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Time Savings Through an AI Speech Assistant for Nursing Documentation: A Pre–Post Time-Motion Study in German Long-Term Care

Katja Schwabe, Drin Ferizaj, Susann Neumann, Sandra Strube-Lahmann, Nils Lahmann

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Abstract

Background: Nurses in long-term care spend up to one-third of their working time on documentation, contributing to administrative burden and limited time for direct care. Artificial Intelligence (AI) speech assistants have shown potential to accelerate documentation, but longitudinal evidence from real-world long-term care settings remains scarce.

Objective: This study aimed to evaluate whether implementing a domain-specific, mobile AI speech assistant reduces documentation time in German long-term care under routine conditions. Secondary objectives included examining usability, perceived documentation effort, interruptions, and workplace satisfaction.

Methods: A pre–post time-motion study with full-shift observation was conducted. Continuous, event-based observations were performed before (t0) and after (t1) implementation of the mobile speech assistant voize. The primary outcome was total documentation time per morning shift. In addition to observations, questionnaires were administered to assess perceived documentation effort, interruptions, satisfaction, and workplace-related satisfaction. Data were analyzed using ANCOVA-of-change models with multiple imputation and Holm–Bonferroni correction across secondary endpoints.

Results: Fifty-two registered nurses from 14 long-term care facilities participated (mean age 42.4 years; 81% female). Across 770 observed hours, total documentation time per morning shift decreased significantly by an adjusted mean of 14.8 minutes, corresponding to a 27% reduction relative to baseline and a large effect size (Cohen’s d = 0.96). Self-reported documentation time and interruptions also declined significantly, while satisfaction with the documentation system increased. Usability was rated as good.

Conclusions: This study provides real-world evidence that an AI-based speech assistant can reduce documentation workload in long-term care. Integrating a mobile, domain-specific speech system into daily workflows substantially decreased documentation time and improved perceived efficiency. Beyond measurable time savings, such technology has the potential to alleviate workload, free time for resident care, and enhance working conditions. These findings are also relevant for policy discussions on addressing the nursing workforce shortage, showing that well-integrated, speech-enabled documentation systems can support more sustainable long-term care environments. Clinical Trial: German Clinical Trials Register (DRKS00035512)

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Abstract

Background: Nurses in long-term care spend up to one-third of their working time on documentation, contributing to administrative burden and limited time for direct care. Artificial Intelligence (AI) speech assistants have shown potential to accelerate documentation, but longitudinal evidence from real-world long-term care settings remains scarce.

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Trial Registration: German Clinical Trials Register (DRKS00035512)

Keywords: nursing documentation time; automatic speech recognition; long-term care; AI speech assistant; mobile nursing documentation

Introduction

Background

In Germany, approximately 1.7 million nursing staff are employed, with nearly 30% working in long-term care facilities, making this the largest sector in the nursing workforce[1]. Demand for care continues to rise while shortages of qualified staff worsen[2] (Statistisches Bundesamt, 2025). Nursing staff, particularly in long-term care, report higher levels of strain compared to other occupational groups[3,4]. They work under considerable time pressure, often lack sufficient time to complete tasks, and frequently perform overtime with irregular or missed breaks[3,5]. Alongside these structural challenges and workload demands, care workers face a high administrative burden: documentation tasks account for about 30% of total working time[6,7], leaving less room for direct interaction and care for residents[8]. Furthermore, the high documentation workload has been linked to reduced job satisfaction and an elevated level of stress[9]. In light of these issues, AI-based speech assistants are presented as promising solutions to accelerate the documentation process and improve its accuracy[10].

Medical Documentation With Speech Recognition

Research on speech recognition has been most widely conducted in clinical medicine, often involving physicians and mixed professional groups. Previous findings show that speech recognition technologies can significantly streamline documentation workflows compared to traditional methods.

For example, Zuchowski & Göller[11] reported notable time savings and lower error rates when using speech recognition versus manual typing. Similarly, Peine et al.[12] found that a voice-based system enabled faster and more accurate documentation among intensive care professionals compared to both electronic and paper-based approaches.

These findings are further supported by systematic reviews. Alboksmaty et al.[13] synthesized findings across several countries, highlighting consistent efficiency gains, reduced administrative burden, and improved provider–patient interaction. Of particular note, Wang et al.[14] found that a digital scribe could accelerate history-taking and physical examination documentation by more than double compared to typing or traditional dictation.

However, reviews also point out that most studies have taken place in controlled or experimental settings, which may limit generalizability to routine care[10,13]. In this context, Ng et al.[15], reviewing 29 research articles, observed that while many reported time savings and improvements in documentation completeness, others described challenges such as increased editing workload, variable cost-effectiveness, and issues with error rates for specialized terminology or accented speech.

Clinical Nursing Documentation With Speech Recognition

Compared to physician documentation, evidence on nursing documentation with automatic speech recognition (ASR) is more limited but growing. Findings to date are still heterogeneous. For example, while many studies reviewed by Joseph et al.[10] indicated beneficial effects, such as reduced documentation time and improved workflow, a substantial number reported no significant impact, given ongoing challenges integrating ASR into real-world nursing environments and existing documentation systems.

However, several recent investigations suggest a promising potential for efficiency gains in real-world nursing environments. In a hospital time-motion study, Ehrler et al.[16] found that a mobile bedside application meaningfully decreased the duration of Electronic Health Record (EHR) documentation for nurses, while also increasing time available for direct patient interaction. Similarly, Mayer et al.[17] reported statistically significant time savings - up to 6.1 minutes per documentation scenario - when using an ASR solution compared to traditional keyboard entry. Mairittha et al.[18] also demonstrated that a smartphone-based dialogue system allowed for 15 percent faster documentation relative to electronic forms in a controlled setting. Likewise, qualitative findings from German long-term care facilities hint at the potential of ASR for care documentation, reporting self-reported time savings, fewer interruptions, greater flexibility, and less reliance on

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stationary computers[19].

Research Gap

In summary, evidence across clinical settings suggests that ASR can shorten documentation time and thus reduce administrative burden, yet findings are mixed and often derive from controlled or pilot evaluations rather than routine practice, which limits generalizability[10,13,15]. In nursing, several studies report faster entries with mobile or dialogue based tools, but most were scenario based, single unit, or acute care focused, with heterogeneous outcomes and little full shift observation, and long term care remains underrepresented despite high documentation burden[12,16–18].

Objectives

Therefore, this study aims to address these gaps by evaluating a domain-specific mobile AI speech assistant under routine conditions in German long-term care using full-shift time-motion observation at two time points, before and after implementation. The primary endpoint is the adjusted change in total documentation time per observed morning shift, defined as the cumulative time spent on a set of predefined documentation-related tasks. Secondary outcomes are self-reported and include usability, perceived documentation effort and interruptions, workplace satisfaction, and self-reported documentation quality.

Hypotheses

The following hypothesis will be tested for the primary endpoint:

H0: There will be no significant reduction measured by the adjusted mean change in total documentation time from baseline to post implementation.

H1: There will be a significant reduction measured by the adjusted mean change in total documentation time from baseline to post implementation.

The secondary outcomes are evaluated exploratory by pre-post changes. To adjust for multiple testing, Holm-Bonferroni correction is applied across all secondary tests.

Methods

Study design and setting

The study was conducted as part of the “PYSA - Nursing Documentation with Hybrid Speech Assistant” project, funded by the German Federal Ministry of Education and Research[20]. The

longitudinal research design follows a pre–post observational time-motion design with two measurement points (baseline t_0 and post-assessment t_1) and takes place in stationary long-term care facilities in Germany. Facilities were approached nationwide to ensure the representation of different conditions and to include both rural and urban areas as well as different types of providers. All participating facilities used either the same electronic health record (EHR) system or paper-based documentation.

The minimum age for inclusion of participants was 18 years, with no upper age limit. Additional inclusion criteria were a completed three-year nursing education, regular involvement in nursing documentation, and at least one year of professional experience. Participants had to be able to understand instructions in German and provide informed consent. Only staff employed in long-term care facilities in which the speech assistant voize was implemented during the study period were eligible. Exclusion criteria were applied to staff who were not permanently employed in the participating facilities, such as agency or temporary nurses.

Recruitment

Participants were recruited through long-term care facilities that planned to implement the speech assistant voize and received written information about the study procedures. Following approval from the employee representative bodies of each facility, nursing staff were approached by the facility management. All participants were informed in writing that participation was voluntary, that data would be pseudonymized and analyzed in aggregated form, and that they could withdraw from the study at any time without facing any negative consequences. Participants were offered a voluntary small financial compensation for their time and effort.

The speech assistant voize

The speech assistant voize is a software-based mobile application that enables users to dictate nursing documentation via smartphone. It employs a continuously trained language model that processes voice inputs locally, assigns the content to the appropriate categories, and automatically generates structured documentation entries. These entries are reviewed and approved by nursing staff before being integrated into the existing documentation system. Developed in close collaboration with nursing professionals[19,20], the application is continuously refined through a collaborative, user-centered design process, and its underlying models are regularly trained with voluntarily submitted

and anonymized documentation data to ensure ongoing improvements and adaptation to the linguistic characteristics and professional terminology used in nursing.

Technically, the system converts spoken language into text (speech-to-text) in real time using an end-to-end streaming ASR model. In conjunction with this, a set of specialized natural language processing models is activated as needed to handle specific tasks - such as understanding context, matching spoken language to planned interventions, extracting key information, or structuring data - ensuring that all components work together to deliver the supported features. As part of the study, voize was introduced in cooperation with voize GmbH. The implementation included planning and roll-out within the facilities.

Power analysis

In a preliminary anonymous survey with 55 nurses already using voize, about 70 % reported subjective time savings of 16 to 30 minutes per shift. It was assumed that about one-third of working time is spent on documentation-related tasks[6,7], which is equivalent to about 20 minutes per hour. A 15% reduction was considered meaningful, corresponding to the mean of reported savings (23 minutes per shift), i.e., 2.9 minutes less per working hour, reducing documentation from 20 to 17 minutes per hour. With an assumed standard deviation of 6 minutes, this equates to an effect size of Cohen's d = 0.5. Power analysis using the R package pwr[21] ($\alpha = 0.05$, two-sided; power = 0.8) indicated a minimum of 34 participants for paired t-tests. To account for an expected 15% dropout, the target sample size was set at 40, compensating for likely reasons such as scheduling conflicts, shift changes, sick leave, or vacation.

Early-stage dropout rates exceeded expectations. Therefore, additional recruitment efforts were employed. Nonetheless, interest from both facilities and individual nurses was high, and incremental participant burden remained low. As a result, a total of 52 nurses were included in this study.

Measures

Primary endpoint: total documentation time per shift

The primary outcome was total documentation time per observed morning shift in minutes, defined as the sum of all documentation-related categories recorded during the time-motion observation. Observation categories were developed and refined during preparatory non-participant observations in a long-term care facility within a pilot study[20]. The identified documentation-related tasks included documentation at the PC or on paper, consulting information at the resident record at

the PC, waiting for a PC, booting up and logging into the PC, walking to the ward office for documentation purposes, making notes and reviewing entries (Appendix 1,Table 1.1). At t_1, after implementation of the application, additional categories were included for documentation with voize and consulting information in voize (Appendix 1,Table 1.2).

Nursing Workplace Satisfaction Questionnaire (NWSQ)

Workplace Satisfaction outcomes was assessed using the NWSQ[22] (Fairbrother et al., 2009). The NWSQ is a brief measure of nursing job satisfaction encompassing three domains: intrinsic, extrinsic, and relational satisfaction. Items are rated on a 5-point Likert scale, and domain scores are computed as the sum of their constituent items. Possible ranges are 6–30 for intrinsic, 5–25 for extrinsic, and 4–20 for relational satisfaction, with higher scores indicating greater satisfaction.

Usability

Technology-related acceptance was measured with the System Usability Scale[23] (SUS), a 10-item questionnaire of perceived usability on a 5-point Likert scale and alternating item valence. Responses were scored using the standard SUS procedure, including appropriate reverse-scoring, and converted to a total score from 0 to 100. Scores around 70 indicate acceptable usability, with higher values reflecting better perceived usability[23].

Self-developed questionnaire

Several single-item measures were developed and employed to capture several facets of potential impact based on a previous study[19]. Items included perceived interruptions during daily work, the perceived time-consuming nature of documentation, satisfaction with the documentation system, expected quality improvement, expected time savings, current documentation quality and completeness, implementation as a good idea, intention-to-use, and self-reported documentation time in minutes per shift. Items used 5-point scales or 10-point scales as shown in Table 3, plus open numerical entries for minutes. Higher ratings indicate more agreement with the item. For example, higher values on “documentation is time-consuming” indicate greater perceived time burden, and higher values on “satisfaction with the documentation system” indicate greater satisfaction. Item wording and differences across t_0 and t_1 are provided in Appendix 2 (Table 2.1; Table 2.2).

Procedure

Data were collected between September 2024 and July 2025 in German long-term care facilities. Trained observers conducted continuous, non-participant full-shift observations of morning shifts lasting approximately 8 hours at two time points, baseline and post-implementation of the speech assistant. Time was captured with an event-based smartphone logging app by starting and

stopping predefined documentation-related task categories. After completing the shift, participants were asked to complete an online questionnaire that included the measures.

Approximately eight weeks after the implementation of voize (t_1), participants were observed again during a full morning shift, and documentation times were recorded using the same procedure. At this second measurement point, participants completed an adjusted online survey, including the SUS.

Prior to data collection, all observers received standardized training in the use of the measurement instruments. In addition, weekly meetings were held throughout the data collection period to address questions, reflect on measurement procedures, and resolve ambiguities in a standardized manner. During the observations, observers also had access to a notes field where they could record questions or uncertainties regarding the assignment to task categories, add comments, and briefly describe the situation. This enabled the study personnel to later compare the selected task category with the descriptive notes.

In addition, the direct observation design can lead to behavioral changes among participants. The presence of an external observer can sometimes prompt improved performance, a phenomenon known as the Hawthorne effect[24] (Franke & Kaul, 1978). To mitigate such influences, repeated briefings and transparent communication of the study objectives were provided to the nursing staff and critical questions were encouraged.

Statistical analysis

Statistical analyses were performed using Python 3.11.9 in Visual Studio Code 1.103.2 with the packages scikit-learn[25], miceforest[26], numpy[27], pandas[28], scipy[29], matplotlib[30].

The primary estimand was the adjusted mean change in documentation time (t_1 - t_0) in minutes, estimated via an ANCOVA-of-change adjusting for centered baseline documentation time, age group, and sex. The intercept equals the adjusted mean change at the sample means. Additionally, a companion ANCOVA of post time reports the adjusted post-implementation mean. Missing data were handled by multiple imputation (m = 40) under a Missing At Random (MAR) assumption via tree-based predictive mean-matching (400 trees, 10 donors, up to 10 iterations). Sensitivity analyses repeated the primary model across alternative engines (parametric, solely tree-based, gradient-boosting, and single imputation).

Models were fitted by Ordinary Least Squares (OLS) within each imputed dataset and pooled using Rubin’s rules with Barnard-Rubin degrees of freedom for small samples. For the secondary

endpoints, we used hetereoskedasticity-consistent standard errors (HC3) within each imputation[31]. We report 95% confidence intervals (CIs), two-sided *p*-values, and the following standardized effect sizes: Cohen's d, Hedges' g, r, and partial eta-squared (ηp^2).

Missing-Not-At-Random (MNAR) sensitivity was examined with two pattern-mixture approaches applied to imputed post values for cases missing at post: (i) Δ-adjusted tipping point analysis to the loss of significances and (ii) Jump-to-Baseline (J2B), followed by Δ-tipping from the J2B baseline. For all tests, a two-sided $\alpha = .05$ was set.

Secondary endpoints were analyzed as pooled paired differences according to Rubin's rules with Barnard-Rubin degrees of freedom and HC3 within-imputation standard errors. Familywise error was controlled via Holm-Bonferroni across 13 exploratory post-pre tests (excluding primary outcome and post-only measures). *p*-values reported as <.001 were set to .001 for the correction. This study is reported in accordance with the STROBE statement[32].

Ethical considerations

The study was reviewed and approved by the Ethics Committee of Charité - Universitätsmedizin Berlin, approval number [EA1/209/24]. All participants provided written informed consent prior to participation. Data were pseudonymized and analyzed in aggregated form. The study was preregistered in the German Clinical Trials Register (DRKS00035512).

Results

Participant characteristics

The sample comprised 52 registered nurses from 14 long-term care facilities in Germany. Eight participants (15.4%) dropped out between baseline and follow-up, primarily due to long-term illness or resignation.

The mean age was 42.4 years (SD = 12.4) with 17.5 years of professional experience (SD = 9.6) and 9.4 years of tenure (SD = 8.1). Most participants were female (80.8%). Among completers (84.6%, n = 44), the mean age was 43.2 (SD = 12.0) and mean experience was 18.2 years (SD = 10.0); 84.1% were female. Dropouts (15.4%, n = 8) were younger on average (mean = 37.6, SD = 14.1) and reported less work experience (mean = 13.8 years, SD = 6.9); 62.5% of them were female. Detailed counts and percentages for all characteristics are provided in Table 1.

Table 1. Participant characteristics of total sample, completers and dropout

Variable	Total (*n*=52)	Completers (*n*=44)	Dropouts (*n*=8)
Age			
Mean (SD)	42.37 (12.37)	43.23 (12.01)	37.62 (14.07)
Work experience (years)			
Mean (SD)	17.52 (9.63)	18.20 (9.95)	13.75 (6.88)
Tenure (years)			
Mean (SD)	9.42 (8.13)	9.75 (8.41)	7.62 (6.52)
Gender, n (%)			
Male	10 (19.2)	7 (15.9)	3 (37.5)
Female	42 (80.8)	37 (84.1)	5 (62.5)
Other	0 (0.0)	0 (0.0)	0 (0.0)
Role, *n* (%)			
Registered nurse	52 (100.0)	44 (100.0)	8 (100.0)
Leadership role	6 (11.5)	5 (11.4)	1 (12.5)
Practical instructor	6 (11.5)	6 (13.6)	0 (0.0)
Other	1 (1.9)	—	1 (12.5)

Note. Values are presented as mean (SD) or n (%), as indicated.

Primary Outcome

Descriptive Analyses

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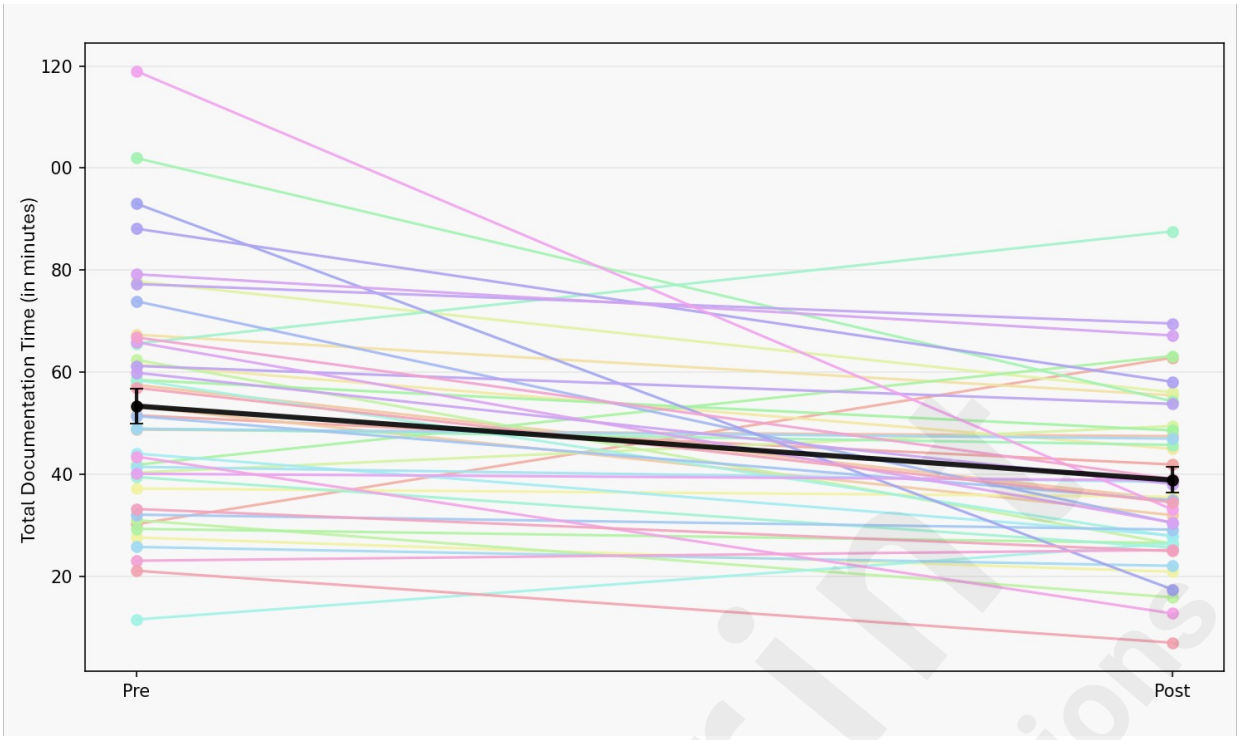


Figure 1: Baseline-to-Post Assessment Changes in Total Documentation Time among Participants.

At t_0 (N = 52), documentation was predominantly PC-based (67.3%), followed by hybrid use (21.2%) and paper (11.5%). Among completers at t_1 (n = 44), the speech assistant voize was reported as the primary documentation mode by 40.9%, PC by 56.8%, and paper by 2.3%. Usage frequency of the speech assistant was high: 75.0% reported daily use, 20.5% used the speech assistant 3–4 times per week, and 4.5% 1–2 times per week.

Overall, around 770 hours of work were observed in long-term care during this study. Total documentation-related time decreased from 53.91 minutes at baseline to 39.10 (16.29) minutes post-implementation in the pooled analysis (Δ = −14.81 min). For the change in total documentation time (post - pre in minutes), complete cases (n=44) had Q1 = -22.48 and Q3 = -2.90 (min = -85.90, max = 32.60), and the pooled analysis (n=52) had Q1 = -23.59 and Q3 = -2.54 (min = -86.95, max = 32.91).

Descriptive reductions were concentrated in active documentation (Δ = −13.28) and note-taking (Δ = −2.38), while reviewing entries (Δ = +0.64) and information retrieval (Δ = +1.28) showed small descriptive increases, consistent with a shift from producing text to checking/retrieving information.

Table 2. Documentation time by task in minutes at baseline and post implementation

Task	Pre *M* (*SD*)	Post-Complete *M* (*SD*)	Post-Pooled *M* (*SD*)
Computer Login	1.45 (1.32)	1.05 (1.13)	1.01 (1.09)
Active Documentation	44.23 (19.72)	30.44 (14.71)	30.95 (14.36)
Reviewing Entries	0.82 (3.65)	1.47 (3.81)	1.46 (3.68)
Information Retrieval	3.48 (4.71)	4.85 (6.69)	4.76 (6.48)
Walking (for documentation)	0.56 (1.56)	0.10 (0.24)	0.09 (0.23)
Taking Notes	3.15 (2.68)	0.84 (1.67)	0.77 (1.56)
Waiting	0.22 (0.88)	0.07 (0.33)	0.06 (0.31)
Total Documentation-related Time	53.91 (23.59)	38.82 (16.75)	39.10 (16.29)

Note. All values are presented in minutes. Pre = observed baseline for all participants (N = 52). Post-Complete = observed post-implementation among completers (n = 44). Post-Pooled = estimates pooled across m = 40 multiply imputed datasets under MAR assumption (n = 52).

Primary Outcome: ANCOVA

The ANCOVA-of-change indicated a 27% reduction of total documentation time with an adjusted mean change of -14.81 minutes (SE = 2.22), $t(42.81) = -6.68$, $P < .001$, 95 % CI [-19.27, -10.34], $d = -0.96$, $g = -0.95$, $r = -.68$, $\eta p^2 = .47$, $R^2 = 57.85$ %, adjusted $R^2 = 55.22$ % (Table 2). The companion ANCOVA-of-post replicated these findings and with an adjusted post mean of 39.10 minutes (SE = 2.22), $P < .001$, 95 CI [34.63, 43.57]. In the change model, the baseline-centered documentation time predicted greater reductions ($\beta = -0.74$, SE = 0.10, $P < .001$), as expected under ANCOVA. Age group ($\beta = -0.85$, SE = 1.97, $P = .669$) and sex ($\beta = 2.33$, SE = 5.92, $P = .696$) were not significant predictors of change.

Sensitivity Analyses for the primary endpoint

The complete-case paired t-test for total documentation time showed a mean difference of -14.51 minutes (SE = 3.33), $t(43) = -4.35$, $P < .001$, 95% CI [-21.23, -7.79], Cohen's $d = -0.66$. The Wilcoxon signed-rank test was also significant ($P < .001$), with a pooled rank-biserial of -.72.

The primary estimand could be replicated across the other imputation procedures with remarkably similar adjusted time reductions, typically between -14.5 and -15.8 minutes (all $P < .001$), and -17.29 minutes for the single-imputation median variant ($P < .001$). Thus, the primary conclusion was insensitive to the imputation algorithm.

MNAR tipping-point analyses.

Adding a constant Δ only to imputed post times for participants missing at t_1, the reduction remained significant for Δ up to +50 minutes ($P = .044$) and reached the tipping point at Δ = + 51 minutes ($P = .051$) where significance was lost.

Replacing imputed post times with each participant's baseline pre time still yielded a significant time reduction of −12.27 minutes (SE = 2.36), $t(46) = -5.19$, $P < .001$, 95% CI [-17.03, -7.52]; adjusted Cohen's $d = -0.72$, $r = -0.61$, $g = -0.71$, $\eta p^2 = 0.369$. Starting from J2B, the first non-significant result occurred at Δ = 36 minutes (last significant: Δ = 35 minutes, $P = .046$). Together, these findings indicate that very large MNAR deviations would be required to conflict the primary conclusion.

Secondary Self-Reported Outcomes

Table 3. Pooled measures of tendency for secondary outcomes.

Variable (Score Range: [min, max])	pre_pooled *M* (*SD*)	post_pooled *M* (*SD*)	Δ (post - pre)	Median (pre)	Median (post)
Interruptions in daily work (Range: 1–5)	4.06 (0.78)	3.40 (0.91)	-0.66***†	4.00	3.97
Self-reported documentation time (in minutes)	67.05 (40.98)	35.91 (24.34)	-31.14***†	60.00	30.00

Documentation is Time-consuming (Range: 1–5)	4.07 (0.79)	2.46 (0.84)	-1.61***†	4.00	2.18
Satisfaction with Documentation system (Range: 1–10)	5.07 (2.07)	6.65 (1.82)	+1.58***†	5.00	7.00
Expected quality improvement (Range: 1–5)	3.69 (0.74)	3.18 (0.81)	-0.51**†	4.00	3.00
Documentation is complete (Range: 1–5)	3.27 (0.85)	2.83 (0.94)	-0.44**	3.00	2.87
Expected Time Savings (Range: 1–5)	3.81 (0.69)	3.46 (0.79)	-0.35*	4.00	3.57
High Documentation Quality (Range: 1–5)	3.38 (0.82)	3.03 (0.75)	-0.35*	3.89	3.00
Implementation as a good idea (Range: 1–10)	7.91 (1.93)	7.35 (2.04)	-0.56	8.00	7.73
Intention to use (Range: 1–10)	8.17 (1.99)	7.88 (1.69)	-0.29	8.13	8.00
NWSQ: Extrinsic (Range: 5–25)	17.60 (2.34)	17.95 (2.94)	+0.35	17.51	18.00
NWSQ: Intrinsic (Range: 6–30)	22.21 (3.94)	22.04 (4.42)	-0.17	22.00	21.63
NWSQ: Relational (Range: 4–20)	15.62 (2.62)	15.31 (2.66)	-0.31	16.00	16.00

Note. *M* = mean; *SD* = standard deviation; Δ = mean difference (post-pre). All values are pooled across 40 multiply imputed datasets according to Rubin's rules. Consequently, some median scores are not restricted to the discrete response categories. Significance of the change is indicated by asterisks based on uncorrected paired t-tests. The dagger symbol (†) indicates effects that remained significant after Holm-Bonferroni correction for 13 tests. *P < .05. **P < .01. ***P < .001.

There was a significant reduction in self-reported documentation time (Δ = −31.14 min, SE = 6.57), $t(43.18) = -4.88$, $P < .001$, 95% CI [−45.31, −18.83], and self-reported interruptions in daily work also declined, $t(47.00) = -3.95$, $P < .001$, 95% CI [−0.95, −0.31]. Participants experienced the documentation process as markedly less time-consuming, $t(46.91) = -9.32$, $P < .001$, 95% CI [−1.97, −1.27], and satisfaction with the documentation system increased after the implementation of voize, $t(46.47) = 4.84$, $P < .001$, 95% CI [1.04, 2.52]. Expectations that the voice assistant would improve documentation quality were also lower after use, $t(46.82) = -3.40$, $P = .001$, 95% CI [−0.75, −0.19]. All five of these effects remained significant after Holm–Bonferroni correction across the 13-test family (Holm-adjusted $P \leq .013$ for each; see Table 3).

Perceiving the implementation of voize as a good idea showed no reliable change, $t(46.29) = -1.09$, $P = .283$, 95% CI [−1.04, 0.31], and intention to use remained essentially unchanged at a high level, $t(46.60) = -0.45$, $P = .655$, 95% CI [−0.77, 0.49]; both remain nonsignificant after correction (Holm-adjusted $P = 1.00$). Ratings that the current documentation is qualitatively high decreased, $t(46.97) = -2.30$, $P = .026$, 95% CI [−0.61, −0.04], as did ratings that it is complete and comprehensive, $t(47.01) = -2.75$, $P = .008$, 95% CI [−0.74, −0.11], and expected time savings with the speech assistant, $t(46.74) = -2.60$, $P = .013$, 95% CI [−0.55, −0.07]. However, none of these three effects survived Holm–Bonferroni correction (Holm-adjusted $P = .156$, .064, and .091, respectively).

Nursing workplace satisfaction measured by the NWSQ did not change significantly (extrinsic: $t(38.94) = 1.48$, $P = .146$, 95% CI [−0.22, 1.45]; intrinsic: $t(39.06) = 0.07$, $P = .948$, 95% CI [−1.03, 1.10]; relational: $t(38.46) = -0.68$, $P = .499$, 95% CI [−0.84, 0.42]), and these remain nonsignificant after correction (Holm-adjusted $P = .73$, 1.00, and 1.00, respectively). The SUS scores indicated good usability[23]: the complete-case mean was 70.42 (SD 14.26; $n = 40$).

Discussion

Principal Findings

This study provides real-world evidence from long-term care that a mobile speech assistant can reduce documentation time during full shifts. The adjusted reduction of roughly 15 minutes per

morning shift - about a 27% decrease relative to baseline - was considered large, statistically robust, and consistent across extensive sensitivity analyses. Additionally, the interquartile range indicated that most participants experienced time savings. Task-level patterns suggest that time was recaptured by streamlining active documentation (see Table 2). In parallel, nurses reported fewer interruptions, lower perceived time burden, and higher satisfaction with the implemented ASR documentation environment. Usability was rated as good. These converging findings indicate that introducing speech-enabled, mobile documentation may save time in daily work while improving the documentation experience and making the overall documentation process more time-efficient.

In stationary long-term care, documentation consumes substantial nurse time. A domain-specific mobile speech assistant can reclaim minutes each shift, possibly reduce interruptions, and improve the overall documentation experience. In labor-constrained markets, recovered time can be redeployed to resident care, coordination, supervision, taking necessary breaks, improving working conditions while lowering overtime[19].

Relation to prior work

These findings are consistent with experimental and simulation studies showing that speech-based input improves speed and, in some contexts, accuracy. In nursing, Mayer et al.[17] found time savings of 2.3 to 6.1 minutes per scenario without increased errors and high user preference. Similarly, Mairittha et al.[18] reported 15% faster entries with a dialogue-based system and another mobile bedside app reduced EHR charting time and increased uninterrupted patient interaction in a pre-post study[16]. In broader clinical samples, speech systems shortened task completion time and reduced error rates versus paper and traditional patient data management systems in intensive care units (ICU) tasks[12], and hospital-wide deployments achieved high adoption with large transcription-cost reductions and perceived gains in quality and efficiency[33]. Observational comparisons have also shown that speech can be substantially faster than typing, even when perceptions may differ[11].

Relative to this body of evidence, this study adds three elements. First, it focuses on long-term care, where evidence has been sparse and documentation burden is high. Second, it evaluates the technology under routine conditions, not only in controlled or simulated scenarios. Third, it employs full-shift observation at both time points, yielding approximately 770 hours of time-motion data and directly aligned with the workflow realities reported in earlier studies[6,7,34]. Together, these features can help bridge the gap highlighted by reviews that call for end-to-end, real-world evaluations beyond transcription accuracy alone[10,15]. The pattern of decreased active entry, waiting, and walking, with slight increases in retrieval and review (see Table 2), also may show that mobile

tools reduce “print-note-retype” loops[16].

The speech assistant likely reduced documentation time through several mutually reinforcing mechanisms. First, in line with previous qualitative findings of Ferizaj and Neumann[19] that has shown fewer interruptions, less walking, shorter information-retrieval times, and higher overall satisfaction with the documentation system, the mobile, as-you-go entry may have further reduced travel and queueing at ward PCs, cutting waiting, walking, and repeated logins. Second, domain-tuned speech and natural language processing (i.e., models adapted to the nursing domain) can lower the friction of capturing structured information, which could reduce the need for interim notes, subsequent re-entry while also minimizing information loss and documentation errors. Third, workflow coupling at the bedside can decrease interruptions and handovers. The descriptive rise in information retrieval and review may reflect appropriate verification behavior within the mobile app. Usability in the good range[23] and stable acceptance[35] suggest the solution was well received with high intention-to-use and satisfaction, albeit with room for refinement.

Limitations

This study has several limitations. The single-group pre–post design without a control condition limits causal inference and leaves room for workload fluctuations or co-occurring process changes as alternative explanations. Participation was voluntary, so self-selection may have favored early adopters. Observations were conducted by multiple observers; despite extensive standardized training and ongoing weekly calibration meetings, no formal interrater reliability was assessed. Direct observation can itself change behavior (Hawthorne effect), which we sought to mitigate with standardized procedures but cannot exclude[24]. Documentation quality was captured perceptually rather than via objective measures such as assessing structured completeness or error rates that other work has examined in standardized tasks[12]. Finally, results reflect stationary long-term care in Germany, German-language ASR, and a specific EHR integration; performance may differ with dialects, accents, terminology, and integration quality[15], and ongoing advances in speech technology may change effect sizes over time.

Future Research

A cluster randomized or stepped-wedge design with an extended follow-up period could strengthen causal inference and adequately observe secular trends. Further evaluation studies should combine time savings with objective documentation quality such as completeness, semantic accuracy, and error rates and with measures of how saved time is reinvested in resident outcomes.

Furthermore, future research should investigate the potential of such technologies to alleviate psychosocial risk factors and perceived workload, and to explore how sustained use translates into improved care quality, staff satisfaction, and retention.

Combining full-shift observation with EHR telemetry could quantify sustainability, diurnal patterns, and learning curves. Additional subgroup analyses could assess heterogeneity by accent, experience, and unit characteristics. Economic evaluation should cover total cost of ownership, productivity, overtime, sick leave, and retention to guide financing.

Conclusion

According to the author's knowledge, this is the first study to demonstrate real-world time savings resulting from the use of a mobile AI speech assistant in long-term care. By integrating a mobile, domain-specific speech documentation system into routine workflows, nurses substantially reduced documentation time - by approximately 15 minutes per morning shift (about 27%). Most participants experienced measurable time savings, with a quarter of nurses saving more than 23.6 minutes per shift. In addition, nurses reported fewer interruptions and higher satisfaction, with good overall usability. These findings extend previous simulation and laboratory research, providing first ecologically valid and well-powered evidence for the practical benefits of speech-enabled documentation under everyday working conditions. Beyond demonstrating measurable efficiency gains, the results have broader implications for workforce policy. In the context of a severe nursing shortage, the automation of administrative and documentation tasks through reliable speech-based systems may help to alleviate workload and free up time for direct resident care, coordination, and recovery. Scaled implementation - supported by consistent funding and robust technical integration - could therefore have the potential to serve as a lever to mitigate staffing shortages and improve working conditions in long-term care. At a systems level, this study provides an empirical foundation for ongoing policy discussions on digitalization and workforce retention in the German long-term care sector. The evidence underscores that digital assistants, when contextually adapted, can promote efficiency, well-being and sustainability in nursing work.

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Conflict of interest

The authors declare no conflicts of interest.

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Appendix 1

Definition of task categories for observations at t_0 and t_1

Table 1.1. Task categories and their definitions for observations before the implementation of voize (t_0)

Task (t_0)	**Description**
Documentation at the PC/on paper	A nurse enters documentation directly into the electronic record at a ward computer or writing documentation on paper: signing off on interventions, writing nursing reports, filling out protocols such as drinking or nutrition. Documentation of wound progress, etc.
Informing on the PC/file	A nurse retrieves information relating to residents from the documentation system (PC or paper file). This information is passed on to other nursing and care staff and doctors, or is required by the nurse for their own nursing tasks.
Booting up and logging into the PC	A nurse starts the PC, logs in to the PC with the password, and/or logs in to the documentation system with the password.
Waiting for PC	A nurse waits for a workstation to become available. No other tasks are performed during this time.
Making notes	A nurse writes temporary notes, such as vital signs or fluid intake for later documentation.
Walking to the computer	A nurse walks to the ward PC with the aim of documenting or retrieving information about residents.
Reviewing entries	A nurse reviews nursing documentation entries, either their own records or those of colleagues such as nursing assistants or trainees.

Table 1.2. Additional task categories measured at t_1, in addition to those defined at t_0

Task (t_0)	Description
Documentation in voize	A nurse takes the smartphone out of their pocket, unlocks it, and documents measures in voize using voice input and/or signs them manually and/or documents them using freehand mode. The smartphone is locked again.
Informing in voize	A nurse takes her smartphone out of their pocket, unlocks it, and retrieves information about residents manually or via voice input.

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Appendix 2

Self-developed questionnaire for assessment at t_0 and t_1

Table 2.1. Constructs and self-developed items for t_0 assessment

Construct	Item
Satisfaction	How satisfied are you with the current documentation process and system? What is your current mode of documentation?
	Do you think it's a good idea to introduce voize for care documentation?
	How likely are you to use voize regularly for care documentation?
Perceived documentation quality and efficiency	voize will improve the quality of my care documentation.
	voize will save me time on care documentation.
	My current nursing documentation is of high quality.
	The current nursing documentation process is time-consuming.
	I am frequently interrupted while performing nursing tasks.
	Currently, I need approximately the following for the entire care documentation per shift:
	What work experiences do you expect from the introduction of voize?

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Table 2.2. Constructs and self-developed items for t_1 assessment

Construct	Item
Satisfaction	How long have you been using voize?
	How often do you use voize per week?
	Which type of care documentation do you currently use most frequently?
	How satisfied are you overall with voize?
	Was it a good idea to introduce voize for care documentation?
Perceived documentation quality and efficiency	voize has improved the quality of care documentation.
	voize saves me time when searching for information.
	I plan to continue using voize for care documentation in the future.
	With voize, my documentation entries are complete and comprehensive.
	Care documentation with voize is time-consuming.
	My current nursing documentation is of high quality.
	I am frequently interrupted while performing nursing tasks.
	With the help of voize, I save time on care documentation.
	With the help of voize, I save approximately per shift:
	With voize, I need about the following for all care documentation per shift:

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Supplementary Files

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Multimedia Appendixes

Definition of task categories for observations at t0 and t1.
URL: http://asset.jmir.pub/assets/9dd46b3dc06df483aeac3f56db419392.docx

Self-developed questionnaire for assessment at t0 and t1.
URL: http://asset.jmir.pub/assets/8e9b795845020e6fcbab7994d893a4d3.docx

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