Original Paper

AI Scribe in Specialized Rehabilitation: Usability Study of Perceived Usability and Usefulness Among Physicians and Psychologists

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Abstract

Background: Clinical documentation in specialized, interdisciplinary rehabilitation is often time-consuming and complex and may contribute to clinician burnout and reduced time for patient interaction. AI-based scribes transcribe and summarize clinical notes and may reduce documentation burden; however, their usefulness and usability in specialized rehabilitation remain uninvestigated.

Objective: This study aimed to assess the use of an ambient AI scribe tool among physicians and psychologists in specialized rehabilitation, focusing on perceived usefulness, usability, note quality, impact on patient interaction, perceptions of time spent on documentation, and documentation-related fatigue.

Methods: Over approximately 4 weeks, physicians and psychologists at 9 specialized rehabilitation centers used an ambient AI scribe during clinical consultations. Usability and user experience were assessed using the System Usability Scale (SUS) and a modified technology acceptance model (TAM). Participants rated an AI-generated note using a modified 8-item Physician Documentation Quality Instrument (PDQI-8) questionnaire to evaluate documentation quality. Additional questions explored perceived impact on patient interaction, documentation-related fatigue, and general attitudes toward AI technology.

Results: Thirty-one clinicians (18 physicians and 13 psychologists) used the AI scribe over approximately one month and completed evaluation questionnaires. The mean SUS score was 78.3 (SD 10.4), with 86.7% of participants scoring above the usability threshold. Perceived usefulness (PU) and perceived ease of use (PEOU) were relatively high (mean PU score 5.65, SD 1.33; mean PEOU score 5.56, SD 1.17), and 87.1% expressed intention to use the AI scribe in future practice. Most participants (80.6%) agreed that using the AI scribe reduced time spent on documentation, while 66.6% reported a reduced perception of documentation-related fatigue. The quality of AI-generated notes was rated relatively high, with a mean modified PDQI-8 score of 4.3 (SD 0.3) out of 5. Comprehensibility received the highest rating (mean 4.6, SD 0.6), whereas thoroughness received the lowest rating (mean 3.9, SD 1.0) among the note quality variables. Overall, 71.0% of participants expressed some level of agreement that the AI scribe enhanced attentiveness during patient consultations, while a similar proportion (70.9%) agreed that it made active listening easier by reducing distractions associated with note-taking. A few participants reported that some notes were incomplete, lacked biopsychosocial details, and contained inaccuracies.

Conclusions: This study demonstrated broad acceptance of an AI-based ambient scribe among physicians and psychologists working in specialized rehabilitation. The AI scribe was generally perceived as valuable, easy to use, and clinically relevant. Most participants reported a reduced perceived documentation burden and improved attentiveness during consultations. These findings suggest that clinicians perceived the AI scribe as supporting more focused patient interactions. Some concerns were noted regarding completeness and occasional inaccuracies, highlighting areas for refinement. Future research should explore

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long-term implementation in routine rehabilitation settings and its effects on workflow, documentation quality, and patient experience.

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KEYWORDS

eHealth; artificial intelligence; AI; rehabilitation; technology; usability; adoption; implementation; scribe

Introduction

Clinical documentation in electronic health records (EHRs) is essential for ensuring the accuracy and comprehensiveness of clinical information, promoting shared decision-making, and enhancing care coordination [1-3]. In specialized rehabilitation, health care professionals must thoroughly document the patient's functional status, therapeutic interventions, and progress over time [4,5]. This requires that medical records accurately reflect the interdisciplinary approach to patient care, often incorporating contributions from various health care professionals. At the same time, fulfilling these documentation requirements often places a heavy burden on clinicians [6,7]. For instance, research indicates that many physicians spend several hours outside regular working hours completing EHRs, leading to career dissatisfaction, negative impacts on work-life balance, and disruption of clinician-patient relationships [8,9].

Manual documentation has been associated with increased cognitive demands and distractions and may contribute to clinician burnout because of the excessive time spent on clinical documentation [10]. This burden may adversely affect health care personnel by reducing productivity and contributing to frustration, emotional exhaustion, and potentially compromised patient care [11,12]. Patients have expressed concerns that the increase in EHR-based administrative tasks leads physicians to spend more time at digital devices, making visits feel impersonal and routine [13]. Recent qualitative research shows that electronic documentation in rehabilitation is perceived as burdensome, limiting time for patient interaction and affecting relational quality [5].

In recent years, advances in AI scribes have offered potential solutions to optimize documentation by reducing the time clinicians spend on manual note-taking, alleviating the administrative burden, and improving the quality and consistency of clinical records [14]. AI scribes use advancements in natural language processing (NLP) and machine learning to record, transcribe, and summarize clinical encounters [15]. Automated digital scribes can capture conversations between clinicians and patients and generate documentation for inclusion in the medical record. By automating the documentation process, AI scribes may potentially reduce the administrative burden on health care providers, allowing them to dedicate more time to direct patient care [14,16]. This could enhance the patient experience and improve clinical outcomes [17]. Recent studies suggest that AI-enhanced medical scribe services can maintain high levels of accuracy and consistency in clinical documentation while minimizing errors associated with manual data entry [17]. Furthermore, integrating AI into health care documentation has shown promise in reducing physician burnout by decreasing the time required for manual medical record documentation [18]. Digital scribes may enable clinicians to engage more with patients, maintain eye contact during consultations, and avoid diverting attention from the patient to a computer for manual documentation, which may ultimately lead to more patient-centered care [19].

Although these developments are promising, evidence from peer-reviewed studies on the benefits of digital scribe technology in rehabilitation settings remains limited. AI scribes may help health care providers in specialized rehabilitation meet documentation requirements and allocate more time to direct patient interactions. In addition, AI scribes may help standardize clinical documentation and improve information flow across interdisciplinary teams, potentially improving care coordination. Despite the potential of AI in clinical documentation, concerns remain about the quality of AI-generated notes [16]. Further research is therefore needed to examine this issue in a rehabilitation setting. To date, no studies have examined clinicians' experiences with the latest version of AI scribe technology in specialized rehabilitation. Unicare Rehabilitation is among the first health care institutions to pilot an ambient AI scribe in this context.

The overall aim of this study was to investigate physicians' and psychologists' experiences using ambient AI-scribing technology as a clinical documentation assistant in specialized rehabilitation. This aim was addressed through 2 specific objectives: first, to evaluate perceived usefulness (PU), perceived ease of use (PEOU), overall usability, perceived interaction support (PIS), the quality of generated clinical notes, and the impact on documentation-related fatigue; and second, to explore the relationship between AI scribe usability, measured using the System Usability Scale (SUS), and key acceptance factors in the modified technology acceptance model (TAM), providing preliminary insight into the relevance of usability in specialized rehabilitation.

Methods

Materials

This exploratory evaluation assessed clinicians' perceptions of the usability and usefulness of the AI scribe Noteless (Noteless AS) following 4 weeks of routine clinical use. The study was reported in accordance with relevant recommendations for observational studies [20].

Product Information and Workflow Overview

The AI scribe evaluated in this study was Noteless, a web-based software application designed to transcribe and summarize medical conversations. The system operates through a series of structured steps to streamline clinical documentation. It uses a transformer-based speech-to-text model, refined to handle

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medical terminology, to enhance transcription accuracy. The AI scribe was accessible via a web-based app. At the beginning of patient consultations, the clinician initiated the recording session. The device's voice-recording hardware (Nedis [Nedis BV], model MICCU100BK), in conjunction with the AI scribe app, captured the conversation between the clinician and the patient. Upon completion, the recording was transmitted to the cloud for processing by AI designed to interpret and analyze speech. The AI scribe analyzed the recording and generated a draft derived from the recorded dialogue. For summarization, it used a combination of large language models integrated with a customized prompt structure and supplementary rules [21]. During the study period, the evaluated system was Noteless version 2.0. The system was used to transcribe and generate clinical documentation from consultations conducted in Norwegian.

The platform used a model-agnostic, modular architecture that allowed different commercially available large language models to be used for specific documentation tasks. Noteless was designed as a clinical documentation support tool rather than a clinical decision-support system and was not intended to provide diagnostic, treatment, or other clinical recommendations. Generated notes were copied into the clinician's EHR system, where they were reviewed, edited as needed, and approved by the clinician before finalization. Clinicians retained full responsibility for the final documentation.

Audio recordings were processed in real time through Speechmatics (Speechmatics Inc) speech-recognition services hosted on Microsoft Azure infrastructure located in Ireland and Spain and were not retained after transcription. Audio data were deleted immediately once the corresponding text transcript had been generated. Resulting transcripts and AI-generated notes were temporarily stored within the Noteless platform for a maximum of 24 hours in a Microsoft Azure data center located in Norway (Norway East region) to support document generation and clinician review before being securely deleted. AI-based note generation was performed using services hosted on Microsoft Azure infrastructure in Sweden and Google Cloud Platform infrastructure in Belgium. Neither Noteless nor its subprocessors retained patient data following processing or used such data for model training or any other secondary purposes. Privacy and security safeguards included encryption in transit and at rest, access controls based on the principle of least privilege, audit logging, periodic access reviews, contractual data-processing agreements with subprocessors, and automated deletion procedures to ensure removal of transcripts and generated notes after the retention period.

Setting

This cohort study was conducted at Unicare's specialized academic rehabilitation centers in Norway. Unicare Rehabilitation comprises 10 specialized centers offering both inpatient and outpatient services. Many rehabilitation programs in Norway are organized as outpatient programs at hospitals or rehabilitation centers near hospitals and as inpatient programs at rehabilitation centers primarily located in rural areas. The current study was conducted in inpatient rehabilitation centers. Unicare provides specialized interdisciplinary rehabilitation services, including professionals such as physical medicine physicians, psychologists, physiotherapists, nutritionists, and occupational therapists. The rehabilitation centers annually receive approximately 9000 patients across all major diagnostic groups. The study was conducted across all centers from January to February 2025.

Recruitment and Participants

Ambient scribe technology was offered to all physicians and psychologists for use during inpatient and outpatient medical appointments, with informed consent obtained from all participants. A convenience sample was used, comprising physicians and psychologists who were invited to use the ambient scribe technology and agreed to participate in the evaluation. Potential participants were recruited through a dual approach: informal recruitment emails to engage interested clinicians and proactive efforts by department leaders to disseminate information about the study across 9 distinct rehabilitation centers. This recruitment strategy successfully identified 31 clinicians, comprising 18 physicians and 13 psychologists, all of whom consented to participate in the pilot program. Patients verbally consented to the use of the ambient scribing tool during clinical encounters; however, the project team did not collect or review any patient information at any point during the study. Participants received no reimbursement for participating.

Procedure

Prior to the commencement of the 4-week pilot period, participants attended a 45-minute orientation session via video call, during which the project leader provided information about the study and basic instructions on using the ambient scribe tool. The training session primarily emphasized practical aspects of setting up and configuring the ambient AI scribe technology, including hardware and software components. While the session deliberately limited detailed guidance on usage to allow participants to explore the system's ease of use independently, it nonetheless introduced key principles for practical and safe application of the technology in clinical practice.

Participants were instructed to use their microphone to record the encounter and generate summarized documentation that was automatically uploaded to and stored on a secure cloud, accessible on their desktop computer through secure web interfaces for later incorporation and text editing into the EHR. During the initial briefing, participants were also told how to obtain patients' permission to use the AI medical scribe for in-person or virtual encounters. Throughout the study, participants used ambient scribing for specialized rehabilitation, with continuous technological support from support staff.

Patient Information Resources

Informational brochures were developed and distributed to the rehabilitation centers where the ambient AI scribe was implemented. These brochures contained essential information, which participants could summarize verbally during the consent process. Additionally, laminated posters were offered for placement in visible areas within the clinics to inform patients that physicians and psychologists might use AI scribe technology during their consultations.

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Inclusion Criteria

Licensed physicians and psychologists working at one of the participating rehabilitation centers are currently involved in patient care and are willing to use an AI scribe during medical appointments.

Exclusion Criteria

Individuals who had previously used any form of AI-based scribe were not eligible to participate.

Outcomes

PU and Usability

The study used a dual-strategy approach, combining the TAM from Information Systems and the SUS from human-computer interaction [22]. Integrating these 2 complementary approaches was intended to provide a comprehensive understanding of both usability and user experience factors, thereby enhancing the evaluation process. In addition, another purpose was to enable a comparison of the measurement tools themselves, offering insights into their respective contributions to assessing technology in this context.

TAM Methodology

TAM is one of the most widely used and researched models for predicting the adoption and use of information technology by individuals, with its validity in health research affirmed by numerous studies [23]. This model highlights 2 key factors that influence user acceptance of technology: PU and PEOU. PU is defined as "the degree to which a person believes that using a particular system would improve his/her job performance" [24], and PEOU is defined as "the degree to which a person believes that using a particular system would be free of effort" [24].

Initially, TAM items elicited likelihood ratings rather than agreement ratings because the model was designed to predict future product use rather than to rate the experience of actual use [24]. Since the aim of this study was to evaluate PU and PEOU following actual product experience rather than to predict future use, the TAM was adapted to align with the usability metric for user experience (UMUX) format [25]. This modification allowed respondents to express their level of agreement with items that reflect real user experience rather than anticipated usage. The TAM questionnaire used in this study consisted of 12 items: 6 to measure PU and 6 to measure PEOU. In addition, 2 dimensions considered determinants of PU according to the TAM methodology were included, as they are highly relevant to the evaluation of an AI scribe: (1) job relevance (JR), defined as "the degree to which an individual believes that the target system applies to his or her job," and (2) quality output (QO), defined as "the degree to which an individual believes that the system performs his or her job tasks well." Additionally, the construct intention to use (IU) was included, defined as "the degree to which an individual intends to use the system." JR, QO, and IU were each measured with 2 items [26]. TAM items were measured on a 7-point Likert scale, from "1=strongly disagree" to "7=strongly agree." The TAM literature does not define any established cutoff values for interpreting mean scores.

SUS

The SUS is among the most used standardized questionnaires for assessing perceived usability [27]. SUS is a 10-item questionnaire that includes an equal number of positive and negative statements. Each statement is rated on a scale from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating better usability. The SUS is a widely used and validated measure of system usability, and extensive normative research offers various methods for interpreting SUS scores, including the Curved Grading Scale (CGS) approach [28]. To calculate the SUS score, one is subtracted from each odd-numbered item score, and 5 is subtracted from each even-numbered item score. Then, these adjusted scores are summed and multiplied by 2.5 to obtain the overall SUS score, which ranges from 0 (extremely poor usability) to 100 (excellent usability). Usability was classified into 7 descriptive categories based on the adjective rating scale proposed by Bangor et al [3]. The corresponding SUS score ranges were "worst imaginable" (0-12.5), "awful" (12.6-20.3), "poor" (20.4-35.7), "OK" (35.8-50.9), "good" (51.0-71.4), "excellent" (71.5-85.5), and "best imaginable" [3,29].

Perception of Documentation Fatigue

Participants were given a question regarding their perception of reduced tiredness following use of the AI scribe: (1) "The use of the AI tool has reduced the experience of fatigue due to decreased documentation work." Items in the questionnaire were measured on a 7-point Likert scale, from "1=strongly disagree" to "7=strongly agree" (Table 1).

Table 1. Participant characteristics.

	All (n=31)	Physicians (n=18)	Psychologists (n=13)
Age (years), mean (range)	47.5 (28-75)	55.4 (33-75)	37.9 (28-56)
Sex (male), n (%)	12 (39)	10 (56)	2 (15)
University education, n (%)	31 (100)	18 (100)	13 (100)

Perceived Benefits and Challenges of Using the AI Scribe

Participants were asked to provide free-text responses to two open-ended questions: (1) Did you experience any benefits from using the AI tool in your work? If so, what were they? and (2) Were there any challenges or difficulties you encountered while using the AI tool in your work? If so, what were they?

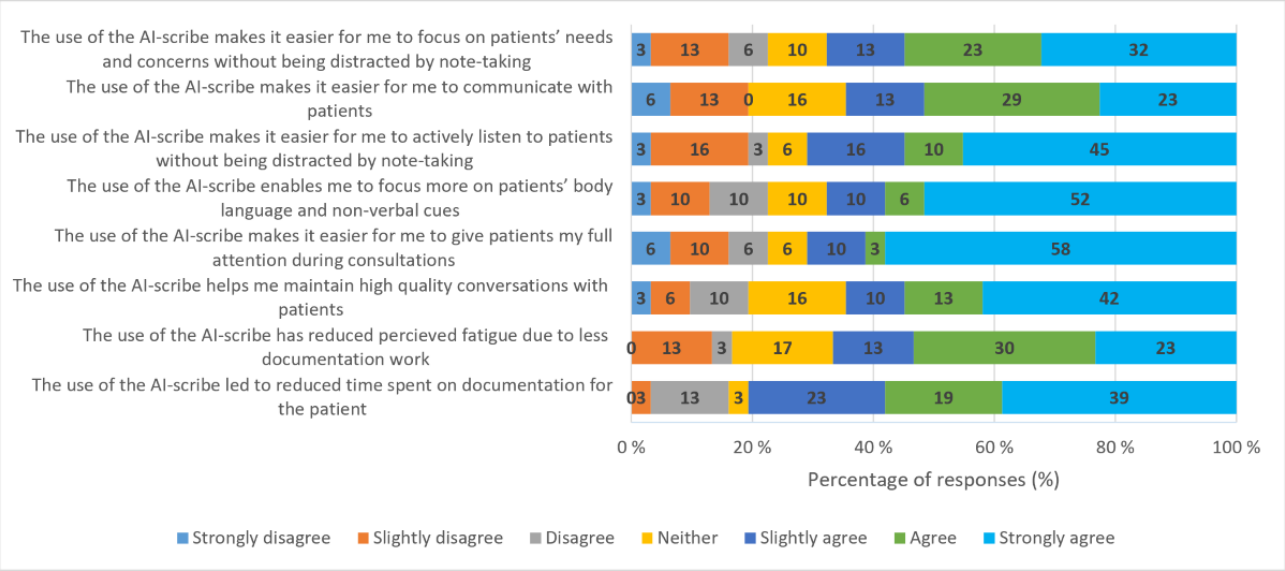
Perceived Impact on Clinician-Patient Interaction

A structured questionnaire, primarily self-developed, with some questions informed by Duggan et al [30], was used to gather data on various aspects of patient interactions. The questions addressed the following dimensions: perceived reduction in time spent on documentation, maintaining high-quality patient

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conversations, ability to give undivided attention to patients, focus on nonverbal cues, ease of active listening, overall interaction effectiveness, and understanding of patient needs and concerns. Items were measured on a 7-point Likert scale, from "1=strongly disagree" to "7=strongly agree" (Figure 1).

Figure 1. Distribution of responses to 8 statements assessing the perceived usefulness of the AI scribe in relation to time consumption, patient interaction, and perceived documentation fatigue. Bars represent the percentage of respondents in each Likert category, with the percentages displayed within the segments.



A composite score, referred to as PIS, was created from 6 study-specific items developed for this exploratory study to capture different aspects of how the AI scribe was perceived to influence clinician-patient interaction. The composite score was used as an exploratory summary measure and to facilitate correlation analyses with factors from the TAM framework. This approach is widely used when multiple items reflect different facets of the same underlying concept [31,32]. PIS was designed to capture participants' overall experience of interaction quality when using the AI scribe and should be regarded as a study-specific exploratory measure rather than a validated scale. Higher scores indicate stronger perceived support for interaction. The PIS score was calculated as the mean of the 6 items. The 6 items are provided in Multimedia Appendix 1.

General Attitude Toward AI Technology

Information regarding participants' general attitude toward AI technology was collected using the AI Attitude Scale (AIAS) [33]. The AIAS is a concise self-report instrument designed to evaluate public perceptions of AI technology. Items were measured on a 10-point Likert scale, from "1=not at all" to "10=completely agree."

Quality of Notes

The primary outcome was clinician-rated note quality, assessed using a modified 8-item version of the 9-item Physician Documentation Quality Instrument (PDQI-9) that differed from the original validated instrument by removal of one item and modification of another item. The PDQI-9 has been validated as a reliable tool for evaluating the quality of progress notes and discharge summaries. This tool assesses note quality in 9 domains on a 9-item scale with responses on a 5-point Likert scale ranging from 1 (not at all) to 5 (extremely). The original items are: up-to-date, accurate, thorough, useful, organized, comprehensible, succinct, synthesized, and internally consistent. As in Tierney et al [34], we excluded "up-to-date" because it was deemed not relevant. In addition, we changed the definition of the domain "synthesized" from "reflects the author's understanding of the patient's status and ability to develop a plan of care" to "The note reflects my understanding of the patient's status as it was presented during the consultation." This change was made because, in the context of this study, the author was the AI scribe itself. Thus, the total score for the modified 8-item Physician Documentation Quality Instrument (mPDQI-8) could range from 8 (worst possible note quality) to 40 (best possible quality). Participants were instructed to rate an AI-generated admission note as presented by the AI scribe. This rating was conducted during the final week of the study.

Data Collection Method

The study used a Microsoft Forms survey to assess PU, PEOU, JR, QO, IU, SUS, patient interaction, perceived documentation fatigue, evaluation questions, and AIAS after the 4-week test period. Participants were instructed to complete a paper version of the modified PDQI-8 to evaluate notes generated by the AI scribe after patient consultations and then return them to the project leader.

Analysis

Descriptive statistics were calculated for all variables, including sociodemographic characteristics and scores from the TAM, SUS, AIAS, and custom items related to patient interaction. Group comparisons by profession were conducted using independent-samples Student *t* tests or Mann-Whitney U tests. Pearson correlation coefficients were computed to assess associations between constructs. Following the approach described by Venkatesh and Bala [35], mean item scores were calculated for each instrument. Construct-level scores were then derived by computing the mean of item means, which were used

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in subsequent statistical analyses. Given the exploratory nature of the study and the modest sample size, no adjustment for multiple testing was performed. Correlation analyses and subgroup comparisons were therefore interpreted as exploratory and hypothesis-generating. To evaluate the internal consistency and dimensionality of the PIS composite variable, reliability and factor analyses were performed. Internal consistency was assessed using Cronbach alpha, and item quality was examined through corrected item-total correlations and interitem correlations. An exploratory factor analysis (EFA) was conducted to assess the underlying structure of the PIS items, including evaluation of sampling adequacy (Kaiser-Meyer-Olkin [KMO]) and the Bartlett test of sphericity. The PIS score was calculated as the mean of the 6 individual items. Results were considered statistically significant at $P<.05$. Data were analyzed using IBM SPSS Statistics.

Qualitative Analysis of Free-Text Responses

The free-text responses were analyzed by means of qualitative content analysis combining deductive and inductive approaches. The deductive component was based on the 2 open-ended evaluation questions regarding perceived advantages and disadvantages associated with the AI scribe. In the first stage of the analysis, the responses to these 2 questions were analyzed separately. Initially, one researcher (IL) gained an overall understanding of the topics addressed and sorted the responses into preliminary codes for each question. This coding structure was reviewed and discussed by 3 researchers (HKE, IL, and KS), who jointly refined the codes into a final codebook. The names of the codes were based on participants' own wording.

In the next step, the entire dataset was coded. Codes were compared in terms of similarities and differences in content and grouped into preliminary code groups. Through several rounds of discussion and revision among 4 researchers, the code groups were abstracted into categories and subtopics (Table 2). The categories represent broader areas of participants' experiences, while the subtopics describe specific aspects within these areas. The coding process and the development of categories and subtopics were inductive.

During the process of developing categories, the research team merged responses from the 2 open-ended questions into a single dataset since the analysis revealed that the participants described both advantages and disadvantages within the same category. For example, in the category of quality of clinical documentation, it was identified as an advantage that the AI scribe improved summaries and captured clinically relevant information and as a disadvantage that the tool occasionally drew incorrect conclusions or generated text that required manual revision. The predefined dimensions of advantages and disadvantages were retained by including a separate column in Table 2 (inspired by Duggan et al [30]). The organization of codes, the development of categories and subthemes, and the selection of illustrative quotations were discussed and refined by all 4 members of the research team. Any differences in interpretation were resolved through discussion until consensus was reached. The study did not include a member-checking procedure.

The originally Norwegian free-text responses were translated into English at the final stage of the analysis. An AI tool was prompted to translate the responses into language resembling the style used by health care professionals. All translations were subsequently reviewed and, where necessary, revised by 3 researchers. The analysis team consisted of 4 researchers with experience in specialized rehabilitation, technology implementation, health services research, and qualitative and quantitative research methods.

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Table 2. Key themes from qualitative comments.

Category and subtopic	Quotes (+ indicates advantages; – indicates disadvantages)
Workload related to documentation task	
Stress and fatigue	• (+) “Less time spent on documentation – reduced fatigue” (K2) • (+) “Time-saving, reduces stress” (K19) • (+) “Easier to go back and write/complete notes later the same day. Noticeably less stress during the workday.” (K22) • (+) “Gives me more time to prepare between sessions” (K29) • (+) “Good summaries of the conversation drastically reduce the time and energy spent on documentation.” (K4)
Documentation burden	• (+) “Because a note was already generated, it was much easier for me to finalize the note right after a session. The threshold for starting documentation was lower since the task felt smaller and already started, which meant I had less backlog.” (K3)
Time spent	
Initial draft/preliminary note	• (+) “Repeats all findings during the examination and explains more to us along the way. Provides a good starting point for documentation if there isn’t time to finish writing between sessions.” (K20) • (+) “Captured the main essence of the conversation, which was transcribed and could be used with only minor edits.” (K11)
Quality of clinical documentation	
Summary	• (+) “Good summary and structure in the notes” (K22) • (+) “More time, more complete notes, better note structure” (K25) • (+) “It summarized longer conversations just fine. Provided a quick starting point for the journal entry.” (K15)
Captures more information	• (+) “It could sometimes pick up things that I didn’t manage to note during the consultation, which was valuable when transcribing the clinical examination.” (K9) • (+) “Reduced risk of missing something important the patient says during the conversation” (K5)
Generates suggestions for follow-up interventions	• (+) “Good summaries of relevant topics in the consultation, along with useful suggestions for the assessment section of the note.” (K10) • (+) “Helpful that AI can assist in generating follow-up interventions after the summary and occasionally provide additional advice.” (K25) • (+) “It did a good job with simple assessments as suicide risk evaluation, and it was helpful for gathering background information/anamnesis.” (K32) • (+) “Suggestions for referrals are useful.” (K4)
Generates its own clinical evaluations	• (–) “It sometimes picked up that the patient was using medications that hadn’t been mentioned at all during the session.” (K32) • (–) “It also added a bit too many interpretations, which means things can easily end up in the note that you don’t fully stand behind if you’re not careful when reviewing.” (K15) • (–) “I’ve also noticed that it occasionally provides incorrect information, which makes it hard to fully trust the tool. The program’s recommendations for next steps are often not very useful for my practice.” (K9)
Selects information	• (+) “Being able to talk with the patient calmly and then get a transcript of the entire conversation, excluding small talk, is a big advantage.” (K17) • (–) “It filters out parts of the conversation about upbringing, conflicts, etc., which can be important to include.” (K18) • (–) “It doesn’t write exactly the way I want, and not everything I’d like to include makes it into the note.” (K11) • (–) “There’s a need for a template, especially to include biopsychosocial context in the note structure and in the summary/assessment section. I feel the wording lacks some holistic perspective.” (K19) • (–) “The software is very selective in? What it listens to, leaving out large parts of information that I find relevant, especially during longer conversations.” (K9)
Proofreading/editing	• (–) “Overall, it took longer to edit the AI-generated note than to write my own notes, and my notes had higher quality and greater relevance to the patient’s course of treatment.” (K32) • (–) “Small errors can slip in and need to be caught during editing/proofreading.” (K23)
Quality of patient consultation	

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Category and subtopic	Quotes (+ indicates advantages; – indicates disadvantages)
Maintains focus on the patient	• (+) "I could focus on history-taking and the clinical examination." (K8) • (+) "I was more focused on the conversation with the patient and wrote a good summary at the end." (K5) • (+) "Able to focus on the conversation without having to take too many notes along the way." (K29) • (+) "Being able to talk with the patient calmly and then get a transcript of the entire conversation, excluding small talk, is a big advantage." (K17)
Patient can access the note immediately after the consultation	• (+) "Reading through the AI note together with the patient helps create a neutral summary of the session and invites the patient to correct or share an alternative perspective without feeling contradicted." (K4)
Sensitive topics	• (–) "I feel the recording limits the ability to talk about difficult topics." (K12)

Role of the Vendor

Noteless provided access to the AI scribe software free of charge during the study period and assisted with user registration in the system. The company provided general information about the technology but did not provide training to participants. Noteless had no role in the study design, data collection, data analysis, interpretation of results, manuscript preparation, or the decision to submit the manuscript for publication.

Ethical Considerations

The study was conducted in accordance with the Norwegian Research Ethics Act, the National Guidelines for Research Ethics, and the Declaration of Helsinki. Approval from a Regional Committee for Medical and Health Research Ethics (REK) was not required under Norwegian regulations. Unicare, as the data controller, was responsible for ensuring a lawful basis for processing personal data in accordance with the General Data Protection Regulation (GDPR). All participants provided informed consent prior to participation, and the processing of personal data was based on consent in accordance with Article 6(1)(a) and Article 9(2)(a) of the GDPR. Participation was voluntary, and participants were informed that participation or non-participation would have no consequences for their employment. All collected data were de-identified and stored securely, and only authorized members of the research team had access to the data. The authors declare no conflicts of interest.

Results

Sample Characteristics

A total of 33 physicians and psychologists attended the information meeting and were invited to participate in the study. One physician declined participation, and another did not complete the evaluation questionnaires. The study sample consisted of 31 participants: 18 physicians and 13 psychologists. All participants used the AI scribe for 4 weeks and completed the evaluation questionnaires. Among the physicians, 8 were women, and 10 were men, with a mean age of 55.4 years (SD 12.5). The psychologist group included 11 women and 2 men, with a mean age of 38.3 years (SD 9.0). Among physicians, the mean number of years since graduation was 16.0 (SD 13.8), while among psychologists it was 9.3 years (SD 7.0). Table 1 presents the demographic information of the included participants.

TAM Constructs, Usability, Attitudes to AI Technology, and Patient Interaction Support

All 31 participants completed the questionnaires, although data were missing for 1 participant on the modified PDQI-8 and SUS. The most relevant and statistically meaningful correlations are reported below, along with other observed results. Table 3 shows the correlations between TAM factors, SUS, AIAS, PIS, and categorical variables.

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Table 3. Pearson correlations between TAM[a] factors, SUS[b], AIAS[c], PIS[d], and categorical variables.

	PU[e]	PEOU[f]	SUS	BI[g]	JR[h]	QO[i]	PIS	AIAS	Age
PU, *r* (*P* value)	1	0.612 (.001)	0.433 (.017)	0.585 (<.001)	0.731 (.001)	0.843 (.001)	0.778 (.001)	0.541 (.002)	0.168 (.37)
PEOU, *r* (*P* value)	0.612 (.001)	1	0.794 (.001)	0.505 (.004)	0.332 (.07)	0.652 (<.001)	0.519 (.003)	0.389 (.03)	0.231 (.20)
SUS, *r* (*P* value)	0.433 (.017)	0.794 (.001)	1	0.601 (.001)	0.296 (.11)	0.486 (.006)	0.413 (.02)	0.355 (.054)	–0.023 (.90)
BI, *r* (*P* value)	0.585 (<.001)	0.505 (.004)	0.601 (.001)	1	0.766 (.001)	0.490 (.005)	0.481 (.006)	0.718 (.001)	0.021 (.91)
JR, *r* (*P* value)	0.731 (.001)	0.332 (.07)	0.296 (.11)	0.766 (.001)	1	0.552 (.001)	0.560 (.001)	0.651 (.001)	0.091 (.63)
QO, *r* (*P* value)	0.843 (.001)	0.652 (<.001)	0.486 (.006)	0.490 (.005)	0.552 (.001)	1	0.832 (.001)	0.411 (.02)	0.205 (.27)
PIS, *r* (*P* value)	0.778 (.001)	0.519 (.003)	0.413 (.02)	0.481 (.006)	0.560 (.001)	0.832 (.001)	1	0.466 (.008)	0.293 (.11)
AIAS, *r* (*P* value)	0.541 (.002)	0.389 (.03)	0.355 (.054)	0.718 (.001)	0.651 (.001)	0.411 (.02)	0.466 (.008)	1	–0.011 (.95)
Age, *r* (*P* value)	0.168 (.37)	0.231 (.20)	–0.023 (.90)	0.021 (.91)	0.091 (.63)	0.205 (.27)	0.293 (.11)	–0.011 (.95)	1
Profession, *r* (*P* value)	–0.046 (.81)	0.019 (.92)	0.068 (.72)	–0.008 (.97)	–0.112 (.55)	–0.108 (.56)	–0.233 (.21)	0.041 (.82)	0.631 (.001)

[a]TAM: technology acceptance model.

[b]SUS: System Usability Scale.

[c]AIAS: AI attitude scale.

[d]PIS: perceived interaction support.

[e]PU: perceived usefulness.

[f]PEOU: perceived ease of use.

[g]BI: behavioral intention.

[h]JR: job relevance.

[i]QO: quality output.

PU

Twenty-two of 31 participants (71.0%) agreed or strongly agreed that the AI scribe was useful, choosing either “agree” or “strongly agree” on the Likert scale. The mean PU score across all participants was 5.65 (SD 1.33), with physicians scoring 5.71 (SD 1.15) and psychologists 5.59 (SD 1.56). There was no statistically significant difference between groups (*P*=.81; Cohen *d*=0.09; 95% CI –0.62 to 0.80). Participants most often strongly agreed with the item “I find the system useful in my job” (51.6%), followed by “Using the AI scribe in my job enables me to accomplish tasks more quickly” (45.2%; Table 4). PU was positively correlated with. No significant correlation was found between PU and age or profession (Table 3).

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Table 4. Descriptive statistics for perceived usefulness, perceived ease-of-use, job relevance, intention to use, and quality output[a].

TAM[b] statements	Rating Scale							
	Strongly disagree	Disagree	Slightly disagree	Neither	Slightly agree	Agree	Strongly agree	Mean (SD)
PU[c] Items								
Using the AI scribe in my job enables me to accomplish tasks more quickly	1 (3.2)	0 (0.0)	1 (3.2)	2 (6.5)	4 (12.9)	9 (29.0)	*14 (45.2)* [d]	5.94 (1.41)
Using the AI scribe improves my job performance	1 (3.2)	1 (3.2)	0 (0.0)	3 (9.7)	*11 (35.5)*	8 (25.8)	7 (22.6)	5.39 (1.41)
Using the AI scribe in my job increases my productivity	1 (3.2)	1 (3.2)	2 (6.5)	3 (9.7)	5 (16.1)	*12 (38.7)*	7 (22.6)	5.39 (1.54)
Using the system enhances my effectiveness on the job	1 (3.2)	1 (3.2)	2 (6.5)	2 (6.5)	4 (12.9)	*13 (41.9)*	8 (25.8)	5.52 (1.55)
Using the system makes it easier to do my job	0 (0.0)	1 (3.2)	0 (0.0)	5 (16.1)	5 (16.1)	*12 (38.7)*	8 (25.8)	5.65 (1.23)
I find the system useful in my job	0 (0.0)	1 (3.2)	0 (0.0)	4 (12.9)	4 (12.9)	6 (19.4)	*16 (51.6)*	6.00 (1.32)
PEOU[e] Items								
Learning to operate the AI scribe was easy for me	0 (0.0)	1 (3.2)	1 (3.2)	2 (6.5)	4 (12.9)	6 (19.4)	*17 (54.8)*	6.06 (1.34)
I found it easy to get the AI scribe to do what I want it to do	1 (3.2)	1 (3.2)	4 (12.9)	4 (12.9)	*9 (29.0)*	*9 (29.0)*	3 (9.7)	4.87 (1.48)
My interaction with the AI scribe was clear and understandable	0 (0.0)	1 (3.2)	2 (6.5)	3 (9.7)	4 (12.9)	7 (22.6)	*14 (45.2)*	5.81 (1.45)
I find the AI scribe to be flexible to interact with	0 (0.0)	0 (0.0)	4 (12.9)	5 (16.1)	6 (19.4)	*8 (25.8)*	*8 (25.8)*	5.35 (1.38)
It was easy for me to become skillful at using the AI scribe	1 (3.2)	1 (3.2)	1 (3.2)	4 (12.9)	*10 (32.3)*	9 (29.0)	5 (16.1)	5.19 (1.42)
I find the AI scribe easy to use	0 (0.0)	0 (0.0)	2 (6.5)	0 (0.0)	5 (16.1)	9 (29.0)	*15 (48.4)*	6.13 (1.12)
Behavioral intention/intention to use								
Assuming I have access to the AI scribe, I intend to use it	0 (0.0)	0 (0.0)	3 (9.7)	0 (0.0)	1 (3.2)	5 (16.1)	*22 (71.0)*	6.39 (1.23)
Given that I have access to the AI scribe, I predict that I would use it.	0 (0.0)	1 (3.2)	1 (3.2)	1 (3.2)	1 (3.2)	4 (12.9)	*23 (74.2)*	6.42 (1.26)
Job relevance								
In my job, usage of the AI scribe is important	1 (3.2)	0 (0.0)	2 (6.5)	6 (19.4)	9 (29.0)	3 (9.7)	*10 (32.3)*	5.29 (1.53)
In my job, usage of the AI scribe is relevant	1 (3.2)	0 (0.0)	0 (0.0)	1 (3.2)	10 (32.3)	5 (16.1)	*14 (45.2)*	5.90 (1.33)
Output quality								
The quality of the output I get from the AI scribe is high	0 (0.0)	2 (6.5)	3 (9.7)	4 (12.9)	8 (25.8)	*8 (25.8)*	6 (19.4)	5.13 (1.48)
I have no problem with the quality of the AI scribe`s output	2 (6.7)	2 (6.7)	3 (10.0)	5 (16.7)	7 (23.3)	*8 (26.7)*	3 (10.0)	4.63 (1.69)

[a]Absolute number and percentage of participants in agreement with the statements.

[b]TAM: technology acceptance model

[c]PU: perceived usefulness.

[d]Italic text indicates the category with the highest response proportion.

[e]PEOU: perceived ease of use.

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PEOU

Twenty-four of 31 participants (77.4%) expressed agreement with the ease of use of the AI scribe, selecting "agree" or "strongly agree" on the Likert scale. The mean PEOU score was 5.56 (SD 1.17) across all participants, with physicians scoring 5.54 (SD 1.16) and psychologists 5.58 (SD 1.22). There was no statistically significant difference between groups (P=.92; Cohen d=–0.04, 95% CI –0.74 to 0.67). Participants most often (strongly) agreed with the item "Learning to operate the AI scribe was easy for me" (54.8%), followed by "I find the AI scribe easy to use" (54.8%; Table 4). There was a significant and positive correlation between PEOU and SUS, QO, PIS, and AIAS. No significant correlation was found between PEOU and age or profession (Table 3).

Behavioral Intention

Twenty-seven of 31 participants (87.1%) agreed with the intention to use the AI scribe in the future, selecting either "agree" or "strongly agree" on the Likert scale. The mean BI score was 6.40 (SD 1.23) across all participants, with physicians scoring 6.41 (SD 0.96) and psychologists 6.39 (SD 1.55). There was no statistically significant difference between groups (P=.97; Cohen d=0.02, 95% CI –0.69 to 0.72). There was a significant positive correlation between BI and PEOU, SUS, and PU. No significant correlation was found between BI and age or profession (Table 3).

JR

Across all participants, the mean JR score was 5.63 (SD 1.35). Physicians had a mean score of 5.76 (SD 1.06), while psychologists had a mean score of 5.46 (SD 1.67). There was no statistically significant difference between groups (P=.55; Cohen d=0.22, 95% CI –0.49 to 0.93).

No significant correlation was found between JR and age or profession (Table 3).

QO

The mean QO score was 4.89 (SD 1.48) across all participants, with physicians scoring 5.03 (SD 1.44) and psychologists 4.71 (SD 1.57). There was no statistically significant difference between groups (P=.57; Cohen d=0.21, 95% CI –0.50 to 0.92). No significant correlation was found between QO and age or profession (Table 3).

System Usability

In total, 26 of 30 participants (86.7%) considered the usability of the AI scribe to be acceptable (SUS score >70). The mean SUS score was 78.3 (SD 10.4) across all participants, with physicians scoring 77.6 (SD 10.3) and psychologists 79.0 (SD 10.9). According to the adjective rating scale by Bangor et al [3] and van der Nat et al [29], this corresponds to the "Excellent" category, indicating a strong perceived usability of the AI scribe. There was no statistically significant difference between groups (P=.72; Cohen d=–0.13, 95% CI –0.85 to 0.59). Participants most often strongly agreed with the item "I think that I would like to use the AI scribe frequently" (80.6%, 25/31), followed by "I would imagine that most people would learn to use the AI scribe very quickly" (70.0%, 21/30). There was a significant positive correlation among SUS, QO, and PIS. No significant correlation was found between SUS and AIAS, age, or profession (Table 3).

General Attitude Toward AI Technology

Across all participants, the average AIAS score was 7.84 (SD 1.60). Physicians had a mean score of 7.78 (SD 1.49), while psychologists had a mean score of 7.91 (SD 1.78). There was no statistically significant difference between groups (P=.83; Cohen d=–0.08, 95% CI –0.79 to 0.63). There was a significant and positive correlation between AIAS and PU, PIS, BI, and JR. No significant correlation was found between AIAS and age or profession (Table 3).

Perception of Documentation Time and Documentation Fatigue

Most participants (80.6%, 25/31) expressed some agreement that the AI scribe could help them save time on documentation. About two-thirds of participants (66.6%, 20/30) expressed some level of agreement that the AI scribe had reduced fatigue due to a lighter documentation burden (Figure 1).

PIS

Most participants agreed that the AI scribe provided positive support for patient interaction (Figure 1). Across multiple items, responses clustered in the upper range of the Likert scale, indicating that the AI scribe facilitates attentiveness, active listening, and patient-centered interaction. Specifically, participants reported that the AI scribe helps them maintain focus on patients' verbal and nonverbal cues (67.7%, 21/31), reduces distractions from notetaking (70.9%, 22/31), and supports clearer, more engaged dialogue (64.5%, n0/31); Figure 1).

Qualitative Comments

In their open-ended feedback, participants described the AI tool as time-saving and reported that it reduced stress and fatigue in daily practice (Table 2). They highlighted that the generated summaries provided a starting point that could be finalized more quickly. Furthermore, participants reported that the AI scribe reduced the documentation backlog, allowed more time between consultations, and decreased the time and energy spent on notetaking.

Psychometric Properties of the PIS Scale

The items of PIS showed excellent internal consistency (Cronbach α=0.983), with corrected item-total correlations ranging from 0.872 to 0.976 and interitem correlations between 0.84 and 0.96. An EFA supported a unidimensional structure, with one factor explaining 92.5% of the total variance (KMO=0.924; Bartlett test P<.001), indicating that the items measured a coherent construct. The internal consistency remained high when any single item was removed, indicating that all items contributed meaningfully to the composite score. There was a significant and positive correlation between PIS and PU, PEOU, SUS, and AIAS. No significant correlation was found between PIS and age or profession (Table 3).

Quality of Notes

The mean modified PDQI-8 score across all participants was 4.3 (SD 0.3). Physicians had a mean score of 4.3 (SD 0.6), and

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psychologists had a mean score of 4.3 (SD 0.6). There was no difference between the groups on the mean modified PDQI-8 score (P=.81). Overall ratings across documentation domains are summarized in Table 4. The thoroughness domain had the lowest mean score (3.9), followed by accuracy (4.1) and synthesis (4.1). The highest mean scores across all participants were observed for comprehensibility (4.6), internal consistency (4.5), and usefulness (4.4). Psychologists reported lower scores on the domain succinct than physicians (3.7 vs 4.7, P=.01; Table 5). One participant had a missing response for the modified PDQI-8 item "Internally consistent"; therefore, analyses for this item were based on 30 responses.

Table 5. Ratings of documentation quality in the modified PDQI-8[a] by domain.

Domain	All (n=30), mean (SD)	Physicians (n=18), mean (SD)	Psychologists (n=12), mean (SD)	*P* value	Cohen *d* (95% CI)
Accurate	4.1 (0.8)	4.1 (0.7)	4.0 (1.0)	.71	0.15 (–0.62 to 0.92)
Thorough	3.9 (1.0)	3.7 (1.3)	4.1 (0.5)	.31	–0.41 (–1.18 to 0.37)
Useful	4.4 (0.6)	4.4 (0.8)	4.5 (0.5)	.51	–0.26 (–1.03 to 0.51)
Organized	4.3 (0.7)	4.4 (0.7)	4.2 (0.8)	.38	0.35 (–0.43 to 1.12)
Comprehensible	4.6 (0.6)	4.7 (0.5)	4.5 (0.8)	.36	0.37 (–0.41 to 1.14)
Succinct	4.3 (1.0)	4.7 (0.5)	3.7 (1.3)	.01[b]	1.08 (0.25 to 1.90)
Synthesized	4.1 (0.7)	4.2 (0.8)	4.0 (0.6)	.50	0.27 (–0.51 to 1.03)
Internally consistent	4.5 (0.6)	4.5 (0.7)	4.5 (0.7)	.96	0.02 (–0.76 to 0.80)
Mean total (SD)	4.3 (0.5)	4.3 (0.5)	4.2 (0.6)	.46	0.29 (–0.49 to 1.06)

[a]PDQI-8: 8-item Physician Documentation Quality Instrument.

[b]Significance at P<.05.

In the open-ended questions, clinicians were divided in their experiences regarding the quality of the generated summaries. Some reported that the summaries were well-structured and occasionally captured more than they themselves had noted during the consultation, such as "it captured things I did not manage to note during the consultation" and "reduced the risk of missing out something important during the conversation." Some participants described the AI scribe as selective in what it included. While some clinicians appreciated that "small talk" was excluded, others considered it a drawback that important information was occasionally omitted. Some noted that the summaries lacked coherence and did not sufficiently capture biopsychosocial aspects, such as upbringing and conflicts, describing them as "lacking a holistic perspective." Participants reported that the summaries contained enough inaccuracies to require editing and proofreading (Table 2).

In open-ended feedback, clinicians reported that the AI scribe allowed them to draw more attention to the patient during consultations. They described being able to speak directly with the patient without taking handwritten notes or typing on a computer as an advantage. Another advantage mentioned was the ability to share the generated summary with the patient immediately after the consultation, enabling the patient to review and provide corrections or additional input. As a potential drawback, some clinicians noted that the recording could make some patients uncomfortable and "might limit the ability to talk about difficult topics" (Table 2).

Discussion

Principal Findings

To our knowledge, this is the first study to explore the PU and usability of an AI-based ambient scribe among physicians and psychologists working in specialized multidisciplinary rehabilitation. The results show that the AI scribe was perceived as both valuable and easy to use by most participants, with no significant differences between physicians and psychologists. Usability ratings were high, with over 86% of participants scoring above the accepted threshold on the SUS [3], indicating a positive usability experience. Although the study did not include a comparison with conventional documentation workflows, the mean SUS score of 78.3 exceeded the widely accepted benchmark score of 68 for average usability. Recent evidence has also suggested that this benchmark is applicable to digital health applications, supporting its use for contextualizing the present findings [36]. Comparisons across studies should nevertheless be interpreted cautiously because of differences in technologies, settings, and study populations. While overall perceptions were positive, some participants noted challenges, including occasional inaccuracies, selective omission of relevant information, and insufficient coverage of biopsychosocial aspects. In sum, these findings suggest that the AI scribe was generally well-received and perceived as useful for supporting clinical documentation in specialized rehabilitation settings.

Most participants considered the AI scribe important and relevant to their clinical work. JR showed a strong positive correlation with PU (r=0.731), indicating that clinicians who viewed the AI scribe as applicable to their professional responsibilities also tended to perceive it as beneficial. About

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87% of participants reported an intention to use (behavioral intention [BI]) the AI scribe in the future, provided they were given the opportunity. These findings indicate a generally high level of acceptance and willingness to adopt the AI scribe among participants. Moreover, intention to use the AI scribe was positively correlated with PU, PEOU, and SUS. The observed correlations indicate that PU and PEOU were associated with intention to use the AI scribe, consistent with the relationships proposed in the TAM model [24]. It should be noted that, in contrast to previous studies, PU has shown a clearly more decisive influence than PEOU on AI adoption in health care [37]. Our findings indicate a more balanced contribution of both constructs to BI (PU: r=0.585; PEOU: r=0.505). This may reflect the practical importance of ease of integration into clinical workflows, where time constraints, cognitive load, and the need for seamless documentation make usability a key consideration. However, it cannot be ruled out that the importance of PEOU might have diminished over time had clinicians gained more extensive experience with the AI scribe beyond the 4 weeks. This assumption is based on previous research suggesting that once the PU of a technology is firmly established, ease of use may become a less decisive factor in adoption decisions [38,39]. Nonetheless, in clinical practice, where time constraints, cognitive load, and the need for seamless documentation present ongoing challenges, continued attention to both PU and usability remains essential to support the long-term adoption of ambient AI scribe tools.

In addition to these system-specific factors, participants' general attitudes toward AI were assessed using the AIAS [33]. The mean score of 7.84 out of 10 indicates a broadly positive attitude toward AI. Although no significant differences were found between professions or age groups, AIAS scores correlated positively with PU, PIS, BI, and JR, suggesting that clinicians with more positive attitudes toward AI also tended to evaluate the AI scribe more favorably. It should be noted, however, that AIAS was administered after participants had used the AI scribe. While designed to measure general attitudes, responses may have been influenced by the specific experience, potentially affecting correlation coefficients. This type of response bias is a known concern in postintervention measurement of attitudes, particularly in technology acceptance research [40]. Future studies should consider measuring general AI attitudes prior to exposure to better distinguish pre-existing dispositions from experience-based evaluations.

Beyond general measures of technology acceptance and usability, a majority of participants reported that the AI scribe contributed positively to their clinical workflow. The results of this study suggest that ambient AI-scribing was perceived as contributing to greater efficiency, reduced documentation burden, and more attentive patient interactions during consultations. Specifically, 81% of participants responded with slight to strong agreement (Likert scale: 5–7) that the AI scribe reduced the time spent on documentation for the patient in question. In comparison, 66% reported reduced fatigue, addressing 2 commonly cited challenges in clinical contexts with high documentation demands [41]. While the current study did not directly measure time spent on clinical notetaking, the high level of agreement suggests that many participants perceived a meaningful reduction in documentation burden. This perception aligns with previous research suggesting that AI scribe technology may reduce perceived documentation burden and documentation-related workload while supporting clinician-patient interaction. However, reported effects on objective measures such as documentation time, EHR use, and productivity have varied across studies and clinical settings [42-47]. In their free-text answers, participants perceived the main benefit of the AI scribe as its ability to produce a well-structured initial draft that served as a foundation for documentation. Participants described the AI scribe as helping streamline note creation, reduce typing effort, and decrease time spent on postconsultation tasks. Several participants also perceived benefits related to reduced backlog, stress, and fatigue. On the other hand, some participants mentioned the omission of relevant information, inaccuracies, and increased editing time as disadvantages.

In addition to supporting documentation and workflow efficiency, participants also highlighted relational benefits of the AI scribe. Importantly, many perceived it as a support for patient interaction during consultations. Participants frequently reported that the AI scribe enhanced attentiveness, reduced distractions associated with notetaking, and facilitated more engaged patient interactions. These qualities are highly relevant in specialized rehabilitation, where therapeutic alliance and interaction are central to the quality of care. In fact, providing care in this context is both cognitively and relationally demanding [48,49], requiring clinicians to maintain focused attention to support complex decision-making, deliver individualized education, document clinical encounters, and foster a trusting relationship. Digital tools perceived as reducing cognitive load and administrative distractions, such as ambient AI scribes, may therefore be perceived as supportive of the therapeutic process.

In free-text responses in our study, participants reported that the AI scribe reduced reliance on memory for notetaking, as the generated draft captured key elements of the dialogue and minimized computer interaction during consultations. Participants reported that this supported more face-to-face engagement and attentiveness to patient needs. The positive impressions reported by many participants in our study are not isolated. Similar experiences have been documented in other clinical environments, reinforcing the notion that ambient AI scribe technology may support both interaction and workflow. For instance, studies have shown that such tools are associated with more personal and effective clinician–patient interactions, reduced clerical workload, and improved attentiveness [30,34,43]. In addition, a recently published study from Australia found that the AI scribe had a positive impact on factors considered important to the therapeutic alliance, such as listening, eye contact, and engagement, both among patients and allied health professionals [50]. These observations align with the results of our study, in which many participants reported increased engagement and attention during consultations.

In addition to the feedback provided in free-text fields by participants, this study introduced a composite variable, PIS, to quantitatively assess how use of the AI scribe influenced clinician-patient interaction and to explore its potential impact

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on technology acceptance constructs. Interestingly, PIS showed a strong correlation with PU (r=0.778), a moderate correlation with PEOU (r=0.519), and a weaker correlation with SUS (r=0.413). These results suggest that PIS was associated with clinicians' perceptions of usefulness and usability. However, the observed correlations reflect associations between variables and do not permit conclusions about causality or the direction of these relationships. However, it should be noted that while the majority of participants in the present study reported supportive effects on patient interaction, some did not. This variability in PU may reflect contextual factors such as professional role, familiarity with digital tools, or integration into existing workflows. For example, some participants noted that the AI scribe did not align well with their documentation routines or clinical setting, which may have limited its perceived value. Thus, the results presented in this study offer a foundation for further research into how contextual factors may influence clinicians' acceptance of AI scribe technology in health care.

The AI-generated clinical notes were generally perceived as clear, well-organized, and clinically useful, according to assessments using the modified PDQI-8 instrument. Domains such as comprehensibility, internal consistency, and usefulness received particularly positive ratings, while thoroughness and accuracy were rated somewhat lower, indicating potential for improvement. Overall quality ratings were similar between physicians and psychologists. The only significant professional difference was related to succinctness, with psychologists rating the generated notes lower than physicians. This may reflect differing documentation preferences, as psychologists may place greater emphasis on preserving psychosocial context and narrative detail that can be reduced in more concise summaries. However, these findings should be interpreted cautiously given the small sample size and exploratory nature of the analyses. The generally positive PDQI ratings observed in this study are consistent with a recent study evaluating AI-generated clinical documentation, in which ambient AI-generated notes achieved quality ratings broadly comparable to physician-authored notes when assessed using modified versions of the PDQI framework [51]. However, methodological differences, including note types, evaluators, and scoring procedures, limit direct comparison with the present findings.

Assessments of output quality, as conceptualized in the TAM model, indicated that most participants rated the AI scribe's documentation as high quality. It should, however, be noted that a few participants in their free-text responses reported the clinical notes as incomplete and insufficiently addressing biopsychosocial dimensions, including social history, psychological factors, and family and work life. Furthermore, a few participants reported that the notes contained inaccuracies, which increased the time spent on proofreading and editing. One participant reported that the tool occasionally produced erroneous conclusions or misrepresented information from the consultation, including information about medication use. Although only a few participants raised these concerns, they highlight the need for a more comprehensive inclusion of biopsychosocial information to enhance clinical relevance and minimize the need for later editing. As the assessment of documentation quality was based on notes from initial patient consultations, future studies should examine how the AI scribe performs across a broader range of clinical contexts, where documentation needs and expectations may differ.

Although our study, along with previous studies, has found that clinicians generally rate AI-generated clinical notes as good to excellent in quality [52], several categories of errors warrant attention. Hallucinations, or fabricated content not present in the conversation, occurred more frequently in AI notes (31%) than in physician-authored notes (20%) [51]. Omission errors were also common, often involving details such as the history of present illness or social factors [52]. Some systems failed to differentiate and emphasize critical problems over less urgent ones, which may affect clinical prioritization [45]. Structural issues included misclassification in key sections of the clinical note and generalization errors, in which specific information was oversimplified (eg, "Colles fracture" reduced to "fracture") [52]. Finally, contextual factors such as off-topic dialogue and multi-speaker interactions affected accuracy, with some systems struggling to distinguish between 3 or more voices [52]. These findings underscore the need for ongoing refinement of AI scribe algorithms to minimize errors and ensure clinical reliability.

Relationship Between System Usability Score and TAM Constructs

To explore the role of usability in technology acceptance, the study examined how SUS scores related to TAM constructs, including BI. The observed correlation between SUS scores and BI (r=0.601) suggests that participants who perceived the AI scribe as more usable also tended to report a stronger intention to use it, complementing the TAM constructs of PEOU and PU. The stronger correlation between SUS and PEOU (r=0.794) than between SUS and PU (r=0.433) indicates that ease of use and usability may capture similar aspects of user experience. This is particularly relevant given that SUS is a standardized usability measure, whereas PEOU is a theoretical construct within TAM. This observation aligns with previous research suggesting that PEOU can reflect perceptions of usability in technology acceptance contexts [53]. Thus, future research could use the TAM framework to investigate the usability aspects of AI scribes further.

Limitations

The interpretation of this study's results must be tempered with an understanding of its limitations. The participants were from a similar rehabilitation organization, which may limit the generalizability of the findings. There was also a potential sampling bias among physicians and psychologists who volunteered to participate. To better understand the use of AI scribes in rehabilitation practices, future studies should consider clinicians who have concerns about incorporating an AI scribe in their practice. This explorative study also had a modest sample size and a relatively short intervention period, which together may limit the representativeness of the results. Unfortunately, due to technical errors, usage data, including the number of consultations and time spent on documentation, were not available. Consequently, individual exposure to the AI scribe could not be quantified, preventing analysis of actual usage patterns or potential differences in experiences according to frequency use. In addition, the study did not include baseline

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measurements or a control group, limiting the ability to determine whether the observed perceptions can be attributed specifically to AI scribe use.

Furthermore, the study did not include objective measurements of documentation time, independent assessments of note accuracy, or patient-reported outcomes. As a result, conclusions are limited to clinicians' self-reported perceptions and cannot establish effects on documentation efficiency, note quality, accuracy, or patient experience. Finally, participants may have been more motivated to engage with new technology than non-participants, and the introduction of a novel tool may have contributed to more favorable responses, resulting in potential selection and novelty bias.

Moreover, self-reported data may introduce recall or reporting bias, limiting the accuracy of the findings. The modified PDQI-8 was administered following a single consultation, limiting the ability to assess the consistency and reliability of note-quality ratings over time. Although the rating of note quality was relatively consistent in this study, repeated assessments across multiple consultations could provide a more comprehensive understanding of the accuracy and quality of clinical notes in routine practice. It should be noted that the free-text answers may have been influenced by the preceding structured questionnaires (SUS, TAM, modified PDQI-8), as participants answered the open-ended questions after completing these scales. Consequently, the identified themes, such as time use, documentation burden, note quality, and patient interaction, reflect categories emphasized in the questionnaires, which may have shaped participants' focus and wording. In addition, questions related to the interaction aspect were phrased as positive statements, consistent with the TAM methodology. This may represent a limitation, as positive wording may lead to a tendency to agree, potentially reducing the ability to capture critical or negative perceptions. A limitation of this study is that participants were not invited to review or comment on the findings following the analysis.

While the composite measure of PIS showed high internal consistency, the strong interitem correlations suggest it may capture a narrow aspect of interaction support. This may imply that the measure primarily captures a specific dimension of clinician-patient interaction, such as attentional presence or reduced distraction, rather than the broader complexity of clinical interaction. Thus, future research should refine item wording to better capture the multifaceted nature of interaction in clinical practice and use qualitative methods to obtain more in-depth data on the communicative aspects of AI scribes.

Conclusion

This study provides initial evidence of acceptance of an AI-based ambient scribe among physicians and psychologists in specialized rehabilitation, with generally positive perceptions of its usefulness, usability, and documentation quality, and future use intentions. Most participants reported a perceived reduction in documentation burden and experienced the AI scribe as supportive of attentiveness during consultations. However, the findings reflect clinicians' subjective experiences and do not establish objective effects on documentation time, documentation accuracy, clinical outcomes, patient safety, or clinician well-being. Participants also reported omissions, occasional inaccuracies, and insufficient coverage of biopsychosocial aspects in generated notes, highlighting the continued need for clinician review and suggesting areas for further development. General attitudes toward AI were associated with key acceptance variables, indicating that broader views on AI may influence how such technologies are received in practice. Overall, the findings suggest that ambient AI-scribing is acceptable to many rehabilitation clinicians and is perceived as supportive of documentation processes and clinician-patient interactions. Future studies should investigate its implementation in routine care using objective measures of documentation time, note accuracy, workflow integration, quality of care, patient outcomes, and safety. Research should also explore long-term effects across diverse clinical contexts and professional roles and improve evaluation instruments to better capture the communicative and clinical impact of AI-assisted documentation.

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Data Availability

The dataset generated and/or analyzed in this study are available from the corresponding author upon reasonable request.

Generative AI Use

Microsoft Copilot was used to support language editing. All AI-assisted text was reviewed and revised by the authors, who take full responsibility for the final content.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Study-specific items included in the perceived interaction support (PIS) composite score.
[DOCX File , 31 KB-Multimedia Appendix 1]

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Abbreviations

AIAS: AI Attitude Scale
BI: behavioral intention
CGS: Curved Grading Scale
EFA: exploratory factor analysis
EHR: electronic health record
GDPR: General Data Protection Regulation
IU: intention to use
JR: job relevance
KMO: Kaiser-Meyer-Olkin
mPDQI-8: modified 8-item Physician Documentation Quality Instrument
NLP: natural language processing
PDQI: Physician Documentation Quality Instrument
PDQI-8: 8-item Physician Documentation Quality Instrument
PDQI-9: 9-item Physician Documentation Quality Instrument
PEOU: perceived ease of use
PIS: perceived interaction support
PU: perceived usefulness
QO: quality output
SUS: System Usability Scale
TAM: technology acceptance model
UMUX: usability metric for user experience

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