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AI in patient communication: a literature review

As digitalization in healthcare advances, more and more people are gaining online access to their health data. Key instruments here are patient portals and, in particular, the electronic patient record (ePA), through which insured persons are provided with findings, physician letters, and other documents. One aim of this system is also to strengthen involvement in one's own care and to promote self-management (Kröner et al. 2025). However, studies show that most health information is textually highly complex and difficult for many of those affected to understand. Original medical documents in particular, such as clinical reports or radiological findings, are often not written for laypeople and can therefore contribute only to a limited extent to informed participation despite being digitally available (Gunn et al. 2017; Karliner et al. 2005; Martin-Carrera et al. 2018; O'Sullivan et al. 2020; Yi et al. 2019).

Health literacy and care

>> Adequate understanding of medical information is a decisive factor in healthcare (Berkman et al. 2011). Higher health literacy is associated with better treatment adherence: people who process and understand health information more effectively follow treatment recommendations more often on average. Conversely, a lack of understanding of one's own findings can impair adherence and even reduce quality of care (Miller 2016). In addition, people with adequate health literacy who are involved in the decision-making process are considerably more satisfied with their care (Altin/Stock 2016). In view of the nationwide implementation of "shared decision making" envisaged for the coming years (Geiger et al. 2026), the comprehensibility of medical information thus becomes a key structural prerequisite.

AI in patient communication

Against this background, the use of artificial intelligence to support patient communication is increasingly being discussed. AI-based systems, particularly those built on modern large language models, enable the automated preparation of medical information. This includes simplifying complex specialist texts, explaining medical terminology, and presenting content in a structured way (Aydin et al. 2024; Miftaroski et al. 2026). These properties make AI-supported information systems appear to be a potential approach to addressing existing comprehension barriers in dealing with medical documents.

Abstract

Introduction: With increasing digital access to health information, patients are often confronted with complex medical documents. AI-based systems are increasingly discussed as a tool to improve patient communication.

Methods: This structured literature review examines studies on AI-supported processing of medical information and evaluates their effects on patient understanding, as well as decision-making and adherence.

Results: Studies consistently show improved comprehension due to reduced text complexity and lower cognitive burden. In addition, there is evidence of positive effects on decision quality, shared decision-making, and health-related behavior. However, relevant error rates in AI-generated content are reported, and the evidence remains heterogeneous.

Discussion: Overall, the evidence suggests that AI can improve patient communication, but its benefits depend on controlled use, quality assurance, and integration into existing healthcare structures.

Keywords

artificial intelligence, patient communication, health literacy, patient understanding, large language models, decision-making, adherence

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Aim of the study

The aim of this study is to analyze and critically assess the influence of AI-supported communication systems on patient understanding, as well as on shared decision-making and adherence.

Methods

To answer the research question, a structured literature review was conducted on AI in patient communication and on the comprehensible presentation of medical information. The search period covered the years 2015 to 2025. PubMed served as the central bibliographic index. In addition, reference lists of the identified publications and freely accessible full texts were screened.

Original studies related to patient care were included in which AI-based systems conveyed or explained medical information or translated it into comprehensible language. Particular consideration was given to applications such as chatbots and automated counseling dialogues, AI- or NLP-supported text simplification and text generation including large language models, as well as other algorithmic systems for explaining medical content to patients. A prerequisite for inclusion was the reporting of patient-related outcomes, particularly regarding comprehension and decision- or behavior-related aspects (e.g., adherence, decision quality). Studies without a recognizable connection to the patient perspective and purely technical developments without patient-relevant endpoints were excluded. The identified studies were summarized in terms of content and evaluated along the target domains of patient understanding and of decision-making and adherence.

Results

Influence on patient understanding

The influence of AI-supported systems on patient understanding was examined in several studies using different designs and measurement instruments. The focus was particularly on the simplification of medical documents and its effects on comprehension

and information processing.

A prospective, controlled, quasi-randomized study (n = 200) examined the use of a large language model (Llama 3.3 70B) to simplify oncologic CT reports. The intervention group received LLM-simplified reports checked by radiologists, the control group standard reports. Comprehension was assessed using Likert scales (cognitive burden, text comprehension, usefulness) and reading time. The LLM group showed reduced reading time (median 2 vs. 7 minutes), lower cognitive burden (adjusted OR 0.18), and higher self-reported scores for comprehension (adjusted OR 13.28) and usefulness (adjusted OR 5.46). The radiological review revealed clinically relevant errors, including factual errors (6%), omissions (7%), and additions (3%) (Prucker et al. 2025).

A cross-sectional study analyzed the simplification of 1,134 pathology reports by large language models (Google Bard, GPT-4). The evaluation was based on readability metrics and on a review of medical accuracy by pathologists. Both LLMs significantly reduced the reading level; the reports were predominantly interpreted correctly (87.57% and 97.44%, respectively). In some cases, however, content errors and hallucinations occurred (Steimetz et al. 2024).

A quasi-randomized study (n = 460) examined the use of a large language model (GPT-4) to simplify a synthetic COPD discharge letter. Participants received either the original letter or an AI-simplified version and then completed a content quiz and a satisfaction survey. The comprehension score was higher in the LLM group (median 4 [IQR 2–4] vs. 2 [IQR 1–2]; $p < 0.001$); satisfaction was also higher ($p < 0.001$). One limitation was the use of a synthetically created discharge letter (Conrado et al. 2024).

A pilot study (n = 12) analyzed the use of a large language model (GPT-4o) to simplify radiological CT and MRI findings. Participants received the original report as well as a long and a short LLM-simplified version and were questioned about their comprehension in semi-structured interviews, with various scores recorded. Mean comprehension rose from 2.00 (original) to 3.28 (long version) and 3.50 (short version); correct classification of the findings improved from 63.9% to 80.6% and 83.3%, respectively. Mean satisfaction was 8.30/10. One limitation is the very small sample (n = 12) (van Driel et al. 2025).

Influence on decision-making and adherence

Decision-making and adherence are key patient-related outcomes, encompassing both the quality of medical decisions and the implementation of recommended measures in everyday care. Several studies examined the extent to which AI-supported systems influence these processes.

A randomized clinical trial (n = 129) compared an AI-based decision aid for knee osteoarthritis with an information brochure. Decision quality (K-DQI, a patient-reported instrument for measuring decision quality, 0–100%) was higher in the intervention arm (+20.0 percentage points; 95% CI 14.2–26.1; $p < 0.001$), as were shared decision making (CollaboRATE, a 3-item short questionnaire for patients' assessment of shared decision-making, 0–27 points: 12% vs. 47% below the median; $p < 0.001$) and satisfaction (NRS 0–10: 14% vs. 33% dissatisfied; $p = 0.01$). Functional scores (KOOS JR, 0–100 points) improved slightly (+4.9 points; $p = 0.02$); the surgery rate did not differ significantly (23% vs. 12%; $p = 0.11$). One limitation was that the trial was conducted at a single specialized center (Jayakumar et al. 2021).

A school-cluster randomized trial (n = 2,671 parents) examined an AI-supported chatbot for HPV vaccination education compared with usual health marketing. The chatbot led to higher vaccination uptake (7.1% vs. 1.8%; relative risk ~3) and to more physician consultations (49.1% vs. 17.6%; $p < 0.001$). The effect was more pronounced in rural regions. One limitation was that structural barriers (e.g., cost, availability) were not addressed by the intervention (Hou et al. 2025).

A randomized controlled trial (n = 294) compared an AI/machine-learning-based nutrition app for type 2 diabetes with routine care. The HbA1c reduction was greater in the AI group (–0.32% vs. –0.06% after 24 weeks; $p < 0.05$) and remained greater after 48 weeks (–0.28% vs. –0.07%). A combined intervention with additional feedback and continuous glucose monitoring showed even stronger effects (–0.49% and –0.44%, respectively). One limitation was the restricted population (no insulin therapy) (Lee et al. 2023).

A randomized controlled trial (n = 374, ≥65 years) examined a hybrid AI chatbot (rule-based + NLP-supported Q&A function) to promote pneumococcal vaccination compared with a simple chatbot with standardized content. Vaccination uptake was higher in the AI group (29.4% vs. 18.7%; $p = 0.01$). In addition, participants in the chatbot group were on average further advanced in their readiness to vaccinate than the control group (2.2 vs. 1.9 on a scale of 1 to 4; $p = 0.02$). Considerably more people also actively participated in the intervention sessions offered (79.7% vs. 57.8%; $p < 0.001$). One limitation was that some eligible individuals declined to participate, which may have led to an overrepresentation of people particularly willing to be vaccinated (Wang et al. 2025).

Discussion

Key findings

The available evidence shows that AI-supported systems – particularly large language models – can improve the understanding of medical information, above all by simplifying complex texts and reducing cognitive burden. Moreover, several studies show that AI-based interventions can positively influence decision quality and health-related behavior. At the same time, there are limitations, particularly with regard to content errors (hallucinations), limited generalizability, and heterogeneous study designs.

Interpretation of the results

The observed effects on patient understanding are plausible and can be attributed primarily to the ability of AI-based systems to adapt medical content linguistically and structurally. In particular, reduced reading complexity and better structuring appear to be key mechanisms that both lower cognitive burden and facilitate the uptake of information. The consistently improved comprehension scores suggest that this is not an isolated effect of individual applications but a fundamental potential of the technology.

At the same time, the documented error rates in AI-generated content put the positive effects into perspective. Even if most of the content is correct, even small proportions of clinically relevant

Studies on patient understanding				
Author, year	**n**	**AI type**	**Measurement**	**Results**
Prucker et al., 2025	200	LLM (Llama 3.3)	Likert scale, reading time, readability indices	Better comprehension, less effort, shorter reading time (7>2 min); error rate 6%
Steimetz et al., 2024	1.134	LLM (Bard, GPT-4)	Readability (FK-GL, FRE), medical accuracy, hallucinations	Readability sig. improved; correct interpretation: Bard 87.6%, GPT-4 97.4%; hallucinations: 2.8% vs. 0.3%
Conrado et al., 2024	460	LLM (GPT-4)	Comprehension score, satisfaction survey	AI group: better comprehension (median 4 vs. 2, p<0.001) and higher satisfaction
van Driel et al., 2025	12	LLM (GPT-4o)	Likert scale, classification of findings, satisfaction	Better comprehension (2.00 to 3.28), better classification of findings (63.9% to 83.3%), mean satisfaction 8.3/10

Table 1: The table provides an overview of studies on the use of AI-supported systems to improve patients' understanding of medical information. Own illustration.

errors can be significant in a medical context.

The effects on vaccination behavior or decision quality suggest that AI-based communication goes beyond merely conveying information and can have a motivational effect. At the same time, it must be borne in mind that such effects depend heavily on the respective setting, the target population, and the specific intervention.

Limitations of the evidence

The current evidence base is methodologically heterogeneous and, in the area of patient understanding, still largely exploratory. The included studies differ considerably in document type, language, setting, control condition, and outcome assessment, so direct comparison is possible only to a limited extent. It is particularly relevant that the strongest radiological study to date, although designed as a prospective controlled trial, was conducted open-label and quasi-randomized; moreover, the simplified CT reports were mandatorily checked by radiologists before being issued. The observed effects therefore do not relate to autonomous routine use of generative AI, but to a supervised hybrid model (Prucker et al. 2025). Other studies are based either on a cross-sectional analysis of pathology reports without direct patient-related outcomes (Steimetz et al. 2024), on an online quasi-experiment with a synthetic COPD discharge letter (Conrado et al. 2024), or on a very small pilot study with only twelve patients from two hospitals in the Netherlands (van Driel et al. 2025). In addition, content errors, omissions, or hallucinations were described even in the positively assessed studies. As a result, both internal validity and transferability to real, uncontrolled care situations remain limited.

Studies on decision-making and adherence				
Author, year	**n**	**AI type**	**Measurement**	**Results**
Jayakumar et al., 2021	129	ML decision aid (Joint Insights, OM1)	K-DQI, CollaboRATE, NRS, KOOS JR, surgery rate	Better decision quality (+20 pp, p<0.001), more SDM (12% vs. 47%, p<0.001) and higher satisfaction; KOOS JR +4.9 points; surgery rate n.s.
– Hou et al., 2025	2.671	LLM (GPT-4, chatbot)	Vaccination rate / appointment, consultation rate, vaccine literacy, vaccine confidence	Higher vaccination rate (7.1% vs. 1.8%, p<0.001) and consultation rate (49.1% vs. 17.6%); improved vaccine literacy
Lee et al., 2023	294	AI-based dietary management (deep learning, image recognition)	HbA1c, body weight, FPG, DTSQ	Greater HbA1c reduction (–0.28% to –0.44% vs. –0.07%); weight loss and FPG improved
Wang et al., 2025	374	Hybrid chatbot (rule-based + NLP/ keyword matching)	Likert scale, classification of findings, satisfaction	Better comprehension (2.00 to 3.28), better classification of findings (63.9% to 83.3%), mean satisfaction 8.3/10

Table 2: The table summarizes studies on the influence of AI-supported systems on decision-making and adherence. Own illustration.

For decision-making and adherence, too, the evidence is encouraging but only partly generalizable. The randomized trial on knee osteoarthritis was conducted at a single specialized center; clinicians were not blinded, and health literacy was not systematically assessed (Jayakumar et al. 2021). The HPV chatbot study took place in a Chinese school setting with an intervention lasting only two weeks; at the same time, vaccine costs, supply shortages, the baseline survey in the control arm, and possible contamination between classes may have influenced the effect size (Hou et al. 2025). The pneumococcal study was limited to smartphone-using older adults in Hong Kong; 22.5% of eligible individuals declined to participate, several variables were self-reported, and transferability to other health systems remains unclear (Wang et al. 2025).

Relevance for healthcare

For real-world care, these findings mean that AI-based tools can usefully complement existing channels of patient communication.

Automated summaries and explanations of hard-to-read physician letters or findings reports could be integrated into patient portals and the electronic patient record (ePA). The ePA is in any case intended to provide insured persons with cross-sectoral health data and to support informed participation. AI-supported simplification could help exploit this potential more fully. Helpful applications for AI-generated lay reports are also emerging in radiology.

Furthermore, the physician–patient interaction benefits when patients have already better understood their findings before the consultation. Informed patients could discuss treatment options more effectively (shared decision making). The studies show that personalized AI aids can increase decision quality and foster a sense of involvement. However, it must be taken into account that information deficits are only part of the problem; structural barriers (e.g., lack of capacity, costs) must be addressed in parallel. Moreover, the transferability of the approaches described to real-world care situations is currently only partly substantiated, as the available evidence stems from controlled study conditions.

Implications and research needs

The results point to several open questions. First, the lack of evidence of sustained effects is central: studies with longer duration and follow-up would be needed to clarify whether information simplified once by AI leads to lasting improvements in treatment adherence or long-term health literacy.

Furthermore, research should examine how AI interventions work in different target groups. It is unclear whether older people or those less familiar with technology benefit equally. Likewise, the influence of prior experience and health literacy on the benefit of the AI application could be investigated.

Another important point is system integration. Studies on implementation in hospital or care settings are needed: how can radiology departments or practices introduce such tools in practice? Research is needed here on user acceptance and workflow.

Finally, the AI models themselves must be further validated: studies on the accuracy of simplified texts (factual errors, hallucinations) should be continued and supported by automatic detection tools. Ethical and data protection aspects of their use in patient portals also need to be clarified.

Conclusion

In summary, the available evidence shows that AI-supported systems have substantial potential to improve patient understanding and to support decision-making processes and health-related behavior. At the same time, there are limitations, particularly regarding content reliability and the transferability of the results to care practice. AI should therefore currently be understood primarily as a complementary tool within validated care processes.

For future development, it appears crucial to systematically

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integrate AI applications into care contexts, evaluate their effects in real-world settings, and at the same time establish quality assurance mechanisms. Only under these conditions can the potential of AI-supported patient communication be harnessed sustainably to improve care. <<

Author declaration

Patrick Heckmann is Managing Director and shareholder of Stratoniq GmbH in Erlangen, the operator of the befundHilfe.com platform, a digital application for presenting medical documents in an understandable way.
Since this article deals with AI-supported patient communication, there is a conflict of interest in the sense of a potential proximity between scientific content and entrepreneurial activity.
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