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Artificial intelligence mediated communication in Polish primary healthcare: A linguistic perspective

Komunikacja zapośredniczona przez sztuczną inteligencję w polskiej podstawowej opiece zdrowotnej: perspektywa językoznawcza

Abstract

Artificial intelligence (AI) tools are increasingly embedded in Polish primary healthcare (Podstawowa Opieka Zdrowotna, POZ), reshaping how clinical encounters are conducted and documented. Based on a narrative review (2015–2026) of applied-linguistics and health-communication literature – spanning Conversation Analysis, narrative medicine, genre theory, and plain-language standards – and illustrated with Polish-language clinical examples, this article argues that AI systems act as algorithmic interactants that introduce evidential “turns” into consultations, shifting epistemic authority away from patients and clinicians; compress or flatten illness narratives by favouring categorical over experiential detail; and push clinical documentation toward standardised, template-based genres at the expense of stance-marking and interpersonal nuance. It further identifies Polish-specific linguistic features – free word order, rich inflection, aspectual distinctions, dialectal variation, and dense medical lexicon – that create systematic risks of symptom misrecognition and misclassification in NLP/ASR-based tools. Drawing these strands together, the article proposes an implementation framework combining plain-language documentation standards, CA-informed repair strategies, genre-sensitive documentation models, and corpus-based sociolinguistic validation, with the aim of reducing communicative and equity risks as AI is adopted in Polish primary care.

Keywords: Artificial Intelligence, Polish primary healthcare, conversation analysis, health communication, Natural Language Processing (NLP), narrative medicine, interactional linguistics, Automatic Speech Recognition (ASR)

Abstrakt

Sztuczna inteligencja (AI) jest coraz częściej wykorzystywana w polskiej podstawowej opiece zdrowotnej (POZ), zmieniając sposób prowadzenia i dokumentowania wizyt lekarskich. Na podstawie przeglądu narracyjnego (2015–2025) literatury z zakresu językoznawstwa stosowanego i komunikacji medycznej, obejmującego analizę konwersacyjną (CA), medycynę narracyjną, teorię gatunków oraz standardy prostego języka, artykuł analizuje wpływ AI na komunikację kliniczną. Ilustrowana polskojęzycznymi przykładami klinicznymi analiza wskazuje, że AI funkcjonuje jako algorytmiczny uczestnik interakcji, wprowadzający do konsultacji dowodowe „wypowiedzi”, przesuwający punkt ciężkości w kwestii autorytetu epistemicznego z pacjentów i klinicystów na inne podmioty. Jednocześnie systemy te spłaszczają narracje chorobowe, faworyzując informacje katagoryczne kosztem szczegółów doświadczeniowych oraz sprzyjają ujednolicaniu dokumentacji klinicznej, ograniczając ślady postawy i niuanse interpersonalne. Artykuł identyfikuje ponadto właściwości języka polskiego – szyk swobodny, bogatą fleksję, kategorię aspektu, zróżnicowanie dialektalne oraz gęsty leksykon medyczny – generujące systematyczne ryzyko błędnego rozpoznania lub klasyfikacji objawów przez narzędzia NLP/ASR. Na tej podstawie proponuje ramy wdrożeniowe łączące standardy prostego języka w dokumentacji, strategię naprawy oparte na CA, modele dokumentacji wrażliwe na gatunek oraz walidację socjolingwistyczną opartą na korpusach, mające ograniczyć ryzyko komunikacyjne i nierówności w dostępie do opieki w miarę wdrażania AI w polskiej POZ.

Słowa kluczowe: sztuczna inteligencja, komunikacja medyczna, analiza konwersacyjna, narracja medyczna, NLP, POZ, Automatic Speech Recognition (ASR)

Introduction

Language is central to how symptoms are articulated, interpreted, and transformed into clinical decisions. With the growing integration of artificial intelligence (AI) tools into Polish primary care (POZ), communication is no longer shaped solely by patients and clinicians but increasingly co-constructed with algorithmic participants such as triage bots, CDSS systems, and automated documentation platforms (Topol, 2019; Chen et al., 2023; Dryl, 2024; Qin et al., 2025). As these systems enter the communicative space of the consultation, they influence not only workflow efficiency or diagnostic pathways but the linguistic fabric through which care is enacted.

A review of the current literature reveals a striking gap: while numerous studies examine the technical, organisational, and ethical aspects of AI in Polish healthcare, very few approach the subject from a linguistic or discourse-analytic perspective. Existing work tends to focus on system performance, data extraction, usability, or policy frameworks. What remains underexplored – and what this article aims to address directly – is how AI reshapes the very language of care, including patient voice, narrative structure, conversational organisation, documentation genres, pragmatic framing, and, ultimately, equity and accessibility in communication.

By adopting a linguistics-centred perspective grounded in Conversation Analysis (Scheffloff, 2007; Barnes, 2019), narrative medicine (Charon, 2006), genre theory (Swales, 1990; Biber, 1995), and plain-language principles (ISO, 2023), this article examines how AI systems reconfigure institutional discourse in Polish family medicine. It aims to articulate

not only what AI does for clinical efficiency, but what it does *to* communication: how it alters epistemic dynamics, compresses or filters patient narratives, changes repair possibilities, and standardises genre features in ways that impact the therapeutic relationship and the patient's ability to express experience.

In addressing this gap, the article contributes a new conceptualisation of AI as an emerging communicative actor in Polish healthcare – one whose linguistic footprint demands systematic examination.

Methods

This study employs a narrative review methodology covering the period 2015–2025, drawing together insights from applied linguistics, medical informatics, communication studies, sociolinguistics, and Polish-language NLP research (OECD, 2021; Szetela, 2025). Rather than focusing on quantitative counts of publications, the review emphasises conceptual depth, theoretical relevance, and the diversity of linguistic approaches used to analyse AI-mediated healthcare communication.

The selection process prioritised materials that explicitly intersect language and healthcare, particularly those addressing:

- AI-driven changes in interactional organisation and turn-taking,
- shifting epistemic authority between patients, clinicians, and algorithmic systems,
- transformations of illness narratives,
- the evolution of clinical documentation genres,
- patient comprehension and health literacy in technologically mediated settings, and
- challenges posed by Polish morphosyntax, dialects, and speech variability.

The narrative review approach allows for the integration of heterogeneous sources – scholarly articles, technical reports, policy documents, linguistic corpora studies, and applied NLP research – facilitating a multidimensional understanding of AI's communicative footprint. This methodology supports theoretical synthesis across traditions such as Conversation Analysis, narrative medicine, genre theory, pragmatics, and sociolinguistics (Chinta et al., 2024; Świącik, 2024). It also enables the identification of emerging patterns in how AI systems influence the structure of clinical encounters, reshape communicative norms, and reproduce or mitigate linguistic inequalities.

Through this synthesis, the methods aim not only to describe the current state of AI-mediated communication in Polish primary care but to construct a robust interdisciplinary framework for analysing future developments at the intersection of language, technology, and healthcare.

Linguistic transformations in AI-mediated communication

Interactional consequences (CA)

AI inserts algorithmic turns within clinician–patient talk, shifting epistemic dynamics and producing hybrid participation frameworks (Greatbatch et al., 2005). CDSS (Clinical Decision Support System) output often occupies a third position in sequences, reframing how clinicians interpret or ratify patient accounts.

Narrative medicine and illness narratives

AI systems tend to compress or flatten patient narratives, prioritising categorical answers over metaphorical, temporal, or emotional detail (Mishler, 1984; Hydén, 1997). This diminishes narrative richness and diagnostic nuance.

Repair failures

AI systems typically lack self-repair mechanisms and cannot engage in negotiated clarification. As a result, misunderstandings introduced by the AI often persist (Jefferson, 2004; Schegloff, 2007).

Genre theory and documentation

AI-generated documentation tends toward template-based standardisation, which reduces stance-marking, interpersonal nuance, and contextual detail (Swales, 1990; Biber, 1995).

Polish-specific linguistic issues

Polish presents a range of linguistic properties that significantly complicate the performance of NLP and ASR systems in clinical settings. These challenges stem not only from grammatical structure but also from sociolinguistic diversity, patient communication norms, and the highly specialised medical lexicon used in primary care (Każmierczyk, Kupis, Maj, 2022).

Free word order and sentence variability

Polish allows considerable syntactic flexibility, meaning that crucial clinical information can appear in different positions without altering meaning. For example:

- “W klatce mnie czasem boli”.
- “Czasem mnie boli w klatce”.
- “Boli mnie czasem w klatce”.

Although functionally equivalent for a clinician, AI systems may segment or prioritise different parts of these utterances, misinterpreting what is symptom, what is temporal framing, and what is emphasis. In triage contexts, such variation can produce incorrect symptom extraction.

Rich inflection and morphological complexity

Polish inflection affects nouns, verbs, adjectives, and pronouns, creating many surface forms for the same lexeme (Grochola-Szczepanek, 2020). For example, the noun “gorączka” (fever) can appear as “gorączki”, “gorączce”, “gorączką”, “gorączek” depending on case and number. ASR systems often struggle with:

- older adults’ reduced articulation,
- regional phonetic variants,
- context-dependent stress patterns.

For AI-driven documentation, misrecognition of inflected forms may lead to incomplete or incorrect symptom coding. Engineering approaches such as synthetic-speech-augmented reinforcement learning have been proposed specifically to improve ASR robustness for Polish medical terminology (Czyżewski, 2023a).

Aspect distinctions and diagnostic timelines

Polish relies on verbal aspect to encode temporal structure. The distinction between “boli” (is hurting) and “zabolało” (suddenly began to hurt) signals clinically relevant information about onset, duration, and episodicity. Many AI models trained on general corpora cannot infer these distinctions.

For example:

- “Boli mnie brzuch”. → *ongoing condition; might indicate chronic issue.*
- “Zabolało mnie w nocy”. → *acute onset; may require urgent evaluation.*

Inaccurate interpretation of aspect can lead to inappropriate triage outcomes or misleading clinical summaries.

Dialects, regiolects, and sociolinguistic variation

Poland features notable regional varieties such as Silesian (Śląski), Highland Podhale speech (podhalański), Kashubian-influenced Polish (kaszubski), and Eastern borderland features (Wyderka, 2014). Patients may say:

- “Godó sie, że zech je łogłupiała od tego bólu” (Śląski).
- “Jo mom ciśnienie wysoki” (Podhale).

Standard NLP models frequently misrecognise these forms, particularly in speech. This risks:

- missing key symptoms,
- misclassifying emotional stance,
- or flagging irrelevant keywords.

Older speakers and individuals with lower health literacy often use idiosyncratic vocabulary or localised metaphorical expressions to describe bodily states, which AI systems frequently fail to decode.

Medicalised lexicon and health literacy barriers

Medical Polish is morphologically dense and often intimidating for patients. Terms like “niewydolność krążeniowo-oddechowa” or “zaostrenie przewlekłej obturacyjnej choroby

pluc” overwhelm many speakers. AI-generated messages that adopt or reproduce these forms without simplification can hinder understanding.

Additionally, patients frequently use colloquial substitutes:

- “zator” instead of “zakrzepica”,
- “zakwasy” for various musculoskeletal pains,
- “skurcz w sercu” for palpitations.

AI systems trained on formal medical datasets may interpret such expressions literally, leading to mismatches between patient intention and system categorisation.

Prosody, emotion, and pragmatic subtleties

Polish intonation and pragmatic markers carry substantial meaning. Utterances like:

- “No... boli, ale to chyba nic takiego”. (*mitigating stance*),
- “Strasznie mnie nasiliło!” (*intensification*),
- “Jakoś tak mnie kłuje czasem...” (*vague evidential marking*),

encode uncertainty, fear, or minimisation strategies. These pragmatic nuances help clinicians gauge severity and patient concern but are often lost in ASR–NLP pipelines.

Tab. 1. Polish-specific linguistic phenomena and their AI/NLP implications in primary care

Linguistic phenomenon	Example (Polish)	AI/NLP risk	Clinical consequence
Free word order	Boli mnie czasem w klatce. / Czasem mnie boli w klatce.	Inconsistent segmentation of symptom vs. temporal framing	Incorrect symptom extraction in triage
Rich inflection	gorączka → gorączki, gorączce, gorączką	Surface-form mismatch in ASR/entity recognition	Incomplete or incorrect symptom coding
Verbal aspect	boli (ongoing) vs. zabolęło (acute onset)	Failure to encode onset/duration distinctions	Misleading triage urgency
Dialect / regiolect	Śląski, Podhalański regional forms	Misrecognition, particularly in speech	Missed symptoms; misclassified emotional stance
Medicalised lexicon / colloquialisms	zakwasy (colloquial) vs. formal musculoskeletal terminology	Literal interpretation of colloquial terms	Mismatch between patient intention and system categorisation
Prosody / pragmatics	mitigating, intensifying, and evidential markers (e.g. “No... boli, ale to chyba nic takiego”)	Loss of stance/uncertainty cues in ASR–NLP pipelines	Misjudged severity or patient concern

Source: Author’s own elaboration, based on Grochola-Szczepanek (2020), Wyderka (2014), Malisz, Foremski, Kul (2024), and Pondel-Sycz et al. (2025).

Theoretical contribution to linguistics

AI's entry into Polish primary care provides a novel testing ground for applied linguistics, extending multiple theoretical traditions:

Conversation analysis and algorithmic participation

AI tools can be understood as algorithmic interactants insofar as their outputs are routinely introduced into clinical encounters and treated as evidential contributions that influence subsequent human talk and decision-making. Unlike human participants, algorithmic outputs typically

- make contributions without being accountable in interactional terms,
- produce recommendations without direct access to the lived, embodied context of the consultation, and
- reconfigure epistemic gradients by introducing external evidence that clinicians must interpret or ratify.

This set of dynamics challenges core Conversation Analysis assumptions about mutual orientation, sequential organisation, and repairability: when one “participant” cannot negotiate meaning or accept responsibility for its moves, intersubjective work must be redistributed across human actors. Recent empirical and conceptual work on clinical decision support and human–AI interaction documents these shifts and argues for re-framing decision support as part of clinicians’ reasoning processes rather than as neutral background tools (van Baalen, Boon, Verhoef, 2021; Funer, Wiesing, 2024; Jiang et al., 2024). Scholarship on algorithmic accountability and epistemic status further explains why algorithmic contributions are both powerful and problematic in interactional settings (Diakopoulos, 2016; Ferrario et al., 2024), while literature on trust and automation clarifies how humans come to treat non-human outputs as warranting deference or scepticism (Chiou, Lee, 2023).

Narrative theory and reconstructed illness accounts

The growing use of generative-AI and NLP for clinical documentation is reshaping the genre of illness narratives in institutional medicine. Recent studies demonstrate that large language models can convert free-text pathology reports into structured, coded data with high fidelity – effectively compressing rich narrative descriptions into algorithm-ready diagnostic vectors (Balasubramanian et al., 2025; Shahid et al., 2025). In this transformation, the patient’s experiential story becomes subordinate to structured fields optimised for computational processing: metaphorical language is attenuated, temporal and causal sequences are regularised, and affective or evaluative elements tend to be stripped away in favour of pattern-recognisable biomedical features. This reflects not only a change in documentation format but the emergence of a new institutional narrative genre shaped by computational constraints, extending earlier critiques of how medical records conventionalise and constrain patient storytelling (Mishler, 1984; Hydén, 1997; Semino, 2010).

Although current evidence stems primarily from pathology and other written-report domains, the implications for spoken clinical encounters are significant. As AI-mediated documentation systems are integrated into real-time workflow, there is a risk that the narrative material clinicians attend to will increasingly mirror what AI can capture – structured, symptom-centred, and diagnostically actionable – rather than the broader experiential and metaphorical dimensions emphasised in narrative medicine (Charon, 2006). This raises the possibility that algorithm-ready illness accounts may shape both how clinicians record stories and how patients learn to present them.

Research agenda

Despite these developments, empirical research on how AI transforms illness narratives *during* real clinical interactions remains limited. No published conversation-analytic studies yet examine how generative-AI suggestions or summaries intervene in the sequential organisation of consultations, nor how algorithmic outputs influence the construction, negotiation or repair of patient stories in situ. Future work should therefore combine Conversation Analysis, linguistic ethnography, and clinical NLP evaluation to trace how spoken narratives are filtered, reformatted or truncated through AI-mediated pathways. Longitudinal studies could further examine whether patients adapt their storytelling practices to align with the expectations of digital triage systems or AI-supported documentation tools. Addressing these gaps will be crucial for assessing whether emerging algorithm-ready genres enhance clinical reasoning or inadvertently diminish narrative richness and patient agency.

Genre evolution in clinical writing

Electronic medical records (EMRs) have reshaped the genre of clinical documentation by shifting from narrative, free-text accounts toward structured, template-based formats designed for standardisation and data reuse (Rosenbloom et al., 2010; Rosenbloom et al., 2011). These systems privilege coded entries, checklists, and predefined fields, reducing the expressive and narrative dimensions of clinical writing traditionally used to capture temporal nuance, uncertainty, and patient-centred detail.

The introduction of artificial intelligence further accelerates this shift by creating hybrid documentation genres that combine clinician input with automated structuring, annotation and summarisation. AI-assisted tools increasingly extract clinical entities, normalise terminology, and generate draft notes or summaries (Perkins et al., 2024; Shemtob et al., 2025), thereby reshaping what counts as clinically salient information. As a result, the boundaries of authorship, narrative form, and evidential framing are no longer determined solely by human clinicians but co-constructed with algorithmic systems. A recently developed Polish voice-input platform illustrates this shift in practice, combining speech recognition and clinical context analysis to generate structured EHR entries directly from clinician speech (Szplit et al., 2026).

Genre theory emphasises that institutional genres shape and constrain patterns of thinking, communication, and professional accountability (Swales, 1990; Biber, Conrad,

2009). In the clinical domain, AI-mediated documentation introduces several significant implications.

First, medico-legal accountability becomes more complex as authorship is distributed across clinicians and machine-assisted drafting systems, raising questions about responsibility for inaccuracies or omissions (Cabitza, Rasoini, Gensini, 2017; Naik et al., 2022).

Second, documentation conventions influence clinical reasoning itself: research demonstrates that the structure and linguistic organisation of clinical records shape how evidence is framed, sequenced, and interpreted within the diagnostic process (Drew, Chatwin, Collins, 2001; Maynard, Heritage, 2005; Rosenbloom et al., 2011).

Finally, patient access to clinical records – now common in many healthcare systems – has been shown to improve engagement and understanding (Walker et al., 2019). However, it remains uncertain how AI-generated notes will affect transparency and comprehensibility, particularly if automated systems prioritise coded data over narrative clarity; this possibility requires dedicated empirical study.

Collectively, these developments highlight the need for applied linguistic, sociolinguistic, and discourse-analytic approaches to examine how AI is generating new clinical subgenres and transforming the communicative ecology of medical documentation. Such research is essential to understand how hybrid human–machine authorship reshapes narrative structure, evidentiality, interactional accountability, and patient participation in clinical communication.

Sociolinguistic and pragmatic expansion

AI foregrounds sociolinguistic inequalities: dialect speakers, older patients, and individuals with lower health literacy risk misrecognition or misclassification. This connects linguistic theory to digital health equity, establishing new cross-disciplinary research domains.

Linguistic framework for implementation

Plain language principles

AI output in clinical documentation should follow standards of plain language, such as those codified in ISO 24495-1:2023 – prioritising clarity, readability, and actionable structure for the intended audience. Evidence from health communication research shows that using plain language and simplifying medical text improves patient comprehension and reduces misinterpretation of clinical information (Stableford, Mettger, 2007; Warde et al., 2018). In healthcare settings, plain-language writing has been proposed as a core competency for clinicians to mitigate low health literacy among patients (Warde et al., 2018). Thus, when generating patient-facing communications or summaries, AI systems should avoid unnecessarily complex syntax, dense nominalisations or opaque medical jargon and, whenever appropriate, adopt patient-centred metaphors and straightforward phrasing consistent with plain-language guidelines.

CA-informed repair strategies

Conversation Analysis shows that repair is a fundamental interactional practice by which participants manage problems of speaking, hearing, and understanding, thereby sustaining intersubjectivity (Schegloff, 2007; Albert, de Ruiter, 2018). In clinical encounters, repair enables clarity, alignment, and mutual orientation – all crucial for safe and effective interaction. In the context of AI-mediated systems, where algorithmic outputs may not respond to clarification or negotiation, clinicians must adopt compensatory strategies. Training for AI-mediated consultations should therefore include prompts that check patient understanding (e.g., “Jak Pan/Pani rozumie komunikat systemu?”), and strategies for reframing ambiguous or opaque AI-generated messages into patient-accessible language. Although no published study yet documents how AI-human repair sequences unfold in clinical consultation, the combination of CA insights on interactional repair and emerging human–AI alignment research suggests that clinician-led repair work will become even more important to maintain interactional symmetry and reduce epistemic confusion (Heritage, Maynard, 2006; Heritage, 2012).

Genre-sensitive documentation models

Clinical documentation is a professional genre whose structure influences clinical reasoning (Swales, 1990; Rosenbloom et al., 2011). AI should support – not overwrite – clinician narrative practices. Research shows that narrative and stance expressions carry diagnostic and interpersonal functions (Charon, 2006; Biber, Conrad, 2009). Systems must:

- preserve patient quotations (Charon, 2006),
- maintain temporal and experiential detail (Mishler, 1984),
- mark stance and uncertainty explicitly (Perkins et al., 2024),
- allow clinicians to override summaries (Perkins et al., 2024).

This ensures documentation retains its interpersonal and evidentiary functions. Applied work on voice-generated documentation within intelligent clinical forms in Poland illustrates this genre-sensitive approach in practice (Czyżewski, 2023b).

Corpus-based sociolinguistic validation

Bias in NLP systems correlates with a lack of dialectal and sociolinguistic representation (Blodgett et al., 2020). Validation must include:

- dialectal corpora — e.g. Korpus Spiski, documenting the speech of inhabitants of Polish Spisz across age cohorts (Grochola-Szczepanek et al., 2019).
- age-specific / generational speech variation – Korpus Spiski was created with informants from “the youngest and middle generations”, as well as older speakers, making it suitable for generational / sociolinguistic variation studies (Grochola-Szczepanek et al., 2019).
- sociophonetic / phonetic diversity – e.g. PRODIS, a large, publicly available Polish speech database designed for phoneme-level analysis, suitable for phonetic and prosodic variation studies (Malisz et al., 2024).

- healthcare-specific Polish / domain-specific speech data – e.g. ADMEDVOICE, a Polish medical-speech dataset collected in realistic (possibly noisy) conditions and including domain-specific vocabulary (drugs, illnesses), which can support development and validation of medical-domain NLP/ASR systems (Czyżewski et al., 2025; Pondel-Sycz et al., 2025) and emerging adaptive AI platforms that combine speech recognition with diagnostic data structuring for Polish clinical decision support (Szplīt et al., 2025).

Such comprehensive coverage – dialectal variation, generational variation, phonetic/sociophonetic diversity, and domain-specific (medical) language – reduces systemic bias by ensuring representation of diverse sociolinguistic backgrounds and registers, particularly for vulnerable or underrepresented populations.

Pragmatics-informed patient education

Research on clinician–patient communication demonstrates that the tone, wording, and structure of medical information significantly influence patient understanding, illness experience, and adherence to treatment. Polish studies show that communication that is respectful, clear, non-authoritarian, and oriented toward the patient’s knowledge and emotional state supports a more positive experience of illness and improves trust in medical staff (Każmierczak, 2011). Likewise, analyses of health and medical communication in public and institutional contexts indicate that overly formal or authoritative language can alienate recipients and decrease the effectiveness of educational messages (Białek-Szwed, 2019). Work on interpersonal communication in healthcare organisations further underscores the need for clarity, empathy, and avoidance of unnecessary medical jargon to ensure that messages are understood and socially appropriate (Meller, Milik, 2014).

Large-scale empirical evidence confirms this: a meta-analysis of over three decades of research shows a strong association between high-quality physician communication and patient adherence (Haskard Zolnierrek, DiMatteo, 2009). Similarly, collaboration-oriented communication – framing recommendations clearly and involving the patient in understanding why an action matters – has been shown to significantly improve adherence to medical advice (Arbuthnott, Sharpe, 2009).

Therefore, AI-generated patient materials should:

- **avoid face-threatening or overly authoritative language**, consistent with findings on the importance of respectful and non-hierarchical communication in healthcare (Każmierczak, 2011; Białek-Szwed, 2019);
- **provide explicit framing of recommendations** – using clear, actionable structures such as “co należy zrobić”, “jak to zrobić”, and “dlaczego ma to znaczenie” – which supports comprehension and treatment uptake (Arbuthnott, Sharpe, 2009);
- **use metaphors, analogies, and everyday language explanations** to make complex medical concepts cognitively accessible and reduce the communicative distance between expert and patient (Meller, Milik, 2014);
- **avoid excessive medicalised morphology and specialist terminology**, replacing it with plain language and patient-centred explanations to minimise misunderstanding and confusion (Białek-Szwed, 2019).

Embedding pragmatics-informed communication – respectful tone, clarity, explicit guidance, and linguistic accessibility – ensures that patient-targeted materials are socially appropriate, comprehensible across different levels of health literacy, and conducive to patient engagement and adherence to recommended care (Arbuthnott, Sharpe, 2009; Haskard Zolnierrek, DiMatteo, 2009).

Implications

Communicative consequences

AI may enhance efficiency but risks reducing patient narrative richness (Hydén, 1997), weakening rapport (Blease et al., 2019), amplifying misunderstandings when outputs are vague or numeric (Peters et al., 2007), and shifting authority toward computational systems (Braun et al., 2021).

Clinical consequences

Potential benefits include standardisation and reduced documentation burden (Lee et al., 2024). Risks include:

- misclassification and performance degradation due to biased or stigmatizing language and linguistic ambiguity (Liu, Wang, Gao, 2023),
- clinician overreliance on system-generated interpretations and risk of reduced human oversight (Hossain et al., 2023; Barwise et al., 2024),
- loss of soft clinical cues or nuanced patient-history that often emerge only through human storytelling, rapport, and in-person dialogue (Barwise et al., 2024).

Ethical and sociolinguistic consequences

Unequal linguistic recognition creates unequal care. Patients with dialects, low literacy, or atypical speech patterns risk being misunderstood or deprioritised by AI systems (Blodgett et al., 2020; Chinta et al., 2024). Ensuring equity requires linguistic calibration and continuous monitoring (Rajkomar et al., 2018).

Institutional consequences

AI influences not only interaction but workflow, policy, and medico-legal accountability. Institutions must establish standards for:

- attribution of responsibility (Cabitza et al., 2017),
- documentation accuracy (Rosenbloom et al., 2011),
- transparency of decision pathways (Regulation (EU) 2024/1689).

Conclusion

AI is not merely a technical tool but a new linguistic participant in Polish primary care. Its presence reshapes the texture of clinical encounters: how stories are told, how evidence is constructed, and how decisions are communicated. To ensure equitable, patient-centred care, implementation must be grounded in linguistic theory – recognising that communication quality is as important as technological accuracy.

Polish primary care stands at a crossroads. With linguistically informed design, AI can enhance clarity, accessibility, and interactional coherence. Without such grounding, it risks deepening disparities, eroding rapport, and diminishing the patient's voice. A robust linguistic framework – supported by CA, narrative theory, genre analysis, and sociolinguistics – offers a pathway toward AI that strengthens rather than weakens the human core of healthcare.

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