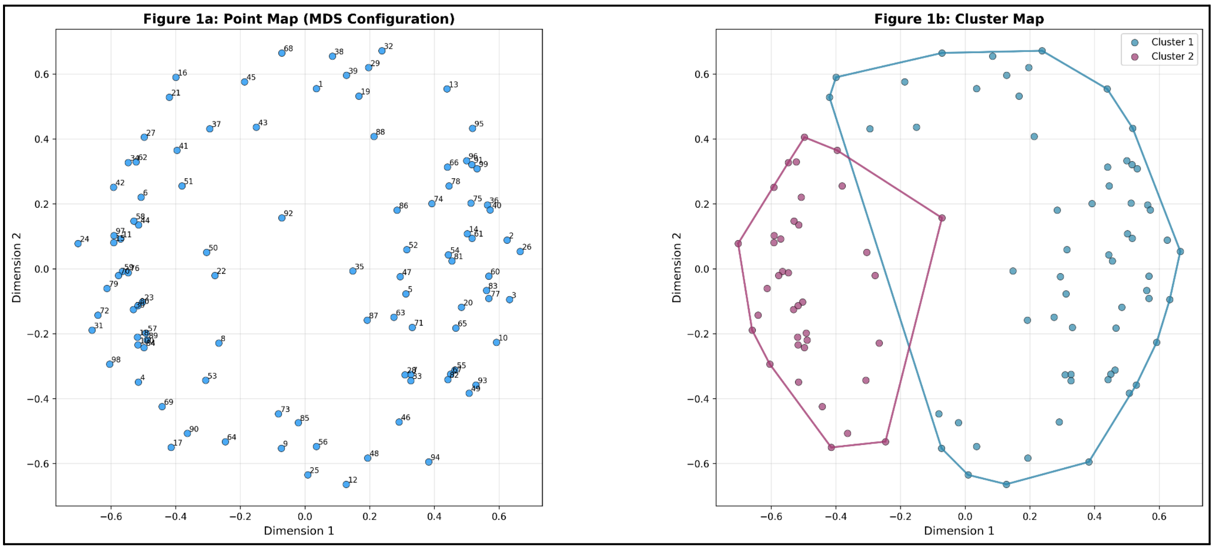
Concept Mapping – Statements

Following statement processing, a final list of 100 statements was obtained. The 13-member expert panel then sorted and rated these statements based on importance and feasibility for concept mapping. The panelists sorted the card statements into an average of 5 piles (mean = 5.0; SD = 2.4; range = 2–9). Furthermore, participants necessitated on average 42.8 minutes to complete both the statement sorting and rating tasks related to concept mapping (mean = 42.8 min; SD = 19.8 min; range = 14.6–71.7 min). **Table 1** displays the final list of statements and their associated mean importance and feasibility ratings.

Concept Mapping – Visual Outputs

Results from statement sorting were subject to nonmetric MDS analysis, yielding a spatial representation of statements where statements grouped together the most often are located more proximately, while those grouped together less frequently are further apart, as shown in **Figure 1a**. The statements are numbered to aid in cross-referencing the spatial relationships of the points on the map with their labels enumerated in **Table 1**. The MDS analysis was performed using co-occurrence data from participant sorting, where statement proximity reflects how frequently statements were grouped together by participants. This approach ensures that spatial relationships represent conceptual similarity rather than rating similarity, providing a more authentic representation of how participants perceive the relationships between AI implementation concepts. Two statistically optimal clusters were identified using Ward's hierarchical clustering, validated through silhouette analysis, elbow method, and gap statistic evaluation (**Figure 1b**). Cluster 1 contained 62 statements (62%) and Cluster 2 contained 38 statements (38%). The cluster boundaries showed clear spatial separation and internal cohesion, with statements within each cluster located proximally in the MDS space. Cluster 1 was labelled as "Challenges and Safeguards for AI Implementation," whereas Cluster 2 was labelled as "Clinical Benefits and Efficiency Gains."

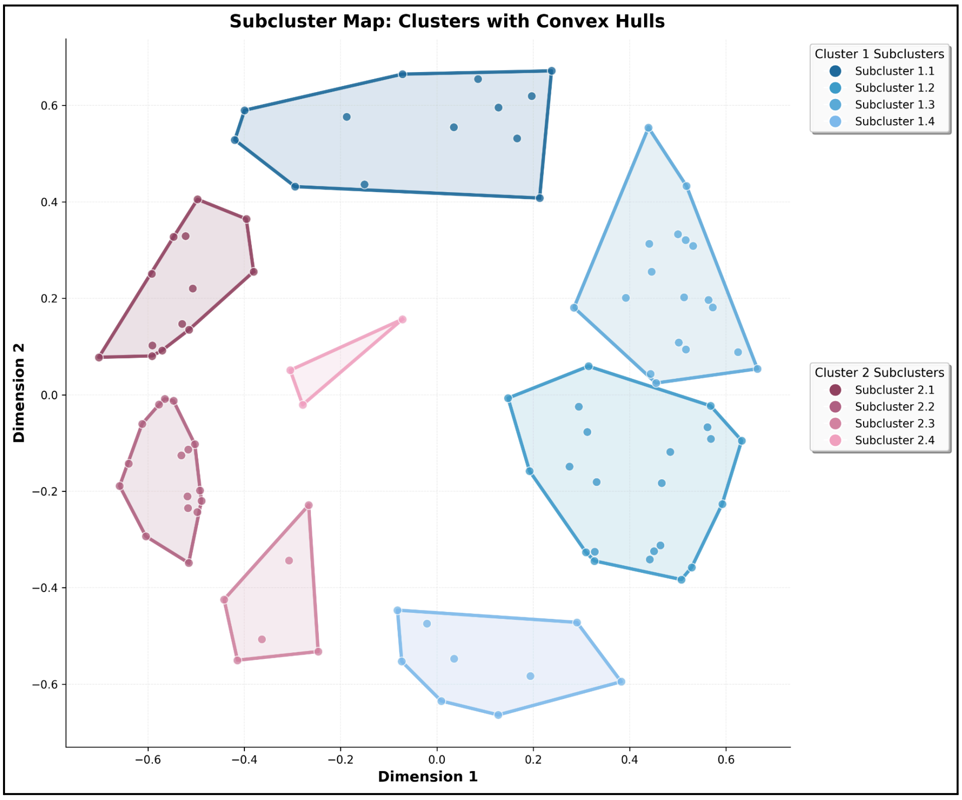
Figure 1. Point map that visually represents the relationships among the 100 statements, with each point on the map representing a statement. Figure 1b. Cluster map showing the final cluster solution with convex hull boundaries around each cluster



The aggregated, mean importance within each cluster was computed, with Cluster 2 showing significantly higher mean importance ratings (M = 3.50, SD = 0.32) compared to Cluster 1 (M = 3.14, SD = 0.43). This difference was statistically significant upon t–test comparison ($P < .001$), with an effect size that was found to be large (Cohen's d = 0.94). Comparison using the Mann–Whitney U test corroborated this finding ($P < .001$). Regarding feasibility, Cluster 2 demonstrated significantly higher mean ratings (M = 3.62, SD = 0.38) compared to Cluster 1 (M = 2.99, SD = 0.41). This difference was also found to be statistically significant ($P < .001$ on both t–test and U test), with a large effect size (Cohen's d = 1.59).

Secondary hierarchical cluster analysis identified subclusters within each main cluster, shown in **Figure 2**. Subclustering within Cluster 1 had 4 subclusters: Subcluster 1.1 (13 statements), Subcluster 1.2 (22 statements), Subcluster 1.3 (18 statements), and Subcluster 1.4 (9 statements). Cluster 2 also had 4 subclusters: Subcluster 2.1 (13 statements), Subcluster 2.2 (16 statements), Subcluster 2.3 (6 statements), and Subcluster 2.4 (3 statements). A full listing of statements assigned to each subcluster, including mean importance and feasibility ratings, is provided in **Additional file 2**. **Figure 2** further elucidates the finer-grained conceptual groups that maintain their position within the broader MDS space, revealing both the hierarchical structure and the nuanced relationships between related concepts.

Figure 2. Subclusters within the MDS space. Subclusters 1.1–1.4 belong to Cluster 1 (Challenges and Safeguards for AI Implementation), and subclusters 2.1–2.4 belong to Cluster 2 (Clinical Benefits and Efficiency Gains)



The pattern match analysis (**Figure 3**) shows the relationship between importance and feasibility ratings at both cluster and subcluster levels. **Figure 3a** presents the cluster-level analysis, revealing distinct patterns in how the 2 clusters differ across rating dimensions. Cluster 2 demonstrates higher ratings in both importance (3.50) and feasibility (3.62), while Cluster 1 shows lower ratings in both dimensions (3.14 importance, 2.99 feasibility). Statistical comparison using the Wilcoxon signed-rank test revealed significant differences between importance and feasibility within both clusters. In Cluster 1, importance ratings were significantly higher than feasibility ratings (*P* = .005), whereas in Cluster 2, feasibility ratings were significantly higher than importance ratings (*P* = .007).

Figure 3a. Cluster-level ratings, revealing distinct patterns between the two main clusters. Figure 3b. Analysis at the subcluster level, showing relationships across the eight subclusters with a correlation coefficient (r = 0.829) indicating a strong positive relationship between importance and feasibility across all subclusters

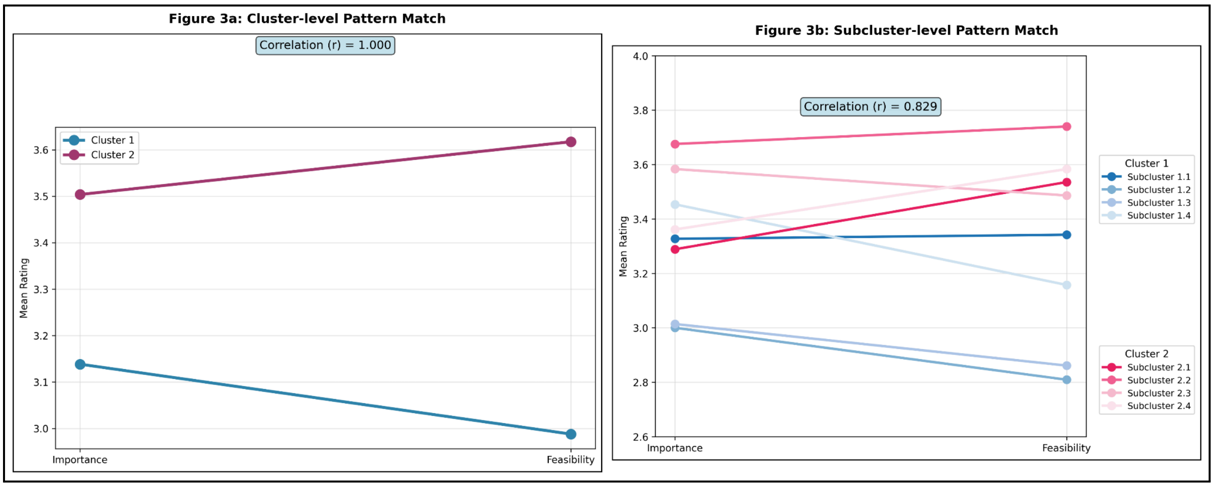
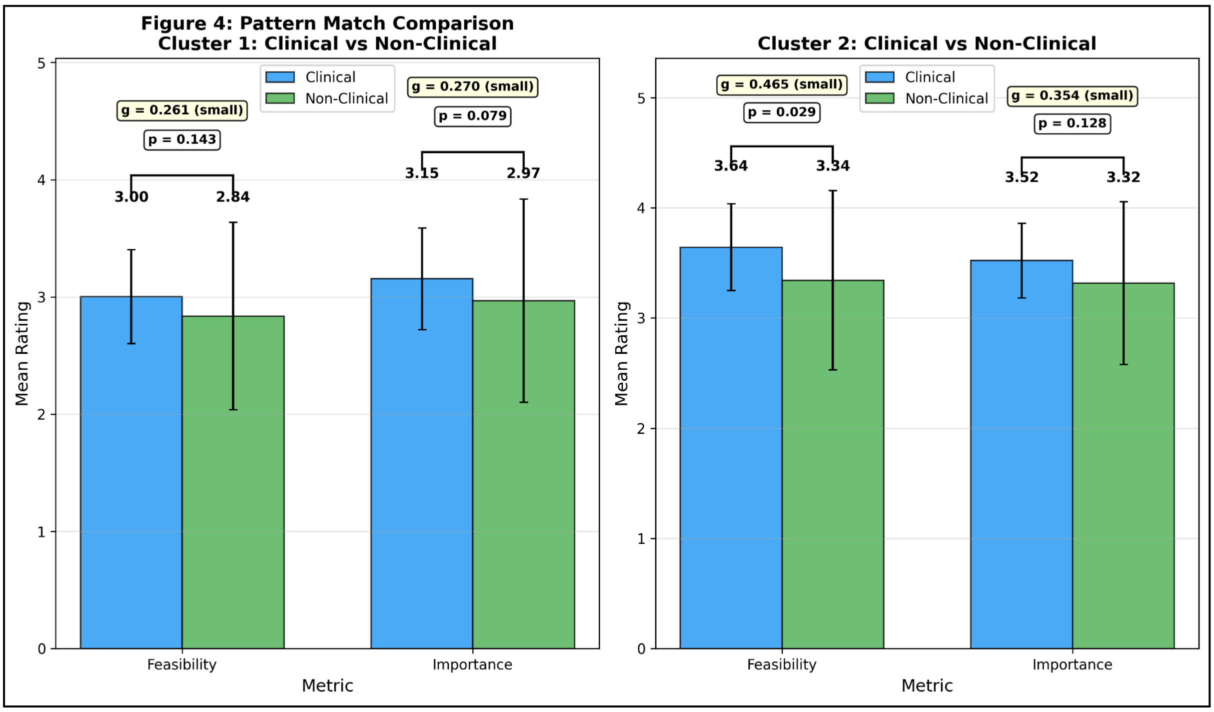


Figure 3b extends this analysis to the subcluster level, revealing distinct patterns across the eight subclusters. Each subcluster is represented by a line connecting its mean importance rating to its mean feasibility rating, allowing for visual comparison of the gap between these dimensions. The analysis revealed a strong positive correlation between importance and feasibility ratings across

subclusters (r = 0.829). However, notable variations exist in the magnitude of the gap between importance and feasibility across subclusters. Subclusters within Cluster 2 (Clinical Benefits and Efficiency Gains) generally demonstrate higher ratings in both dimensions compared to those in Cluster 1 (Challenges and Safeguards). Specifically, Subcluster 2.2 shows the highest mean ratings in both importance (3.68) and feasibility (3.74), while Subclusters 1.2 and 1.3 show the lowest ratings in both dimensions. The pattern match visualization highlights subclusters with differing relationships between importance and feasibility ratings.

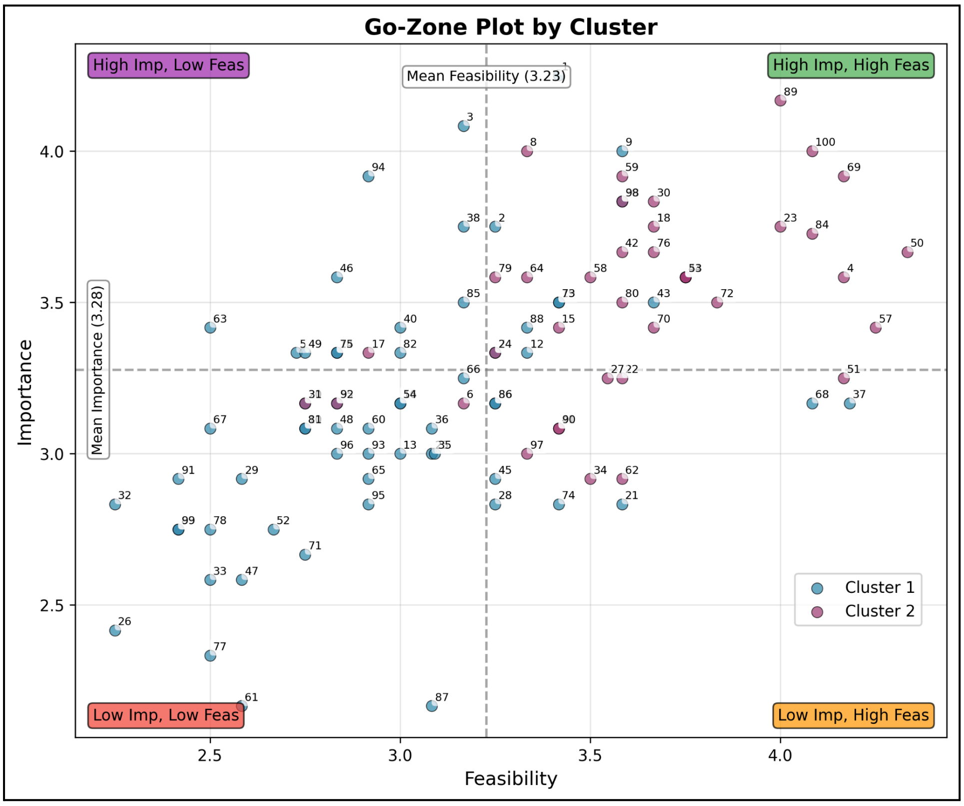
Results from subgroup analysis comparing ratings of clinical and nonclinical panel members are shown in **Figure 4**. For Cluster 1, no difference was found for both importance (Clinical: 3.15 vs Non-Clinical: 2.97; *P* = .079) and feasibility (Clinical: 3.00 vs Non-Clinical: 2.84; *P* = .144) ratings. For Cluster 2, clinical participants showed significantly higher mean feasibility ratings (Clinical: 3.64 vs Non-Clinical: 3.34; *P* = .029), though effect size was only small to medium (Hedge' g = 0.465). No subgroup difference in mean importance ratings was found (Clinical: 3.52 vs Non-Clinical: 3.32; *P* = .128).

Figure 4. Subgroup analysis of mean importance and feasibility ratings between clinical and nonclinical professionals



Finally, the go-zone plot is shown in **Figure 5**, which positions statements relative to the average importance and feasibility ratings. The plot is divided into four quadrants based on overall mean values for each rating scale. Quadrant I (High–High) contains 36 statements (36%) that are above average in both importance and feasibility, representing immediate implementation opportunities. Quadrant II (Low–High) contains 16 statements (16%) that are above average in feasibility but below average in importance, representing quick wins. Quadrant III (High–Low) contains 13 statements (13%) that are above average in importance but below average in feasibility, representing research and development priorities. Quadrant IV (Low–Low) contains 35 statements (35%) that are below average in both dimensions, representing low priority items. A per-quadrant compilation of statements from the go-zone plot is further provided in **Additional file 1**.

Figure 5 presents the go-zone plot identifying statements based on their performance relative to average importance and feasibility ratings.



DISCUSSION

To our knowledge, this study represents the first use of concept mapping to examine end-user perspectives on AI implementation in cancer care. Prior work, including systematic reviews, has synthesized barriers and facilitators thematically; however, these studies have not applied a structured, participatory approach that organizes stakeholder-generated statements into relational clusters and quantitatively derived priority spaces. By using concept mapping, we extend the existing literature through an analytic process that integrates qualitative interpretation with quantitative, multivariate spatial analysis, generating a framework that can help organizations translate stakeholder perspectives into actionable implementation priorities and sequence implementation efforts strategically. This approach aligns with recent concept mapping studies that emphasize the importance of combining stakeholder engagement with quantitative structuring to inform implementation planning and strategy selection[42,43].

The 2-cluster structure and associated subclusters reveal how stakeholders distinguish between domains related to system-level safeguards and those focused on clinical benefits and efficiency gains. The consistent pattern of higher importance and feasibility ratings observed for benefit-oriented domains, particularly those related to workflow efficiency and clinical quality, suggests that stakeholders differentiate between AI applications that extend existing clinical practices and those that require broader organizational or governance changes. While this study does not attempt to assess the objective validity of these judgments, the observed pattern aligns with implementation science literature highlighting the influence of workflow compatibility, perceived usefulness, and organizational readiness on early adoption[48,49].

The subcluster structure reveals how stakeholders distinguish between different types of implementation challenges and opportunities. Within challenges and safeguards (Cluster 1), stakeholders differentiated between immediate operational concerns (Subcluster 1.1), ethical and safety considerations (Subcluster 1.2), regulatory and privacy issues (Subcluster 1.3), and quality assurance requirements (Subcluster 1.4). The differential feasibility and importance ratings across these subclusters suggest that implementation challenges are not uniform and require tailored strategies to address them. Similarly, within the benefits cluster (Cluster 2), the subclusters differentiate between research and knowledge applications (Subcluster 2.1), direct workflow improvements (Subcluster 2.2), clinical quality enhancements (Subcluster 2.3), and patient-facing communication tools (Subcluster 2.4). The clusters associated with higher feasibility ratings coalesced around tools that integrate directly into existing clinical workflows, provide cognitive support, and alleviate documentation or triage burdens—patterns most evident in Subclusters 2.2 and 2.4, which showed the highest feasibility ratings. These themes are consistent with prior concept mapping studies in implementation science in which stakeholders prioritized interventions addressing immediate workflow bottlenecks and clinician workload pressures[50]. Conversely, subclusters rated as less feasible were dominated by system-level requirements such as data governance, algorithmic transparency, and regulatory clarity, concerns that were particularly concentrated in Subclusters 1.2, 1.3, and 1.4. These domains typically require organizational- or policy-level infrastructure rather than individual clinician action. Taken together, this thematic contrast suggests that near-term implementation efforts in AI may benefit from emphasizing workflow-aligned tools while simultaneously initiating longer-term capacity building for governance and system readiness.

Understanding these thematic groupings is important because stakeholder perceptions can signal both adoption readiness and likely points of resistance. Concept mapping studies show that feasibility ratings reflect not only technical considerations but also concerns related to trust, accountability, and institutional preparedness. In our study, the clustering patterns suggest that AI-enabled workflow support is viewed as an extension of existing practice norms, whereas governance-related functions are perceived as requiring broader infrastructural or cultural change. These distinctions help identify where uptake may be smoother and where additional engagement or capacity building is likely needed. These findings align with established implementation science frameworks, including the Consolidated Framework for Implementation Research (CFIR), which emphasizes the interaction between intervention characteristics, inner setting, outer setting, and implementation processes[51]. In our analysis, higher-feasibility domains corresponded to CFIR constructs such as workflow compatibility, relative advantage, and perceived usefulness, particularly within the intervention characteristics and inner setting domains. In contrast, lower-feasibility domains mapped more closely to CFIR constructs related to the outer setting and implementation climate, including regulatory environments, data governance, accountability, and institutional readiness.

Importantly, these patterns have direct implications for the sequencing of implementation strategies. AI applications embedded within familiar clinical workflows, such as documentation support, triage, and communication tools, were perceived as both important and feasible, suggesting they may be appropriate targets for early-stage implementation efforts. Conversely, domains related to equity, validation, privacy, and regulatory preparedness were rated as highly important but less feasible, indicating a need for longer-term, system-level investment, cross-sector coordination, and policy development. This distinction reinforces the view that AI implementation in cancer care is not a single-step process, but rather a staged endeavor requiring differentiated strategies aligned with contextual demands. The go-zone analysis further supports this sequencing logic by distinguishing areas of perceived readiness from those requiring additional planning. Subcluster-level prioritization provides a pragmatic mechanism for identifying domains where early testing or pilot implementation may be feasible, while simultaneously highlighting areas where foundational governance and infrastructure must be strengthened.

Taken together, this study contributes to the implementation science literature on AI in cancer care by offering a structured, stakeholder-informed framework that can assist organizations in sequencing implementation activities. The thematic patterns highlight that the implementation of AI in cancer care is not a uniform challenge but a layered one, where the subcluster analysis reveals that even within broad thematic categories, stakeholders distinguish between different types of applications, concerns, and requirements. By integrating cluster and subcluster analysis with a feasibility–importance prioritization framework, the findings provide an actionable mechanism for identifying specific areas where stakeholders perceive readiness versus domains likely to require additional investment, offering a high-level blueprint that organizations can tailor to their local contexts. This synthesis suggests that balanced attention to both workflow-level readiness and system-level governance may support more sustainable and responsible adoption of AI tools in cancer care, providing a more actionable roadmap for implementers, policymakers, and organizations seeking to navigate the complex landscape of AI adoption in oncology.

Limitations

While these findings provide insight into stakeholder perspectives on AI implementation in cancer care, several limitations should be considered. The expert panel involved in concept mapping tasks (n = 13) was purposively sampled to ensure representation across key domains: clinical cancer care (n=7), AI research and development (n=4), health system administration (n=1), and patient expertise (n=1). This approach aligns with concept mapping methodology, which supports validity and reliability with relatively small samples, including single-digit participation in some cases[38], with diminishing gains beyond approximately 10 participants[50]. However, the limited sample size may affect the stability of finer-grained structures, particularly at the subcluster level. Subcluster distinctions should therefore be interpreted as indicative rather than definitive. The 48 workshop participants represented a range of professional roles, but the sample was geographically concentrated within Canada, primarily British Columbia, which may limit transferability to other healthcare systems and cultural contexts. The workshop-based recruitment approach may also have introduced selection bias, as workshop participants were likely already engaged with AI in cancer care and may not reflect the perspectives of the broader healthcare workforce. Subgroup analyses comparing clinical (n=7) and nonclinical (n=6) panellists were limited by small numbers within each group, constraining the ability to detect meaningful differences. In addition, the study captured perspectives at a single point in time, and stakeholder views may evolve as AI technologies and implementation contexts change. Finally, while the 2-stage clustering approach enabled more nuanced interpretation, it involved additional analytic decisions that may influence the resulting structure.

Future Directions

Future research should extend this work to further inform AI implementation in cancer care. Longitudinal studies could examine how stakeholder perceptions evolve over time and whether the identified cluster and subcluster structures remain stable as technologies and organizational contexts change. Studies involving larger and more diverse samples across multiple institutions and jurisdictions would help assess the robustness and transferability of the conceptual structure, including cross-cultural validation. Further research examining how different stakeholder groups organize and prioritize AI implementation considerations could support more tailored implementation planning. Empirical studies evaluating the effectiveness of implementation strategies aligned with the identified priority domains, particularly those emerging from subcluster-level feasibility and importance analyses, would strengthen the evidence base. Finally, testing the practical utility of this prioritization framework in real-world implementation initiatives could clarify how concept mapping outputs can support phased, context-sensitive adoption of AI technologies in cancer care.

CONCLUSIONS

The integration of AI into cancer care holds substantial promise for improving clinical workflows and care delivery, but its successful adoption depends on how implementation challenges and opportunities are navigated in practice. Using concept mapping, this study provides a structured, stakeholder-informed analysis of how perceived benefits, concerns, and prerequisites for AI implementation relate to one another, offering insights beyond surface-level qualitative themes.

Our findings highlight a clear distinction between workflow-aligned AI applications that stakeholders view as both important and feasible, and system-level governance and accountability requirements that are perceived as highly important but less immediately actionable. This pattern underscores the value of a phased implementation approach, in which organizations prioritize workflow-integrated tools that address immediate clinical pressures while concurrently investing in longer-term governance, policy, and infrastructure development. By integrating cluster and subcluster analysis with feasibility–importance prioritization, this study offers a practical framework to support strategic planning and sequencing of AI implementation efforts in cancer care. These findings provide an initial foundation for future research and may assist healthcare organizations, implementation scientists, and policymakers in developing context-sensitive, sustainable approaches to AI adoption.

Table 1. Concerns, Perceived Benefits, and Implementation/Research Priorities Regarding AI in Cancer Care, with Mean Importance and Feasibility Ratings

(Given that this table was larger than one A4 or Letter page in length, it was placed at the end of the document text file. It should be added after the first paragraph of the section entitled "Concept Mapping – Statements.")

#	Statement	Importance	Feasibility
1	Human oversight during implementation in early days	4.25	3.42
2	Concerns with confidentiality	3.75	3.25
3	Concerns with patient acceptability	4.08	3.17
4	Efficiency improved for documentation	3.58	4.17
5	False confidence	3.33	2.73
6	AI could provide alternate perspectives	3.17	3.17
7	AI could perpetuate existing biases	3.33	3.25
8	Minimizing bias and increasing performance and accuracy	4.00	3.33
9	Ensuring accountability and oversight of AI	4.00	3.58
10	Concerns with digital literacy and digital divide barriers	3.08	2.75
11	Better detection (of moles, cancer lumps)	3.58	3.75
12	Diversification of AI training data and sources	3.33	3.33
13	Too much bureaucracy slowing progress	3.00	3.00
14	Concerns with liability	3.33	2.83
15	AI could decrease false positives	3.42	3.42
16	Proactive preventative care	3.17	3.00
17	Benefits in equitable access	3.33	2.92
18	AI could free up time for pt care	3.75	3.67
19	Developing a rigorous privacy and quality assurance framework	3.50	3.42
20	AI could be misused	3.17	2.75

21	Helps with generation of ideas can act as a sounding board	2.83	3.58
22	Benefits with accessibility & communication (translating languages lay terms)	3.25	3.58
23	AI allows access vast information very quickly to help diagnosis	3.75	4.00
24	Benefits in early distress screening	3.33	3.25
25	Establishing proper consent	3.00	3.08
26	Concerns with job security	2.42	2.25
27	Benefits with patient access to accurate information	3.25	3.55
28	Concerns about personalizing care	2.83	3.25
29	Data governance policies and regulations to enhance data quality and accountability	2.92	2.58
30	Savings in time, can integrate different information and improve in treatment especially when there is less number of human specialist	3.83	3.67
31	AI could remove human bias	3.17	2.75
32	Regulation framework and a good understanding of the medico–legal implications	2.83	2.25
33	AI could lead to excessive human delegation, assuming that AI will take care of it!	2.58	2.50
34	Knowledge repositing for learning and research	2.92	3.50
35	AI could be of concern regarding its ongoing validation	3.00	3.09
36	AI could be of concern to patient privacy	3.08	3.08
37	Consultation recording and transcription	3.17	4.18
38	Ensuring cybersecurity of AI tools	3.75	3.17
39	Educating end–users about properly navigating AI	3.83	3.58
40	Concerns with protection of personal health identifiers	3.42	3.00
41	Facilitation of clinical research	3.08	3.42
42	Improve access to services	3.67	3.58

43	Ensuring accessibility and translation	3.50	3.67
44	AI could help improve accuracy	3.58	3.75
45	Embed research / quality improvement into all areas	2.92	3.25
46	Garbage in, garbage out' – data that the AI model is trained on must be good, clean, large, and diverse	3.58	2.83
47	Concerns with attrition of skills in healthcare providers	2.58	2.58
48	Preservation of human touch	3.08	2.83
49	Loss of human connection/interactions	3.33	2.75
50	Summarization of large amounts of text or data – increases digestibility/highlighting key points	3.67	4.33
51	Collate large databases	3.25	4.17
52	AI could engender issues with trust	2.75	2.67
53	Pooling large volume of data can improve accuracy of AI system and allow for more timely diagnosis and treatment recommendation	3.58	3.75
54	Concerns with responsibility accountability of AI recommendations	3.17	3.00
55	AI hallucinations	3.17	2.83
56	Multidisciplinary collaboration and training in developing AI models	3.17	3.25
57	24/7 availability, AI doesn't get tired or brain fog	3.42	4.25
58	Noticing patterns and new things humans haven't noticed	3.58	3.50
59	Prediction/prognosis/treatment recommendations	3.92	3.58
60	Concerns with standards for quality, accuracy, etc.	3.08	2.92
61	Concerns with power outages and downtime procedures	2.17	2.58
62	Increased opportunities for innovation	2.92	3.58
63	Distress is nuanced and often detected in the unsaid of human communication and in a trusting therapeutic relationship	3.42	2.50
64	Personalization of AI support tools for patients	3.58	3.33

65	Concerns with difficulty to know older data for training and missing new breakthrough information	2.92	2.92
66	Concerns with consent of patient	3.25	3.17
67	Racism bias through research (history of medical research)	3.08	2.50
68	Phased roll–out: Start with simple, "low stakes" tasks continue in stages	3.17	4.08
69	Reduce admin burden	3.92	4.17
70	Potential in navigation and directing to self–management resources	3.42	3.67
71	Over reliance by physicians and reduced problem solving skills	2.67	2.75
72	Ability to make text/conversation more digestible for patients (less technical)	3.50	3.83
73	Ensuring clinical validation of AI tools	3.50	3.42
74	Concerns with maintaining up to date information, sources and programming	2.83	3.42
75	Data privacy concerns	3.33	2.83
76	Triage diagnostic results for clinicians	3.67	3.67
77	Concerns with going too far and can't come back	2.33	2.50
78	Control of data by corporations	2.75	2.50
79	AI could help address the human health resources issue	3.58	3.25
80	Faster assessments to inform decision–making	3.50	3.58
81	Concerns with transparency	3.08	2.75
82	AI could make mistakes	3.33	3.00
83	Concerns with stability of the system (during virus attack, power outage, system interruption)	2.75	2.42
84	Live translation and/or transcription of conversations	3.73	4.08
85	Establishing guidelines for "best practices" for training AI + clinical validation	3.50	3.17
86	Lack of training/knowledge for those using the AI tool in the real world	3.17	3.25

87	Can existing healthcare servers support the use of AI?	2.17	3.08
88	Ensuring interpretability of AI tools	3.42	3.33
89	Allow clinicians to focus on tasks requiring their expertise	4.17	4.00
90	Identifying and focusing on high–priority areas, such as prevention	3.08	3.42
91	Concerns that data is held by private companies	2.92	2.42
92	Maintaining competency with changing best practices and approved standards	3.17	2.83
93	Minority groups are being marginalized	3.00	2.92
94	Patient/parent/caregiver/provider acceptability	3.92	2.92
95	Data ownership and standards and guidelines on AI developed are not been established	2.83	2.92
96	Possibility of data breaches / data leaks	3.00	2.83
97	Potential for widening differential diagnosis, widening perspective of patient	3.00	3.33
98	Lists possible outcome and risks for the patient	3.83	3.58
99	Cybersecurity concerns	2.75	2.42
100	Automation of routine tasks	4.00	4.08

ADDITIONAL FILES

1. **Additional file 1:** Supplemental Table 1. Per-quadrant compilation of statements from go-zone analysis. Table presenting statements classified into four quadrants (High–High, Low–High, High–Low, Low–Low) based on their importance and feasibility ratings relative to the overall average, including statement IDs, full text, importance scores, and feasibility scores. (.docx)
2. **Additional file 2:** Supplemental Table 2. Statement composition of subclusters. Table presenting all 100 statements assigned to their respective subclusters (1.1–1.4 and 2.1–2.4), including statement IDs, full text, and mean importance and feasibility ratings. (.docx)

LIST OF ABBREVIATIONS

- AI: Artificial intelligence
- BC: British Columbia
- CFIR: Consolidated Framework for Implementation Research
- EB AI: Evidence–based artificial intelligence
- MDS: Multidimensional scaling
- UBC: University of British Columbia

DECLARATIONS

Ethics approval and consent to participate

This study was approved by the UBC Research Ethics Board (H24–03306). All workshop participants provided informed consent for data collection and research purposes.

Consent for publication: Not applicable.

Availability of data and materials

The dataset supporting the conclusions of this article are included within the article and its additional files. The code and scripts used for analysis are publicly available on GitHub (https://github.com/chhaviiiii/concept_mapping).

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Authors' contributions

- Conceptualization: H.H.X., J.J.N., A.T.B., C.C., A.F.B.
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- All authors approved the final version of the manuscript.

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