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Review

The Impact of AI-driven Remote Patient Monitoring on Cancer Care: A Systematic Review

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Abstract. *The coronavirus disease 2019 (COVID-19) pandemic necessitated a shift in healthcare delivery, emphasizing the need for remote patient monitoring (RPM) to minimize infection risks. This review aimed to evaluate the applications of artificial intelligence (AI) in RPM for cancer patients, exploring its impact on patient outcomes and implications for future healthcare practices. A qualitative systematic review was conducted using keyword searches across four databases: Embase OVID, PubMed, PsychInfo, and Web of Science. After removing duplicates and applying inclusion and exclusion criteria, the selected studies underwent quality assessment using the Critical Appraisal Skills Programme (CASP) tools and a risk of bias assessment. A thematic analysis was then performed using Delve, an application that facilitates deductive coding, to identify and explore themes related to AI in RPM. The search yielded 170 papers, from which 11 quantitative studies were selected for detailed analysis. Deductive coding resulted in the generation of 12 codes, leading to the identification of six subthemes and the construction of two primary themes: Efficacy of the RPM intervention and patient factors. AI systems in RPM show significant potential for enhancing cancer patient care and outcomes. However, this review could not conclusively determine that RPM provides superior outcomes compared to traditional face-to-face care. The findings underscore the preliminary nature of AI in medicine, highlighting the need for larger-scale, long-term studies to fully understand the benefits and limitations of AI in RPM for cancer care.*

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Key Words: Artificial intelligence, remote patient monitoring, cancer care, patient outcomes, telemedicine, review.

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The advent of the coronavirus disease 2019 (COVID-19) pandemic ushered in an era of unprecedented challenges for global healthcare systems (1). The COVID-19 pandemic had a significant impact on cancer care, leading to fewer diagnosed cases, delayed presentations, postponed treatments, and potentially worse mortality outcomes (2). For instance, COVID-19 and mucormycosis in a patient with an underlying malignancy may impact the anti-cancer treatment, including chemotherapy, immunotherapy, or targeted treatment (3). The COVID-19 pandemic has also impacted the training of junior

and middle-grade doctors during the first and second waves, due to increased workloads and both physical and mental burnout (4). Central to these challenges was imperative to balance the need for continuous patient care with the necessity of implementing social distancing measures to curb viral transmission. This dichotomy was particularly pronounced in the management of chronic health conditions such as cancer, where regular, face-to-face interactions between patients and healthcare providers are pivotal for effective disease management (5). The traditional modalities of patient monitoring and care delivery were disrupted, necessitating innovative approaches to ensure that patient outcomes did not deteriorate amidst the pandemic's constraints (6, 7).

In response to these challenges, telemedicine emerged as a viable strategy to bridge the gap created by the reduction in in-person consultations. Within the broader spectrum of telemedicine, remote patient monitoring (RPM) has been instrumental in maintaining continuity of care (8, 9). Between November 2020 and January 2023, RPM initiatives supported approximately 487,000 individuals, facilitated by national funding as part of the Regional Scale Programme (10). RPM systems and devices are designed to frequently monitor physiological status of patients, in order to shift medical services from hospital and clinical settings to an in-home monitoring scenario (11). This shift not only addresses the immediate challenges posed by the pandemic but also aligns with a broader trend towards patient-centered care models that prioritize convenience and accessibility.

Parallel to the evolution of RPM has been the rapid advancement of Artificial Intelligence (AI) technologies. Historically, AI has experienced ebbs and flows in its development trajectory (12, 13). However, recent years have witnessed a renaissance in AI capabilities, driven by improved machine learning algorithms, more computing power, more massive datasets and improved open-source code libraries and frameworks (13–15). These advancements have transcended domains, with healthcare standing out as a particularly fertile ground for AI integration. In medical imaging, for instance, AI systems can automatically make a quantitative assessment of complex medical image characteristics and achieve an increased accuracy for diagnosis (16, 17). Beyond diagnostics, AI offers promise in complex algorithms to provide decision aids offering information and guidance to physicians (18). These capabilities are transformative, potentially enhancing the precision, efficiency, and personalization of medical care.

The confluence of AI and RPM has given rise to innovative strategies aimed at augmenting patient care, especially for those with chronic conditions like cancer. A notable example is the "COVID Oximetry @ Home" service in the Northwest, which has facilitated the safe monitoring of over 3,200 patients from their homes. This initiative has been pivotal in early detection of declining oxygen saturations, reducing hospital admissions, and averting 787 referrals in primary care to date within National Health Services (NHS) England (10). Another groundbreaking development is the "Liberty" device by Entia, which epitomizes the integration of AI into RPM. Launched in 2023 and rolled out across four NHS trusts, Liberty is heralded as the world's first at-home full blood count analyzer. Requiring only a pinprick amount of blood, it enables comprehensive monitoring encompassing symptoms, Patient-Reported Outcome Measures (PROMs), and vital signs. The reception has been overwhelmingly positive, with "100% of patients" expressing willingness to recommend Liberty to others. Personal testimonies highlight feelings of empowerment and psychological benefits derived from taking an active role in one's cancer journey (19). Such innovations not only enhance patient autonomy but also have the potential to alleviate burdens on healthcare infrastructures by optimizing appointment allocations and ensuring that in-person consultations are reserved for those who most need them.

Despite the promise that AI-infused RPM strategies hold, several limitations warrant attention. The nascent nature of many of these technologies means that comprehensive data on their long-term efficacy and impact on patient outcomes remain scarce. For instance, while the Liberty device has shown early success, its recent introduction precludes robust analyses of its sustained benefits across diverse patient demographics. Furthermore, public perception and acceptance of AI in healthcare present challenges. Misinformation and skepticism pervade social discourse, as evidenced by a social media content analysis revealing that of 200 posts discussing AI's role in replacing human doctors, 47.5% posited complete replacement, while 32.5% anticipated partial replacement (20). Such sentiments underscore the potential for misconceptions to shape public attitudes.

Empirical studies further elucidate this ambivalence. Research conducted in London university hospitals indicated that a mere 10.6% of patients strongly trust AI in healthcare, while 22.9% were unfamiliar with the term AI altogether (21). These findings spotlight a knowledge gap and a trust deficit that could impede the widespread adoption of AI-driven healthcare solutions. Delving deeper, a focus group study identified concerns encompassing AI safety, data security, preservation of patient autonomy, and the risks associated with over-reliance on AI systems. Crucially, it was determined that patient acceptance of AI is contingent on mitigating these possible harms (22). Addressing these concerns necessitates a concerted effort to educate the public, ensure transparency in AI applications, and prioritize patient-centric designs that uphold ethical standards.

Given the transformative potential of AI in RPM, particularly in the realm of oncology, there is an imperative to systematically evaluate existing literature to ascertain the efficacy, challenges, and future directions of these technologies.

While preliminary studies and pilot programs offer insights, there remains a dearth of large-scale research that places patient outcomes as central trial endpoints. This systematic review seeks to bridge this knowledge gap by comprehensively analyzing current applications of AI in RPM for patients with cancer, evaluating their impact on patient outcomes, and exploring their potential for broader implementation in healthcare systems worldwide. The rationale for this review lies in the rapid advancements in AI technologies, which offer promising tools for real-time symptom tracking and early detection of complications. However, despite the potential, there is limited comprehensive evidence evaluating the effectiveness of AI-driven RPM in cancer care. The primary objective of this review is to systematically analyze existing literature to assess the efficacy, challenges, and potential of AI-enhanced RPM systems in improving cancer patient outcomes, thereby providing insights into their future integration into routine clinical practice.

Methodology

This systematic review was conducted following the guidelines outlined in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 checklist (23), focusing specifically on items 5 to 10. The methodology employed in this review encompasses a comprehensive search strategy, a rigorous study selection process, systematic data extraction, quality assessment, thematic analysis, and a detailed consideration of ethical principles.

Search strategy. The search strategy was meticulously designed to capture all relevant literature pertaining to the application of AI in RPM for cancer patients. Four major databases were selected for the literature search: Embase OVID, PubMed, PsychInfo, and Web of Science. The goal was to achieve data saturation, ensuring that the search captured all pertinent studies available within the specified criteria.

Keywords. Keywords used in the search were derived from the Population, Intervention, Comparison, and Outcome (PICO) analysis. The keywords included: Cancer patients, Artificial intelligence, Remote patient monitoring, Early detection, Health deterioration, Early intervention, and Patient outcomes. The PICO tool was essential in refining the search, as it "forces the questioner to focus on what the patient or client believes to be the single most important issue and outcome", while also guiding the selection of appropriate language and key terms for the search (24).

Search string. The search strings employed varied between the selected databases to optimize results. Boolean operators "AND" and "OR" were used to combine keywords, maximizing the sensitivity and specificity of the search. After retrieving the initial search results, the studies were filtered through a multi-step process. First, duplicate entries were removed. Then, studies were screened using the inclusion and exclusion criteria outlined in Figure 1. This filtering process included an initial review of titles and abstracts, followed by a full-text review to assess the relevance and quality of the studies. The goal was to retain only those articles that were directly pertinent to the research question.

Selection criteria. The study eligibility criteria for this systematic review were carefully defined to ensure the selection of relevant and high-quality studies that could address the research question effectively. The inclusion criteria were as follows: studies that specifically analyzed the use of AI in RPM for cancer patients, were published after the onset of the COVID-19 pandemic, were written in English, and focused solely on adult populations. Studies also had to be original research articles with free full-text access, allowing for a thorough analysis of their content. Exclusion criteria included research that did not investigate any modality of AI in remote patient care, studies that did not focus on oncology patients, systematic or scoping reviews, grey literature, and snowballing methods. Furthermore, literature published before 2020 or studies involving participants lacking capacity were excluded to maintain a current and relevant focus. These criteria were designed to filter out studies that might not provide direct insights into the application of AI in RPM for cancer care, ensuring that the review concentrated on the most pertinent and recent research in this emerging field.

Data extraction. Data extraction is a critical step in systematic reviews, as it involves capturing the key characteristics of each study in a structured and standardized format. According to Schmidt *et al*., data extraction is a necessary precursor to assessing the risk of bias in individual studies and synthesizing their findings (25). For this review, data were extracted on various parameters, including study date/duration, study setting, study design, participant demographics (*e.g*., mean age, groups), the outcomes measured, and the main findings. The extracted data provided the foundation for subsequent quality assessment and thematic analysis, as outlined in section 8 below.

Quality assessment. The quality of the included studies was assessed using established tools to ensure the validity and replicability of the findings. The Critical Appraisal Skills Programme (CASP) checklists were utilized for both cohort studies and randomized controlled trials (26, 27). These checklists helped in evaluating factors such as study validity, reliability, and applicability to the local population. To further ensure the rigor of the review, the Cochrane RoB 2 tool for randomized controlled trials and the Risk Of Bias In

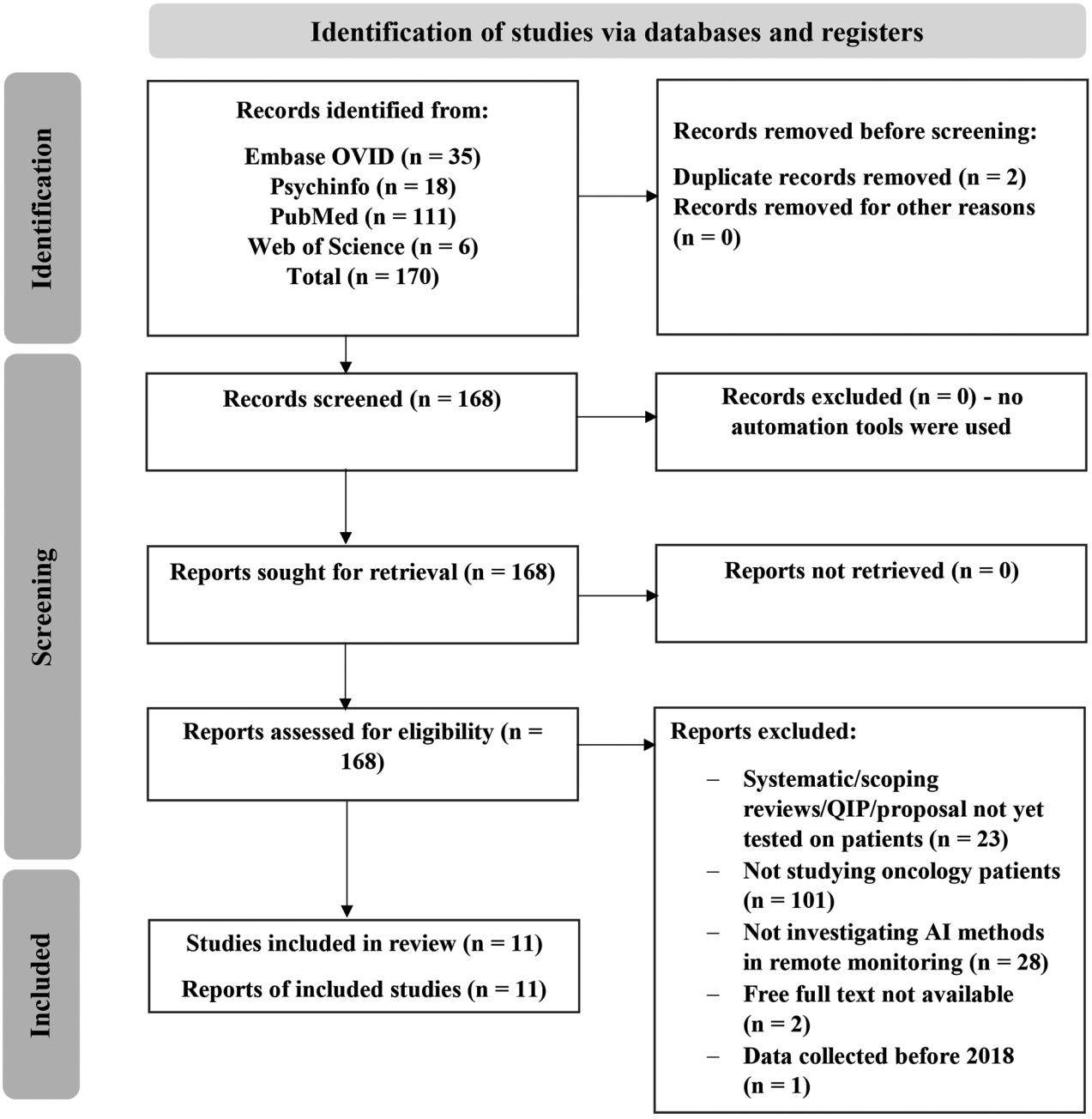

Figure 1. *Prisma flowchart showing selected studies across different databases.*

Non-randomized Studies - of Exposures (ROBINS-E) tool for cohort studies were used to assess the risk of bias (28, 29). These tools specifically address selection bias, performance bias, and other potential sources of bias that could compromise the study's findings. Studies identified as having a high risk of bias were excluded from the final analysis to maintain the review's overall validity.

Data synthesis and analysis. A thematic analysis approach was employed to synthesize the data, guided by the need to answer the research question comprehensively. The process began with the use of Delve, a qualitative analysis application, to code the data (30). Delve facilitated the organization of data into codes related to how patient outcomes were measured in the studies, ensuring a thorough and systematic approach to

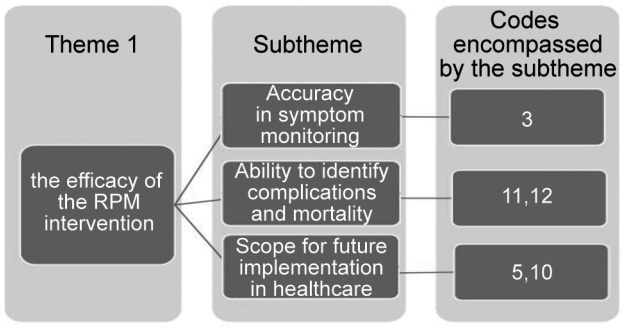

Figure 2. *Theme 1, subthemes, and codes.*

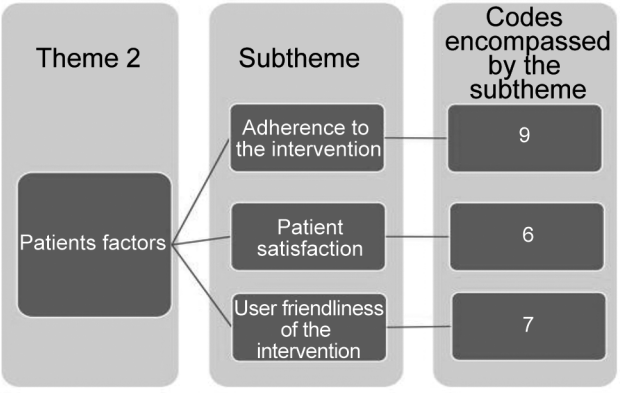

Figure 3. *Theme 2, subthemes, and codes.*

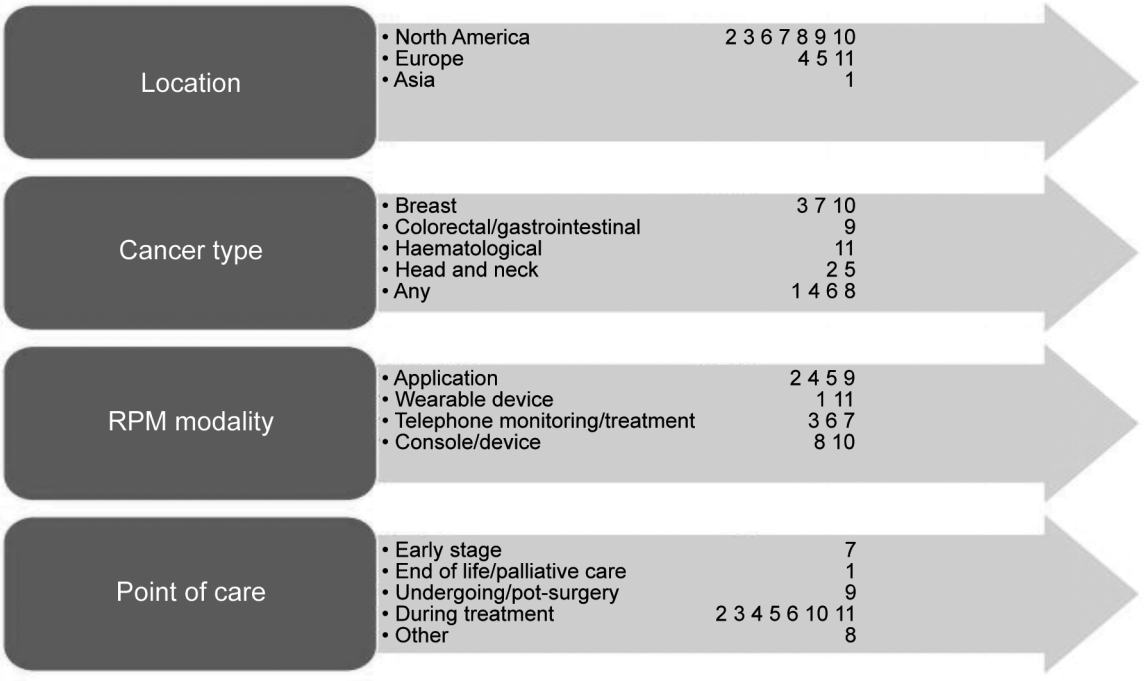

Figure 4. *Overview of study characteristics.*

data analysis. Themes were then developed from these codes, following Braun and Clarke's six-step guide to thematic analysis, as it is shown in Table I (31). This approach ensured that the themes were well-defined and encompassed the breadth of data necessary to answer the research question. Table II displays the codes generated using Delve. Column A assigns a number to each code, corresponding to the codes in Figure 2 and Figure 3. Column D shows the number of quotes from all papers that fall under each respective code. The codes were assigned numerical identifiers and analyzed based on their relevance to patient outcomes in AI-supported RPM for patients with cancer. The initial coding process identified several key themes and subthemes, which are illustrated in Figure 2 and Figure 3.

Certainty assessment. To ensure the reliability of the findings, the certainty of the evidence was assessed by an independent reviewer. This process involved re-evaluating the selected studies to confirm their relevance and methodological quality. By having a single reviewer independently assess the articles, the review minimized the potential for bias and increased the robustness of the conclusions drawn.

Table I. *Braun and Clarkes 6 step thematic analysis with rationale.*

Number	Step	Rationale
1	Familiarising yourself with the data	1. Having read through the 11 papers, the next steps were to draw conclusions on important topics covered in the articles 2. Then to make rough notes on these to build from when generating codes
2	Generating initial codes	1. Using the Delve application, it was possible to highlight snippets of text from all 11 articles and organise them under different codes 2. Deductive coding was employed which is where codes are generated using preset expectations from the aims and objectives of the study, thus not without prior preconceptions
3	Searching for themes	The codes were reviewed to allow similarities to be identified
4	Reviewing potential themes	Having review the articles again, it was possible to ensure whether the rough themes encompassed all the data needed to answer the research question
5	Defining and naming themes	Defined and finalised the themes
6	Producing the report	Having completed the steps, a thematic analysis and discussion was created

Results

A total of 11 studies were included in this systematic review, selected from four major databases following a rigorous filtering process. These studies were found to be relevant for a comprehensive descriptive and thematic analysis on the application of AI in RPM for patients with cancer. Table III presents a summary of the data extraction from the selected studies, providing an overview of the bibliographic information, study duration, setting, design, sample size, participant characteristics, outcomes measured, and main findings. Figure 4 offers deeper context for the articles, including the corresponding number code for each article that fits into the respective category.

Efficacy of RPM. The efficacy of RPM is supported by several subthemes. First, the accuracy in symptom monitoring – Studies consistently reported that AI-enhanced RPM systems accurately monitored symptoms, contributing to timely interventions. For example, Liu *et al*. found that heart rate data from wearable devices could predict mortality events with high accuracy (32). Second, the ability to identify complications and mortality – Several studies highlighted the capacity of RPM systems to identify complications early, potentially reducing mortality rates. Dawson *et al*. demonstrated reduced readmission and death rates within 30 days post-discharge in a telemonitoring group (39). Third, the scope for future implementation in healthcare—The potential for broader implementation of AI-driven RPM systems was evident, with multiple studies suggesting their scalability and adaptability across various patient demographics and settings.

Patient factors. Regarding patient factors, the review identified several subthemes. Adherence to the intervention varied across studies, but overall, patients exhibited high levels of adherence to RPM interventions. Constantinescu *et al*. reported adherence rates as high as 83.5% at the beginning of a 6-week program (33). Patient satisfaction was generally high, particularly in interventions where AI enhanced symptom tracking and reporting, as seen in Sprave *et al*.'s study (36). Additionally, the user-friendliness of the intervention played a significant role in patient satisfaction and adherence. Limbach *et al*. noted high satisfaction levels linked to the user-friendly nature of the telemonitoring technology employed (40).

Excluded themes. Three codes were excluded from the final thematic discussion: 'Health Care Personnel views', 'quality of life', and 'accuracy and specificity of the AI model'. These topics were either too broad to be adequately discussed within the scope of this review or were already encompassed within other subthemes, thus rendering them redundant for the purposes of this analysis.

Discussion

Accuracy in symptom monitoring. The studies reviewed highlight the significant potential of AI-enhanced RPM systems in maintaining symptom burden at manageable levels during cancer treatment. For example, Maguire *et al*. demonstrated that patients using the Advanced Symptom Management System (ASyMS) maintained symptom levels similar to pre-chemotherapy baselines, while control groups experienced increased symptom burden (35). This suggests that real-time reporting and direct communication facilitated

Table II. *Codes generated using Delve*.

Order of codes	Nested level	Code name	Number of snippets
1	>	Hospital admissions	6
2	>	HCP views	3
3	>	Efficacy in symptom monitoring	17
4	>	Quality of life	7
5	>	Further research needed	6
6	>	Patient satisfaction	9
7	>	Practicality and usability	18
8	>	Accuracy and specificity of AI model	5
9	>	Adherence	15
10	>	Future application	13
11	>	Predicting mortality	6
12	>	Detecting physiological changes early	5

by RPM can enhance patient support and potentially improve outcomes. However, the effectiveness of RPM interventions is contingent on user understanding, as evidenced by Arch *et al*., where participants expressed a need for more detailed guidance on managing side effects (41).

The contrasting findings of Sprave *et al*. and Krzyzanowska *et al*., further underscore the complexity of symptom monitoring (36, 38). While Krzyzanowska *et al*. (38) reported lower toxicity events in a telephone-monitored group, Sprave *et al*. (36) found an increase in symptom burden, particularly pain, following radiotherapy. This may be attributed to increased patient awareness of symptoms through self-reporting, emphasizing the need for large-scale studies to validate these findings and explore the psychological impact of RPM systems. Interestingly, Coombs *et al*. found that the efficacy of RPM systems was consistent across different age groups, challenging the assumption that older patients may struggle with technology (37). This finding highlights the adaptability of AI-driven RPM systems across diverse patient populations, reinforcing their potential for broader application in cancer care.

Ability to identify complications and mortality. The ability of RPM systems to detect complications and predict mortality was a key focus in several studies. Liu *et al*. (32) and Jacobsen *et al*. (42) demonstrated that AI models could accurately predict clinical deterioration, with Liu *et al*. (32) identifying heart rate as a critical predictor of 7-day mortality in end-of-life patients with cancer. Similarly, Jacobsen *et al*. achieved high sensitivity and specificity in detecting serious clinical complications (SCC), even predicting SCC up to 48 hours before clinical diagnosis (42). These findings suggest that RPM systems could significantly reduce hospital admissions and improve patient outcomes by enabling preemptive management of complications. Dawson *et al*. extended these findings by exploring the impact of telemonitoring on hospital readmissions and mortality (39). Their study showed a reduction in emergency department visits and a lower risk of readmission or death within 30 days among high-risk patients using home-installed monitoring equipment. The combination of AI-driven predictive models and real-time monitoring could, therefore, revolutionize cancer care by reducing morbidity and mortality through early intervention.

All reviewed studies underscored the potential for AI in RPM to be integrated into future healthcare systems. Krzyzanowska *et al*. (38) emphasized the relevance of scalable remote care strategies in the post-COVID-19 era, advocating for the incorporation of RPM early in the patient care continuum, as demonstrated by Limbach *et al*. (40) and Maguire *et al*. (35). Jacobsen *et al*. further suggested that automated SCC detection could lead to continuous surveillance in oncology, improving complication management and patient outcomes (42). However, the preliminary nature of these studies highlights significant gaps in knowledge, particularly concerning the scalability, cost-effectiveness, and long-term impact of AI-driven RPM systems. Most studies concluded that further research is needed to validate their findings and explore the broader implications of integrating AI into routine cancer care.

Adherence to the intervention. Adherence to RPM interventions was generally high across the studies, with Liu *et al*. (32) reporting a 77.42% wear time for wearable devices and Constantinescu *et al*. (33) documenting 84% adherence in the first week of their study. However, adherence tended to decline over time, as seen in Arch *et al*., where the effect of the intervention on adherence to adjuvant endocrine therapy (AET) did not persist through the 6-month follow-up period (41). This suggests that while initial engagement with RPM systems is strong, sustained adherence may require additional support, particularly for long-term interventions. Anxiety and stress were identified as significant barriers to adherence, with patients expressing concerns about the reminders of their cancer diagnosis and the perceived burden of participating in the studies. These findings highlight the need for interventions that are not only technologically user-friendly but also psychologically supportive to maintain long-term adherence.

Patient satisfaction. Patient satisfaction was generally positive, with studies like Jacobs *et al*. reporting high levels of enjoyment, usefulness, and convenience (34). Sprave *et al*. found that RPM systems improved satisfaction with various aspects of care, including interpersonal interactions and financial considerations (36). However, dissatisfaction arose from practical issues, such as the design of wearable devices, as reported by Liu *et al*. (32). This indicates that

Table III. *A summary of the data extraction from the selected studies.*

Code/Author (Reference)	Study setting	Study design	Sample size	Participants	Mean age (years)	Groups	Outcomes measured	Main findings
1/Liu *et al.* (32)	National Taiwan University Hospital	Cohort study	40	Terminal cancer patients over 20-year-old	70.5	All in treatment group using wearable devices	Prediction of 7-day mortality rate	1. 28 death events identified 2. Heart rate most predictive 3. XGBoost best model
2/Constantinescu *et al.* (33)	Tertiary referral centers across Alberta, Canada	Quasi-experimental pre-test and post-test design	20	Post head and neck cancer treatment patients	61.9	All in treatment group, no controls	Adherence to treatment and quality of life	1. High adherence (83.5% Week 1, 71.8% Week 6) 2. More research needed on adherence factors
3/Jacobs *et al.* (34)	Massachusetts General Hospital Cancer Center, Boston, USA	Open pilot study	5	Breast cancer patients post-AET	57.5	Trial group only, divided into small groups	1. Adherence 2. Symptom management 3. Distress	1. High acceptability, enjoyableness 2. More research needed for STRIDE intervention effectiveness
4/Maguire *et al.* (35)	12 cancer centers across Europe	Stratified randomized control trial	829	Non-metastatic cancer patients	Not stated	415 in ASyMS group, 414 in control group	1. Symptom burden 2. Quality of life	3. ASyMS group maintained pre-chemo symptom levels 4. Controls had increased burden
5/Sprave *et al.* (36)	University of Freiburg Medical Center, Germany	Randomized control trial	100	Head and neck cancer patients scheduled for radiotherapy	60 (ePRO), 66 (control)	50 in ePRO group, 50 in control	1. Feasibility 2. Compliance 3. Satisfaction	1. High compliance and satisfaction in ePRO group 2. Improved symptom burden reporting
6/Coombs *et al.* (37)	Community and academic oncology practices in Tennessee and Utah, USA	Prospective, longitudinal randomized clinical trial	358	Chemotherapy patients	Not stated	Older adults (≥60) *vs.* younger adults (<60)	1. Adherence 2. Symptoms' outcomes	1. High adherence 2. No significant difference in symptoms' outcomes between age groups
7/Krzyzanowska *et al.* (38)	20 cancer centers in Ontario, Canada	Pragmatic, cluster randomized trial	580	Early-stage breast cancer patients	55	Proactive remote management *vs.* routine care	1. ED visits 2. Hospital admissions 3. Toxicity 4. Quality of life	1. No significant reduction in ED visits or admissions 2. QoL decreased more in control group
8/Dawson *et al.* (39)	Mayo Clinic Florida and Mayo Clinic Arizona, USA	Modified randomized control trial	1,380	High readmission risk patients	66	High-risk group *vs.* control	Readmission or death within 30 days	Reduced readmission/ death rate and ED visits in telemonitoring group
9/Limbach *et al.* (40)	Not stated (North America)	Randomized control trial	65	GI oncologic surgery patients	52	Telemonitoring intervention *vs.* control	1. Feasibility 2. Patients' satisfaction	1. High satisfaction and adherence 2. Further research needed on generalizability

Table III. *Continued*

Table III. *Continued*

Code/Author (Reference)	Study setting	Study design	Sample size	Participants	Mean age (years)	Groups	Outcomes measured	Main findings
10/Arch *et al*. (41)	Rocky Mountain Cancer Centers, Colorado, USA	Mixed methods randomized control trial	88	Breast cancer patients on AET	56	REACH *vs*. Education group	1. AET adherence 2. Attitudes 3. Intentions	1. 100% session completion, high satisfaction 2. Adherence declined after 3 months
11/Jacobsen *et al*. (42)	University Hospital Düsseldorf, Germany	Single-arm observational cohort Study	79	Hematology-oncology patients	55	Inpatient *vs*. outpatient	Detection/ prediction of SCC	1. High sensitivity and specificity for SCC detection and prediction 2. Feasible for early intervention

XGBoost: eXtreme Gradient Boosting; AET: adjuvant endocrine therapy; STRIDE: Symptom-Targeted Randomized Intervention for Distress and Adherence on Adjuvant Endocrine Therapy; AsyMS: Advanced Symptom Management System; ePROs: electronic patient-reported outcomes; ED: emergency department; QoL: quality of Life: GI: gastrointestinal; REACH: Resources and Education for Adherence to Cancer Hormonal therapy; SCC: serious clinical complications.

while AI-driven RPM systems are well-received, there is room for improvement in their design and functionality to enhance patient experience further.

User friendliness of the intervention. The user-friendliness of RPM interventions is crucial to their success, as it directly impacts both satisfaction and adherence. Most studies reported that participants found the systems easy to navigate, with no significant technical difficulties. However, some patients felt overwhelmed by the technological requirements, leading to dropout in studies like Limbach *et al*. (40). This suggests that while AI-driven RPM systems are generally accessible, additional support and training may be necessary for certain patient populations, particularly those less familiar with technology. The specific challenges faced by end-of-life patients, as highlighted by Liu *et al*., further underscore the need for RPM systems that are adaptable to the unique needs of different patient groups (32). Future research should focus on developing non-wearable devices that offer the same benefits as current RPM systems while being more practical for vulnerable patients.

Limitations of the review. This systematic review is subject to several limitations. The relatively small number of studies included – 11 in total – may limit the generalizability of the findings. The selection of only four databases and the exclusion of non-English language studies and those without free full-text access may have introduced selection bias, potentially omitting relevant research. Additionally, the specificity of the keywords and eligibility criteria may have further restricted the scope of the review. The thematic analysis process, while thorough, was conducted by a single reviewer, which may introduce reporting bias. The use of deductive coding, based on pre-existing research outcomes, might have overlooked other significant topics, such as healthcare provider factors and the accuracy and specificity of AI models. The rapid development of AI in healthcare also means that new data may have emerged since the completion of this review, necessitating further studies to incorporate the latest findings. Finally, the constrained timeframe and resources available to a single university student author may have limited the depth of the analysis and the robustness of the conclusions. Future reviews would benefit from a more extensive and collaborative approach, incorporating peer review and additional resources to enhance the reliability of the findings.

Implications of the Results for Practice, Policy, and Future Research

This review highlights the potential for AI-driven RPM systems to enhance cancer care by improving symptom monitoring, reducing hospital readmissions, and increasing patient satisfaction. The findings suggest that AI-enhanced RPM could serve as a valuable adjunct to traditional face-to-face care, particularly in a post-pandemic healthcare landscape where remote care is increasingly sought after. However, the limitations identified in this review underscore the need for further research to validate these findings, particularly in large-scale, long-term studies. Future research should explore the cost-effectiveness of AI systems, the scalability of these interventions, and their impact on healthcare providers' workflows and patient outcomes.

Additionally, developing interventions that address the psychological barriers to adherence and satisfaction will be crucial in ensuring the success of AI-driven RPM systems.

Conclusion

This systematic review has explored the potential of AI in RPM to enhance cancer care outcomes compared to traditional face-to-face symptom monitoring. Through the analysis of 11 studies, key insights into the efficacy of AI-driven RPM systems have been identified, highlighting their ability to maintain symptom burden, predict complications, and reduce hospital readmissions. Moreover, the review has underscored the importance of patient factors, such as adherence, satisfaction, and the user-friendliness of these interventions in determining their overall success.

While the findings demonstrate that AI-enhanced RPM systems offer unique benefits, such as real-time symptom monitoring and early detection of clinical deterioration, these technologies have not yet proven to be superior to traditional care methods. The variability in outcomes across different studies and the preliminary nature of much of the existing research indicate that more extensive, long-term studies are needed to validate these findings and explore the broader implications of integrating AI into routine cancer care. Several limitations, including the small number of studies reviewed, potential selection bias, and the rapid pace of technological advancements, may have outpaced the research included in this analysis. These limitations point to the need for ongoing research and refinement of AI-driven RPM systems to ensure their scalability, cost-effectiveness, and long-term impact on patient outcomes.

Overall, while AI in RPM holds significant promise for transforming cancer care, it is not yet positioned to replace traditional face-to-face care entirely. Instead, it should be viewed as a complementary tool that, with further development and validation, could significantly enhance the quality of care provided to cancer patients. Future research should focus on addressing the gaps identified in this review, particularly in terms of scalability, cost-effectiveness, and the integration of AI into standard healthcare practices. By doing so, the full potential of AI in RPM can be realized, ultimately improving the lives of patients with cancer worldwide.

Conflicts of Interest

The Authors declare no conflicts of interest in relation to this study.

Authors' Contributions

Conceptualization: F.A., and D.B.; Data curation: F.A., and D.B.O.; Formal analysis: F.A., D.B., and D.B.O.; Funding acquisition: S.B.; Investigation: F.A., D.B., and D.B.O.; Methodology: F.A., and D.B.; Project administration: S.B.; Resources: D.B., and S.B.; Software: D.B.O.; Supervision: D.B., and S.B.; Validation: D.B.O.; Visualization: F.A., D.B., and D.B.O.; original draft: F.A., and D.B.; Writing – review & editing: F.A., D.B., D.B.O., and S.B.

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