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Diabetes management in an ageing society: The role of nursing support in primary care

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ABSTRACT

A growing share of the global population is affected by chronic conditions, prompting the development of various organizational models for chronic disease management. These models often emphasize the pivotal role of General Practitioners (GPs) and community health nurses in leading chronic care efforts.

Recognizing the significant burden of diabetes as a leading cause of disability and mortality, the Emilia-Romagna Region of Italy introduced clinical guidelines for diabetes management in 2010 to enhance the quality of care for patients with type 2 diabetes. This initiative enables GPs working within Community Health Homes to collaborate with Nursing Outpatient Clinics (NOCs) for more effective chronic disease management.

This study evaluates the impact of NOCs on key indicators of patient adherence with clinical guidelines. Using a balanced panel of administrative, individual-level data, we analyse the diabetic population over 65 years old within the largest Local Health Authority in Emilia-Romagna over a seven-year period (2010–2016). To assess the impact of NOCs on patient adherence, we employ alternative difference-in-differences approaches while accounting for heterogeneous treatment effects due to varying patient exposure periods.

Our findings indicate that patients enrolled with GPs who integrate NOCs into diabetes management exhibit significantly improved adherence to clinical guidelines. These results offer valuable insights for policymakers designing diabetes management programs that incorporate nursing support to enhance patient engagement and adherence.

Introduction

The current demographic landscape is shifting towards a scenario marked by a rapidly growing aging population with increasing health care needs and multiple comorbidities. As the share of elderly individuals grows, the prevalence of chronic conditions is also on the rise. This shift places a considerable burden on society, affecting the long-term sustainability of National Health Systems (NHSs), which are struggling to adapt to these changing demographics. This phenomenon, especially in countries characterized by an accelerated population ageing, also significantly affects the total economic burden, in terms of foregone gross domestic product (Bloom et al., 2020; Schindler and Scott, 2025). In Italy, data from year 2022 reveals that 24 % of the population is over 65 years old, with 71 % of individuals aged 65 to 74 experiencing at least one chronic condition, a figure that rises to 83 % among those aged over 75 (Istat, 2023). The growing prevalence of chronic diseases underscores the need for effective management strategies to address the challenges of aging society.

Diabetes ranks among the most prevalent Non-Communicable Diseases and is associated with a range of complications that can ultimately result in disability. In year 2021, 527 million of adults in OECD countries was living with diabetes, a figure projected to rise to 783 million by year 2045 (OECD, 2023). In Italy, the prevalence of the disease in year 2022 was 7 % overall, rising sharply among older adults to 18.5 % in those aged 65–74 and 24 % in individuals over 75 (Istat, 2023). The management of diabetes is particularly complex, especially due to the frequent coexistence of multiple chronic conditions (Kamradt et al., 2019; Wilkinson and Preston, 2021). To address this challenge, numerous diabetes management programs have been introduced in recent decades, shifting the focus from a hospital-centered approach to a

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community-based model for managing cases that require ongoing, low-intensity care (Ferreira-Batista et al., 2023). These initiatives aim to provide services directly within patients' communities, fostering an integrated, patient-centered model that adapts interventions to individual needs (Geurts et al., 2022). This holistic approach is introduced with the belief that it better aligns with the principles of proactive medicine, enhancing the prevention and management of diabetes at every stage, from primary prevention and early diagnosis to clinical care, complication prevention, and proactive follow-up (Goldzahl et al., 2022; Griebenow, 2023; Pascucci et al., 2021).

Within this community-based model, nursing management of diabetes plays a crucial role and is expected to bring numerous expected benefits, both for patients and the healthcare system. First, care provided by nurses dedicated to managing chronic diseases could ensure more continuous and personalized monitoring, improving patient adherence to care pathways and clinical guidelines. Following diabetes clinical guidelines is crucial for preventing complications, maintaining stable blood sugar levels, and improving overall health. It reduces hospitalizations, delay disease progression, enhances quality of life, and supports timely medical interventions. Adherence also ensures proper follow-up care, medication adjustments, promoting therapeutic education and encouraging healthier lifestyles. Additionally, nursing management could strengthen the comprehensive care of patients, relieving pressure on general practitioners and hospitals, enabling a more efficient allocation of resources and enhancing community-based care, in line with a model that is closer to the patient and less reliant on hospitals.

A substantial body of literature examines the impact of skill mixing and task-shifting between GPs and community health nurses on health outcomes, patients' use of health care services and satisfaction (Maier et al., 2022). Research shows that enhancing collaboration between GPs and nurses, along with delegating certain responsibilities from GPs to nursing professionals, significantly improves patient outcomes (Laurant et al., 2018; Röttger et al., 2017). However, despite their prominence in many institutional settings, evidence on the impact of nursing management on patient adherence remains largely descriptive or based on studies with limited sample sizes. Furthermore, the field of integrated care is dominated by diverse initiatives implementing different programs, making direct comparisons challenging (Aldahmashi et al., 2024).

A notable exception to the limited evidence on the impact of collaborative healthcare models on patient adherence to diabetes guidelines is the study by Gilles de la Londe et al. (2023). The authors employ a staggered difference-in-differences (DiD) design to evaluate the effects of Action de santé libérale en équipe (Asalée), a French pilot program implemented between 2010 and 2018. This initiative fostered collaboration between General Practitioners (GPs) and nurses, leading to significant improvements in patient adherence to diabetes clinical guidelines. While this study examines a mutualistic healthcare system such as that of France, our contribution seeks to expand the evaluation of a collaborative model between doctors and nurses within a structured public healthcare setting, Romagna LHA, one of the largest Local Health Authority in Italy. Institutional differences between these contexts emerge in guideline implementation, funding mechanisms, and follow-up strategies. France adopts a mixed public–private approach, whereas the Romagna LHA follows an integrated public health system that prioritizes coordination, chronic disease management, and standardized follow-up care. These features are potentially relevant, as the existing literature indicates that the efficacy of diabetes management may be influenced by multiple factors, including patient-related characteristics, such as the sociodemographic profile of the assisted population, as well as structural aspects of the healthcare system, such as the coordination across providers and the integration of multidisciplinary teams (Thorsen et al., 2020).

In the Romagna LHA, Nursing Outpatient Clinics (NOCs) for managing chronic conditions were established since 2010 in line with national and international guidelines, highlighting the need for multidisciplinary care for chronic and multi-chronic patients. Embedded within Community Health Homes (CHHs), NOCs play a central role in diabetes management by coordinating care, collaborating with GPs to identify at-risk patients, and ensuring follow-up. Within this framework, nurses deliver specialized care and support to diabetic patients, focusing on disease management, preventive care, and follow-up services. This approach serves to bridge the gap between primary care provided by GPs and hospital-based care, fostering greater continuity and coordination across healthcare settings.

This paper aims to contribute further to research in this area by assessing the causal impact of patients' enrolment in NOCs on diabetes management focusing on their ability to induce patients' adherence to diabetes clinical guidelines. To identify the effect of teamwork between GPs and nurses on yearly quality of care process indicators for type II diabetes patients, we employ different empirical strategies, exploiting the fact that we observe GPs prior to and after their entry into a CHH, and that not all GPs entered a CHH. As baseline estimation procedure, we use two-way fixed effects (TWFE) linear regression models, where, since patients are enrolled with the same GP throughout the period, patient fixed effects allow us to control for time-invariant differences between GPs who entered a CHH and those who did not. We assess the robustness of our estimates using alternative DiD methods that enable comparison of outcomes between treatment and control groups, while allowing for a causal interpretation of the estimated effects. We investigate whether patients whose GP operates within a CHH and benefits from NOC monitoring show better outcomes compared to those whose GP does not. We assess outcomes based on patients' adherence to diabetes follow-up tests, using varying levels of adherence with clinical guidelines. The analysis covers the first seven years of NOCs' implementation in the Romagna LHA, between year 2010 and 2016.

Our estimates of the effect of NOC monitoring on patient adherence with clinical guidelines are robust across different estimation methods. We find that, other things equal, being registered with a GP who benefits from nursing management is associated with a short-term increase in patient adherence ranging between 9 % and 11 % approximately, although treatment effects appear to vanish with elapsed treatment time. These findings highlight the importance of targeted interventions to improve adherence to clinical guidelines, as non-adherence can contribute to worsening health outcomes and an increased risk of complications (Bussière et al., 2020; WHO, 2016).

Institutional setting

The Local Health Authority (LHA) of Romagna is the public entity responsible for providing healthcare services in the historical region of Romagna, which includes the provinces of Ravenna, Forlì, Cesena, and Rimini. It is one of the largest LHAs in Italy, both in terms of population served and territorial extension (De Belvis et al., 2024). It was established through the merger of several provincial healthcare entities, creating a single, integrated healthcare system that covers a vast area in the Emilia-Romagna region. With a population of over 1.1 million residents, AUSL Romagna serves a population size comparable to entire - Italian regions such as Marche, Liguria, or Friuli Venezia Giulia. Its territorial extension and healthcare infrastructure also make it similar in scale to the healthcare systems of some Northern European countries, like Slovenia or Estonia. This vast dimension means that LHA Romagna operates a highly complex healthcare network, including multiple hospitals, local health districts, specialized medical centers, and a wide range of community services. It plays a crucial role in ensuring universal healthcare coverage, integrating public health, emergency care, and preventive medicine into a single, coordinated system.

Since 2010, the introduction of CHHs has sought to integrate community and primary care by offering GPs the opportunity to join a team-based care model, promoting collaboration with other healthcare professionals (Emilia-Romagna Region, 2010). Newly opened CHHs allocate dedicated practice space for community GPs within the facility, with many operating costs covered by the Regional Health Service, which creates a strong financial and organisational incentive for GPs to co-locate in the CHH.

In CHHs, the management of diabetes is entrusted to the NOC, who undertakes several key responsibilities in coordinating patient care. These includes collaborating closely with GPs to identify and engage at-risk individuals, facilitating patient outreach and follow-up, and ensuring multi-professional and interdisciplinary assessments and care. The NOC also oversees follow-up and monitoring aligned with established care pathways, delivers therapeutic education to empower patient self-management and to encourage healthy lifestyles, and ensures continuity of care during hospitalizations or transitions to intermediate care facilities like community hospitals.

Once the Regional Health Authority identifies the area where a CHH is to be established, typically serving around 50,000 inhabitants, it coordinates with the Local Health Authority to plan the opening of a NOC within that CHH. NOCs are not established in all CHHs, but rather represent a territorial service mainly concentrated in the larger facilities. Consequently, the timing of NOC activation depends on the availability of nursing staff and facility resources at the CHH level, rather than on GP-related decisions or factors. After a CHH has been established and its NOC activated, GPs may choose to locate their practices within the CHH, allowing their diabetic patients to benefit from the nursing support and chronic care services provided through the NOC.

Eligibility for enrolment in the NOC is restricted to patients below a certain severity threshold, meaning they must either be free of complications or have only minor complications. Patients with more severe conditions are managed by the hospital-based diabetology units. Typically, patients eligible for integrated diabetes management within the NOC are identified either by their GP or the hospital's diabetes centre. A key aspect of the nurse's role in this setting is to strengthen patient relationships by ensuring regular diabetic follow-ups. These follow-ups typically involve monitoring weight and body mass index, as well as conducting blood tests to track specific disease marker, primarily the Glycated Haemoglobin (HbA1c) test, which is recommended at least twice a year. Notably, during periodic visits, the nurse gathers information and assesses the patient's condition, potentially suggesting corrections or adjustments to the care plan to the GP.

Data

The analysis is based on a balanced panel derived from administrative database flows, comprising individual-level data on patients over 65 years, diagnosed with type II diabetes mellitus before year 2010, and residing in the Romagna LHA in Italy. We linked this cohort of patients registered with GPs to two regional administrative data sources – outpatient specialist claims and laboratory test claims – which we used to construct the three guideline-adherence outcome measures described below.

Patient identification is based on an algorithm developed by the Regional Department of Health, which selects adult individuals who have received at least two diabetes drug prescriptions (either oral agents or insulin) over the previous three years. Since this criterion may fail to capture cases managed through diet and exercise alone, the dataset is supplemented with outpatients who visited a Diabetes Centre and with inpatients diagnosed with diabetes during the same time. We tracked this cohort from 2010 to 2016, a period corresponding to the early years of NOC implementation. To ensure continuity of care and avoid potential confounding from selective reallocation of patients across GPs, we restricted the sample to individuals who remained enrolled with the same GP throughout the study period. During the sample period, recognizing the substantial burden of diabetes as a leading cause of mortality and disability, the Emilia-Romagna Region of Italy formally introduced diabetes clinical guidelines providing standardized protocols for diabetes prevention, diagnosis, and treatment. As part of this initiative, GPs and nurses were given responsibility for territorial diabetes care, with particular emphasis on areas where CHHs were established, providing the possibility of activating a NOC within them.

Since NOCs provide support only to patients in the early stages of diabetes, our cohort consists of individuals following dietary recommendations and, in some cases, oral therapy, while excluding insulin-dependent patients receiving care from hospital-based diabetology units. Our final sample consists of 87,332 observations, referring to 12,476 diabetic patients enrolled with 677 GPs.[4] About 11 % (74) of these GPs adhere to a CHH with an active NOC during years 2010–2016. Over this timeframe, a total of 24 CHHs were established, and 22 NOCs were activated.

Descriptive statistics

Patients are assigned to the treatment group if, from 2011 onward, they are enlisted with a GP who works in a CHH with an activated NOC between 2010 and 2016.[5] Patients registered with GPs in traditional practices or in groups working outside CHHs through all the study periods are considered untreated and form the control group. Fig. 1a depicts the cumulative number of patients switching to treatment status over years. As this Figure shows, treatment adoption occurred progressively over time, with the number of patients joining treatment status increasing from 88 in 2011 to 1501 in 2016. Fig. 1b shows the cumulative number of CHHs with an active NOC by province (Rimini, Forlì, Ravenna, and Cesena) and year (2010–2016). The first activations occurred in the Rimini district, followed by Forlì and Ravenna starting from 2013. The Cesena district joined the implementation phase after 2017. This pattern confirms that NOC activation was territorially driven, reflecting the regional schedule for establishing CHHs, with no relationships to individual GP characteristics.

Table 1 provides summary statistics separately for treated patients, who are exposed to treatment at some point during the study period, and for control patients, who were never treated between 2010 and 2016. Patient's characteristics include gender, age, foreign status, and the presence of at least one chronic condition in addition to diabetes. We assess the balance of patient characteristics by calculating standardized differences for continuous and dichotomous covariates.[6] All patient-year standardized differences are below 0.10, indicating well-balanced observable characteristics between groups. Both groups are substantially equally distributed by gender. The average age is 77 years for both treated patients and controls. Foreign patients represent a small proportion of the sample (less than 1 %). Approximately 72 % of patients suffers from at least one additional chronic condition besides diabetic type-2.

Since our goal is to assess the impact of NOC implementation on adherence with diabetes clinical guidelines, we develop indicators of patient adherence, by referring to the guidelines issued by the Emilia-Romagna Region during the study period, as well as the relevant literature on follow-up care for diabetic patients (Höglinger et al., 2023; Huber et al., 2016; Ugolini et al., 2019). Specifically, using data on

[4] Due to the administrative nature of the dataset, no clinical information, such as blood glucose or HbA1c levels, is available.

[5] If a CHH activates a NOC in the first half of the year, all GPs in that CHH receive NOC support for managing diabetic patients, and thus all patients registered with these doctors are considered treated starting from that year. However, if the NOC is activated in the second half of the year, patients are classified as treated from the beginning of the following year.

[6] Unlike t-tests, the standardized difference remains unaffected by sample size, enabling the assessment of relative balance in measured variables between treated and control groups. Since the seminal work of Rosenbaum & Rubin (1985), it has been widely used to evaluate the comparability of treated and untreated units. While no formal threshold is established in the literature, a commonly adopted rule of thumb considers values below 0.10 as indicative of negligible differences in means.

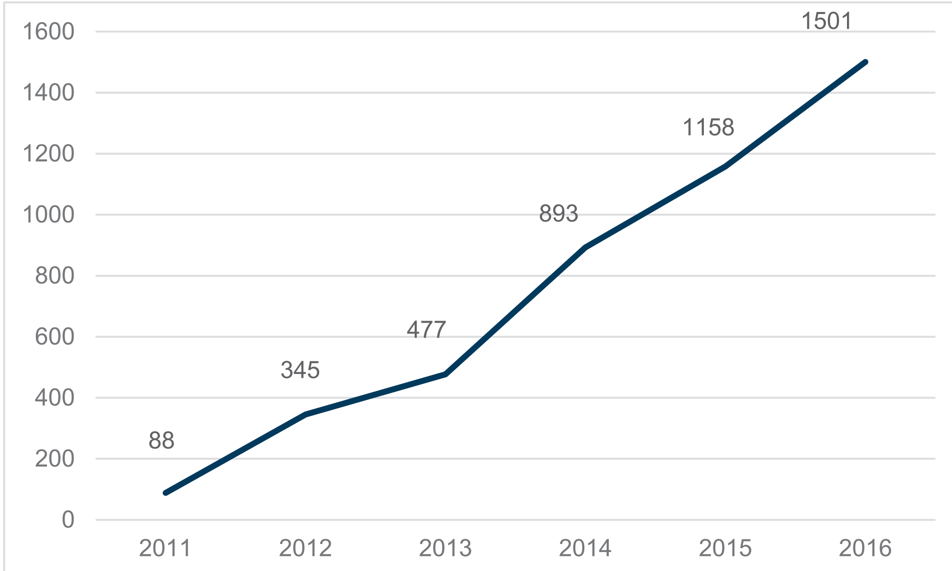

Fig. 1a. Cumulative number of treated patients by first year of treatment. *Notes*: The graph plots the cumulative number of patients switching to treatment between year 2011 and year 2016. Treated patients are those assisted by GPs working within a CHH with an activated Nursing Outpatient Clinic (NOC).

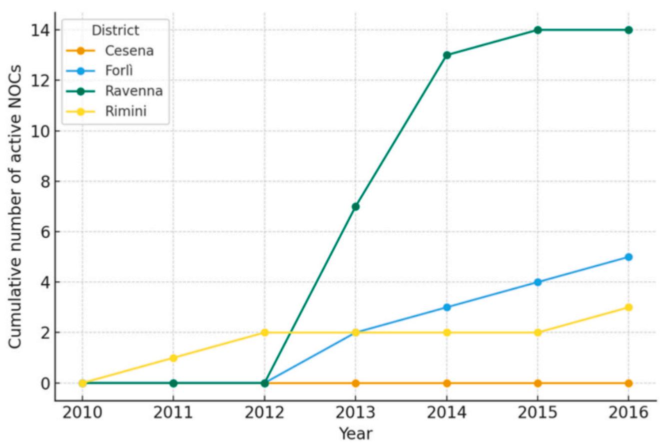

Fig. 1b. Cumulative number of active NOCs in the Romagna LHA (2010–2016). *Notes*: The graph plots the cumulative number of CHHs with an active NOC between 2010 and 2016 across the four districts of the Romagna LHA.

Table 1
Descriptive statistics: patient characteristics.

	All	At some point treated	Never treated	Standardized difference
	Mean (SD)	**Mean (SD)**	**Mean (SD)**	
Female	0.514	0.537	0.510	0.053
	(0.500)	(0.499)	(0.500)	
Patient age	77.069	77.420	77.020	0.063
	(6.422)	(6.439)	(6.418)	
Foreign	0.008	0.006	0.008	−0.021
	(0.086)	(0.077)	(0.088)	
Patients with at least one other chronic condition	0.717	0.715	0.717	−0.005
	(0.451)	(0.452)	(0.451)	
No. observations	87,332	10,507	76,825	
No. patients	12,476	1,501	10,975	

Notes: Pooled data from year 2010 to 2016.

scheduled and completed follow-up tests, such as HbA1c monitoring, lipid profile assessments, and fundoscopy (medical examination of the fundus of the eye), we classify patients into three nested categories reflecting increasing levels of adherence to clinical follow-up guidelines (Basic ⊂ Medium ⊂ High). By definition, patients classified in the group of *High* adherence also meet the criteria of the lower tiers. The basic level requires the completion of at least two HbA1c tests per year. The medium level includes two HbA1c tests along with at least one supplementary test, such as microalbuminuria, lipid profile, glomerular filtration, or fundoscopy, conducted within the same period. The high level consists in the performance of two HbA1c tests in conjunction with at least two additional tests annually.

Based on the three levels of adherence, we include a dummy variable for each of the three groups. Table 2 shows the summary statistics of the adherence indicators as defined above using data pooled from year 2010 to 2016. The first level of adherence to clinical guidelines is met by 46 % of sample patients. The share is higher for patients whose GP is affiliated with a CHH with an activated NOC (about 55 %) compared with those whose GP is not (45 %). We observe slightly decreasing shares as adherence levels widen. Specifically, adherence to clinical guidelines at the second and third levels is observed in 45 % and 44 % of the sample patients, respectively. The proportion of patients meeting these adherence levels is higher among those whose GP is affiliated with a CHH with an active NOC (53–55 %) than among those whose GP is not (42–45 %).

Table 2
Descriptive statistics: indicators of patient adherence with diabetes clinical guidelines.

	All	At some point treated	Never treated
	Mean (SD)	**Mean (SD)**	**Mean (SD)**
Basic adherence level	0.460	0.550	0.448
	(0.498)	(0.498)	(0.497)
Medium adherence level	0.454	0.546	0.442
	(0.498)	(0.498)	(0.497)
High adherence level	0.437	0.529	0.424
	(0.496)	(0.499)	(0.494)
No. observations	87,332	10,507	76,825
No. patients	15,136	1,501	10,975

Notes: Pooled data from year 2010 to 2016.

Empirical strategy

In the early years of NOC activation, which this analysis focuses on, it was not feasible to retrieve the actual lists of patients treated by nurses. Instead, our identification strategy relies on the assumption that if a GP chooses to join a CHH with an activated NOC, all diabetic patients registered with that GP will receive nursing disease management support provided by the NOC. This approach aligns our analysis to the intention to treat perspective (ITT) that is based on the initial treatment assignment and not on the treatment eventually received.

The institutional context described above supports the conjecture that the timing of NOC activation is independent of the underlying characteristics of GPs. The staggered adoption of the model is more likely driven by supply-side constraints rather than physicians' discretionary choices. When a new CHH opens, while the decision of a GP to join may be endogenous to their characteristics, the timing of such entry is largely determined by the availability of local infrastructure, a factor that is plausibly exogenous to the outcome of interest. Indeed, these decisions are primarily top-down in nature (such as determining where to open a CHH and whether a NOC should be included) and depend on resource constraints and the organizational planning implemented by LHA policymakers. Consequently, the timing of program adoption is dictated by when these resources become available in a specific area, making the timing of a GP's entry into the CHH essentially exogenous, further reinforcing the identification strategy through the program's staggered rollout.

To address potential unobservable confounding factors related to specific patient characteristics that may influence selective reallocation across GPs, we incorporate patient fixed effects in our empirical analysis. Since our sample is restricted to patients who remained with the same GP during the whole observation period, GP fixed effects are absorbed into the individual fixed effects. This approach, therefore, allows to account for fixed differences at both patient and GP levels, thereby further reducing the impact of GP self-selection into the program.

Since NOC activation within CHH occurs at different times, we include in the sample any transitions from "never treated" to "treated" for each year. To ensure the validity of our estimation strategy, we adopt the assumption of treatment irreversibility, commonly known in the literature as the staggered treatment adoption assumption. This implies that once patients receive treatment, they remain in the treated group for the entirety of the study period. The rationale for this exclusion is that, for these units, the counterfactual untreated outcomes remain unobserved, preventing the identification of treatment effects (Callaway and Sant'Anna, 2021).

Two-way fixed effects

As our baseline estimation, we use a two-way fixed effects (TWFE) model to estimate the effect of NOC implementation on adherence to diabetes clinical guidelines. Specifically, our baseline model takes the following form:

$$E\left(y_{ijt}|X_{ijt}\right) = \alpha_0 + \alpha_1 Post_{jt} \times Treatment_j + \alpha_o Z_{it} + \gamma_i + \delta_t + \varepsilon_{ijt}$$

where y_{ijt} is the outcome variable of interest, assuming value 1 if, in the year t, patient i from GP j is compliant with diabetic clinical guidelines, and 0 otherwise. We define $Treatment_j$ as a binary variable that equals 1 if the patient's GP j 's practice is located within a CHH that hosts an active NOC, and 0 otherwise. This definition refers to physical co-location within the CHH, rather than the mere presence of a CHH/NOC in the GP's catchment area. Therefore, the treatment indicator turns on when both conditions hold, namely co-location and NOC activation. $Post_{jt}$ is a dummy variable equal to 1 if GP j operates within a CHH that has an active NOC by time t; Z_{it} is a vector of patient characteristics; γ_i are patient fixed effects; δ_t are year fixed effects; and ε_{ijt} is the white noise error.

We estimate Equation (1) using a Linear Probability Model (LPM) separately for each dependent variable. Specifically, we define three binary indicators as dependent variables, taking a value of 1 for patients classified within the basic, medium, or high adherence groups, and 0 otherwise. The three adherence levels are hierarchically structured, meaning that patients attaining a high level of adherence also fulfil the criteria for medium and basic adherence levels. The primary coefficient of interest is α_1, capturing changes in adherence levels that are specific to practices following their transition to the treatment condition. Controlling for GP fixed-effects, absorbed into the individual fixed effects, we account for time-invariant, unobserved differences between GPs who receive NOC support in disease management and those who do not. This approach mitigates the influence of systematic differences in outcomes between the treatment and control groups attributable to time-invariant GP-specific characteristics, such as professional attitudes and practice styles, which can influence patient-physician interactions and associated health outcomes. The year fixed effects are expected to absorb changes in outcomes for all patients.

While the TWFE approach remains widely employed in empirical research, recent econometric literature has identified potential weaknesses of this method in settings involving multiple periods and staggered interventions implemented at different times. TWFE may perform poorly in contexts characterized by treatment heterogeneity across units and time or in presence of dynamic treatment effects (Borusyak et al., 2024; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021; Nguyen, 2020; Roth et al., 2023; Sun and Abraham, 2021). To address these challenges, we complement the TWFE estimation with two alternative methods recently proposed in the literature, which are detailed in the next sub-section.

Difference-in-Differences with staggered adoption

The second method that we employed is the one proposed by Callaway & Sant'Anna (2021), to which we refer as CS-DID. By recognising that treatment effects may differ across cohorts based on their timing of treatment, this method is suitable in our context of study with multiple time periods and variation in treatment timing. By relaxing the assumption of common cohort effects, this method allows to identify Average Treatment Effects on the Treated (ATTs) for different groups and time periods, while also accounting for the heterogeneity in the length of exposure to the treatment.

We use the "never treated" group as the control group and we apply the doubly robust (DR) estimator proposed by Sant'Anna & Zhao (2020), which applies the inverse probability of tilting to weight observations. This method involves estimating propensity scores for each individual and period using pre-treatment covariates, with the same set of variables included in the subsequent outcome regression, weighted by the inverse probability of treatment (Guan and Tena, 2022). Although the expected ATT under the DR estimator is equivalent from the identification perspective to that of other methods, it offers more flexible modelling conditions for the estimation (Callaway and Sant'Anna, 2021). For each treated group within a given time frame, this approach identifies an appropriate control group from the never-treated groups by using matching techniques. As a result, each treatment group is paired with a distinct control group. After matching, the model estimates treatment effects for each cohort, over different calendar times, as well as aggregate treatment effects. The analysis was conducted using the default method (drimp) of the csdid package in STATA 19. As a robustness check, we also add the "not-yet treated" group in our control group.

Additionally, we employ an extended version of TWFE using the approach proposed by Lee & Wooldridge (2023) designed to enhance efficiency and flexibility in estimating treatment effects for panel data under staggered interventions. Unlike the Callaway & Sant'Anna (2021) approach, which relies on "long differences" using only the period immediately prior to treatment as control, the proposed method uses a "rolling" approach, transforming the outcome variable by incorporating all suitable control observations over time. This broader use of data can ensure greater statistical efficiency and can allow for more robust inference.

Results

Baseline estimation results

Table 3 presents the results from the TWFE linear regression specified in Equation (1). Columns 1–3 display the results for the three different levels of patient adherence: Basic, Medium, and High. The key coefficient of interest, α_1, is positive and statistically significant across all models. Since adherence outcomes are nested and protocol-driven, treatment effects are consistent across the three tiers. The estimates indicate that diabetic patients whose GP operates within a CHH with an activated NOC experience an increase in adherence of about 11 % across all levels of adherence considered. The consistency of the estimated coefficients across adherence thresholds supports the interpretation that NOC nurses contribute to standardising follow-up practices according to clinical guideline routines, bringing patients above the minimum standard and often fulfilling the broader bundle of recommended checks. The three-tier outcome specification supports the robustness of the estimated treatment effect to the choice of adherence thresholds, allowing us to rule out concerns of patient outcome selection. Moreover, it aligns with a policy-relevant structure of compliance, separating the achievement of minimum standards (*Basic*) from fuller bundles of recommended tests (*High*). From a policy perspective, the key achievement lies in the shift from non-adherence to at least minimum guideline compliance, with additional gains at higher tiers likely occurring as a result of protocolised care pathways.

Staggered Difference-in-Differences results

The primary output that we derive using the CS-DID methodology is the group-time ATT, which represents the expected difference between the observed outcomes for the treated and untreated units at time t. This approach allows for heterogeneity in ATT, capturing variations across cohorts and over time. Table 4 presents the overall estimated ATT using the "never treated" group as control. As shown in the table, the results from the CS-DID method are generally consistent with those obtained using the TWFE regressions: nursing support in disease management increases adherence by a percentage of approximately 9 % across all the three levels of adherence. These results suggest that nursing support is more effective in encouraging patients with lower initial engagement to reach acceptable adherence levels, rather than in driving those who already exhibited some degree of adherence toward full adherence. We replicate the analysis by using the "not-yet treated" cohort as counterfactual. The results, presented in Table 6, closely mirror those derived when using the "never treated" group, again indicating an overall improvement in adherence of roughly 9 %.

We leverage the flexibility of the CS-DID method in analysing treatment effect heterogeneity by examining event study dynamics. We consider both the length of exposure to the treatment and the temporal evolution of its overall impact, as measured by the average treatment effect (Callaway and Sant'Anna, 2021). First, we report the results of the event study analysis for the three adherence outcomes. Fig. 2 plots the ATTs across periods before and after treatment. Each plotted dot represents the mean conditional outcome for individuals exposed to the intervention relative to the control group, while the bars indicate the 95 % confidence intervals. These results provide evidence supporting the conditional parallel trends assumption. The blue bars, representing pre-treatment periods, indicate that there are no statistically significant changes. In contrast, in the post-treatment periods, the effect of patients' exposure to the NOCs on adherence is both positive and significant in the first two years after treatment, while vanishing in the following years. Overall, the estimated ATTs indicate that the effect initially strengthens with increasing length of exposure, followed by a decline from the third year of exposure to the treatment. Across all adherence levels, the point estimates derived in the last three years after treatment should be interpreted with caution. The wider confidence intervals associated with these estimates suggest greater variability, likely attributable to the relatively smaller sample size of patients with more than two years of exposure. Table 5 presents the ATT estimates by post-treatment year. The analysis reveals that, compared to the control group and baseline values (pre-enrolment), patients exhibit higher levels of adherence following the enrolment of their GPs in the CHH, thereby gaining exposure to the treatment. The impact is insignificant in 2011 and 2012, while becoming significant from 2013 onwards, with patient adherence increasing by a proportion ranging from 8 % to 13 %. It is plausible that the role of NOCs was not fully established or uniformly effective across all areas during the initial years of implementation. We may expect that best practices may become more widely adopted with experience, as the relationship between nurses and patients likely strengthens. Nevertheless, a clear positive trend is evident over many of the analysed years Table 6.

As an alternative estimation method, we ran the approach proposed by Lee and Wooldridge (2023) (JW-DID), which can enhance statistical efficiency relative to Callaway & Sant'Anna (2021). This improvement can be achieved by leveraging all available pre-treatment observations, rather than restricting the control group definition to the period immediately preceding treatment. Table 7 compares the overall ATTs estimation obtained using TWFE, CS-DID, and JW-DID. The results obtained using the JW-DID approach further corroborate our findings, remaining consistently positive and statistically significant. As Table 7 shows, the estimated ATTs of NOC across all adherence levels range from 9 % to 11 %, with the highest impact estimated using the TWFE approach.

Table 3
Two-way fixed effects (TWFE) results.

	Model 1	Model 2	Model 3
	Basic	**Medium**	**High**
Post X Treatment	0.106***	0.108***	0.112***
	(0.0182)	(0.0186)	(0.0182)
Year FEs	Yes	Yes	Yes
Patient FEs	Yes	Yes	Yes
No. observations	87,332	87,332	87,332

Notes: All regressions control for patient age and a dummy for patients having at least another chronic condition besides. Standard errors clustered at the GP level are included in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4
Average treatment effect (ATT) estimates using Callaway & Sant'Anna (2021) method.

	Model 1 Basic	Model 2 Medium	Model 3 High
ATT	0.0879***	0.0863***	0.0893***
	(0.0171)	(0.0175)	(0.0177)
No. observations	87,332	87,332	87,332

Notes: The results are obtained using the Stata command *csdid*. For further details, refer to Rios-Avila et al. (2021). The counterfactual consists of units that are "never treated". The estimates are derived using the doubly robust estimator. Standard errors clustered at the GP level are included in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Discussion and conclusions

Our analysis focuses on a framework where nurses supplement or extend the work of GPs with the goal of improving the quality of care. Within this framework, we analysed the impact of NOC activation

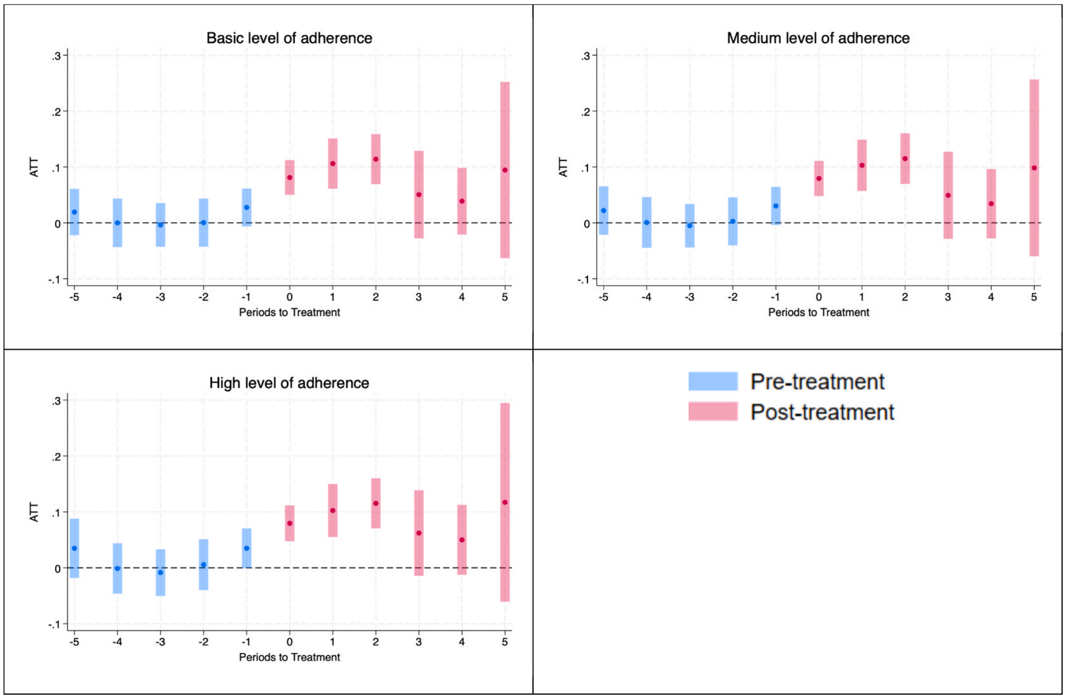

Fig. 2. Average treatment effect (ATT) estimates by the length of exposure to the treatment. *Notes*: The ATTs are estimated following Callaway & Sant'Anna (2021). The counterfactual consists of units that are "never treated". The estimates are derived using the doubly robust estimator. The circles represent the point estimates, while the vertical bars denote the 95% confidence intervals.

Table 5
Average treatment effect (ATT) estimates by calendar year.

	Model 1 Basic	Model 2 Medium	Model 3 High
Year 2011	0.0392	0.0269	0.0254
	(0.0416)	(0.0504)	(0.0523)
Year 2012	0.0507	0.0460	0.0579
	(0.0311)	(0.0316)	(0.0317)
Year 2013	0.129***	0.126***	0.125***
	(0.0344)	(0.0348)	(0.0353)
Year 2014	0.0823***	0.0795**	0.0851***
	(0.0247)	(0.0250)	(0.0247)
Year 2015	0.0863***	0.0865***	0.0854***
	(0.0237)	(0.0238)	(0.0232)
Year 2016	0.0910***	0.0903***	0.0944***
	(0.0178)	(0.0181)	(0.0192)
No. observations	87,332	87,332	87,332

Notes: The results are obtained using the Callaway & Sant'Anna (2021) method. The counterfactual consists of units that are "never treated". The estimates are derived using the doubly robust estimator. Standard errors clustered at the GP level are included in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6
ATT CS-DID results with different control group.

	Model 1 Basic	Model 2 Medium	Model 3 High
ATT	0.0868***	0.0852***	0.0880***
	(0.0172)	(0.0176)	(0.0178)
No. observations	87,332	87,332	87,332

Notes: The results are obtained using the Stata command *csdid*. For further details, refer to Rios-Avila et al. (2021). The counterfactual consists of both groups: "never treated" and "not-yet treated" units. The estimates are derived using the doubly robust estimator. Standard errors clustered at the GP level are included in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 7
Comparison of Average treatment effect (ATT) estimates using alternative DID estimators.

	Model 1 Basic	Model 2 Medium	Model 3 High
JW-DID	0.0879***	0.0864***	0.0893***
	(0.0148)	(0.0152)	(0.0160)
CS-DID	0.0879***	0.0863***	0.0893***
	(0.0171)	(0.0175)	(0.0177)
TWFE	0.106***	0.108***	0.112***
			(0.0182)
	(0.0182)	(0.0186)	
No. observations	87,332	87,332	87,332

Notes: Abbreviations: JW-DID, Lee & Wooldridge (2023) estimator; CS-DID, Callaway & Sant'Anna (2021) estimator; TWFE, two-way fixed effects regressions. Standard errors clustered at the GP level are included in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

within CHHs to support GPs in managing diabetic patients. Our objective was to evaluate the overall impact of this integrated care model on patients' adherence, without disentangling the specific contributions of each professional group. As we are considering the early years of intervention, the effects observed are preliminary. However, the findings already show a positive impact on patient adherence with clinical guidelines.

Few studies in the literature assess the impact of nursing support in chronic disease management, with most focusing on reducing hospitalizations, rather than enhancing adherence with clinical pathways. To the best of our knowledge, in-depth analyses of adherence, beyond largely descriptive studies or those with limited sample sizes, are rare. A key exception is the study by Gilles de la Londe et al. (2023), which shows that a French pilot program enhancing GP-nurse collaboration improved diabetes management. Overall, our study aligns with these findings within an integrated public healthcare system, highlighting the role of nursing support in patient adherence to follow-up guidelines.

Despite our efforts to provide a thorough assessment of the NOC initiative's impact, this study has some limitations. The primary limitation lies in the lack of information to identify the individuals who directly benefit from NOC support, and our identification strategy relies on using the GP's decision to join a CHH with an active NOC as a proxy. This analysis employs an intention-to-treat (ITT) approach, assuming that all diabetic patients registered with the respective GP are exposed to NOC support. This limitation notwithstanding, our results provide evidence that nursing support contributes to enhanced patient adherence with diabetic clinical guidelines. Using individual-level data sources capable of identifying patients directly managed by primary care nurses, future research would contribute to the understanding of the specific mechanisms driving the observed improvements in patient adherence.

Secondly, the lack of detailed information on patients' socio-economic status—currently unavailable in the administrative data—limits this analysis. Future research would benefit from integrating broader data sources to better capture patient heterogeneity, including factors such as education level and health literacy.

Finally, to broaden the scope of the analysis, future research could expand the dataset to include a longer observation period, thereby enabling a more comprehensive evaluation of the long-term effects of this policy intervention. Evidence in the initial post-treatment years indicates that the effect first strengthens with elapsed treatment time until the second year of exposure, and then declines thereafter. The limited sample size for patients with extended exposure constrains our ability to assess long-term effects. Future research would benefit from a longer observation window to determine whether the impact of nursing support persists over time or nuances in the long run. Additionally, extending the analysis to encompass groups of patients with other chronic conditions, beyond diabetes, would shed light on the generalizability of the NOC model. Identifying whether its benefits are specific to diabetes management or applicable to other areas of chronic care would facilitate a broader understanding of the effectiveness of this integrated care approach, offering valuable insights to inform policy decisions aimed at improving the management of chronic diseases. Further investigation in this field is crucial, as enhancing primary care through a more advanced community-based approach is becoming a key policy priority in developed countries, which are increasingly challenged by aging populations.

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Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Ethics approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. The study, based on routine administrative information, was carried out in compliance with Emilia-Romagna Regional Authority data processing regulations and the Italian Data Protection Act that harmonized with the European General Data Protection Regulation 2016/679 by means of the Legislative Decree 101/2018. Administrative data were anonymized prior to the analysis at Local Health Authority of Romagna, where each patient is assigned a unique identifier. This identifier does not allow to trace the patient's identity and other sensitive information. Anonymized administrative data may be used for retrospective studies, with no specific written patient consent, when the aim is health-care quality evaluation and improvement, which was the primary objective of this analysis. Given the characteristics of the study, no ethical approval was required.

Data availability statement

The data used in this study were released by the data holder (Local Health Authority of Romagna, Italy) under specific data sharing agreements, only for the purpose of this study, and are not publicly available due to privacy restrictions. The data sharing agreements do not permit further sharing or publication of the data. Interested parties may seek to obtain data directly from the data holder.

CRediT authorship contribution statement

Marta Giachello: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Cristina Ugolini:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Rossella Verzulli:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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