PONTIFICIA UNIVERSIDAD CATOLICA DE CHILE

SCHOOL OF ENGINEERING

MULTIDISCIPLINARY COLLABORATION IN DIABETES CARE TEAMS THROUGH ELECTRONIC MEDICAL RECORDS ANALYSIS

CECILIA SAINT-PIERRE CORTÉS

Thesis submitted to the Office of Graduate Studies in partial fulfillment of the requirements for the Degree of Doctor in Engineering Sciences.

Advisor:

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MARCOS SEPÚLVEDA

Santiago de Chile, January, 2019

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ABSTRACT

Type 2 Diabetes Mellitus (T2DM) is a multisystemic chronic disease that affects around 415 million people in the world and is expected to rise beyond 642 million by 2040. In Chile, prevalence of T2DM is estimated to be between 10 and 12% of the adult population, and only 36% of them maintain good metabolic control. When T2DM is not controlled, a series of complications can arise, impacting patients' quality of life and increasing their risk of mortality, e.g. cardiovascular complications, diabetic retinopathy, and kidney failure.

As a multisystemic disease, T2DM requires a multidisciplinary approach for its treatment. Multidisciplinary collaboration among team members from different disciplines improves clinical outcomes such as glycated hemoglobin (HbA1c), blood pressure and cholesterol, and reduces hospitalization costs and readmission rates in complex cases. Additionally, continuity of care (COC), understood as the "extent to which medical care services are received as a coordinated and uninterrupted succession of events consistent with the medical care needs of patients" has also been associated with improved clinical results in patients with chronic diseases, including T2DM. Most of the studies assess COC for physicians, without considering other disciplines involved in the treatment.

Even though multidisciplinary collaboration and professionals' COC have shown to be beneficial in T2DM treatment, some aspects remain unclear, e.g.: which characteristics of the collaboration have more impact in the treatments, whether it can be identified collaboration patterns related to better patient outcomes, and whether the continuity of the whole team is relevant to the patient evolution. To explore these issues, the aim of this thesis is *"to deeply understand how multidisciplinary teams collaborate, which collaboration patterns obtain better results, and how the interactions may be modeled from a patient-centered approach in order to detect patterns and assess the collaboration*".

We conducted a systematic literature review about multidisciplinary collaboration in primary care that allowed us to classify collaboration by disciplines involved, as well as by collaborative activities performed. We applied this classification to our dataset and found that the previously defined types were valid in our settings. To measure collaboration and discover patterns, we used data from the electronic medical records (EMR) and two different

approaches: process mining (PM) and social network analysis (SNA). Using PM and focusing on the disciplines involved in the treatment, we found seven interaction patterns that differed in the structure of the handover of patients' network. Statistical analysis showed an association between more balanced participation of the disciplines and better patient evolution. Using SNA, we proposed a methodology to model multidisciplinary collaboration as a social network, defining and measuring team continuity. Unlike previous studies, our work considered team changes over time. This methodology allowed us to identify an association between the topology of team continuity networks and clinical outcomes.

Through this thesis work, we validated three hypotheses: H1) *Different collaboration patterns exist among professionals treating patients diagnosed with T2DM;* H2) *Collaboration patterns among professionals treating patients diagnosed with T2DM can be obtained from EMR data analysis; and* H3) *Patients with diabetes treated according to different collaboration patterns have different clinical outcomes.*

This methodology provides tools to assess teams and objectively compare their collaboration as related to the patient outcomes. The proposed methodology can be applied to other settings in chronic diseases that require a multidisciplinary approach. Results of those analyses can help to improve clinical outcomes, create or update clinical guidelines and to support public policy definitions oriented to enhance collaboration and team continuity. The obtained results are valid only in our setting: primary care centers in a low-income urban area, for adults diagnosed with T2DM.

As our work proposes a quantitative data-driven methodology, it could be used to study collaboration in other settings of T2DM treatment, as well as different fields, such as computer supported collaborative work, computer supported collaborative learning, software development or business processes. Therefore, we consider as future work two lines of research: a first one related to the impact of our results for the treatment of T2DM and to validate the proposed methodology in other chronic diseases that require multidisciplinary collaboration, and a second line oriented to validate the methodology in other fields.

Keywords: Diabetes Mellitus, Primary care, Multidisciplinary collaboration, Team Continuity Networks, Process Mining, Social Network Analysis.

RESUMEN

Diabetes Mellitus Tipo 2 (DMT2) es una enfermedad crónica multisistémica que afecta a alrededor de 415 millones de personas en el mundo, y se espera que aumente a 642 millones al 2040. En Chile, la DMT2 afecta a entre un 10 y 12% de la población adulta, y solo un 36% de ella mantiene un correcto control metabólico. La diabetes no controlada correctamente puede provocar complicaciones que impactan la calidad de vida y aumentan el riesgo de muerte del paciente, como complicaciones cardiovasculares, retinopatía diabética, neuropatía periférica y falla renal, entre otras.

Como enfermedad multisistémica, la DMT2 requiere un tratamiento colaborativo y multidisciplinario. Esta forma de tratamiento ha mostrado mejores resultados clínicos como la hemoglobina glicosilada (HbA1c), presión arterial y colesterol, y menor costo de hospitalización y tasa de readmisión en caso de complicaciones. A pesar de esto, pocos estudios asocian cuantitativamente qué formas de colaboración tienen mayor impacto en estos resultados. Por otra parte, la continuidad del cuidado (COC), entendida como la medida en que la atención médica se recibe como una sucesión coordinada e ininterrumpida de eventos de acuerdo a las necesidades clínicas de los pacientes, ha sido también asociada con mejores resultados clínicos en DMT2.

Aun cuando la colaboración multidisciplinaria y COC han mostrado ser cruciales en el tratamiento de la DMT2, algunos aspectos no han sido profundamente estudiados, como cuáles actividades colaborativas tienen mayor impacto en los resultados, si existen patrones de colaboración relacionados con resultados clínicos, y si la continuidad del equipo multidisciplinario de cuidado, es también relevante para la evolución del paciente.

A partir de estas preguntas formulamos tres hipótesis: H1) *Existen distintos patrones de colaboración en el tratamiento de distintos tipos de pacientes*; H2) *Es posible identificar dichos patrones mediante el análisis de datos*; y H3) *Existen diferencias significativas entre los resultados clínicos de pacientes tratados con distintos patrones de colaboración*. Así, objetivo general de la tesis fue proponer una metodología basada en análisis de datos, para medir la colaboración y continuidad de los equipos multidisciplinarios en el tratamiento de DMT2, identificando patrones y analizando su relación con los resultados clínicos.

Para cumplir con este objetivo, desarrollamos una revisión sistemática de literatura sobre colaboración multidisciplinaria en atención primaria, que nos permitió clasificar la colaboración por disciplinas involucradas en el tratamiento, como también por actividades colaborativas utilizadas. Esta clasificación fue aplicada a nuestro set de datos, encontrando que la tipología identificada en la literatura era válida también en nuestro contexto. Para medir la colaboración e identificar patrones, utilizamos datos de registros clínicos electrónicos con dos enfoques metodológicos diferentes: Minería de Procesos (MP) y Análisis de Redes Sociales (ARS). Utilizando MP, encontramos 7 patrones de colaboración con diferente estructura de derivación de pacientes entre las disciplinas involucradas en el tratamiento. Un análisis estadístico mostró asociación entre una participación más equilibrada de las disciplinas y una mejor evolución de los pacientes. Usando ARS, propusimos una metodología de modelamiento de la colaboración multidisciplinaria bajo el concepto de “continuidad del equipo de cuidado”. A diferencia de estudios previos, este modelo consideró los cambios en los equipos a lo largo del tiempo. Esta metodología permitió identificar asociación entre la topología de las redes y los resultados clínicos. Con este trabajo se validaron las tres hipótesis planteadas.

Nuestros resultados son prometedores, en cuanto fuimos capaces de medir cuantitativamente la colaboración con un enfoque basado en datos. En el ámbito médico, esta metodología nos da herramientas para evaluar equipos y comparar objetivamente su colaboración en relación con la evolución de los pacientes, y puede ser aplicada a otras enfermedades crónicas que requieran un tratamiento similar. Esta metodología puede ser también aplicada a otros campos como desarrollo de software, aprendizaje colaborativo soportado por computadores o procesos de negocios de distinta naturaleza.

Como trabajo futuro identificamos dos líneas de investigación, una primera relacionada al impacto de nuestros resultados para el tratamiento de la DMT2 y otras enfermedades crónicas, y una segunda orientada al modelamiento y cuantificación de colaboración, validando la metodología propuesta en otros dominios.

Palabras clave: Diabetes Mellitus, Atención Primaria, Colaboración multidisciplinaria, Redes de continuidad de equipos, Minería de Procesos, Análisis de redes sociales.

1. INTRODUCTION

Collaboration has been related with efficiency and effectiveness in diverse fields including software development, scientific research, education and healthcare. Inside healthcare domain, collaboration in primary care has been widely studied in different settings, specially in multisystemic and chronic diseases, where a multidisciplinary and collaborative approach are highly recommended. Many studies about chronic diseases treatments have assess collaboration in relation to clinical outcomes, however, most of them use qualitative methodologies or low-scale randomized controlled trials.

The aim of this work is to develop a data-driven methodology to model and measure collaboration in a multidisciplinary context, applied in healthcare domain, in order to analyze the relationship between collaboration and clinical outcomes. We focus our research in type 2 diabetes mellitus, due to the high and increasing prevalence that make it a public healthcare issue.

1.1. Background

The following sections present a brief context about type 2 diabetes mellitus and most recommended treatment approaches, followed by a review of the most relevant used through the present work.

1.1.1. Type 2 diabetes mellitus: context and relevance

Globally, around 415 million people suffer from type 2 diabetes mellitus (T2DM) and this number is expected to rise beyond 642 million by 2040 (International Diabetes Federation, 2015). In Chile, the percentage of patients with diabetes for 2015 was estimated to be between 10 and 12% (International Diabetes Federation, 2015; Ministerio de Salud de Chile, Facultad de Medicina, & Observatorio Social, 2013). Only 36% of patients with diabetes in Chile maintain good metabolic control (Subsecretaria de Redes Asistenciales, 2010). When DMT2 is not controlled, a series of complications can arise that can impact the quality of life of the patient and increase their risk of mortality, e.g. cardiovascular complications, diabetic retinopathy, peripheral neuropathy, and kidney failure (American Diabetes

Association, 2017; Tuligenga et al., 2014). It is possible to prevent these complications through the use of medication and an appropriate diet (C.-C. Chen, Tseng, & Cheng, 2013; Gamiochipi, Cruz, Kumate, & Wacher, 2016; Wagner et al., 2001).

1.1.2. Collaboration concept

In general terms, collaboration means working together towards a common goal (Durugbo, Hutabarat, Tiwari, & Alcock, 2011). It could be found in different fields and at different levels (e.g. individuals, institutions, countries). Among the most common domains where collaboration have been studied, we found scientific research, business processes, learning and healthcare.

In scientific research and productivity, collaboration between countries, institutions and researchers have been conducted, commonly to analyze co-authorship in some specific research field (for instance: (Huerta-Barrientos, Elizondo-Cortés, & de la Mota, 2014; W. Liu, Zheng, Wang, & Wang, 2014; Manuelraj & Amudhavalli, 2008). In business processes, collaboration have been widely analyzed in order to improve quality and increase productivity, for instance, analyzing collaboration in task assignment (R. Liu, Agarwal, Sindhgatta, & Lee, 2013), discovering interaction patterns between workers from information systems' data (Rattanavayakorn & Premchaiswadi, 2015; W. M. P. van der Aalst & Song, 2004) and analyzing decision-making processes (Slotegraaf & Atuahene-Gima, 2011). Computer supported collaborative learning (CSCL) is a complete field in computer science, that include the study of collaboration in the use of mobile-technologies (Fu & Hwang, 2018), augmented reality (Ibáñez & Delgado-Kloos, 2018), multiuser virtual worlds (Liaw et al., 2018), among other.

In healthcare field, collaboration has also been widely studied through the analysis of different face-to-face interactions' types, such as direct communication between peers, coordination meetings and shared consultation, as well as a wide range of computer-supported interactions such as e-mail, short messages systems, telemedicine, even the common access to patients' electronic medical records (EMR) (Saint-Pierre, Herskovic, & Sepúlveda, 2018). For this thesis purposes, we define collaboration in healthcare as a process of problem-solving, shared responsibility for decision-making and the ability to carry out a care plan while working towards a common goal (Saint-Pierre, Herskovic, & Sepúlveda, 2018). Collaboration has been studied at high-level, analyzing inter-organizations and intra-organizations dynamics, and at low-level, analyzing interaction within team members in small groups of providers. This work will be focused on collaboration between professionals within care teams.

1.1.3. Multidisciplinary collaboration in healthcare

The term *multidisciplinary team* is used to refer to a group of professionals from two or more disciplines that work on the same project, independently or in parallel. Previous research encourages multidisciplinary treatment for diabetic patients (American Diabetes Association, 2017; Appleyard, Frcpch, Rawaf, & Frcp, 2015; Benagiano & Brosens, 2014; Gucciardi, Espin, Morganti, & Dorado, 2016; International Diabetes Federation, 2015; J. McDonald, Jayasuriya, & Harris, 2012), showing evidence that multidisciplinary teams achieved better outcomes than those that were not multidisciplinary, demonstrating improvements in glycated hemoglobin (HbA1c), plasma glucose levels, low-density lipoprotein cholesterol, cardiovascular disease risk, microvascular complications and mortality (Borgermans et al., 2009; Conca et al., 2018; Farsaei, Karimzadeh, Elyasi, Hatamkhani, & Khalili, 2014; Maislos & Weisman, 2004; Wan et al., 2017; Wishah, Al-Khawaldeh, & Albsoul, 2015). Research on multidisciplinary treatment has revealed an association between multidisciplinarity and a reduction in specialist visits, emergency visits, hospitalizations and total diabetes-related costs (Ackroyd & Wexler, 2014; Uddin & Hossain, 2012; Wan et al., 2017). The most frequently used clinical outcomes to evaluate the effects of multidisciplinary collaboration in diabetic patients are HbA1c levels, systolic blood pressure, cholesterol levels, and weight (Ong et al., 2018; Schepman, Hansen, de Putter, Ronald S. Batenburg, & de Bakker, 2013).

Healthcare practice is highly dynamic, increasingly multidisciplinary, ad-hoc, and largely dependent on distributed human collaboration (Homayounfar, 2012). Primary care may comprise multidisciplinary teams of up to 30 professionals, including physicians, nurses, midwives, dentists, physiotherapists, social workers, psychiatrists, dietitians, pharmacists, administrative staff and managers (World Health Organizacion, 2008). Furthermore, primary care is patient-centered, so the disciplines of the professionals who treat a patient, and the distribution of their roles (e.g. who will be team leader), change according to patient needs. Collaboration between team members in order to deliver integrated patient-centered care is considered crucial (Abramson & Mizrahi, 2003; Rubino, Chassiakos, & Freshman, 2010; Sicotte, D'Amour, & Moreault, 2002; Tang, Sun, Zhang, Ye, & Zhang, 2015), and has been found to improve outcomes in patients with diabetes (Chwastiak et al., 2017; Tang et al., 2015), anxiety, depression (Archer et al., 2012), and other conditions (Brooten, Youngblut, Hannan, & Guido-Sanz, 2012; Katon et al., 2010).

Diabetes treatment teams usually consist of a physician/general practitioner (GP), diabetes nurses, dietitians, and in some cases, counsellors, psychologists, and pharmacists (Wigert & Wikström, 2014). Medical specialists are included depending on patient needs, e.g. endocrinologists, ophthalmologists, cardiologists, nephrologists, diabetic foot specialists (M. J. Campmans-Kuijpers, Baan, Lemmens, & Rutten, 2015), and in cases with mental health comorbidities, psychiatric consultants (Chwastiak et al., 2017).

Quantitative studies have given rise to evaluations of collaboration by considering the evolution of HbA1c, hospitalization costs and readmission rates as clinical outcomes. One study found that the hospitalization costs and readmission rates decreased as the healthcare team became more integrated in terms of collaboration between physicians (Uddin & Hossain, 2012). T2DM patients receiving treatment from multidisciplinary teams achieved better outcomes than those that did not, demonstrating improvements in HbA1c, LDL cholesterol and an increased use of statins, as well as progress in statin and anti-platelet therapy (Borgermans et al., 2009). Furthermore, differences have been identified in outcomes related to HbA1c, blood pressure and cholesterol, according to a report compiled by treating professionals (Bosch, Dijkstra, Wensing, van der Weijden, & Grol, 2008). A controlled study into the two-year treatment of geriatric patients with DMT2 by a multidisciplinary team, in comparison with a control group that received no collaborative treatment, found differences in the outcomes during the second year of collaborative treatment (Counsell et al., 2007).

The organization and composition of the treating team can be an influential factor in patient evolution, as well as in terms of the coordination between the different clinical disciplines present within the team. For example, in one study, referrals to DMT2 educators and dietitians were minimal, even between overweight and obese patients (J. McDonald et al., 2012).

1.1.4. Continuity of care

Continuity of care (COC), understood as the "extent to which medical care services are received as a coordinated and uninterrupted succession of events consistent with the medical care needs of patients" (Shortell, 1976) has been associated with improved clinical results in patients with chronic diseases (Pereira Gray, Sidaway-Lee, White, Thorne, & Evans, 2018; J. W. Saultz & Lochner, 2005). Research shows a relationship between COC and greater patient satisfaction (Adler, Vasiliadis, & Bickell, 2010), falling hospitalization rates and emergency department visits (Chang, Chien, Bai, Lin, & Chiou, 2018; Dreiher et al., 2012; Gulliford, Naithani, & Morgan, 2007; Sveréus, Larsson, & Rehnberg, 2017), and a reduction in mortality (Pereira Gray et al., 2018). In the case of diabetes, continuity is particularly important (Haggerty et al., 2003; Salisbury, Sampson, Ridd, & Montgomery, 2009; Uijen, Schers, Schellevis, & Van den bosch, 2012; van Servellen, Fongwa, & Mockus D'Errico, 2006), with evidence showing the relationship between low continuity and poor glycated hemoglobin (HbA1c) control, and high continuity and positive control of low-density lipoprotein cholesterol (LDL-C) (Younge, Jani, Rosenthal, & Lin, 2012).

There are more than 30 indices for measuring COC, which can be classified according to 5 categories: duration, density, dispersion, sequence, and subjective-based (Jee & Cabana, 2006; Salisbury et al., 2009). Among the non-subjective indices, the most frequently used are the Usual Provider Continuity (UPC) index (also called most frequent provider continuity (MFPC)), which measures the *density* of appointments with the main provider (John W. Saultz, 2003); the Herfindahl Index (HI) and the Bice-Boxerman Continuity of Care Index (COCI), which both measure *dispersion* among different providers in a certain period of time (Bice & Boxerman, 1977; Rhoades, 1993); and the Sequential Continuity

(SECON) index, which uses the *sequence* of appointments to evaluate the continuity of the provider in consecutive visits (Ejlertsson & Berg, 1985).

UPC, measured as the percentage of the attentions performed by the most frequent provider, is the most frequently used metric for density. One study used this metric to study newly diagnosed cardiovascular patients with conditions such as hypertension, diabetes, and hypercholesterolemia, with the goal of determining impact on mortality, costs, and health outcomes. Participants with UPC below the median were compared to those with values above the median using multivariable-adjusted hazard ratios, concluding that lower indices of COC were associated with higher mortality, more frequent cardiovascular events, and higher healthcare costs (Shin et al., 2014). A study used both UPC and COCI to compare COC between primary health practices that were using new appointment scheduling methods and those using the existing methods, finding no COC differences between both groups (Salisbury et al., 2009). Another study in general practice with 22 health conditions found that higher COC was associated with fewer admissions for ambulatory care sensitive conditions, concluding that implementing strategies that improve COC may reduce secondary care costs (Barker, Steventon, & Deeny, 2017). These three studies segmented patient according to their COC levels and conducted statistical analysis to identify differences in outcomes for each group. However, this metric only calculates density for one provider without considering other providers that the patient may have seen.

One of the most frequently used metrics for dispersion is COCI. One study of patients with hypertension calculated COCI and analyzed differences in differences (DID) to compare clinical outcomes between patients with high and low COC, finding that a long-term physician-patient relationship may improve health-related quality of life (Ye et al., 2016).

Several studies have used two or more metrics to evaluate COC, considering density, dispersion and sequence (C.-L. Chan, You, Huang, & Ting, 2012; Dreiher et al., 2012; Kohnke & Zielinski, 2017; Pollack et al., 2016; Romano, Segal, & Pollack, 2015; Steinwachs, 1979). For instance, a study on patients with multiple chronic conditions, including diabetes, used UPC, COCI and SECON to propose an integrated COC index (ICOC) using principal component analysis. This study analyzed COC at physician and medical facility levels and found that higher COC was related to lower emergency room use and lower hospitalization rates, also finding that the combined COC index was more stable than each metric considered separately (C.-L. Chan et al., 2012). Another study used UPC, COCI and SECON to analyze the relationship between COC and emergency service use, and also found a negative relationship between COC and lower emergency room use (Kohnke & Zielinski, 2017).

Regarding patients with diabetes, low levels of COC have been found to be associated to poor HbA1c control (Younge et al., 2012), and higher risk of end-stage renal disease and hospitalization (Chang et al., 2018), while high levels of COC were associated to good LDL control (Younge et al., 2012), lower costs (considering diabetes-related hospitalization and emergency visits) (C. C. Chen & Cheng, 2011) and lower odds of being admitted to the hospital (Cho et al., 2015). Some studies have found no association between COC and HbA1c, lipid, or eye exam frequency (Gill et al., 2003).

Only one of the reviewed studies considers a second discipline of healthcare professionals beyond physicians, comparing COC of physicians with COC of a nurse-physician team (Salisbury et al., 2009). Other studies mention the importance of other disciplines but do not calculate COC for them (Barker et al., 2017; Gulliford et al., 2007). None of the reviewed studies have evaluated COC separately for the other involved disciplines.

Literature highlights the importance of incorporating other professionals within T2DM treatment teams (American Diabetes Association, 2017; Gucciardi et al., 2016; J. McDonald et al., 2012). However, although certain researches mentioned the importance of other disciplines, their continuity has not yet been investigated in detail (Barker et al., 2017; Chang et al., 2018; Gulliford et al., 2007).

1.2. Related work

In the present thesis, multidisciplinary collaboration was studied from two different approach: Process Mining (PM) and Social Network Analysis (SNA). This section presents a literature review of those approaches applied to healthcare domain.

1.2.1. Process mining applied to healthcare processes

Process mining (PM) is a relatively new research discipline that has been used in health care to extract knowledge from information systems, such as EMR systems, to analyze process design (RS S Mans, Aalst, Vanwersch, & Moleman, 2013). The algorithms developed in this discipline create graphical representations of models from the real execution of processes, which can be easily understood by individuals from a wide range of disciplines (Fernandez-Llatas, Lizondo, Monton, Benedi, & Traver, 2015). These models frequently demonstrate that reality differs to the perceptions, opinions, and beliefs held by parties directly involved in health care processes (Ronny S Mans, van der Aalst, & Vanwersch, 2015). Process mining also facilitates the analysis of processes from an organizational perspective, which may help improve the understanding of how collaboration occurs within treatment teams (W. Van Der Aalst & van der Aalst, 2011). From the analysis of event logs, social network algorithms and analysis have complemented process analysis in this discipline.

The inherent variability of healthcare processes has been addressed in several different ways. Some traditional control-flow discovery algorithms help to understand the different pathways that can be executed on a model and to distinguish the most common behaviors by managing the thresholds that indicate the frequency of activity sequences. The Heuristic Miner and Fuzzy Miner algorithms have been used to identify and study the main flow of the model, based on data from the information systems of a hospital in Seoul, South Korea (E. Kim et al., 2013). However, this approach generates a single model and, in order to discover different behaviors, it is necessary to test distinct thresholds, which can result in the analysis of unstructured processes becoming particularly complex. Another approach for creating simpler models for unstructured processes involves grouping several low-level activities with the same name at a higher level (Ronny S Mans, Schonenberg, Song, van der Aalst, & Bakker, 2008). The proposed procedure is useful when the event log describes different activities and the traces differ not only in the sequence of activities, but also in terms of the presence or absence thereof.

A different perspective is to create groups of patients according to certain pre-selected characteristics and to subsequently generate models for each group to capture the variability of the associated healthcare processes (P. Harper, 2005). Once these groups of patients have been established, it is possible to generate models to represent the clinical flow followed by patients, including their progression across departments, specialists, and types of medical appointments, or over the natural course of an illness. This method has been applied to patients with T2DM using variables associated with related complications including those concerning HbA1c, blood pressure and cholesterol (P. R. Harper et al., 2003). The results were used to analyze the circulation of the different groups and the probabilities of passing from one state to another.

Similar to the previous approaches, other studies have successfully generated several simple models to represent highly flexible processes by applying different clustering techniques prior to the execution of discovery algorithms. The purpose of this additional step is to ensure that the logs with highly variable records become more manageable, by grouping cases according to behavior similarity. Sequential clustering has been used during log pre-processing to identify regular behaviors, process variants and exceptional cases (Rebuge & Ferreira, 2012). While sequential clustering groups traces according to sequences of similar activities (Ferreira, Zacarias, Malheiros, & Ferreira, 2007), trace clustering provides a set of grouping techniques based on distance that seeks to differentiate traces according to certain characteristics, such as the frequency of activity occurrence, the number of events, or the number of events executed by each resource in a trace (Song, Günther, & van der Aalst, 2009).

1.2.2. Social network analysis applied to collaboration

Social Network Analysis (SNA) has been used to model and deeply understand collaboration in the healthcare domain. In a social network, individuals (nodes) are connected by links (edges) that represent the relationship between them. The simplest collaboration network's definition describes it as an undirected graph $G = \{V, E\}$, where V corresponds to a set of individuals or organizations, and E is the set of pairs (j, k), where j and k are two different individuals connected by some relationship. Other definitions could establish directed relationships instead undirected ones, or values (weights) associated to nodes and/or edges. (Anderson, 2002). Social networks can have different structures or topologies, in which each individual may have a particular position, given by the number of connections they have or how they are linked to others.

The application of SNA techniques in the healthcare domain has been widely used to analyze social structures and relationships between providers (Bae, Nikolaev, Seo, & Castner, 2015). These analyses have allowed researchers to understand interaction between professionals and their roles inside care teams (Anderson, 2002; T. Barnett, Hoang, Cross, & Bridgman, 2015; Benton, Perez-Raya, Fernandez-Fernandez, & Gonzalez-Jurado, 2015; Groenen et al., 2016; Keating, Ayanian, Cleary, & Marsden, 2007), to study the impact of interaction on prescribing behavior in primary care (Fattore, Frosini, Salvatore, & Tozzi, 2009), and to understand patient satisfaction with the structure of their care team network (L. H. M. Cheong, Armour, & Bosnic-Anticevich, 2013; J. E. Gray et al., 2010). In the last few decades there has been a considerable amount of work in this area. Several of these works have analyzed self-reported data regarding relationships between individuals (Benton et al., 2015). However, there is also a line of work that analyzes collaboration from information system data. One such work has studied collaboration networks between physicians by using shared patients to define relationships (M. L. Barnett, Landon, O'Malley, Keating, & Christakis, 2011). These networks have been analyzed and compared with outcomes in different settings, finding differences between hospitals when considering structure and network metrics (Landon et al., 2012), and that these results are correlated with outcomes such as total cost, days of hospitalization, average number of specialist visits, and laboratory and image costs (M. L. Barnett et al., 2012). Other studies have constructed networks by considering referrals between general practitioners and specialists, with the goal of identifying communities and predicting which relationship is more likely to occur (Almansoori et al., 2014). Studies that have analyzed collaboration between professionals at hospital-level have used metrics such as density, centrality or betweenness to evaluate collaboration (Almansoori et al., 2014; Effken, Gephart, Brewer, & Carley, 2013; K. M. McDonald et al., 2014; Rastegar-Panah, Hosseini-Motlagh, Babaei, & Noughani, 2013), exponential random graphs (Uddin, Hamra, & Hossain, 2013; Uddin, Khan, & Piraveenan, 2015), community detection (Almansoori et al., 2014; Uddin, Hossain, & Khan, 2018), coreperiphery analysis (Mascia, Cicchetti, & Damiani, 2013) and triad census (Uddin et al., 2018).

Another form of modeling is patient-centric collaboration networks, which have been analyzed using SNA metrics [23]. In these networks, the patient is connected to the units from which they have received medical services, and the units are connected to each other when there are interdependencies among them. The relationship between patients and service units, and between different service units, have an impact on the structure of the network (e.g., frequency of physician-visit or laboratory test) and performance metrics (e.g., hospital length of stay (LoS) and patient satisfaction). Studies that have used these networks to model collaboration around a patient have shown a positive correlation between degree centrality and LoS, and between tie strength and LoS [23]. Other studies have related collaboration through the use of SNA at a patient-centered level using patient handoff for building the network, so as to perform a quantitative analysis and to study the relationship between network structures and clinical outcomes [14], [27].

1.3. Discussion

In section 1.1 the relevance of T2DM was presented and the main concepts reviewed. Through this review we understand that multidisciplinary approach is useful to treat chronic conditions and is related to better outcomes, and COC of individual disciplines is also relevant in chronic patient treatment. Both concepts have shown to be crucial in T2DM. However, continuity in multidisciplinary collaborative care has not been previously studied.

Section 1.2 shows two different approaches to model collaboration and some ways to measure the interactions between different providers in a patient's treatment. In the PM approach, collaboration is modeled as patient-level networks represented by directed graph where the relationship is associated to the handoff of patient between disciplines. On the other hand, SNA approach has been widely studied as practice-level or hospital-level networks, where the structure or metrics related can be associated directly to each individual patient evolution. Previous studies using patient-level networks to model collaboration have not been considered the multidisciplinary nature of the teams or the relation with clinical outcomes. At the same time, patient-level networks have not been used in chronic conditions context.

With this knowledge, we centered the aim of this thesis is to deeply understand how multidisciplinary teams works in healthcare context, in order to model and measure collaboration quantitatively and to analyze whether collaboration are related to clinical outcomes. To accomplish this goal, in a first stage we analyzed team composition and interactions in primary care context to discover collaboration patterns and related them with different clinical outcomes. A second stage was to model and measure collaboration between professionals working together in a patient-centered approach, in order to detect differences between patients treated with different kinds or level of collaboration.

This research focuses on the analysis of collaboration based on the study of the data generated by the information systems, specifically the Electronic Medical Records (EMR).

1.4. Research Question, Research Hypothesis and Goals

1.4.1. Research question

The aim of this thesis is to deeply understand the collaboration process used to treat patients with diabetes in primary healthcare. Therefore, our research question is: *"Is it possible that different multidisciplinary collaboration patterns have different clinical outcomes in patients?"*

We understand, as *collaboration patterns*, the structures of relationships between the professionals involved in each patient care, and the collaborative activities related to each case.

1.4.2. Project Scope

We limited our study to patients diagnosed with Type 2 Diabetes Mellitus (T2DM) treated in primary care settings.

1.4.3. Hypothesis

To answer the research question it is necessary to validate three elements contained in it: i) the existence of multidisciplinary collaboration patterns in primary care settings, ii) the feasibility of identifying those patterns through the analysis of the EMR, and iii) whether there was any relationship between the patterns and the clinical outcomes.

The three hypotheses to be validated were stated as follows:

> *H1: It is possible to identify different collaboration patterns in the treatment given by multidisciplinary teams to diabetic patients with different characteristics, such as age, gender or comorbidities.*
>
> *H2: It is possible to identify existing collaboration patterns through the analysis of EMR data and the use of process mining and SNA tools.*
>
> *H3: There are statistically significative differences in the clinical outcomes in patients treated with different collaboration patterns.*

Those hypotheses were rewritten in a simpler way, in order to clarify the acceptance or rejection of each one. The hypotheses restated are as follows:

> *H1: Different collaboration patterns exist among professionals treating patients diagnosed with T2DM.*
>
> *H2: Collaboration patterns among professionals treating patients diagnosed with T2DM can be obtained from EMR data analysis.*
>
> *H3: Patients with diabetes treated according to different collaboration patterns have different clinical outcomes.*

1.4.4. General Objective

Within the context of T2DM treatment, the general objective of the thesis was defined as follows:

"To model team collaboration and identify patterns study whether those patterns are associated with different clinical outcomes"

Through this objective, we seek to deeply understand how multidisciplinary teams collaborate in terms of team composition and interactions as well as which collaboration patterns obtain better results. We also aim to understand how the interactions may be modeled and measured from a patient-centered approach in order to detect patterns and assess collaboration patterns.

1.4.5. Specific Objectives and Methodology

Based on the three hypotheses and general objective, four specific objectives were established. Table 1 shows the specific objectives, the related activities, and a brief description of the methodology used for each one.

Table 1. Table of specific objectives, related activities and applied methodologies.

Specific Objectives	Activities	Methods
[Obj1] Propose patterns for multidisciplinary collaboration in primary care settings.	[A1] Literature review on collaboration in primary care settings.	• Systematic literature review.
	[A2] Fieldwork in the three centers included in our study.	• Non-participant observation. • Individual and group interviews with primary care professionals involved in diabetes care. • Surveys of professionals involved in diabetes care.
	[A3] Propose and validate patterns.	• Clustering technique (k-medoids) to group papers by team's composition and by set of interactions present in the treatment, in order to stablish collaboration patterns. • Apply the same patterns to available data.
[Obj2] Improve or create PM and SNA algorithms to detect collaboration.	[A4] Analyzing and cleaning data.	• Meetings with information system manager to understand structure and database. • Meetings with professionals involved to understand the semantic of the data. • Standard methods to clean data
	[A5] Transform raw data in a proper event log.	• Identify required granularity • Identify relevant information • Build log
	[A6] Test existing algorithms used in previous literature.	• Systematic testing of PM algorithms
	[A7] Improve/Develop proper PM algorithm to analyze study case.	• Improve algorithms based on testing results and knowledge of the domain.

Specific Objectives	Activities	Methods
	[A8] Improve/Develop proper SNA algorithm to analyze study case.	• Design an algorithm to construct social networks considering settings and context. • Improve/develop algorithms to analyze networks.
[Obj3] Propose a methodology to model and measure multidisciplinary collaboration and assess the relationship with clinical outcomes.	[A9] Consolidate previous analysis and conclusions to propose a methodology to study multidisciplinary collaboration in primary care settings.	• Literature review about continuity of care for metrics selection • Calculate metrics over available data.
	[A10] Test the relationship between collaboration patterns and clinical outcomes	• Create social networks and apply metrics. • Statistical methods to compare metric values in different patients divided by evolution.

1.5. Study Context and Settings

Approximately 75.2% of the Chilean population is insured by the public health care system, which is funded by a 7% mandatory deduction from salaries. An insured person may provide a fixed copay to be able to select their preferred healthcare provider, or may be treated at a predetermined facility, which provides free services to the 18.1% with lowest income of the overall population (Ministerio de Salud de Chile, 2018). For the lowest income population, primary healthcare is provided at healthcare centers called *Centro de Salud Familiar* (Family Health Centers, or CESFAM), that are the first point of contact of users with the public health care network. CESFAM treat acute morbidities that may be solved or referred to a more complex center and chronic morbidities that require periodic assessment, e.g., diabetes, hypertension, and chronic pulmonary disease.

One of the main issues faced by the public Chilean healthcare system is a lack of physicians: particularly in the CESFAM, there is a lack of general practitioners (GP) and family physicians (FP). In Chile, the average number of patients per physician in primary care is 920, whereas the average in the private sector is 276, and in member states of the Organization for Economic Co-operation and Development it is 294 (Guillou, Carabantes C, & Bustos F, 2011; Indicators, 2017). Regardless, in metrics such as mortality amenable to health care, Chile has been found to have rates comparable to the OECD average and slightly superior to the United States (Gay, Paris, Devaux, & Looper, 2011).

The Chilean Ministry of Health establishes a treatment protocol for chronic conditions such as T2DM, published as a clinical guideline (Subsecretaria de Redes Asistenciales, 2010). Treatment of patients with diabetes in Chile is in accordance with these guidelines, which establish the frequency by which appointments, laboratory tests and pharmacological treatment should be undertaken, according to HbA1c measurements. They divide patients into three categories: stable (patients with HbA1c lower than 7%); moderately decompensated (patients with HbA1c between 7% and 9%); and highly decompensated (HbA1c greater than 9%). While treatment is ultimately determined by treating professionals, the guidelines are expected to form the basis for treatment.

This thesis work was conducted in three university-affiliated primary healthcare centers located in low-income districts with high social vulnerability in Santiago, Chile. These centers attend an average of 8,000 persons per year, more than 30% of which experience T2DM. Two practices operate within each center, each one with its own multidisciplinary team composed of general practitioners (GP), family physicians (FP), nurses, dietitians, and psychologists, among others. One notable characteristic of these centers is their very high turnover rate of physicians. This is due to the way in which physicians are trained in Chile, whereby professionals who have recently graduated as GPs begin their work experience in these centers. Within one to two years, GPs generally begin their specialist studies, leaving the primary healthcare environment.

1.6. Contributions

The main purpose of this thesis is to study multidisciplinary collaboration in the healthcare domain through process mining and social network analysis. Table 2 summarizes the contributions of the overall thesis to this purpose. This table includes the following aspects: a title of the contribution, the specific objective addressed, and the chapter of this document in which the contribution is presented. Each contribution is described in detail below.

Table 2. Contributions of the overall thesis.

Contribution	Objective	Chapter
[C1] Systematic Literature Review of multidisciplinary collaboration in primary care settings	[Obj1]	Chap 2
[C2] Team interactions typology in collaborative treatments	[Obj1]	Chap. 2
[C3] Team composition typology in collaborative treatments	[Obj1]	Chap. 2
[C4] Application of collaboration typology in local settings	[Obj1]	Chap. 3
[C5] Use of process mining techniques to identify and measure collaboration	[Obj2]	Chap. 4
[C6] Measure continuity of care in the studied population	[Obj3]	Chap. 5
[C7] Propose a model to build social networks for multidisciplinary treatment in primary care settings	[Obj3]	Chap 6
[C8] Establish a relationship between social network and clinical outcomes.	[obj3]	Chap 6

[C1] to [C8] denote the identified contributions of this thesis. [Obj1] to [Obj3] denote the specific objectives associated to each contribution.
Specific objectives are presented in section 1.4.5, while section 1.6 presents the detail of each contribution.

[C1] Systematic Literature Review. A fully up-to-date systematic literature review was conducted into multidisciplinary collaboration in primary care. The reviewed articles reported case studies with evidence of application of a collaborative approach and containing a description of the collaborative activities. This work facilitates the process of identifying all published case studies and the subsequent analysis thereof. In this review, filtering process was performed by the candidate and a second researcher to reduce potential bias. After pre-select 286 articles that match the inclusion and some of the exclusion criteria, the candidate processes the information and made the analysis.

[C2] Team interactions typology in collaborative treatments. We classified the types of collaboration in 4 groups according the collaborative activities present in the patients' care: Co-located teams, Non-hierarchical, Shared consultations, and Referral and counter-referral**.** This work was performed by the candidate with supervision of her advisors.

[C3] Team composition typology in collaborative treatments. We classified the types of care teams in 4 groups according the disciplines present in the treatment: Specialist; Highly multidisciplinary; Doctor-nurse-pharmacist triad; and Physician-nurse centered. This work was performed by the candidate with supervision of her advisors.

With typologies from [C2] and [C3] we established patterns associated to different patient's condition, diseases and care settings.

[C4] Application of collaboration typology in local settings. The collaborative patterns from [C3] were analyzed over the available data. This work allowed us to see how different patterns treat different kind of patients. This work validated the patterns previously detected in out settings. In addition, professional of the centers declared that these results were useful to detect differences between the protocol and the as-is process.

[C5] Identification and measurement of multidisciplinary collaboration within care teams treating T2DM. We grouped patients by collaboration characteristics of the care team establishing patterns of collaboration using process mining techniques. We linked the patient evolution with the collaboration patterns and detected significant differences between them. In this work, the candidate contribution was the creation of a proper event log from the available raw data and the definition of collaborative networks and metrics. She also collaborated in the data analysis and discussion.

[C6] Measure continuity of care in the studied population. We were able to establish statistically significant differences between patients segmented by evolution and the continuity of professionals' care for each patient. The candidate was the main researcher who collected data, applied methods, and analyzed results.

[C7] Propose a model to build social networks for multidisciplinary treatment in primary care settings. We proposed an algorithm to build social networks for multidisciplinary collaboration teams, the relationship between individuals and between disciplines, and that contemplates changes in the composition of the team over time. The candidate was the main researcher who developed the model.

[C8] Establish a relationship between social network and clinical outcomes. New metrics were defined which capture different aspects of the collaboration that could not be detected with de existent metrics and techniques. We established a relationship between the metrics and patient evolution and propose it as a methodology to assess collaboration in primary care settings for multidisciplinary collaborative teams treating chronic patients. The candidate was the main researcher who developed the model. The candidate was the main researcher who applied methods and analyzed results.

1.7. Impact

1.7.1. Academic Impact

During the execution of the tasks involved in compiling this thesis, the following publications were obtained:

Journal Publications

[SLR] C. Saint-Pierre, V. Herskovic, and M. Sepúlveda. 2017. *Multidisciplinary collaboration in primary care: a systematic review*. Family Practice.

[PMApproach] T. Conca, C. Saint-Pierre, V. Herskovic, M. Sepúlveda, D. Capurro, F. Prieto, and C. Fernandez-Llatas. 2018. *Multidisciplinary Collaboration in the Treatment of Patients with Type 2 Diabetes in Primary Care: Analysis Using Process Mining*. Journal of Medical Internet Research.

[Adherence] C. Alvarez, C. Saint-Pierre, V. Herskovic, and M. Sepúlveda. (2018). *Analysis of the Relationship between the Referral and Evolution of Patients with Type 2 Diabetes Mellitus*. International Journal of Environmental Research and Public Health.

[COC] C. Saint-Pierre, V. Herskovic, and M. Sepúlveda. 2019. *Relationship between continuity of care in the multidisciplinary treatment of patients with diabetes and their clinical results*. Applied Science Journal, for the Special Issue “Computing and Artificial Intelligence”.

[SNA] C. Saint-Pierre, V. Herskovic, and M. Sepúlveda. 2019. Team collaboration networks and multidisciplinarity in diabetes care: Implications for patient outcomes. IEEE Journal of Biomedical and Health Informatics.

Conference Publications

[StudyCase] C. Saint-Pierre, V. Herskovic, and M. Sepúlveda. 2017. Analysis of multidisciplinary collaboration in primary healthcare: The Chilean case. In Proceedings of 23th International Conference on Collaboration and Technology (CRIWG'2017)

1.7.2. Society Impact

In the clinical and social domain, this research provides a set of tools to analyze collaboration in settings that need multidisciplinary teams. We also provided useful information to the centers with which we work and made our analysis. The most significant of these are the following ones:

a) Definition of collaboration patterns based on collaborative activities and team composition.

b) Detection of referral patterns associated with patients' evolution in diabetic care.

c) Definition of the concept "team continuity network".

d) Definition of new measures for team continuity in chronic conditions treatments.

e) Methodology developed to analysis and measurement of collaboration in multidisciplinary teams.

1.8. Document Structure

The remainder of this thesis is structured as follows:

Chapter 2 presents a systematic literature review of multidisciplinary collaboration reported in primary care settings. A total of 109 articles are reviewed and analyzed, and a typology of team composition and collaborative activities is defined.

Chapter 3 presents an analysis of the collaboration types detected in the literature review applied to our data. Results of this study show statistically significant differences in the patients treated by each type. These results reflect that, in our settings, different types of collaboration are used in different contexts.

A process mining approach to detect collaboration patterns is presented in Chapter 4. Through this analysis, seven collaboration patterns are detected and associated with patient evolution. In particular, this work shows that a more participatory treatment with balanced participation of the treating professionals is related with lower proportion of highly decompensated patients.

Chapter 5 contains an analysis of the measurement of continuity of care over our data. Continuity metrics are assessed for more than 1,800 patients.

Chapter 6 approaches the analyzed data with a SNA perspective. A methodology for social network construction is developed and new metrics are defined. Results show an association between network topology and patient evolution and provide quantitative data about the interaction between disciplines and professionals that cannot be obtained with other techniques.

Finally, Chapter 7 presents the general conclusions of this thesis, a discussion of its limitations, and future work.

2. SYSTEMATIC LITERATURE REVIEW: COLLABORATION IN PRIMARY HEALTHCARE:

2.1. Introduction

Although a large volume of research into multidisciplinary collaboration in primary care has been conducted, the mode of collaboration itself remains unclear in terms of how those involved collaborate in practice (Eikey, Reddy, & Kuziemsky, 2015) across disciplines and diagnoses.

The term *multidisciplinary team* is used to refer to a group of professionals from two or more disciplines who work on the same project, independently or in parallel (D'Amour, Ferrada-Videla, San Martin Rodriguez, & Beaulieu, 2005). The concept of *collaboration* in the healthcare context is a process of problem solving, shared responsibility for decision making and the ability to carry out a care plan while working toward a common goal (Baggs & Schmitt, 1988; McKay & Crippen, 2008). Two key elements have been identified: (1) the construction of a collective action that addresses the complexity of patient needs; and (2) the daily team dynamics that help integrate the perspective of each professional and in which team members respect and trust one another (D'Amour et al., 2005). These dynamics may include telemedicine consultations, computer-mediated interactions (Fitzpatrick & Ellingsen, 2012), joint care, and home visits (L. B. Cohen et al., 2011; Counsell, Callahan, Buttar, Clark, & Frank, 2006; Farsaei et al., 2014; Turner, Thomas, Wagner, & Moseley, 2008).

Due to the complexity of the multidisciplinary collaboration dynamic, we structure our analysis using a five component model, with the following dimensions: *interdependence*, whereby team members contend that their jobs are dependent on one another*: newly created professional activities*, through which joint acts can achieve more than what might be achieved by acting independently; *role flexibility*, which demands less hierarchical relationships; *collective ownership of goals*, which includes sharing responsibility throughout the entire process; and *reflection*, whereby members' awareness of their teamwork strengthens relationships and effectiveness (Bronstein, 2003).

This work aims to describe in a structured way how collaboration actually takes place, especially focusing on the disciplines involved in the collaboration and the collaborative activities that are undertaken. The goal of this work is twofold: (1) to characterize the mode of collaboration according to team composition and collaborative activities, identifying whether certain ways of collaboration are repeatedly found in primary healthcare settings, and (2) to determine whether collaboration has an impact on patient outcomes. To accomplish our goal, we conducted a systematic literature review of articles that describe implementation of collaborative multidisciplinary care in primary care across different settings.

2.2. Methods

2.2.1. Search strategy

The following databases were searched: i) MEDLINE (PubMed and OvidMedline); ii) ScienceDirect; and iii) Web of Science. The search string was: ***('collaborat*' or 'teamwork' or 'cooperat*') and ('multidisciplinary' or 'interprofessional' or 'between professionals' or 'interdisciplinary' or 'multiple disciplines') and 'health'***.

2.2.2. Inclusion and exclusion criteria

We reviewed articles in English, published in scientific journals with peer reviewing processes between January 2005 and October 2016. The articles pertained to the area of healthcare and described patient care delivered by multidisciplinary teams working collaboratively. Only articles related to primary care cases were included.

Non-primary source articles (e.g. systematic reviews), investigations unrelated to health conditions (e.g. collaborative learning), and articles pertaining to veterinary research were excluded. Articles that did not describe collaborative activities in detail and articles with no evidence of implementation (e.g. protocols, theoretical articles) were also excluded.

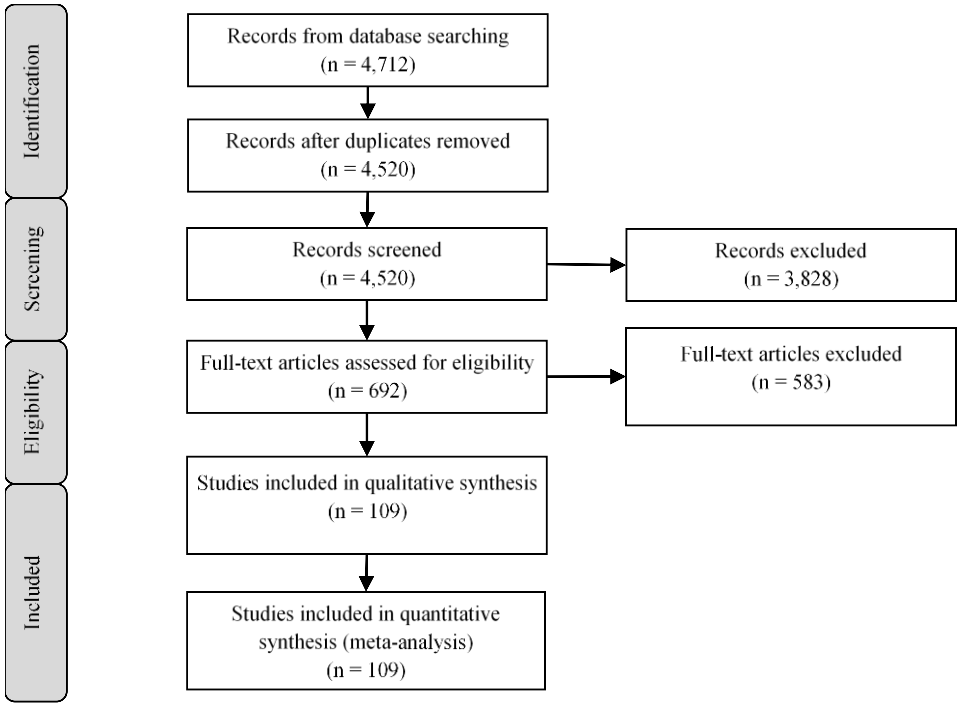
2.2.3. Study selection and bias assessment

First, two researchers (R1 and R2) performed independent screenings of titles and abstracts, cross-checking them against the inclusion/exclusion criteria. If discrepancies arose, each researcher reviewed the article a second time. If the discrepancy was still not resolved, the article was included in the next phase. At this point, 692 articles remained.

Second, one researcher (R1) re-reviewed all the articles, focusing especially on removing those that were not related to primary care. At this point, 281 articles remained. Then, five articles were randomly chosen, and R1 and R2 independently extracted the following categorical data from each article: 1) collaboration context: country, year, urban/rural setting, comparison of results with the non-collaborative alternative; 2) patient characteristics: diagnosis, average age, number; 3) disciplines present in the team; 4) existing roles; and 5) collaborative activities. The data extracted by R1 and R2 had a response match of 83%. Results were discussed, adjusted and the exercise was repeated with a new set of five articles, achieving a match rate of 93%. Then, having achieved consensus about the categorical data, R1 extracted it for the rest of the papers.

Third, R2 reviewed the full-text of the 281 articles, excluding articles that did not comply with the criteria, e.g. those that did not include evidence of implementation. After this step, 109 articles remained. For the full-text analysis, the NVivo 10 software for qualitative research was used with an inductive codification methodology (Thomas 2006). R2 started by coding each article using the following predefined categories: *collaborative activities*, *teams and roles*, and *results*. During this process, new categories and subcategories emerged, e.g. subcategories for each type of collaborative activity found in the articles were created under collaboration activities. The filtering process is described in Figure 1 and the final corpus of selected papers can be found in Table 7.

Figure 1. Filtering process.



2.3. Results

2.3.1. Results of the search

Overall, the 109 articles reported on the treatment of more than 200,000 patients (between 1 and 105,310, median: 147). The average intervention duration was 19 months. 86 articles were outpatient studies, and 5 corresponded to inpatients, i.e. primary care patients hospitalized due to acute complications. In addition, 18 articles were about home-based treatments. The studies were conducted in 18 countries, of which the most frequent were: United States (30%), Canada (24%) and the Netherlands (10%). The studies were mostly from urban settings (93%). 52% of articles reported positive results when comparing collaboration against the non-collaborative alternative, while 16% showed no difference and 32% did not present a comparison. The years in which articles were published remained relatively constant, with an increase observed after 2013.

The articles were classified according to the condition that was being treated using the International Classification of Diseases (ICD) 10 catalog, which is divided into 22 chapters (World Health Organization (WHO)., 2016). After the classification, chapters with less than 3 articles were grouped into the "Others" category. Articles that mentioned conditions pertaining to more than one chapter were also grouped, as "Articles with two or more conditions". The 109 articles were then classified into the following 8 groups: Endocrine, nutritional and metabolic diseases (Chapter IV) (Anichini et al., 2007; Arevian, 2005; Bluml, Watson, Skelton, Manolakis, & Brock, 2014; Brahm, Palmer, Williams, & Clancy, 2015; Brooks, Rihani, & Derus, 2007; M. J. E. Campmans-Kuijpers et al., 2015; J.-H. Chen et al., 2016; Chwastiak et al., 2017; L. B. Cohen et al., 2011; S. Cohen, Hartley, Mavi, Vest, & Wilson, 2012; Eichler, Zoller, Steurer, & Bachmann, 2007; Farsaei et al., 2014; Gamblen et al., 2007; Greene et al., 2009; Gucciardi et al., 2016; S. B. Harris et al., 2015; Heuer, Hess, & Batson, 2006; Hogg et al., 2009; Knowles, Chew-Graham, Adeyemi, Coupe, & Coventry, 2015; Lalonde et al., 2011; Malone, Alger-Mayer, & Anderson, 2005; Martin, Wu, Taveira, Eaton, & Sharma, 2007; J. McDonald et al., 2012; Osborn et al., 2009; Raaijmakers et al., 2013; Rasmussen et al., 2015; Rawal et al., 2015; Reichert, Harris, & Harvey, 2014; Sakakibara et al., 2011; Shortus et al., 2007; Tobe et al., 2013; Wigert & Wikström, 2014; Wishah et al., 2015; Yeh, Chang, Hsieh, & Wu, 2014; Yu & Beresford, 2010),Mental and behavioural disorders (Chapter V) (Bell, Aslani, McLachlan, Whitehead, & Chen, 2007; Callahan et al., 2006; Franx, Oud, de Lange, Wensing, & Grol, 2012; Gidding, Spigt, & Dinant, 2014; Goncalves et al., 2013; Gum, Dautovich, Greene, Hirsch, & Schonfeld, 2015; Haggarty, O'Connor, Mozzon, & Bailey, 2015; Harpole et al., 2005; T. W. Kim et al., 2011; Köhler et al., 2014; Langkamp, McManus, & Blakemore, 2015; Lee et al., 2014; Munns, Forde, Krouzecky, & Shields, 2015; Rojas-Fernandez, Patel, & Lee, 2014; Shedden-Mora et al., 2016; Stergiopoulos et al., 2015; van der Feltz-Cornelis et al., 2010; Zeiss & Karlin, 2008), Diseases of the respiratory system (Chapter X) (L. H. Cheong, Armour, & Bosnic-Anticevich, 2013; Cochrane, Foster, Boyd, & Atlantis, 2016; Kruis et al., 2014; Wynn & Moore, 2012), Diseases of the musculoskeletal system and connective tissue (Chapter XIII) (Andermo, Sundberg, Forsberg, & Falkenberg, 2015; Bain, Mierdel, & Thorne, 2012; Bültmann et al., 2009; Howarth, Warne, & Haigh, 2012; E.-L. Hultberg, Lönnroth, &

Allebeck, 2005; E. Hultberg, Lonnroth, & Allebeck, 2007; Jensen, Jensen, Christiansen, & Nielsen, 2011; Maiers, Westrom, Legendre, & Bronfort, 2010; Stapelfeldt et al., 2011), Injury, poisoning and certain other consequences of external causes (Chapter XIX) (Fiss, Ritter, Alte, van den Berg, & Hoffmann, 2010; Jordan Sanders & Moore-Nadler, 2014; McKinnon & Jorgenson, 2009), XXI. Factors influencing health status and contact with health services (Chapter XXI) (Anonymous, 2013; Berglund et al., 2013; Counsell et al., 2007; de Graaf, Zweers, Valkenburg, Uyttewaal, & Teunissen, 2016; Dijkstra, 2007; Eckstrom et al., 2016; Engel, Spencer, Paul, & Boardman, 2016; Klaasen, Lamont, & Krishnan, 2009; Moore et al., 2012; Pype et al., 2014; Quist, Counsell, Schubert, & Weiner, 2016; O. Rose et al., 2016; P. Rose & Yates, 2013; Rothschild et al., 2016; Smith-Carrier & Neysmith, 2014; Stijnen, Jansen, Duimel-Peeters, & Vrijhoef, 2014; van Eijken, Melis, Wensing, Rikkert, & van Achterberg, 2008; van Gurp, van Selm, van Leeuwen, Vissers, & Hasselaar, 2016), Other chapters (Boult et al., 2011; Bryce, Butler, Gnich, Sheehy, & Tappin, 2009; Doubova, Espinosa-Alarcón, Flores-Hernández, Infante, & Pérez-Cuevas, 2011; S. J. Harris et al., 2012; Louis et al., 2010; Montgomery-Taylor, Watson, & Klaber, 2016; Newman et al., 2013; Pechacek, Drake, Terrell, & Torkelson, 2015; Price et al., 2005; Pridham Mary M.: Limbo, Rana K.: Paradowski, Jill: Rudd, Nancy: Meurer, John R.: Uttech, Ann: Henriques, Jeffrey B., 2006; Rogers, Mansour, Mattinson, & O'Sullivan, 2007; Sisson et al., 2016; Wharton, Manu, & Vitale, 2015; Williams, Clinton, & Biscaro, 2008; Wulff, Vedsted, & Søndergaard, 2013), Articles with two or more conditions (B. C. Chan et al., 2010; Donnelly, Brenchley, Crawford, & Letts, 2013; Foley, Dunbar, & Clancy, 2013; D. Gray, Armstrong, Dahrouge, Hogg, & Zhang, 2010; Myers-Wright & Lamster, 2016; Russell et al., 2009; Tourigny et al., 2010). Of these, the final two categories were excluded from subsequent analyses.

2.3.2. Multidisciplinarity

The multidisciplinary teams identified in the literature review contained an average of 4.5 disciplines. The teams included a family physician (FP) or general practitioner (GP) in 89% of the articles and a nurse in 72% of the articles. Other disciplines, from most to least common, were: dietitian, social worker, pharmacist, psychologist, physiotherapist, and occupational therapist. 50% of the teams included a specialist and 47% included a complementary professional such as an educator, counselor or chiropractor. The most notorious differences between teams according to patient diagnoses are: a lower participation of nurses and dietitians, and higher presence of occupational therapists, physiotherapists and social workers in articles about musculoskeletal disorders (p-value<0.05); a greater participation of dietitians in articles about endocrine, nutritional and metabolic diseases, and no participation of dietitians in articles about mental disorders and external causes (p-value<0.05). No significant differences were identified in the analysis according to countries, due to the small number of articles pertaining to most countries and the limited number of quantitative variables that were compared. There were also no statistically significant differences considering type of care (outpatient, inpatient or home-based care), nor urban/rural settings.

2.3.3. Team composition typology

We categorized teams according to the presence of disciplines therein, by clustering using a k-medoids algorithm (Park & Jun, 2009). We identified four groups of articles in which the teams had a similar composition, which are described below. Details of the participation of each discipline in each group are shown in Table 3.

Specialized teams (35 articles). These are teams with one primary care doctor and one specialist, who interact with one or more professionals from other primary care disciplines. These teams treated pathologies that were less common in our review, including pregnancy among women smokers, palliative care, and dementia, and which require specialist assistance. Almost half of the articles (49%) were related to mental care and musculoskeletal disorders. On average, these teams consisted of 4 disciplines (SD=1.7), although in 4 articles where teams had between 7 and 9 disciplines.

Highly multidisciplinary teams (31 articles). These are multidisciplinary teams composed of a doctor-nurse duo that works with the support of a nutritionist, specialists, and with participation from at least one professional from a complementary discipline, e.g. podiatrist, midwife, or counselor. The articles were primarily related to diabetes and other cardiovascular conditions (48%), involving complex treatments and frequently requiring the participation of a specialist. This complexity demanded the participation of several disciplines, with an average of 6.1 (SD=1.5) disciplines per case.

Doctor-nurse-pharmacist triad (24 articles). These are teams with three main professionals, usually a GP, nurse and pharmacist, with support from other primary care professionals, such as a social worker or nutritionist. The articles in which this triad was found were treatments with large numbers of comorbidities that, without presenting further complexities, required the use of multiple medicines that may interact with one another and, thus, potential side effects needed to be controlled. On average, these teams consisted of 4.1 disciplines (SD=1.8).

Physician-Nurse centered teams (19 articles). These are small teams based on a doctor-nurse duo, with participation of professionals from primary care disciplines, such as psychologist, social worker and dietitian. These teams worked across all diagnoses, except for musculoskeletal disorders. Teams in this cluster consisted of 3.2 disciplines (SD=1.4) on average.

Table 3. Presence of disciplines in each cluster. In a comparison by cluster for discipline.

Team Type	Number of papers	Family physician	Family nurse	Social worker	Pharmacist	Dietician	Occupational therapist	Physiotherapist	Psychologist	Specialist physician	Other
Specialized	35	89%	31%	40%	11%	3%	14%	14%	31%	71%	34%
Highly multidisciplinary	31	84%	94%	26%	13%	77%	10%	23%	29%	74%	97%
Doctor-nurse-pharmacist triad	24	96%	79%	38%	100%	33%	17%	17%	4%	25%	13%
Physician-nurse centered	19	89%	100%	26%	0%	21%	5%	21%	26%	0%	32%

Grey tones show statistically significant differences (p-value<0.05).

2.3.4. Team roles

Among the teams, we identified three roles as the most relevant in primary care: the *clinical leader*; the *case manager*; and the *expert consultant*. The clinical leader role is usually fulfilled by the FP or GP. However, in articles related to mental illness, even when care is provided by primary care teams, this role is undertaken by a mental care specialist (Gum et al., 2015; Harpole et al., 2005; Rojas-Fernandez et al., 2014; van der Feltz-Cornelis et al., 2010). In cardiovascular-related diseases, the role is provided by FPs and GPs, although we also found pharmacist-led multidisciplinary teams in settings related to medication management (Farsaei et al., 2014; Martin et al., 2007). The case manager role is often added to improve coordination and continuity of care for patients with complex care needs (Wulff et al., 2013). This role is commonly performed by nurses and is identified as an improvement to traditional practice (Jordan Sanders & Moore-Nadler, 2014; Raaijmakers et al., 2013; Tobe et al., 2013). The declared goals of case managers include: maintaining team coordination; managing the treatment schedule of patients; tracking patient progress; supplying an instrument for communicating the patient's current clinical status to the entire care team (Callahan et al., 2006; Price et al., 2005); providing counseling to patients; engaging in education for self-management; encouraging adherence to treatments (Callahan et al., 2006; Jordan Sanders & Moore-Nadler, 2014; Lalonde et al., 2011); promoting self-management and preventive care (Arevian, 2005; Doubova et al., 2011); and making referrals to specialists, as required (Arevian, 2005; Doubova et al., 2011). The role of the expert consultant is particularly prominent in aged care, where the high presence of comorbidities requires the participation of a geriatrician (Anonymous, 2013; Counsell et al., 2007; Eikey et al., 2015; Moore et al., 2012), as well as in mental health care, which dictates the participation of psychiatrists and psychologists (Callahan et al., 2006; Franx et al., 2012; Goncalves et al., 2013; Gum et al., 2015; Harpole et al., 2005).

2.3.5. Collaborative activities in primary care

Teams perform several collaborative activities that enable them to share information about patients, coordinate care, identify problems, develop intervention plans, and define shared goals (Pinelle & Gutwin, 2002). To understand how teams collaborate, we identified the activities devised by the professionals to meet their objectives. To structure these activities, we used the five component model (Bronstein, 2003) as our theoretical framework, classifying the activities according to each of its first four components (see Table 4). The fifth component, *reflection*, was not described in the reviewed articles (and it was not possible to infer its occurrence from the details provided in the articles about the collaboration).

Table 4. Collaborative activities identified in each component.

Interdisciplinary model component	Collaborative activities identified	Articles where the activity is present	
		(n)	(%)
Interdependence	Referrals	37	34%
	Face-to-face communication	79	73%
	Non-face-to-face communication	28	27%
Newly created professional activities	Telemedicine	4	4%
	Shared consultation	30	28%
	Shared home visit	10	9%
Collective ownership of goals	Meetings	55	51%
	Case manager	59	54%
Role flexibility	No leader role declared	49	45%

In the interdependence component, we found that referrals (collaborative relationships established between professionals for the purpose of referring patients) tend to develop on a case-by-case basis, and rely on personal knowledge and trust (Howarth et al., 2012; J. McDonald et al., 2012). We also found that the closeness of this activity is varied, from teams where professionals have practically no contact (L. B. Cohen et al., 2011), to those in which, besides referring patients, professionals experience direct face-to-face communication, regular meetings and the presence of a case manager as coordinator (Pype et al., 2014). Types of referrals can be classified into four categories: (1) those from a specialist to a multidisciplinary primary care team (counter-reference), following a specialized intervention (Anichini et al., 2007; Anonymous, 2013; Brahm et al., 2015; Louis et al., 2010; Smith-Carrier & Neysmith, 2014; Wharton et al., 2015); (2) those from any professional, regardless of their discipline, to a lifestyle-changing program or preventive initiative (Raaijmakers et al., 2013; Turner et al., 2008); (3) those from a professional to another team member, in order to complement the professional intervention through services provided by other disciplines available within the team (Bell et al., 2007; B. C. Chan et al., 2010; Doubova et al., 2011; Franx et al., 2012; Gidding et al., 2014; S. B. Harris et al., 2015; Lalonde et al., 2011; Lee et al., 2014; Price et al., 2005; P. Rose & Yates, 2013; Shortus et al., 2007; Smith-Carrier & Neysmith, 2014; van der Feltz-Cornelis et al., 2010; Wigert & Wikström, 2014; Yeh et al., 2014; Zeiss & Karlin, 2008); and (4) those from primary care to a specialized program or secondary/tertiary level (commonly done by physicians or nurses), when the necessary skills are absent from the team (Andermo et al., 2015; Bain et al., 2012; Bryce et al., 2009; L. H. M. Cheong et al., 2013; Counsell et al., 2007; Goncalves et al., 2013; S. J. Harris et al., 2012; Jensen et al., 2011; Köhler et al., 2014; Moore et al., 2012; Newman et al., 2013; Reichert et al., 2014; Rogers et al., 2007; Rojas-Fernandez et al., 2014). Some articles were found to contain explicit referrals, although the majority was implicit or difficult to identify.

Regarding direct communication, or the informal interaction between team members regarding the treatment of a case, we found evidence of face-to-face and non-face-to-face interaction. Several articles report regular face-to-face contact between professionals for case discussion purposes and describe this as more beneficial than communication via email or telephone (van Eijken et al., 2008). Professionals also declared that collaboration with colleagues was facilitated by co-location (Howarth et al., 2012; Stijnen et al., 2014) and there was a perception that direct contact is more conducive to multidisciplinary collaboration (Raaijmakers et al., 2013), increased awareness and, simultaneously, improved independency of their own practice (Franx et al., 2012). Furthermore, collaboration was evident when professionals interacted via systems or equipment, although even when communication of this type was direct between two professionals, it was perceived as distinct from other forms of contact. Direct non-face-to-face communication provided opportunities for the development of rapport, respect and trust in ways not afforded by referral letters and feedback reports (Gum et al., 2015; J. McDonald et al., 2012). Several articles mention telephone communications between team members aimed at counseling, discussion or reflection about a particular case, as a relevant collaborative tool (Bell et al., 2007; B. C. Chan et al., 2010; Franx et al., 2012; Lalonde et al., 2011; Lee et al., 2014; Moore et al., 2012; Pype et al., 2014; Rasmussen et al., 2015). Drawbacks perceived by professionals regarding telephone communication included: absence of non-verbal cues; how deliberation is most often limited to two professionals; and that the call receiver may be busy and therefore not fully focused on the conversation. Video-conferencing (Pype et al., 2014) was not used in the reviewed articles. We also found e-mail and fax as a non-face-to-face collaborative activity. The objectives of this type of communication included discussion about more complex cases (Lee et al., 2014; Moore et al., 2012) and sharing data, documents or information among team members (McKinnon & Jorgenson, 2009; Wynn & Moore, 2012).

The second component, newly created professional activities, includes telemedicine, which enables collaborative care and the synchronous connection of primary care providers, specialists and patients. In telemedicine, a primary care professional contacts another professional for a specialized consultation. The role of the primary care professional becomes the physical manifestation of the work of the specialist by supervising treatment and ensuring continuity (Foley et al., 2013; Langkamp et al., 2015; Rasmussen et al., 2015). Team members from different disciplines usually conduct shared visits, defined as a patients' consultation with two or more providers simultaneously. In almost every case, nurses form part of the team, working in conjunction with physicians (Foley et al., 2013; Klaasen et al., 2009; Wigert & Wikström, 2014; Williams et al., 2008) and, to a lesser extent, pharmacists (Brooks et al., 2007), dietitians (Martin et al., 2007), social workers, occupational therapists (Anonymous, 2013; Bluml et al., 2014; Rojas-Fernandez et al., 2014), and psychologists (S. Cohen et al., 2012). Shared home-visits are also a part of multidisciplinary care, with the objective of following up patient treatment and performing various assessments, concerning psychosocial issues, caregivers, home safety or depression (Anonymous, 2013; Berglund et al., 2013; Counsell et al., 2007; de Graaf et al., 2016; Donnelly et al., 2013; Langkamp et al., 2015; Moore et al., 2012; Pridham Mary M.: Limbo, Rana K.: Paradowski, Jill: Rudd, Nancy: Meurer, John R.: Uttech, Ann: Henriques, Jeffrey B., 2006; Pype et al., 2014; Smith-Carrier & Neysmith, 2014). Home-visits represent a further instance for primary care providers to interact with additional care professionals (Stijnen et al., 2014).

In the collective ownership of goals component, we found the presence of meetings, understood as a structured form of contact that responds to a protocol. Common objectives of meetings include setting goals and developing care plans, usually for complex cases that require the intervention of several disciplines (Anonymous, 2013; Bell et al., 2007; Berglund et al., 2013; E. Hultberg et al., 2007; Jordan Sanders & Moore-Nadler, 2014; Raaijmakers et al., 2013), or following-up patient progress on a multidisciplinary basis (Arevian, 2005; E.-L. Hultberg et al., 2005; Jordan Sanders & Moore-Nadler, 2014; Newman et al., 2013; Smith-Carrier & Neysmith, 2014). Other studies report the use of meetings as a feedback tool in team management (Pridham Mary M.: Limbo, Rana K.: Paradowski, Jill: Rudd, Nancy: Meurer, John R.: Uttech, Ann: Henriques, Jeffrey B., 2006; Reichert et al., 2014; Yu & Beresford, 2010). We also incorporated an evaluation of the presence of, and activities performed by, a case manager that were identified in the literature as important for defining a collaboration model.

For the fourth component, role flexibility, we found that teams with a non-hierarchical structure where the role of leader was not explicit, were more flexible.

2.3.6. Collaborative team interactions typology

We grouped the articles by considering only the presence or non-presence of collaborative team activities, using the k-medoids algorithm (Park & Jun, 2009), resulting in four types of collaboration activities. Table 5 shows the percentage of articles in which each collaboration activity appears in each cluster.

Co-located collaboration (38 articles). These are co-located teams that work in a highly coordinated manner via regular meetings and direct face-to-face communication, but without shared consultations. Furthermore, they include one professional who acts as case manager who, in collaboration with a clinical leader, provides coordination and management. The diagnoses in this cluster are diverse, but primarily relate to diabetes and other cardiovascular diseases.

Non-hierarchical collaboration (35 articles). These teams manage treatment with direct and face-to-face communication between members and have the distinctive feature of not having a clinical leader, which results in continuous horizontal collaboration. The presence of other collaborative activities is anecdotal in this cluster and does not exceed 23% of articles. The diagnoses identified in this cluster are primarily diabetes and other cardiovascular and chronic conditions, corresponding to 54% of articles.

Collaboration through shared consultations (20 articles). These teams collaborate via shared consultations involving two or more professional(s) per patient. Team members coordinate by means of a case manager and hold regular meetings to design and monitor intervention plans. These teams are generally co-located and their main form of communication is face-to-face. This means of communication is found across all diagnoses, except for musculoskeletal and nutritional disorders.

Collaboration via referral and counter-referral (16 articles). These teams are characterized by their non-face-to-face communication, providing individual consultations to patients and collaborating by means of the referral and counter-referral of patients between team members. They work with a clinical leader who guides treatment and collates overall information on the patient progress. This form of working is multidisciplinary, if not particularly collaborative given the absence of a collective definition of goals and shared consultation.

Table 5. Percentage of cases in which each collaborative activity appears in each cluster.

Collaboration type	Number of papers	Non-face-to-face communication	Direct face-to-face communication	Telemedicine	Shared visits	Shared home visits	Meetings	Case manager role	No clinical leader role
Co-located teams	38	18%	79%	5%	0%	11%	68%	87%	26%
Non-hierarchical	35	9%	80%	6%	23%	3%	23%	20%	86%
Shared consultations	20	15%	90%	0%	100%	25%	85%	75%	40%
Referral and counter-referral	16	94%	19%	0%	13%	0%	25%	25%	44%

Grey tones show statistically significant differences (p-value<0.05).

2.3.7. Collaboration patterns

Following analysis, we classified the articles according to team composition and collaboration activity clusters. The resulting 16 forms of collaboration are shown in Table 6. This classification enables us to see how some typologies recur throughout the literature. We identified two recurring combinations of team compositions and collaborative activities that were each present in 14 articles. For example, non-hierarchical collaboration in highly multidisciplinary teams is present mainly in teams that treat diabetes and other chronic diseases (11 of 14 articles), with associated comorbidities that require the participation of teams with more disciplines working in a coordinated manner to ensure continuity of care. We call these forms of collaboration that are present recurrently across different articles, *collaboration patterns*, since they reflect models that serve as a reference for common ways of collaboration.

Table 6. Team and collaboration typologies.

Collaboration type \ Team type	Specialist	Highly multidisciplinary	Doctor-nurse-pharmacist triad	Physician-nurse centered	Total
Co-located teams	14	8	8	8	38
Non-hierarchical	10	14	3	8	35
Shared consultations	6	4	8	2	20
Referral and counter-referral	5	5	5	1	16
Total	35	31	24	19	109

Number of articles according to team composition.

2.4. Discussion

This work aimed to characterize how collaboration was performed in a structured manner in clinical practice, based on evidence presented in case studies. However, the variables initially designed to characterize the teams, such as group size, interaction frequency and level of awareness, were in some cases absent. Therefore, we searched for identifiable factors in our review, such as team composition and collaborative activities. This differs from factors identified previously, e.g., team size and organizational support (Xyrichis & Lowton, 2008).

It was not possible to find a relationship between the characteristics of the collaboration (team composition, collaborative activities, or other information e.g. country, setting) and the clinical outcomes of the studies. This happened for two reasons: first, almost a third of the studies did not provide a comparison of outcomes, and second, in the case of articles that did compare outcomes, the evaluated variables differed in each case, making the studies not comparable.

We identified four distinct groups according to the presence of different professional disciplines. Among these groups, the presence of a group of highly multidisciplinary teams was particularly noteworthy. This group was in almost a third of articles, which highlights the existence of situations in which a "traditional" team is insufficient. Rather than simply incorporating a specialist, these teams require the presence of at least one complementary discipline. Consequently, an interesting area of future research is to identify whether evidence exists regarding the benefits that may arise from the incorporation of new disciplines into daily practices.

We used a systematic process to divide the articles into four collaboration types, according to their similarity in terms of the presence of different collaborative activities in the treatment. The types identified share certain similarities with previous work (Virani, 2012) in which five collaboration models were found: (1) interprofessional team models; (2) nurse-led models; (3) case management models; (4) patient navigation models; and (5) shared care models. Interestingly, our study has produced a similar conclusion through a different methodology, whereby significant differences are evident in teams in which a leader is present, the role of case manager exists, or shared consultations are provided by several professionals to just one patient.

This study presented a relationship between team and collaboration types, finding e.g. a high number of articles in which specialist teams collaborated in co-located settings. We also studied whether there were relationships between team types and collaborative activities, and between collaboration types and the presence of disciplines in each type. We found one statistically significant result through this analysis: family nurses are present at a higher rate in shared consultation collaborations (90%) than in those who collaborate through referral and counter-referral (50%). The literature proposes that nurses tend to collaborate more closely with their teammates, either through meetings or face-to-face, while physicians tend to work in a more isolated way, collaborating indirectly (Donnelly et al., 2013).

We found a concentration of articles in certain combinations of team and collaboration styles that determine collaboration patterns that recur systematically throughout the literature. It is not possible to link these combinations to treatment settings or evaluation clinical results, since these depend on a series of variables that cannot be captured in an analysis of this type. However, this analysis can be undertaken using this typology and by comparing, for equivalent patients in similar settings, the results obtained in care provided by teams in which different forms of collaboration are used.

2.5. Limitations

The review was limited to primary source studies and, consequently, consolidations from previous studies were excluded. Some of the reviewed articles did not describe the way in which teams collaborate with enough detail, which resulted in parts of the information being unavailable upon extraction. Since this article is a literature review, it was not possible to obtain information regarding the intensity of collaboration in each case, which must be measured via questionnaires or surveys aimed at professionals. The differences between the contexts of each case, in addition to the lack of detail with which collaboration is reported, did not enable us to conduct comparisons.

2.6. Conclusion

This systematic review analyzed 109 articles related to multidisciplinary collaboration in primary care. Overall, collaboration was found to be positive or neutral in every study that compared collaboration with a non-collaborative alternative. A collaboration typology based on objective measures was proposed.

Table 7. Selected papers analyzed in the systematic review.

Authors	Year	Diagnosis classification[1]	Outcome vs. no collaboration[2]	Team Composition													Collaborative activities								
				Family Physician / General Practitioner	Nurse	Social worker	Pharmacist	Dietician	Occupational therapist	Physiotherapist	Psychologist	Specialist Physician	Other	Total disciplines	Team composition type[3]	Referrals[4]	Face-to-face communication	Non-face-to-face communication	Telemedicine	Shared visits	Shared home visits	Meetings	Case manager role	No clinical leader role	Collaboration type[5]
Chwastiak et al.	2016	1	B	X	X			X				X	X	5	2			X				X	X	X	3
Farsaei et al.	2013	1	B	X	X		X	X						4	1			X		X			X		1
Cohen et al.	2011	1	B	X	X		X	X		X				5	1					X		X	X	X	1
Turner et al.	2008	6	B	X	X					X	X		X	5	4	X		X		X				X	2
Raaijmakers et al.	2013	1		X	X		X	X		X		X	X	7	2	X		X					X	X	2
McDonald et al.	2012	1		X	X		X	X		X		X	X	8	2		X	X							4
Brooks et al.	2007	1	B	X	X		X	X						4	1			X		X		X	X		1
Heuer et al.	2006	1	B		X			X				X	X	5	2									X	2
Tobe et al.	2013	1	B	X	X		X							3	1			X					X		3
Gamblen et al.	2007	6	B	X				X						2	3			X				X	X		3
Brahm et al.	2007	1		X	X	X	X							4	1	X		X						X	2
Arevian	2005	1	B	X	X	X		X				X	X	6	2			X				X	X		3

[1] 1: Diabetes and other cardiovascular diseases; 2: Diseases in child patients (except diabetes); 3: Aged care; 4. Mental health care; 5: Musculoskeletal disorders; 6: Nutritional disorders; 7: Other chronic diseases; 8: Other non-chronic diseases.
[2] B: Better; ND: No difference; Blank: Not reported.
[3] 1: Doctor-nurse-pharmacist triad; 2: Highly multidisciplinary teams; 3: Specialized teams; 4: Traditional primary care teams.
[4] This derivation data was not used in the quantitative analyses.
[5] 1: Shared consultation; 2: Non-hierarchical; 3: Co-located teams; 4: Referral and counter-referral.

Wigert and Wikstrom	2014	1		X	X			X			X		X	6	2	X		X		X		X		X	2
Shortus et al.	2007	1		X				X				X	X	5	2	X	X						X		4
Rasmussen et al.	2015	1		X	X									2	4		X	X	X				X		3
Wishah et al.	2015	1	B	X			X							2	1			X					X		3
Knowles et al.	2015	4		X	X						X			3	4			X		X		X	X	X	1
Rawal et al.	2014	1		X	X			X				X	X	7	2										4
Yeh et al.	2014	1	B	X	X			X				X		5	2	X		X						X	2
Reichert et al.	2014	1		X	X	X		X				X	X	7	2	X		X				X		X	2
Osborn et al.	2013	1	B		X			X			X	X	X	6	2							X	X	X	3
Yu and Beresford	2010	1	B	X								X		2	3		X	X		X		X		X	2
Hogg et al.	2009	1	B	X	X		X							3	1									X	2
Greene et al.	2009	1	B	X	X			X					X	5	2			X				X		X	2
Anichini et al.	2006	1	B	X								X	X	7	3	X								X	2
Martin et al.	2007	1	B	X	X	X	X	X		X		X		8	1			X		X		X			1
Malone et al.	2005	6	B				X				X	X		3	3			X					X		3
Lalonde et al.	2011	1	B	X			X							2	1	X	X	X					X		3
Harris et al.	2015	1	B	X	X	X		X						4	4	X		X				X			3
Bluml et al.	2014	1	B	X	X	X	X	X				X	X	7	2			X		X			X	X	2
Cohen et al.	2012	6	B	X	X	X		X		X	X			6	4			X		X				X	2
Eichler et al.	2007	6	B	X	X									2	4			X							2
Chen et al.	2016	1	B	X	X		X	X						4	1								X	X	3
Gucciardi et al.	2016	1	B	X	X			X						3	4			X		X		X			2
Campmans-Kuijpers et al.	2015	1	ND	X	X			X				X	X	5	2									X	2
Franx et al.	2012	4				X	X			X	X	X	X	6	3	X	X	X				X		X	2
Callahan et al.	2006	4	B	X	X						X	X	X	6	2			X				X	X		3
Bell et al.	2007	4		X			X							2	1	X	X	X				X			3
Rojas-Fernandez et al.	2014	4	B	X	X	X	X		X					5	1	X		X		X		X	X		1
Gidding et al.	2013	4		X		X					X		X	4	3	X		X				X		X	2
Goncalves et al.	2013	4	ND	X	X	X					X	X		5	3	X		X						X	2

Kim et al.	2011	4	ND		X	X						X		3	3			X					X	X	2
van der Feltz-Cornelis et al.	2010	4	B	X								X		3	3	X	X	X		X			X		1
Harpole et al.	2005	4	ND	X	X						X	X		4	3			X				X	X		3
Gum et al.	2015	4	B	X							X	X		3	3		X			X			X		4
Lee et al.	2014	4	B	X	X	X	X		X			X		6	1	X	X	X		X					4
Zeiss and Karlin	2008	4		X	X	X					X	X		5	3	X		X					X	X	2
Langkamp et al.	2015	8	B	X	X									2	4			X	X		X				2
Haggarty et al.	2016	4	B	X		X						X		3	3		X	X						X	4
Stergiopoulos et al.	2015	4	B	X	X							X	X	4	2		X	X						X	2
Shedden-Mora et al.	2016	8	B	X							X			2	3		X					X			4
Munns et al.	2015	2			X								X	2	4		X							X	4
Kruis et al.	2014	7	ND	X	X			X		X			X	5	2					X				X	2
Kohler et al.	2014	4	ND	X								X		3	3	X	X					X			4
Cheong et al.	2013	7		X			X					X		3	3	X							X		3
Wynn and Moore	2012	8	B	X	X	X	X	X						5	1		X					X			4
Cochrane et al.	2016	7		X	X							X	X	4	2		X						X		4
Stapelfeldt et al.	2011	5	B			X			X	X			X	5	3			X					X	X	2
Hultberg et al.	2007	5	ND	X		X			X	X	X			5	3					X				X	2
Bain et al.	2012	5	B			X	X	X	X	X		X	X	10	2	X		X						X	2
Howarth et al.	2012	5			X					X	X	X	X	5	2			X						X	2
Hultberg et al.	2005	5	ND	X		X			X	X			X	5	3			X				X			3
Jensen et al.	2011	5	ND	X		X				X		X		4	3	X		X				X	X	X	3
Maiers et al.	2010	5		X									X	7	3							X	X	X	3
Andermo et al.	2015	5		X									X	6	3	X						X			3
Bültmann et al.	2009	5	B	X		X			X		X	X	X	9	3							X	X	X	3
Jordan and Moore-Nadler	2014	2		X	X	X						X		4	3			X				X	X		3
McKinnon and Jorgenson	2009	7	B	X			X							2	1		X							X	4
Fiss et al.	2010	8		X	X								X	3	4			X							2
Anonymous	2013	3	B		X	X	X		X	X		X	X	7	1	X		X		X	X	X	X	X	1

Pype et al.	2014	8		X									X	2	3		X	X			X	X	X		3
Klaasen et al.	2009	3	B	X									X	2	3			X		X		X	X		1
Counsell et al.	2007	3	ND	X	X	X						X		5	3	X		X		X	X	X			1
Moore et al.	2012	3		X	X	X	X	X				X		6	1	X	X	X		X	X	X			1
Dijkstra	2007	4			X	X		X	X	X	X	X	X	8	2			X		X		X	X	X	1
Smith-Carrier and Neysmith	2014	3		X	X	X			X				X	5	4	X		X		X	X	X	X		1
Berglund et al.	2013	3	B		X	X				X			X	4	4			X			X	X	X	X	3
Rose and Yates	2013	8		X	X	X		X					X	7	2	X		X				X	X		3
Van Eijken et al.	2008	3		X	X							X		3	3			X				X	X		3
Stijnen et al.	2014	3	ND	X	X									2	4			X				X	X		3
Eckstrom et al.	2016	3	B	X	X	X	X		X	X			X	7	1			X						X	2
Rose et al.	2016	3		X			X						X	3	1		X					X		X	4
de Graaf et al.	2016	8		X	X			X					X	6	2		X	X			X	X	X	X	3
Rothschild et al.	2016	3	B	X		X	X		X		X	X	X	7	3		X						X	X	4
van Gurp et al.	2016	7		X	X									2	4				X				X	X	2
Engel et al.	2016	3	B	X	X	X	X	X			X	X		7	1			X		X		X	X	X	1
Quist et al.	2016	3		X	X		X					X		4	1			X				X	X		3
Doubova et al.	2011	8		X	X						X			3	4	X		X					X		3
Pridham et al.	2006	2	ND	X	X								X	3	4			X			X	X	X		3
Price et al.	2005	8	B	X	X	X						X	X	7	2	X		X				X	X		3
Bryce et al.	2009	8	B	X								X	X	3	3	X		X					X		3
Newman et al.	2013	7	B	X	X							X	X	4	2	X		X				X		X	2
Wulff et al.	2013	8	ND	X	X							X		3	3		X	X					X		3
Rogers et al.	2007	7	B	X								X		2	3	X		X							2
Louis et al.	2010	7	ND	X	X		X							3	1	X							X		3
Wharton et al.	2013	7	ND	X	X	X		X		X	X			6	4	X						X	X	X	3
Harris et al.	2012	8	B	X	X							X	X	5	2	X		X		X		X	X	X	1
Boult et al.	2011	7	ND	X	X									2	4			X					X	X	2
Williams et al.	2008	2		X	X							X		3	3			X		X			X		1

Sisson et al.	2016	1	B	X	X		X							3	1		X							X	4
Montgomery-Taylor et al.	2015	2	B	X	X							X		3	3			X		X		X		X	1
Pechacek et al.	2015	8	B	X	X			X			X	X	X	8	2			X		X		X		X	1
Donnelly et al.	2013	7		X	X	X		X	X		X		X	10	2		X			X	X	X	X		1
Foley et al.	2014	2	B	X	X							X		3	3			X		X		X	X		1
Chan et al.	2010	7	B	X	X			X		X	X		X	6	2	X	X	X				X			3
Gray et al.	2010	1	B	X	X		X							3	1			X	X				X		3
Tourigny et al.	2010	7	B	X	X									2	4			X				X	X	X	3
Russell et al.	2009	7	ND	X	X			X					X	5	2			X						X	2
Myers-Wright and Lamster	2016	1		X	X			X			X	X	X	6	2		X							X	4

3. STUDY CASE: IDENTIFYING COLLABORATION TYPES IN PHC

3.1. Introduction

In our previous systematic review, we classify multidisciplinary primary healthcare teams into four types: (i) *Physician-nurse-pharmacist triad*, working with other primary care professionals with patients having several comorbidities and consuming multiple medicines, (ii) *Highly multidisciplinary teams*, composed of a doctor-nurse duo that works with other medical and complementary disciplines, e.g. medical coordinator, podiatrist, midwife, diabetes educator, or counselor, (iii) *Specialized teams*, where a GP - specialist physician duo treat, with support of one or more primary care disciplines, patients who require specialist assistance for less common comorbidities, and (iv) *Physician-Nurse centered teams*, in which care is provided by small teams based on a doctor-nurse duo, with participation from primary care disciplines for treatment of cases with few complications or comorbidities (Saint-Pierre, Herskovic, & Sepúlveda, 2018). The aim of this paper is to analyze whether these teams can be found through data analysis, to analyze their characteristics, and to discover whether primary healthcare professionals in Chile are carrying out collaboration.

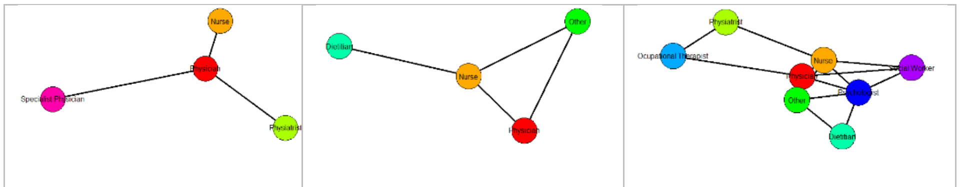
On the analysis of team structure, some articles refer to specific roles, such as care coordinator or leader (Ackroyd & Wexler, 2014; Lynch et al., 2016), and to specific disciplines within a team, such as nurses as team leaders (Virani, 2012), or the incorporation of pharmacists (L. B. Cohen et al., 2011). A qualitative study defined a compositional typology for healthcare teams, specifying four types of teams based on stability/variability of roles and personnel in the team (Andreatta, 2010). A literature review focused on nurses organized team structure in five types of interprofessional care models: Interprofessional team, Nurse-led, Case management, Patient navigation and Shared care (Virani, 2012). Another review analyzed 51 interventions and grouped multidisciplinary collaboration by structure, process and outcomes (Schepman et al., 2013). By structure, they considered whether there was a primary care physician in the team or not, the number of disciplines, the patient population and the sectors included. Although the authors in this case describe team composition, they did not classify cases in terms of different compositions.

The review on which we base the present study included 109 papers describing collaborative treatments in primary care (Saint-Pierre, Herskovic, & Sepúlveda, 2018). This study described collaboration in terms of team structure and proposed four collaboration categories (physician-nurse-pharmacist triad, highly multidisciplinary, specialized, and physician-nurse centered teams).

3.2. Methods

Data was obtained from three primary healthcare centers, operated by the University to which the researchers belong to. We obtained an anonymized database log, containing 15 years of data (2002–2016), corresponding to 13,501 patients under cardiovascular disease treatment. We selected patients with Type 2 Diabetes Mellitus (DM2) diagnosis in a timeframe from May 2012 to November 2016, with at least two measurements of HbA1c, and at least one appointment at the healthcare center (so they were not occasional patients). This filter left us a population of 2,838 patients.

Patients were classified according to the disciplines involved in their treatment. First, we set out to find the four types of primary healthcare teams described in (Saint-Pierre, Herskovic, & Sepúlveda, 2018). Since there were no pharmacists in the analyzed centers, the physician-nurse-pharmacist triad was not present in our data. However, the other types of teams were found: highly multidisciplinary (849 patients), specialized (319 patients), physician-nurse centered (1581 patients), and we also found a fourth non-collaborative type (which naturally had not been discussed in (Saint-Pierre, Herskovic, & Sepúlveda, 2018)), with only one discipline during the time window (89 patients).



(a) Specialized team	(b) Physician-nurse centered team	(c) Multidisciplinary team

Figure 2. Example collaborative structures

Classification of the patients into each team category was done by evaluating team composition as follows. Cases with only one professional were classified as non-collaborative. Specialized teams were cases where there was a family physician and a specialist, and in total they did not have more than 4 disciplines (Figure 2a). Cases with up to 4 disciplines with no specialist, and cases with 5 disciplines and no specialists or complementary disciplines were classified as physician-nurse centered (Figure 2b). Finally, cases with 5 disciplines that did not belong to the previous categories, and those with 6 or more disciplines were classified as highly multidisciplinary (Figure 2c). The disciplines in the data were: family physician, nurse, social worker, dietician, occupational therapist, physiologist, psychologist, specialist, and other complementary disciplines.

Table 8. Percentage of the cases where the discipline is present for each team type.

Team type	**Family Physician**	**Nurse**	**Social Worker**	**Dietician**	**Occupational Therapist**	**Physiologist**	**Psychologist**	**Specialist Physician**	**Other**	**Disciplines (mean)**
Highly multidisciplinary	100%	100%	41%	88%	3%	42%	23%	64%	92%	5,5
Specialized	100%	89%	5%	37%	0%	3%	1%	100%	33%	3,7
Physician-nurse centered	100%	92%	9%	55%	0%	8%	3%	0%	48%	3,1
Non-collaborative	87%	10%	0%	1%	0%	0%	0%	0%	2%	1,0
Total	99%	92%	18%	61%	1%	17%	9%	30%	58%	3,9

The number of disciplines present in each case was, on average, 3.9. Averages by team type varied according to their definition, from 5.5 in highly multidisciplinary teams, to 1 in the non-collaborative cases. Percentage of patients in which each discipline was present for each team type is presented in Table 8.

We tested independence for categorical variables with Pearson's Chi-squared test, and in case the null hypothesis was rejected, a test of proportions to establish the significance of the differences. In cases of numerical variables, we used the Shapiro–Wilk test to test whether population is normally distributed. When it was not, we used the Kruskal-Wallis test and we used ANOVA otherwise.

3.3. Results

3.3.1. Demographic Analysis

The team types treat different proportions of men and women. Gender and team type are dependent variables (p-value << 0.01) and the different proportions are statistically significant (p-value << 0.01). Table 9 displays the number, percentage, and normalized percentages (if there were an equal number of men and women) per team type. Highly multidisciplinary teams treat 37% of women and only 19% of men, while physician-nurse centered teams more often treat men than women. Non-collaborative treatment, although infrequent, is more likely for men (5%) than women (2%). Average age for the entire population was 62.2, with no statistically significant differences among team types (p-value = 0.071).

Table 9. Gender vs team type.

Team type	F (n -%)	M (n -%)	Normalized F (%)	Normalized M (%)	Total
Highly multidisciplinary	620 (37%)	229 (19%)	65.8%	34.2%	100%
Specialized	145 (9%)	174 (15%)	37.4%	62.6%	100%
Physician-nurse centered	857 (52%)	724 (61%)	45.8%	54.2%	100%
Non-collaborative	35 (2%)	54 (5%)	31.3%	68.7%	100%
Total	1657 (100%)	1181 (100%)	58%	42%	100%

3.3.2. Analysis by healthcare center

We compared how the 4 types of teams are present in each of the 3 centers. There is a clear dependence between healthcare center and team types (p-value << 0.01), with statistically significant differences for the types of collaboration within each center (p-value << 0.01), except for the non-collaborative cases that are similar for all centers.

As shown in Figure 3. , the biggest difference is in Center 1, in which physician-nurse centered teams are present in only 32% of cases, compared to 66% and 67% in the other centers. On the other hand, in this same center, highly multidisciplinary teams treat 46% of the patients, versus 20 and 25% in the other cases.

3.3.3. Years living with DM2

On average, the patients in the dataset have been living with DM2 for 6.3 years (SD = 3.6). Patients that are treated non-collaboratively have been living with DM2 for fewer years, while patients who have longer disease spans require more specialized care (Table 10) All differences are statistically significant (p-value << 0.01).

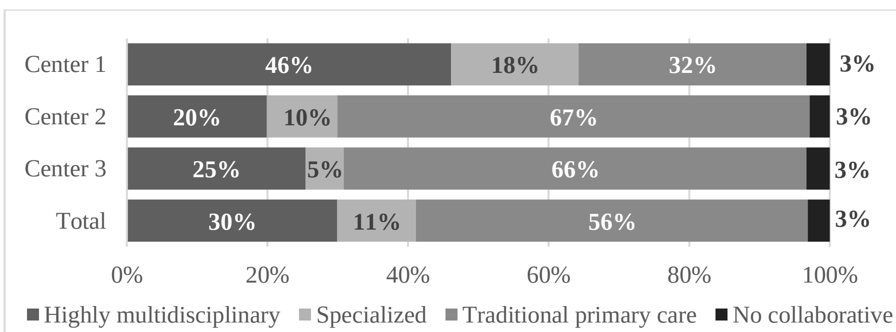


Figure 3. Presence of collaboration types in each healthcare center.

Table 10. Years living with DM2.

Team type	Years living with DM2 (mean / σ)
Highly multidisciplinary	6,7 (3,5)
Specialized	6,9 (3,6)
Physician-nurse centered	6,1 (3,6)
No collaborative	4,4 (3,8)
Total	6,3 (3,6)

Time elapsed from diagnosis until the end of time window.

3.3.4. Severity and comorbidity

Diabetes severity was assessed by assigning a score (0 to 2) on presence and severity of 7 categories of complications: cardiovascular, nephropathy, retinopathy, peripheral vascular disease, stroke, neuropathy and metabolic disorder (Glasheen, Renda, & Dong, 2017). For comorbidity, we used the Charlson index, which considers those comorbidities that increase mortality risk (Sundararajan et al., 2004). The index assigns a score (0 or 1) to the presence of pathologies grouped into 6 categories: cancer, gastrointestinal, skeletal muscle, pulmonary, mental and substance abuse. The averages of both indices are presented in Table 11. As we are working with data from primary care patients, the indices take low values. Highly disciplinary teams treat patients with greater complexity, while specialized and physician-nurse centered groups treat patients with a lower comorbidity index.

Table 11. Average of comorbidity index and severity index in patients by type of collaboration.

Team type	Charlson comorbidity index (mean)	Diabetes complication severity index (mean)
Highly multidisciplinary	1.5	1.2
Specialized	1.1	1.1
Physician-nurse centered	1.1	0.7
Non-collaborative	0.8	0.4
Total	1.2	0.9

3.3.5. Number of appointments

We define the *core team* as a subset of the team, considering only the three main disciplines present in DM2 treatment in Chilean healthcare centers: family physician, nurse and nutritionist. The follow-up protocol establishes that patients should have visits with these three professionals, regardless of their state of health.

Table 12 presents the number of patient visits per year for the core team and the whole team. Both variables presented statistically significant differences (p-value << 0.01).

Table 12. Number of patient visits with the core team/whole team according to team type.

Team type	Core team visits / year (mean)	Whole team visits / year (mean)
Highly multidisciplinary	10.9	14.8
Specialized	7.2	8.2
Physician-nurse centered	6.2	7.3
No collaborative	2.4	2.4
Total	7.6	9.5

The analysis shows that in patients treated by highly multidisciplinary teams, the number of visits per year is significantly higher in both cases. Given that specialized teams consider the participation of a secondary care specialist in 100% of cases, that extra attention is associated with this treatment characteristic.

Table 13. Average of physician visits and number of different physicians/year.

Team Type	Physician visits/year	Number of different physicians/year
Highly multidisciplinary	6.9	2.7
Specialized	4.5	2.2
Physician-nurse centered	3.7	1.8
No collaborative	2.2	1.4
Total	4.7	2.1

More than 99% of patients have physician visits, regardless of team type; however, the number of visits per year is different (Table 13). The number of different physicians is correlated with the number of physician visits ($r = 0.73$), but causality is not clear.

3.4. Discussion

Analysis using data from healthcare centers found that the collaborative team types described theoretically in (Saint-Pierre, Herskovic, & Sepúlveda, 2018) are actually found in practice. We found that in some cases, treatments were not collaborative at all, against diabetes clinical guidelines.

Treatment team size and composition is partially determined by the needs of the patients (Sevin, Moore, Shepherd, Jacobs, & Hupke, 2009), which explains to a large extent the differences among teams. However, as is well known, other factors (e.g. team cohesion, culture, history) impact collaboration, so we found that, even with a similar population of patients, different healthcare centers employed different collaboration styles. Patient characteristics also may affect team collaboration. For example, diabetes-related comorbidities such as obesity are more frequent in women than men (Sandína, Espeltb, Escolar-Pujolarc, Arriolad, & Larrañaga, 2011), which may explain that more women are treated by highly interdisciplinary teams, since they require additional treatment. Also, the lower participation of women in the workforce (Instituto Nacional de Estadísticas, 2016) may explain a higher availability to participate in more complex treatment, with a higher number of healthcare appointments. The number of visits in highly multidisciplinary teams is significantly more than in the other groups. Again, this corroborates that highly multidisciplinary teams not only have more disciplines, but also that they possibly treat patients of higher complexity, that require more hours of dedication.

The number of visits provided by professionals is similar in all groups. This can be explained by the high turnover of professionals in the centers. In the other groups, physician participation in the total care is also around 60%, with exception of the non-cooperative group who is 94%. The latter is reasonable because for diabetic patients dealing with just one professional, it is most likely to be with the physician.

3.5. Conclusion

This paper presented an analysis of collaboration styles in primary healthcare, for the treatment of diabetes mellitus type 2. We used 4 years of data from 3 healthcare centers, finding empirical evidence of the types of teams that have been described qualitatively in the literature. We also found particular characteristics of each team, describing e.g. the gender, comorbidity and severity, and how they are related to each team type. Future work will evaluate how collaboration affects patient outcomes, as well as recruiting patients and healthcare professionals to conduct qualitative analysis of how teams work and how patients interact with these teams.

4. MULTIDISCIPLINARY COLLABORATION USING PROCESS MINING.

4.1. Introduction

Our first approach in the analysis of Electronic Clinical Records (ECR) was to use process mining algorithms and tools to verify whether it is possible to determine certain patterns of collaboration using data from ECR and to study if these patterns are related to the clinical outcomes of patients. Accordingly, we propose a methodology to analyze collaboration between healthcare professionals to: (i) identify collaboration patterns in the treatment of patients with DMT2 in primary care, i.e., the distinct interaction networks within the treatment teams; and (ii) evaluate the performance of the discovered patterns, confirming whether they relate to the clinical evolution of patients (represented by HbA1c measurements). This approach uses information that is already being recorded in the relevant healthcare institutions and, therefore, does not require the collection of new data.

4.2. Methods

4.2.1. Data source

After obtaining IRB approval, the dataset was extracted from the information system used in the three healthcare centers. Its database stores information related to patients, including their appointments, diagnoses and test results. For each visit to the healthcare center, the system records the date, type of appointment, and the professional in charge of the episode. Importantly, this work only considers patients with DMT2 and activities associated with periodic cardiovascular appointments (CTCV) that are performed by specialists from the professional triad team consisting of physician, nurse and dietitian. Every time one of these professionals completes a CTCV, she/he must specify the discipline and approximate date of the patient's next appointment.

The percentage of HbA1c was selected as a metric to represent patient evolution. The HbA1c test measures the glycemic history of the patient over the preceding 120 days (Goldstein et al., 2004) and is one of the tests used to monitor diabetic patients. The frequency of the test depends on the state of compensation of the patient, the treatment used, and medical judgment. While the specific treatment objectives should be individualized for each patient, the American Diabetes Association recommends that the goal of therapy should be to reduce HbA1c below 7%. For values higher than this, the clinical guidelines of the Chilean Ministry of Health clinical guidelines and the internal guidelines of the healthcare centers included in this study establish two categories of decompensation for patients: moderately decompensated, for values between 7% and 9% (included); and highly decompensated, for values higher than 9% (Subsecretaria de Redes Asistenciales, 2010). The date on which a patient undergoes a test and its result are both logged in the records.

4.2.2. Patient selection

A total of 3,369 patients with DMT2 were identified across the three healthcare centers. Subsequently, to measure their respective evolution, we included individuals who had at least two recorded HbA1c test results. In total, 2,843 patients met these conditions.

To isolate external factors that might influence a patient's evolution beyond the clinical team's collaboration patterns we included diabetic patients with no comorbidities or diabetes-related complications, and good adherence to prescribed appointments and tests. We used the diabetes complication severity index (DSCI) and the chronic illness with complexity (CIC) index count as measures of comorbidities and complications (C.-C. Chen et al., 2013; Meduru et al., 2000; Young et al., 2008), and an interval under 4 months between the prescribed appointment and the actual appointment as a reasonable proxy for adherence.

Adherence to follow-up appointments is important for the evolution of patients, since through them professionals can intervene in the habits and self-care of the patient (Vermeire, Hearnshaw, Van Royen, & Denekens, 2001). Greater rates of missed appointments are associated with significantly higher HbA1c measurements (Karter et al., 2004). Moreover, if patients do not show adherence to their treatment, the effectiveness of treatment is compromised and they might develop complications (Sabaté, 2003). In general, the diabetic population presents a low adherence, both to medications and timely attendance to scheduled appointments (Toth et al., 2003). To isolate the influence of the adherence to appointments, those patients who do not adhere to the HbA1c tests were excluded. Nevertheless, a margin of time must be considered to determine that the patient attended the appointment "on time" (Melnikow & Kiefe, 1994). The protocol of the healthcare centers stipulates that patients with higher states of decompensation should undergo more regular HbA1c tests. In the context of the period under analysis, the following periodicity was considered acceptable by the healthcare centers studied: that patients in a state of compensation took the HbA1c test up to one year after their last measurement; that patients who were moderately decompensated did the same after up to six months; and that highly decompensated patients did so after up to three months.

Given the context of the healthcare centers studied, in particular, their scarce resource availability, their restrictions for taking appointments (in general, patients cannot schedule appointments more than one month in advance), and the availability of hours for taking exams, it is normal that there is a delay that goes beyond the responsibility of the patient. To address these restrictions that depend on the healthcare center, a tolerance of up to 4 months for taking the HbA1c test was considered. This time frame was discussed with and suggested by the healthcare professionals.

Finally, patients who were tested for HbA1c at intervals greater than those established for the clinical protocols according to their degree of compensation, considering a four-month tolerance, were not considered in the analysis. This restriction ensures more complete information and greater consistency in terms of data evolution because the longer the time elapsed between tests, the more difficult it becomes to determine the variability in terms of patient compensation during that period. Of the 579 patients with neither severe conditions nor comorbidities, 319 had acceptable levels of adherence for inclusion in this study.

To normalize the period of study for all included cases, this paper considered a horizon of one and a half years to analyze the impact of multidisciplinary collaboration on the treatment of patients. The first measurement of HbA1c that is available for a patient marks point zero of the period of study. To determine the end of the period, a subsequent HbA1c measurement was sought as close as possible to 18 months after point zero. A tolerance period of 8 months was considered prior to and following the year-and-a-half mark, i.e., the final measurement included had to fall within a range running from month 10 to month 26 (18±8), factoring in the possibility that other previous measurements may have been taken during this period. Of the 319 patients, 231 had a minimum acceptable study period of 10 months. As the study analyzed the response of the patient to the intervention and organization of the triad of professionals within a defined time frame, detailed information related to the complete evolution during the lifetime of the patient was not required.

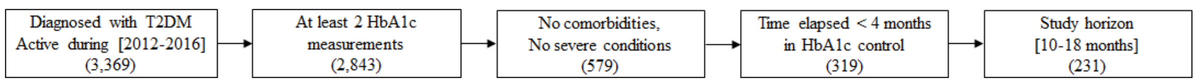


Figure 4. Patient selection process: applied criteria.

Regarding the sample, 133 out of 231 patients were men (57.6%) and 98 out of 231 were women. Overall, 50% were aged 60 or over and 81% were 50 or over (average age 59.7; range: 20 to 89). The mean amount of CTCV appointments was 4.8 per patient (range: 1 to 15). Table 14 outlines this information.

Table 14. Description of the studied population.

Variable	Average (Std. Deviation)
Age	59.7 (12.6)
Years with DMT2	4.6 (3.8)
No. of HbA1c measurements	3.7 (0.95)
No. of CTCV	4.8 (2.3)

Figure 5 outlines the duration of the periods of study considered. The X-axis shows the number of months included in the analysis while the Y-axis shows the number of patients related to the corresponding horizon.

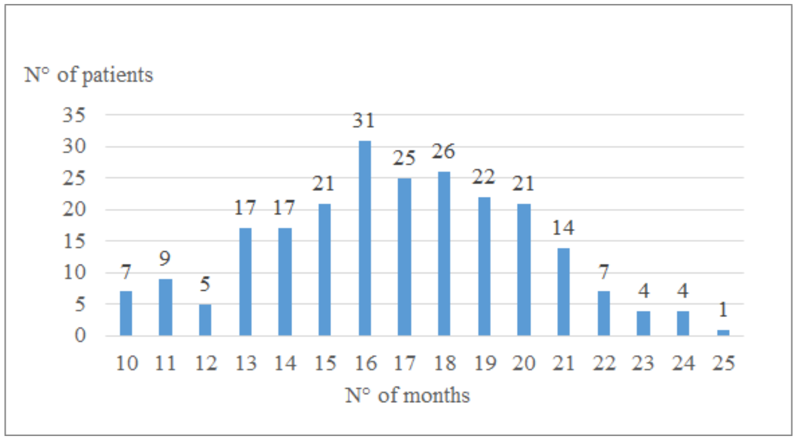


Figure 5. Periods of study used in the analysis.

4.2.3. Collaboration through network analysis

Clinical records were used to build a log, with the following information for each CTCV: the ID of the patient; a timestamp; and the relevant attending discipline (physician, nurse or dietitian). The timestamps were used to identify the sequence or order in which the disciplines intervened.

Definition 1 (Discipline log).

Let V represent the set of the three disciplines: physician (P), nurse (N) and dietitian (D), and $H = \{h_1, \cdots, h_n\}$ the set of patients. Let c_{hi} be the sequence of disciplines in V who attend to patient h_i. We define L, the discipline log, as $L = \{c_{hi}\} \forall\ h_i \in H$.

With information from the discipline log, a collaborative network can be created to show the relationship between the clinical disciplines in the treatment of patients. Specifically, a collaborative network related to a group of patients is defined as a directed graph in which the nodes refer to different clinical disciplines that intervene in the treatment of the disease, while the arcs represent the existing derivations among the disciplines in the case of each patient. It should be noted that following a CTCV appointment of a patient, the professional may assign the subsequent appointment to either a professional from a distinct discipline or from the same discipline. Therefore, the generated graphs could include self-loops.

Definition 2 (Collaborative network).

Let V represent the set of the three disciplines: physician (P), nurse (N) and dietitian (D), and H = {h_1, ⋯, h_n} the set of patients. A collaborative network will be the directed graph G^W = (V, E), where V = {P, D, N} is the set of distinct disciplines that constitute part of the treatment of the patients in H and E ⊆ {V × V} are the directed arcs that represent all the different derivations that occur when considering all the patients of set H.

Figure 6 shows an example of a collaborative network that represents the multidisciplinary structure of treatment received by a group of patients. In this case, the three disciplines make referrals among themselves, and the dietitian (D) makes self-referrals for certain CTCV appointments.

Three metrics were defined for both the nodes and the arcs of the collaborative network:

Participation index: the proportion of CTCV appointments performed by a specific discipline in relation to the total number of CTCV appointments. It is calculated for each discipline (node). It ranges from 0%, which represents no participation of the discipline in the treatment, to 100%, whereby all appointments were undertaken by the particular discipline. This value can be interpreted as the prominence of a clinical discipline with regard to the patient intervention.

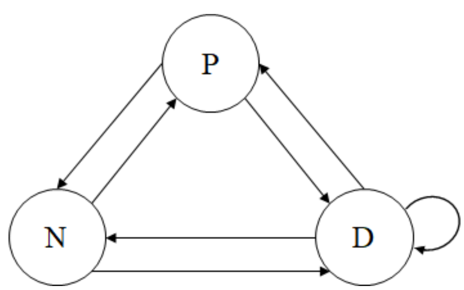


Figure 6. Collaborative network model.

Self-referral index: the proportion of CTCV appointments which are referrals to the same discipline in relation to the total number of CTCV appointments that a particular discipline refers in total. It is calculated for each discipline (self-loops). It ranges from 0%, which represents no self-referrals made by the discipline, to 100%, whereby all referrals made by the professionals of one discipline are to the same discipline.

Referral index: the proportion of CTCV appointments which one discipline refers to a different discipline in relation to the total number of CTCV appointment referrals made by that particular discipline. It is calculated for each ordered pair of disciplines (directed arcs between different nodes). It ranges from 0%, which represents no referrals to the other discipline, to 100%, whereby all referrals made by the professionals of one discipline are to the other discipline. This value can be interpreted as the level of support among different disciplines.

4.2.4. Pattern identification

The process mining algorithm selected for discovery was PALIA (Fernandez-Llatas, Valdivieso, Traver, & Benedi, 2015), which was applied using the PALIA Web (Fernandez-Llatas, Lizondo, et al., 2015) application. PALIA Web is a process discovery application created for the analysis of flexible and unstructured workflows. This tool was chosen because it receives an event log as input and outputs visualizations that are easy to understand for people who are not experts in process mining. In addition, it has filters that can be applied to the data prior to performing discovery, including, for example, trace clustering for the creation of different models based on groups of patients showing similar behavior.

The first step to identify the distinct forms of treating patients was to apply the PALIA process mining algorithm to the discipline log, complemented by trace clustering. This activity included the use of the flow disintegration functionality, which groups similar traces (sequences of disciplines that attend to each patient), and the application of the PALIA algorithm to create a visualization of the different groups/trace clusters.

The PALIA algorithm was executed with the following parameters for the flow disintegrations: similarity of 15% and outliers of 3%. The similarity percentage indicates that by conducting trace clustering, individuals from the same group are unable to differentiate by more than 15% according to the measurement of dissimilarity used by the algorithm, which is based on a heuristic topological editing distance (Fernández-Llatas, Benedi, García-Gómez, & Traver, 2013). Therefore, individuals from distinct groups differed by more than 15%. Conversely, the percentage of outliers indicates the minimum proportion of individuals that can be grouped under a single cluster. If the algorithm identifies a smaller group than the one established under that parameter, those patients are grouped together with the outliers. In this case, the 3% identified is equivalent to seven patients. In addition, a heat map was applied to the diagrams (arcs and nodes) with a scale of red to green, where red indicates high frequency and green low frequency.

4.2.5. Clinical Outcome

The test used to monitor and control the state of the patient was HbA1c. The clinical guidelines of the Chilean Ministry of Health, used by the healthcare centers, propose three categories for HbA1c values: below 7% (called *compensated*, the clinical goal for patients), between 7 and 9%, and above 9%, each corresponding to a different course of action and time frame for follow-up (Subsecretaria de Redes Asistenciales, 2010). Since we had several measurements for each patient in our data, we propose a segmentation of patients considering their temporal trend (Concaro, Sacchi, Cerra, & Bellazzi, 2009). We tried several different segmentations, with the help of healthcare professionals, until we achieved a four-segment categorization that is described below. The healthcare professionals stated that the most interesting category of patients, for them, were patients with high HbA1c who, within the time frame, managed to reach the clinical goal (below 7%). Patients were separated into four segments according to the evolution of their HbA1c results, as follows:

a) *Compensated*: patients with all measurements under 7%, or at the most one measurement between 7% and 9%, inclusive, but with an average in terms of all measurements under 7%, i.e., it was accepted that these patients had exceeded the compensation limit once, but their average remained at a compensated level.

b) *Improved:* patients with a negative HbA1c slope and whereby their final measurement of the period was less than 7%, i.e., regardless of their initial value, such patients showed a tendency to reduce their HbA1c and end the study period in a compensated state.

c) *Moderately decompensated**:*** patients who did not reach or exceed 9% in any of their measurements, but who do not belong to the 'Compensated' or 'Improved' segments.

d) *Highly decompensated**:*** patients who recorded some measurements over 9% and who do not belong to the 'Improved' segment.

For example, Figure 7 shows a graphical representation of one patient from each defined segment. The HbA1c values of 7% and 9% are marked with dotted green and red lines, respectively. It can be seen that even though the compensated patient has one measurement equal to 7%, the average of his/her measurements is below 7%. In the case of the improved patient, despite that his/her HbA1c increased at one point, the overall trend for HbA1c was to decrease and the patient completed the period of study in a compensated state. The moderately decompensated patient never exceeded 9%, but failed to qualify as either improved or compensated. Finally, the highly decompensated patient spent the majority of the time with values in excess of 9% and failed to achieve compensated status by the end of the period.

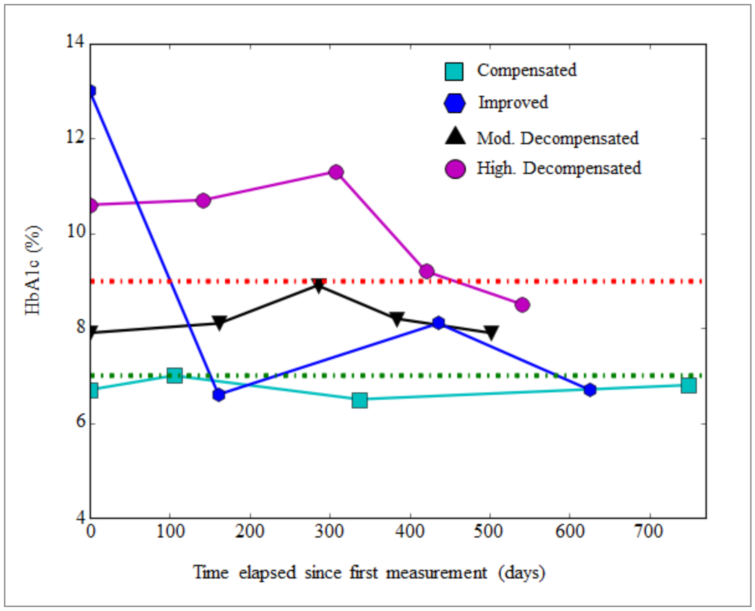


Figure 7. Example of the graphic representation of the clinical evolution of a patient of each segment.

4.2.6. Statistical analysis

The CTCV data of the 231 patients were collected, with a total of 1,116 CTCV appointments. The analysis to study whether there is a statistically significant relationship between the identified patterns and patient evolution was undertaken using a proportion test. Fisher's test was used when the evaluation sample proved to be too small. For each pattern, the proportion of patients who evolved in a specific manner was compared to those who evolved in the same manner in the total population studied. For all tests, the statistical significance was set to 0.05 and analysis was undertaken using R.

4.3. Results

4.3.1. Collaboration patterns

PALIA created 12 different models and 7.8% (18 patients out of 231) of outliers (see Figure 8, Figure 9, and Figure 10). As is the norm in healthcare processes, there is a high variability in the obtained results. The most frequently occurring behavior is present in 23.4% of cases (54 out of 231), followed by 11.3% (26 out of 231) with respect to the second group, decreasing to 3.0% for the final group (7 out of 231). Of the 12 models: six (models A, B, C, D, E and F) have three nodes; four (models G, H, I and J) have two nodes; and two (models K and L) have only one node.

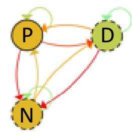
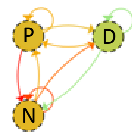
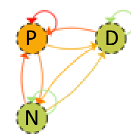
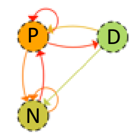
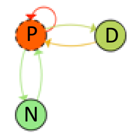
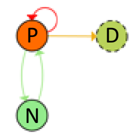
Models with Three Nodes						
Name	**Model A**	**Model B**	**Model C**	**Model D**	**Model E**	**Model F**
Diagram						
N° of Patients (% - out of 231)						
	23 (10.0%)	12 (5.2%)	21 (9.1%)	14 (6.1%)	9 (3.9%)	8 (3.5%)
Participation Index						
Physician	38%	37%	51%	54%	76%	76%
Nurse	37%	40%	23%	30%	4%	3%
Dietitian	25%	23%	26%	16%	20%	21%
Self-referral Index						
Physician	9%	24%	46%	38%	76%	68%
Nurse	17%	41%	6%	41%	0%	0%
Dietitian	4%	10%	9%	0%	0%	-
Referral Index						
P → N	49%	52%	32%	26%	7%	4%
N → P	38%	24%	63%	59%	100%	100%
P → D	42%	24%	22%	36%	17%	28%
D → P	28%	80%	54%	64%	100%	-
N → D	46%	35%	31%	0%	0%	0%
D → N	68%	10%	37%	36%	0%	-

Figure 8. Models with three nodes created by the PALIA Web application with parameters: similarity = 15% and outliers = 3%.

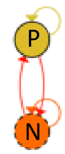
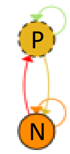
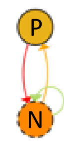
Models with Two Nodes				
Name	**Model G**	**Model H**	**Model I**	**Model J**
Diagram				
N° of Patients (% - out of 231)				
	54 (23.4%)	7 (3.0%)	13 (5.6%)	11 (4.8%)
Participation Index				
Physician	68%	34%	41%	41%
Nurse	32%	66%	59%	59%
Dietitian	-	-	-	-
Self-referral Index				
Physician	52%	25%	22%	0%
Nurse	13%	44%	38%	22%
Dietitian	-	-	-	-
Referral Index				
P → N	48%	75%	78%	100%
N → P	87%	56%	62%	78%

Figure 9. Models with two nodes created by the PALIA Web application with parameters: similarity = 15% and outliers = 3%.

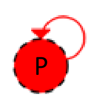
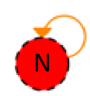
Models with One Node		
Name	**Model K**	**Model L**
Diagram		
N° of Patients (% - out of 231)		
	26 (11.3%)	15 (6.5%)
Participation Index		
Physician	100%	-
Nurse	-	100%
Dietitian	-	-
Self-referral Index		
Physician	100%	-
Nurse	-	100%
Dietitian	-	-

Figure 10. Models with one node created by the PALIA Web application with parameters: similarity = 15% and outliers = 3%.

By reviewing the models in greater detail, certain similarities between the identified behaviors can be observed. To identify the collaboration patterns, differences and similarities regarding the participation and self-referral indexes were analyzed for the 12 clusters created by the algorithm. This analysis was conducted separately according to the number of nodes present (disciplines that participated in the intervention) in each model.

There are two groups of patients that are treated by only one discipline during the entire period of study. One of these is treated solely by a physician (model K) and another solely by a nurse (model L). Both behaviors were classified under one pattern we called *Self-contained*, since, in this instance, only a single discipline attends to the patient.

Conversely, in the models with two nodes it is possible to observe that clusters G and H have one node that takes the lead in treatment, with a participation percentage that exceeds 65% in both cases (68% for the physician and 66% for the nurse, respectively). In addition, the 'leader' makes self-referrals in approximately half of all their CTCV appointments (52% and 44%, respectively) and refers the other half to a distinct discipline. In turn, the second node plays an important ancillary role in relation to the first one by referring the majority of their CTCV appointments to the discipline leader (over 70% of cases) while making very few self-referrals. These behaviors are classified under the *Tacit Leader* pattern, since one discipline has a greater participation because the other discipline refers the majority of their cases to the former. In particular, it can be observed that the physician is the leader in model G, while the role of leader is performed by the nurse in model H.

In the other two clusters with two nodes (clusters I and J), evident similarities also enable to group them into a single pattern. The participation index is the same in each node for both clusters, and the participation index for both disciplines are in the range 50%±10% (59% and 41%), i.e., the disciplines participate in an equitable way. By reviewing the referrals of the CTCV appointments, it can be seen that the level of self-referral is lower than in the aforementioned cases. Upon receiving a CTCV appointment, each discipline prefers to refer the patient to the other discipline (over 60% of cases in each model). This pattern was called *Shared*, since the participation of both disciplines is equitable, with no clear leader and whereby referrals among different disciplines are more prevalent than self-referrals.

Subsequently, the diagrams with three nodes underwent comparison. In clusters A and B, even though the dietitian participates to a lesser extent, the three disciplines have a more equitable participation than the other clusters according to their participation indexes. The node with the highest participation has a participation index of 40%. Therefore, there is no single discipline that acts as leader. There is some interaction across all disciplines, regardless of the direction of the interaction. In general, both clusters work in an integrated way and make referrals in a more equitable manner than the rest. Consequently, these clusters are grouped under a single pattern called *Participatory*.

Clusters C and D are characterized by the physician occupying the central role in the collaboration, with a participation index of 51% and 54%, respectively, compared to the nurse and dietitian who have a lower participation index. However, it can be seen that there is more integration in cluster C than in cluster D, in which there is almost no interaction between nurse and dietitian (in either direction). Rather, the nurse makes self-referrals in the majority of the CTCV appointments and refers almost no cases to the dietitian, compared to cluster C. Therefore, they are deemed two distinct patterns. Cluster C is called *Equitably Centered*, since the physician is at the center of collaboration and the other two disciplines participate equitably. The physician occupies the role of the sole leader, since he or she self-refers a significant proportion of cases (46%, compared to 6% for the nurse and 9% for the dietitian). The cluster D is identified as a *Hierarchically Centered* pattern, since the nurse occupies the role of secondary leader after the physician, by self-referring a significant portion of CTCV appointments. Furthermore, there is almost no interaction between nurse and dietitian.

Finally, clusters E and F are related in that the physician in both possesses almost complete control over all treatment. The physician presents a participation index that exceeds all other cases (76% in both clusters), which can be explained by the high self-referral index of the discipline (over 65%). In both clusters, the main interaction is between physician and dietitian, while the nurse's participation index is below 5% in both clusters. Clusters E and F have been grouped under a *Self-referred Leader* pattern.

The seven identified patterns are summarized in Table 15.

Table 15. Identified collaboration patterns.

Pattern	Description
Self-contained	Only one discipline (either nurse or physician) intervenes in patient treatment.
Tacit Leader	Two disciplines, nurse and physician, one of whom is the leader of the treatment.
Shared	Two disciplines, without a leader. Each discipline refers the majority of their CTCV appointments to another discipline.
Participatory	Three disciplines participate equitably. There is no leader.
Equitably Centered	Three disciplines, in which the physician is the leader. The nurse and the dietitian respond primarily to the physician, but they also interact among themselves (to a lesser extent).
Hierarchically Centered	Three disciplines, in which the physician is the leader. The nurse and the dietitian respond primarily to the physician, and they do not interact among themselves.
Self-referred Leader	Three disciplines, in which the physician has almost complete control over treatment, receiving only minimal support from the other disciplines, primarily the dietitian.

4.3.2. Clinical Outcome

By applying the aforementioned segmentation by clinical outcome to the 231 studied patients, 4 segments of patients were obtained. These segments are outlined in Table 16.

Table 16. Patient segments according to their HbA1c evolution.

Segments	No. of Patients (%)
Compensated	114 (49.4%)
Improved	37 (16.0%)
Moderately decompensated	45 (18.6%)
Highly decompensated	37 (16.0%)
Total	231 (100%)

Figure 11 shows the evolution of the segments, displaying the values of the HbA1c test for each patient over time. Each patient is represented by a line that corresponds to the value of his/her respective tests. The X-axis shows the time elapsed since the first measurement of each patient, according to the period of study (which is not the same calendar date for all patients).

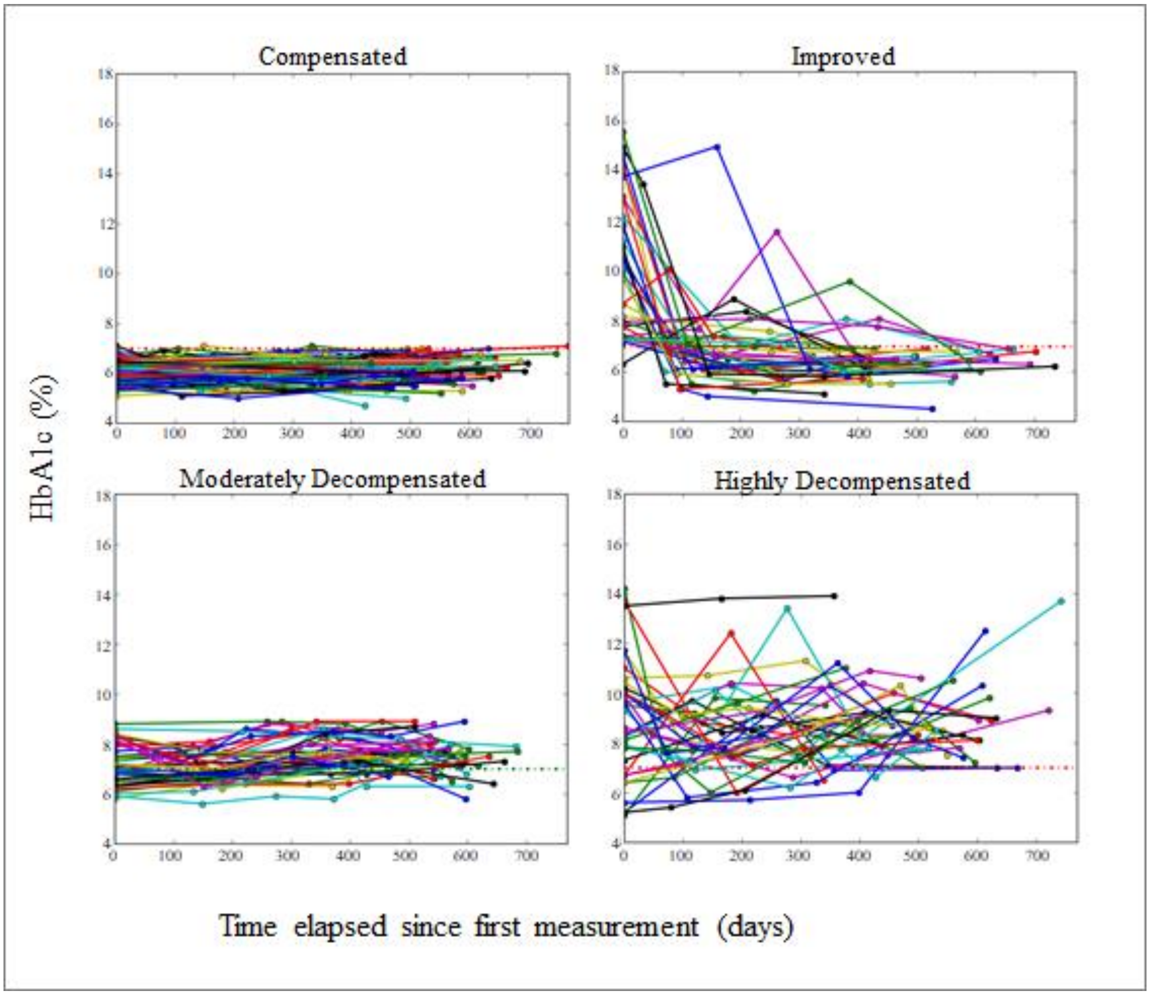


Figure 11. Clinical evolution of the patients in the different segments.

4.3.3. Relationship between collaboration and clinical outcomes

The final step of the proposed methodology is to conduct a statistical analysis to evaluate whether there is a statistically significant relationship between the different patterns identified and the evolution of patients. A proportion test was performed, and Fisher's test was used when the evaluation sample proved to be too small. For each pattern, the proportion of patients who evolved in a specific manner was compared to those who evolved in the same manner in the total population studied. For all tests, the statistical significance was set to 0.05 and analysis was undertaken using R.

In performing the proportion test, patients grouped under each collaboration pattern were considered as different subpopulations. For each subpopulation, the proportion of patients who evolved in a specific way in accordance with the four aforementioned compensation segments was calculated. As the number of patients is different in each subpopulation, the previous proportions were compared with the proportions of the total population. Table 17 outlines the overall frequencies and percentages obtained for each subpopulation and the total population, respectively.

Table 17. Number of patients according to collaboration pattern and clinical evolution segment.

	Compensated	Improved	Mod. Dec.	High. Dec.	Total
Self-contained	30 (73%)	3 (7%)	4 (10%)	4 (10%)	41 (100%)
Tacit Leader	23 (38%)	12 (20%)	15 (25%)	11 (18%)	61 (100%)
Shared	14 (58%)	2 (8%)	4 (17%)	4 (17%)	24 (100%)
Participatory	17 (49%)	10 (29%)	7 (20%)	1 (3%)	35 (100%)
Equitably Centered	7 (33%)	3 (14%)	5 (24%)	6 (29%)	21 (100%)
Hierarchically Centered	5 (36%)	1 (7%)	3 (21%)	5 (36%)	14 (100%)
Self-referred Leader	5 (29%)	2 (12%)	4 (24%)	6 (35%)	17 (100%)
Outliers	13 (72%)	4 (22%)	1 (6%)	0 (0%)	18 (100%)
Total	114 (49.4%)	37 (16.0%)	43 (18.6%)	37(16.0%)	231(100%)

The proportion test showed statistically significant differences for certain patterns versus the total population studied. The greatest difference was observed on patients treated under the Self-contained pattern, in which 24% more remained compensated compared to the total population (73% vs. 49%, P <0.01). The second difference occurs in the Participatory pattern, in which a lower proportion of highly decompensated patients is recorded compared to the total population (3% vs. 16%, P= 0.03). Finally, treatment under the Self-referred Leader pattern shows the worst result, with 19% more patients highly decompensated than the total population (35% vs. 16%, P= 0.05).

4.3.4. Evaluation by professionals

The results obtained were initially presented to a primary care physician. The physician noted that the Self-contained and Participatory patterns coincided with her experience. The relationship of compensated patients with the Self-contained pattern may be understood as: if a patient remains in a stable condition, it is more common for fewer disciplines to provide the medical attention. Conversely, the Participatory pattern provides evidence that suggests the importance of having a multidisciplinary team that oversees patient care, and also supports the significant role played by the dietitian in the treatment process, since they are the main promoters of change in terms of patient lifestyles.

After this preliminary evaluation, we assessed the results with three different groups of primary care physicians (one for each of the healthcare centers involved in the study). During each session, one of the researchers presented the results and answered questions. Then, the physicians filled out an informed consent form and answered a questionnaire aimed at understanding whether our results matched their experience, and gathering their perceptions, observations and concerns about the results. Finally, we conducted a brief discussion in which participants were free to voice their opinion, and one researcher took notes.

In total, 23 physicians participated in the evaluation. First, the participants stated whether they had observed each pattern and each segment. They were also able to name patterns and segments that had not been identified by the researchers. Then, participants answered a series of statements in a 5-point Likert Scale, and several open questions (e.g., "How useful are the relationships between patterns and segments?"). Some answers are provided below, translated from Spanish. A summary of the results is presented in Table 18.

The participants stated that, in their experience, treatment of DMT2 patients was Participatory or Equitably Centered. One participant wrote, *"I was surprised by the existence of a Self-contained pattern".* They did not identify additional patterns, but did state the existence of other interventions in their centers, e.g., educational workshops (to teach patients about how to handle DMT2), as well as other factors that may explain that a patient is always treated by a physician (One wrote: *"The disobedient pattern. Patients that go back* *to a physician although they were explicitly told to go to another professional (or that reject referrals)"*).

Regarding the patient segments, these were more commonly identified by the participants – all of the segments had been observed by at least 18 out of 23 (78%) of participating physicians. When asked whether other segments were missing from our proposal (according to their experience), 4 mentioned the *worsened* segment and 4 mentioned a *fluctuating* segment (which are both covered by the highly decompensated segment).

Table 18. Evaluation Results.

Patterns	**Observed by (%)**	**Segments**	**Observed by (%)**
Self-contained	5/23 (22%)	Compensated	20/23 (87%)
Tacit Leader	6/23 (26%)	Moderately Decompensated	21/23 (91%)
Shared	11/23 (48%)	Highly Decompensated	18/23 (78%)
Participatory	20/23 (87%)	Improved	21/23 (91%)
Equitably Centered	14/23 (61%)		
Hierarchically Centered	10/23 (43%)		
Self-referred Leader	8/23 (35%)		

Statement	**Agreement**
The patterns describe the main ways of collaboration in DMT2 treatment in this Center	4.4
The patterns allow a correct classification of the ways of collaboration in DMT2 treatment in this Center	4.2
Knowing these patterns may allow a better treatment of DMT2 in this Center	4.3
The segments describe the main behaviors of DMT2 patients in this Center	4.2
The segments allow a correct classification of the groups of patients treated for DMT2 in this Center	4.3
It would be useful to treat differently patients classified in each segment	4.4

Overall, the evaluation by healthcare professionals was positive. The physicians mentioned that the results could help them improve their protocols, patient treatment, and the management of human resources. Some mentioned that as there was no causal link established, they could not be certain that these changes would bring improvement.

4.4. Discussion

Main Results

The application of process mining techniques to the electronic clinical records of the healthcare centers enables the analysis of the collaboration among healthcare professionals. The advantage of the chosen algorithm is that it creates models that are easy to understand by healthcare professionals. With these visualizations, the professionals in question may be able to view the work undertaken in the healthcare centers and comprehend how their protocols are actually taking place.

Leveraging the availability of data to control and improve processes can facilitate finding deviations from established protocols. One concrete example of the usefulness of this capacity is to assess non-compliance with the norm that establishes appointments across three disciplines over the course of a year. It can be seen that 36.8% (85 out of 231) of patients had appointments with two disciplines during the period of study, while 17.7% (41 out of 231) with only one. Understanding how professionals collaborate may be useful in allocating resources according to existing requirements. It should be noted that in order to monitor processes, it is necessary to establish metrics that are aligned to that which professionals are seeking to control and improve.

In particular, the use of clustering techniques by graph topology facilitated overall management of the variability inherent to healthcare processes, in order to further understand the process. PALIA helped enable the observation of the variability with which patient care was undertaken and, within this variability, those characteristics that differentiate certain behaviors from others.

Comparison with Prior Work

By contrasting clinical evolution with the identified patterns, a number of differences can be observed. Certain comparisons showed statistically significant differences, which may signal a relationship between the collaboration pattern and overall patient evolution. Specifically, the Self-contained pattern has a higher proportion of compensated patients compared to the total population. It may be possible to explain because compensated patients are treated by a sole specialist and this type of medical appointment is generally sufficient for them to remain stable, given the state of their condition. Other papers have published results that correlate collaboration with clinical outcomes, as randomized collaboration studies versus a control group (Borgermans et al., 2009; Counsell et al., 2007; Wishah et al., 2015), or via classifications of collaboration (Bosch et al., 2008). However, these studies have been unable to provide objective evidence of the collaboration patterns by means of quantitative analysis and their correlation with patient evolution.

Treatment under the Participatory pattern is positively associated with patients who experience improvements in their evolution and it is also associated with a lower proportion of patients who remain highly decompensated. If the level of significance is relaxed to 0.1, both characteristics are statistically significant. This outcome differ with the findings of Uddin and Hossain (Uddin & Hossain, 2012), whereby their analysis considers only integration between physicians, in contrast to this paper, which incorporates evaluation by discipline.

The Hierarchically Centered and Self-referred Leader patterns are associated with significantly higher proportions of patients who are highly decompensated. This differs from the findings of Bosch et al. (Bosch et al., 2008), who have found no statistically significant differences between the types of hierarchical collaboration. The typology introduced by Bosch is based on qualitative analysis and is self-reported, which could produce a bias that explains the discrepancy. Teams working under these patterns may view themselves as providing treatments that are failing to reduce the number of decompensated patients to the desired extent. In the case of the Self-referred Leader, this discrepancy is statistically significant. Conversely, the Shared and Equitably Centered patterns show no statistically significant differences compared to the total population. Therefore, the conclusion is that these particular types of treatment approaches cannot explain the evolution of patients with DMT2. Finally, the Tacit Leader pattern shows a lower proportion of compensated patients, when compared to the total population studied (P=0.06). It can be inferred that this type of treatment focuses on patients who show some type of decompensation.

In light of the foregoing, it can be observed that the main difference between the patterns with positive and negative performance is a distribution of participation between the distinct disciplines, which in the best-case scenario relates to higher equitable participation. It also relates to more integrated interactions between different disciplines than the other models. More participatory forms of work function better than those in which there is just one leader with significant control over treatment. The correlation between treatments that are primarily controlled by the physician (Self-referred Leader) and an increase in HbA1c, compared to Self-contained treatment and its respective correlation with compensated patients, is particularly interesting. It could be reasoned that one specialist is sufficient to monitor the state of patients who are well controlled, whereas a multidisciplinary intervention may be more beneficial for patients who are poor controlled or have other diabetes-related conditions.

This paper presents preliminary empirical results in relation to the organization of healthcare teams and the response of their patients to DMT2 treatment. In contrast to the findings of Bosch in (Bosch et al., 2008), whereby the way in which teams organized themselves was self-reported, in this paper the used approach involved obtaining data from electronic clinical records to ensure the type of collaboration was more objectively verifiable. However, despite their use of a completely different methodology, certain similarities arose with the Bosch typification, which divided groups into Group Culture, Developmental Culture, Hierarchical Culture, Rational Culture, Cultural Balance and Team Climate. The relationships identified between the patterns and the evolution of patients does not necessarily constitute a causal link. A relationship in the opposite direction may, in fact, be possible. Indeed, certain external factors and individual characteristics of the patients could affect comparisons. For example, lifestyles, compliance with clinical indications, amount of exercise, or nutritional habits are all factors that may impact the evolution of patients with DMT2.

4.5. Limitations

The main limitation of the proposed methodology is that the analysis procedure and information used will be determined by the availability and quality of the data collected by information systems. The reception of incomplete and inconsistent data was one of the main problems faced. While the professional expert in the field is the individual who is able to guide analysis objectives, the availability of data is the factor that determines the steps that must be taken in order to address these objectives. Some relevant data, that may affect patient outcomes, were not available, e.g., some healthcare centers undertake education efforts in the form of workshops. Also, there was no available information about medication adherence. Therefore, there may be certain steps described in this paper that require adaptation if they are to be extended to other cases with additional (or fewer) data. One available variable that was not used in the analysis was age (e.g., the clinical goal for HbA1c at the centers for patients over 80 is 8% instead of 7%).

A further limitation is that multidisciplinarity was only measured at the level of the cardiovascular team and did not include other types of professionals. Moreover, data were only analyzed at the discipline level, regardless of the particular professional who provided care.

This study is based on data from 2012 on, so some results may not be representative to the present day. The clinical appointments included in this study relate to scheduled visits explicitly registered as CTCV appointments in the information systems. A comparison of collaboration between the different healthcare centers could also have been beneficial, although the proportion of patients in the related sample would have been extremely small to generate statistically significant results. The analysis was applied to a strictly select population (diabetic patients, in treatment without complications or relevant comorbidities). Therefore, we cannot assure that the results are extendable to other populations. In the future, it would be useful to execute this analysis using a larger sample.

Finally, future studies are recommended to include the severity of the patient condition and their comorbidities as variables in order to measure patient evolution via changes in these indexes over time, rather than using them as filters.

4.6. Conclusions

The use of process mining represents an opportunity for healthcare centers to understand how their processes are being executed, and which forms of collaboration lead to improved outcomes. The definition of simple clinical-based segmentations is critical for facilitating the interpretation of results. The process mining tool used in this research, PALIA Web, allows to analyze how different healthcare professionals collaborate in flexible and unstructured processes, such as the treatment of DMT2 patients. By combining trace clustering (to manage the diversity of patients present in the log) and collaboration pattern discovery techniques, it is able to identify several collaboration patterns among healthcare professionals in the treatment of patients. It also allows to easily visualize the obtained collaboration patterns so as healthcare professionals can interpret the differences between them. The methodology used in this study made it possible to analyze the relationship between these collaboration patterns and the clinical evolution of patients, so as to identify the most successful patterns. Finally, healthcare centers can then promote the most successful patterns among their professionals so as to improve the treatment of DMT2 patients.

5. CONTINUITY OF CARE AND CLINICAL RESULTS IN T2DM

5.1. Introduction

After the systematic literature review on multidisciplinary collaboration (Chapter 2) and the use of process mining approach (Chapter 4), we notice that the analysis of the disciplines interactions was not enough to understand the collaboration pattern. Due to that, we decided to include not just the disciplines, but the individual professionals participating in each patient's treatment.

The aim of the following analysis was to understand how the number of different professionals, and the changes of treating professional between consecutive visits could impact the metabolic control of T2DM patients. To do that, we measure different COC indexes and compare the results through pre-defined evolution segments using statistic tools.

5.2. Research Methodology

The reviewed research studying the relation between COC and clinical outcomes in patients with diabetes, shows that although all disciplines participating in the treatment of T2DM are important, COC has only been studied in depth for physicians. Furthermore, the specific features of the setting of the present study, which includes a high turnover of physicians in the healthcare centers, could affect the characteristics of COC for physicians. These issues generate the following research questions:

- Does a scenario with high turnover of physicians in primary care affect the positive relation between continuity of care and patient outcomes described in the literature?
- Is it possible to find an association between COC for the other disciplines involved in the treatment of diabetes (nurse and dietitian), and patient evolution?

To answer these questions, we analyzed data regarding appointment scheduling and HbA1c test results captured by information systems in three primary healthcare centers. We calculated COC using the most frequently used metrics available in the literature (UPC, HI, COCI, SECON) for the three involved disciplines, separately (physicians, nurses and dietitians). As clinical outcome, we used patient evolution, described as a categorical variable (stable, improved, worsened, moderately decompensated, and highly decompensated). We compared whether there were statistically significant differences in COC for the different patient evolution segments.

This section describes the research methodology used in this study in detail. First, we describe the setting of the study, followed by the patients that were selected for it. Then, we describe how the patient evolution segments were determined, the continuity metrics that we used, the descriptive variables of the population, and the statistical methods employed.

5.2.1. Subjects

The patients in this study were chosen from the healthcare center information records, in particular the appointments schedule and laboratory results, between 2012 and 2016. Only individuals diagnosed with T2DM were selected, and only appointments marked as CVPA with either GPs or FPs, nurses and dietitian were selected.

For analysis purposes, we consider as inclusion criteria that the patient has at least 12 months of treatment in the centers, in which time each individual was subject to at least 2 HbA1c tests, in order to establish evolution. Time of analysis was bounded to a maximum of 24 months, similar to timeframes utilized in previous research (Gulliford et al., 2007; Pollack et al., 2016; Younge et al., 2012). Most of the patients had been receiving care for a longer period of time. For those cases, we only considered the most recent 24-month period. As exclusion criteria, adherence to medical appointments was used. Only patients with acceptable adherence, established as 4 months beyond the expected date of appointment (Conca et al., 2018), were selected.

To analyze the results, we segmented patients by evolution of their HbA1c measurements. To do so, we used definitions similar to those utilized in a previous study: 3 segments of patients who could be categorized as belonging to a particular treatment segment (stable, moderately decompensated and highly decompensated), and another segment with positive evolution (Alvarez, Saint-Pierre, Herskovic, & Sepúlveda, 2018). The higher number of patients in our study, compared to previous studies using this segmentation, allowed us to identify a fifth category: patients with a negative evolution. Accordingly, the segments were defined as follows:

Improved: patients with an initial HbA1c equal to or greater than 7% and a final score lower than 7%, or with an initial HbA1c equal to or greater than 9% and a final score lower than 9%. In cases with more than 2 measurements, only those in which their linear regression had a negative slope were included.

Worsened: patients with an initial HbA1c lower than 7% and a final score equal to or greater than this value. In cases with more than 2 measurements, only those in which their linear regression had a positive slope were included.

Stable: patients with an average HbA1c lower than 7%, at most one score greater than this value but lower than 9%, and who do not belong to any of the aforementioned groups.

Moderately decompensated: patients with all their HbA1c results lower than 9%, and who do not belong to any of the aforementioned groups.

Highly decompensated: patients with at least one result over 9%, and who do not belong to the Improved group.

5.2.2. Continuity metrics

To measure COC, we used 4 metrics that have been used in several previous COC-related studies, in regard to diabetic patients as well as other chronic diseases: COCI (Bice & Boxerman, 1977), HI (Rhoades, 1993), UPC (John W. Saultz, 2003) and SECON (Ejlertsson & Berg, 1985). These 4 metrics were applied to each discipline separately. All these indices produced values between 0 and 1, where 1 corresponds to the case in which all appointments were provided by the same professional.

Table 19 outlines the formulas used to calculate the indices.

Table 19. Formulas for computing continuity of care indices used in the study.

Metric	Formula	Continuity aspect measured
Bice-Boxerman Continuity of Care Index (COCI)	$\frac{(\sum_{i=1}^{P} {n_i}^2) - N}{N(N-1)}$	Dispersion of appointments among the different professionals
Herfindahl Index (HI)	$\sum_{i=1}^{P} \left(\frac{n_i}{N}\right)^2$	Dispersion of appointments among the different professionals
Usual Provider of Care (UPC) Index	$\max_{i} \frac{n_i}{N}$	Concentration of appointments in a main professional
Sequential Continuity of Care (SECON) Index	$\frac{(\sum_{j=1}^{N-1} c_j)}{N-1}$ Where $c_j = \begin{cases} 0 \ if \ p_{j-1} = p_j \\ 1 \ if \ no \end{cases}$	Patient handoff among professionals

The variable n_i corresponds to the appointments of professional *i*, *N* to the total patient appointments, *P* to the total number of treating professionals, and p_j to the provider of the *j*-th appointment.

The indices for the three disciplines relevant to this study were calculated separately to understand how the types of care provided by each professional discipline related to patient evolution. For reference purposes, the Number of Providers (NOP) indicator was also considered for each discipline (Eriksson & Mattsson, 1983). This index can be used as a dispersion measurement, although it is not sensitive to changes in the appointment distribution among providers or to the differences in the total number of appointments of each patient.

The results of the measured indices can be interpreted as having high continuity if greater than 0.75 (75% of appointments provided by the same professional); a medium continuity for values between 0.30 and 0.74; and a low continuity for values less than 0.3 (Tousignant et al., 2014).

5.2.3. Descriptive variables of the population

The following population variables were taken into account: age; time spent living with diabetes; Chronic Illness with Complexity (CIC) index (Young et al., 2008); Diabetes Complications Severity Index (DCSI) (Meduru et al., 2000); sex; and medical practice where the appointment was undertaken.

The DCSI and CIC index describe the level of severity and complexity of the patient based on the presence of certain diseases that are relevant in the context of diabetes. The DCSI reflects the severity of the complications associated with diabetes, considering diagnoses belonging to the following seven categories: cardiovascular complications, nephropathy, retinopathy, peripheral vascular disease, cerebrovascular accident, neuropathy and metabolic disorders. The value of the index is the sum of the scores assigned to each category (without abnormality = 0, some abnormality = 1, or severe abnormality = 2). Exceptionally, the neuropathy can only have score 0 or 1. Therefore, the severity index reaches values between 0 (without abnormalities in any category) and 13 (in case of severe abnormality in all categories) (C.-C. Chen et al., 2013; Young et al., 2008). On the other hand, CIC measures the number of pathologies that the patient presents that are not related to diabetes, but that can also impact on their health condition. It considers the presence of diseases grouped into six categories: gastrointestinal, skeletal muscle, lung, cancer, substance abuse and mental illness. The index is calculated as the sum of the scores assigned to each category (0 = none of the diseases considered in the category is presented, 1 = one or more diseases belonging to the category are presented). Then, the comorbidity index reaches values between 0 (no disease on the list) and 6 (at least one disease for each category specified) (C.-C. Chen et al., 2013; Meduru et al., 2000).

5.2.4. Statistical analysis

Descriptive variables of the population were assessed for normality using a Shapiro-Wilk test. For variables with normal distribution, mean and standard deviation are presented. For variables that were not normally distributed, median, minimum and maximum values are presented. The dependence of patient segmentation with each descriptive variable was evaluated with a two-tailed chi-squared test.

In the case of continuity metrics, values of each metric are bounded to a (0,1) interval, so they are not normal by construction. However, as our objective was to verify if there is a relationship between each of those indices and the patient's evolution, we used a two-tailed Student's t-test to evaluate differences between the mean of each segment and the mean of the complete population. This analysis is possible because, in big samples with finite variance, we can assume that the mean is distributed approximately as a normal by the central limit theorem. Similar studies have used statistical tests of mean differences to assess the relationship between continuity and clinical results (Chang et al., 2018; C.-C. Chen et al., 2013; Romano et al., 2015; Younge et al., 2012).

The results of the continuity metrics are presented using the mean and the median. The minimum and maximum values are not presented since in each segment we found values 0 and 1 (limits of the metric).

Statistical significance was determined with p-value lower than 0.05. Analyses were performed using the R software (https://www.r-project.org/).

5.3. Results

1,836 out of a total of 3,369 patients met the inclusion criteria and were classified into the 5 defined segments. 60% of all patients were women, with a lower proportion in the worsened segment (50%) and higher in the highly decompensated segment (67%). The average age was 61 (SD = 11.5), and the average number of years with which patients had lived with diabetes was 4.4 (SD = 3.4). The CIC index scored an average of 1.30 (SD = 1.10), while the DCSI scored an average of 0.91 (SD = 1.37).

Table 20 outlines the descriptive variable values, and the p-value of the statistical test of independence between these values and the 5 defined patient segments.

Table 20. Characterization of patients by segments and total population of the study.

	Stable	Improved	Moderately Decompensated	Worsened	Highly Decompensated	Total population	χ^2 p-value between segments	Normality test p-value
Total [N (%)]	655 (36%)	325 (18%)	247 (13%)	221 (12%)	388 (21%)	1,836 (100%)		
Gender [N (%)]							< 0.001	
Male	246 (38%)	142 (64%)	104 (42%)	110 (28%)	129 (40%)	731 (40%)		
Women	409 (62%)	183 (56%)	143 (58%)	111 (50%)	259 (67%)	1,105 (60%)		
Age [mean (SD)]	63.1 (11.7)	61.0 (11.3)	63.1 (10.6)	59.4 (11.8)	58.4 (11.1)	61.3 (11.5)	0.519	0.025
Years w/T2DM [med (min, max)]	2.8 (0.0, 16.9)	5.2 (0.0, 24.9)	5.4 (0.0, 20.5)	3.5 (0.0, 17.4)	5.6 (0.0, 23.0)	4.6 (0.0, 24.9)	0.331	<0.001
CIC [med (min, max)]	1 (0, 5)	1 (0, 5)	1 (0, 5)	1 (0, 4)	1 (0, 5)	1 (0, 5)	0.181	<0.001
DCSI [med (min, max)]	0 (0, 8)	0 (0, 7)	0 (0, 7)	0 (0, 7)	0 (0, 8)	0 (0, 8)	0.018	<0.001
HbA1c [med (min, max)]								
First	6.2 (4.5, 6.9)	9.1 (7.0, 16.1)	7.6 (6.2, 8.9)	6.5 (4.7, 6.9)	8.9 (4.2, 16.4)	6.9 (4.2, 16.4)	< 0.001	<0.001
Last	6.1 (4.7, 6.9)	6.8 (4.5, 8.9)	7.5 (5.7, 8.8)	7.5 (7.0, 17.4)	9.7 (5.1, 15.3)	7 (4.5, 17.4)	< 0.001	<0.001

T2DM: Type 2 Diabetes Mellitus. CIC: Chronic Illness with Complexity index. DCSI: Diabetes Complications Severity Index.
A χ^2 test was used to assess dependence between each variable and the segmentation, obtaining as result that only DCSI is dependent of the evolution. A Shapiro-Wilk test for normality was also applied to the variables. Normal variables are described with mean and standard deviation, and non-normal variables are described with median value (med), accompanied by minimum (min) and maximum (max) values. Statistical significance was established as p-value < 0.05.

Table 21 shows the number of total appointments and appointments by discipline for the 5 patient segments. The number of appointments of physicians and nurses had values below average in the stable and worsened segments, and above average in the other segments. This is consistent with the difference in appointment frequency outlined in the treatment guidelines. Conversely, in the case of dietitians, it can be seen that the value is significantly lower only among patients from the worsened segment. By comparing the patients who remained stable with those who were stable but subsequently worsened, the only significant differences appear in appointments with the dietitian, with more appointments (p-value = 0.01) and more professionals (p-value < 0.01) than stable patients. All these differences are captured by the continuity metrics, thereby enabling comparisons to be made between patients.

Table 21. Patients and visits for each discipline by segments and total population.

VISITS	Stable	Improved	Moderately Decompensated	Worsened	Highly Decompensated	Total population
Patients (n (%))	655 (36%)	325 (18%)	247 (13%)	221 (12%)	388 (21%)	1,836 (100%)
Total visits (mean (med))	5.61 (5) *	9.30 (7) *	7.76 (7)	5.98 (5) *	10.48 (8) *	7.63 (6)
Physician visits (mean (med))	2.93 (3) *	3.94 (4) *	3.77 (4)	3.11 (4) *	4.27 (4) *	3.53 (3)
Nurse visits (mean (med))	1.89 (2) *	4.46 (2) *	3.14 (2)	2.29 (2) *	5.36 (3) *	3.30 (2)
Dietitian visits (mean (med))	0.80 (0)	0.90 (1)	0.85 (0)	0.58 (0) *	0.85 (1)	0.81 (0)

med: median. We applied a Shapiro-Wilk test for normality for each variable, obtaining that none were normally distributed (p-value < 0.001). Due to the large size of the sample, we applied a t-student test for comparing the mean of each segment with the mean of the total population. Statistically significant differences (p-value < 0.05) are marked with *.

Table 22 shows that Physician COC achieved a higher score in the case of stable patients according to the indices of UPC concentration (p-value = 0.03) and HI dispersion (p-value < 0.01), while highly decompensated patients showed a significantly lower continuity in the HI (p-value = 0.02). In the case of nurses, the behavior of the COC indices was similar, with the UPC and HI indicators generating higher scores in stable patients (p-value = 0.01 and < 0.01), and lower scores in highly decompensated patients (p-value < 0.01 in both indicators). In addition, the HI was significantly lower in the case of improved patients. The COC for dietitians showed no significant differences in the moderately decompensated segment, with lower continuity in the COCI, UPC and HI indices (p-values = 0.08, 0.08 and 0.07, respectively). However, the major difference in this segment was the adherence to treatment with the dietitian, with a lower participation of patients who worsened, but greater among those who improved (p-value < 0.01). The SECON index showed no significant differences in any of the 3 disciplines.

Table 22. Continuity of care indices for segments and total population.

COC METRICS	Stable	Improved	Moderately Decompensated	Worsened	Highly Decompensated	**Total population**
Physician						
Patients (n (%))	631 (96%)	319 (98%)	239 (97%)	208 (94%)	371 (96%)	**1,768 (96%)**
NOP (mean (med))	2.48 (2)*	2.92 (3)	2.97 (3)*	2.64 (3)	3.16 (3)*	**2.79 (3)**
COCI (mean (med))	0.30 (0.10)	0.27 (0.11)	0.26 (0.11)	0.30 (0.10)	0.28 (0.13)	**0.29 (0.10)**
UPC (mean (med))	0.57 (0.50)*	0.53 (0.50)	0.52 (0.50)	0.56 (0.50)	0.52 (0.50)	**0.55 (0.50)**
HI (mean (med))	0.54 (0.50)*	0.48 (0.38)	0.47 (0.38)	0.52 (0.41)	0.46 (0.38)*	**0.50 (0.40)**
SECON (mean (med)	0.33 (0.00)	0.34 (0.25)	0.31 (0.20)	0.33 (0.17)	0.35 (0.25)	**0.33 (0.20)**
Nurse						
Patients (n (%))	572 (87%)	289 (89%)	222 (90%)	189 (86%)	354 (91%)	**1,626 (89%)**
NOP (mean (med))	1.79 (2)*	2.42 (2)*	2.15 (2)	1.89 (2)*	2.65 (2)*	**2.15 (2)**
COCI (mean (med))	0.50 (0.33)	0.45 (0.33)	0.48 (0.33)	0.50 (0.33)	0.43 (0.32)	**0.47 (0.33)**
UPC (mean (med))	0.72 (0.67)*	0.66 (0.57)	0.68 (0.67)	0.72 (0.67)	0.64 (0.55)*	**0.69 (0.67)**

COC METRICS	Stable	Improved	Moderately Decompensated	Worsened	Highly Decompensated	**Total population**
HI (mean (med))	0.70 (0.56)*	0.61 (0.50)*	0.65 (0.56)	0.69 (0.56)	0.58 (0.50)*	**0.65 (0.50)**
SECON (mean (med)	0.51 (0.50)	0.51 (0.50)	0.52 (0.50)	0.52 (0.50)	0.48 (0.48)	**0.50 (0.50)**
Dietitian						
Patients (n (%))	319 (49%)	182 (56%)	118 (48%)	86 (39%)	200 (52%)	**905 (49%)***
NOP (mean (med))	1.25 (1)	1.21 (1)	1.31 (1)	1.21 (1)	1.21 (1)	**1.24 (1)**
COCI (mean (med))	0.79 (1.00)	0.82 (1.00)	0.74 (1.00)	0.81 (1.00)	0.84 (1.00)	**0.80 (1.00)**
UPC (mean (med))	0.89 (1.00)	0.91 (1.00)	0.87 (1.00)	0.90 (1.00)	0.92 (1.00)	**0.90 (1.00)**
HI (mean (med))	0.89 (1.00)	0.90 (1.00)	0.85 (1.00)	0.90 (1.00)	0.91 (1.00)	**0.89 (1.00)**
SECON (mean (med)	0.80 (1.00)	0.84 (1.00)	0.76 (1.00)	0.81 (1.00)	0.86 (1.00)	**0.82 (1.00)**

NOP: Number of Providers, COCI: Continuity of Care Index, UPC: Usual Provider of Care, HI: Herfindahl Index, SECON: Sequential Continuity, med: median.
Metrics are not normal by construction (they are bounded between 0 and 1). The minimum and maximum values for all metrics are 0 and 1, respectively. We applied a Shapiro-Wilk test for normality for each variable, obtaining that none were normally distributed (p-value < 0.001). Due to the large size of the sample, we applied a t-student test for comparing the mean of each segment with the mean of the total population. Statistically significant differences (p-value < 0.05) are marked with *. For each discipline, metrics were computed only for patients with at least one visit to a provider from this discipline.

5.4. Discussion

Approximately 75.2% of the Chilean population is insured by the public health care system, which is funded by a 7% mandatory deduction from salaries. An insured person may provide a fixed copay to be able to select their preferred healthcare provider, or may be treated at a predetermined facility, which provides free services to the lowest income population (18.1% of the overall population) (Ministerio de Salud de Chile, 2018). For them, primary healthcare is provided at centers called Centros de Salud Familiar (Family Health Centers, or CESFAM). CESFAM treat acute morbidities that may be solved or referred to a more complex center, and chronic morbidities that require periodic assessment, e.g., diabetes, hypertension, and chronic pulmonary disease. This study analyzed data pertaining to three university-affiliated CESFAM centers.

One of the main issues faced by the public Chilean healthcare system is a lack of physicians: particularly in the CESFAM, there is a lack of GP and FP. In Chile, the average number of patients per physician in primary care is 920, whereas the average in the private sector is 276, and in member states of the Organization for Economic Co-operation and Development it is 294 (Guillou et al., 2011; Indicators, 2017). Regardless, in metrics such as mortality amenable to health care, Chile has been found to have rates comparable to the OECD (Gay et al., 2011). Another relevant shortcoming of the primary healthcare system in Chile is the high turnover of healthcare professionals, particularly of physicians, due to the statutes that establish their working conditions. This reduces system effectiveness and impacts quality of care (Bass del Campo, 2012).

This study used a sample of 1,836 patients, with similar demographic characteristics to previous studies (C. C. Chen & Cheng, 2011; Younge et al., 2012). The results show two variables with differences among the segments: the DCSI score and gender. However, no correlation was found between DCSI and the metrics used to measure COC, or between any of the indices and the gender of the patients.

In this descriptive analysis, we did not propose an intervention – rather, we studied the data captured by the information systems while the healthcare professionals were using guidelines and protocols that should have been applied in every case. Considering this, we sought to understand whether the care provided by the centers varied in patients with different clinical outcomes.

Continuity of care has been extensively studied in previous research, particularly for physicians or multi-providers of care (Adler et al., 2010; Barker et al., 2017; Chang et al., 2018), but the particular characteristics of primary care in Chile (few physicians, with high turnover), which are also present in other countries, may impact the characteristics of continuity (Reddy, Pollack, Asch, Canamucio, & Werner, 2015). However, previous research had not focused on continuity of care for dietitians and nurses, which are two essential roles for the treatment of diabetes. Our results show that, as expected from previous research, physician continuity of care is related to patient evolution, and that nurse continuity of care has a similar relevance.

Physicians had a greater COC when treating patients from the stable segment and lower continuity for highly decompensated patients, with the latter also having appointments with the largest number of different professionals. Due to the high turnover of physicians in the centers, it is possible that patients who require more frequent visits encounter difficulties in reserving appointments with the same professional, therefore impacting COC. These results are consistent with findings from previous studies, in which more appointments and a greater number of different physicians have been associated with lower COC (Menec, Sirski, Attawar, & Katz, 2006).

The results showed the same tendency regarding nurses, albeit with higher COC values, which reflects a lower turnover of nursing staff compared to physicians. Noticeably, the stable and worsened segments were very similar. This could be due to the fact that both groups of patients begin the period with treatment similar to that outlined in the guidelines, which only varies when patients who worsen begin to show HbA1c results greater than 7%. These results suggest that the continuity of the nurse is as important as that of the physician for diabetic patients, which is consistent with the provisions outlined in national and international guidelines as well as in multiple studies (American Diabetes Association, 2017; Subsecretaria de Redes Asistenciales, 2010). Previous research in this area was qualitative or based on self-reported information, in contrast to our findings in which the metrics were calculated according to data extracted from an information system.

By comparing our results with previous studies, we see that values of the UPC index are similar to the results of previous studies in the case of physicians (Kohnke & Zielinski, 2017), but significantly higher for nurses. The same studies have identified a relationship between lower continuity and the rate of emergency services utilization. The relationship between COC and blood pressure in diabetic patients and those with cardiovascular diseases has also been studied previously, without identifying significant relationship between BP control and personal continuity after adjustment for total number of visits (Hanafi et al., 2015).

It should be noted that not only the participation or continuity of care of nurses in the treatment is relevant, but also their level of specialization. The role of Nurse Practitioner performed by the nurses of the centers is based on a model that is characterized by its holistic, quality, preventive and health promotion, for which nurses take certain tasks of physicians. This is important because, when we say that the continuity of nurses is important, we are referring to nurses who have a more advanced and preponderant role in the treatment of the patient and that can replace part of the physicians' functions. Proving that the continuity of nurses is as relevant as that of the physicians validates this role and the existing collaboration within the work team (Bass del Campo, 2012; Brooten et al., 2012).

Continuity in dietitians is somewhat different, since the indices show no major discrepancies between the segments but do demonstrate variations in terms of adherence to the protocol. According to the guidelines, all patients should visit the dietitian with the same frequency as a physician or nurse. However, during the period of analysis, approximately 50% of the patients failed to visit the dietitian, with the greatest adherence in the improved patient segment, and the least in the worsened segment. Previous studies have presented quantitative evidence on the link between the participation of a dietitian within a clinical team, which is to ensure the provision of balanced treatment among the 3 professionals of a care team, and a positive evolution in HbA1c levels (Conca et al., 2018). We should consider the possibility that patients with a lower adherence to dietitian appointments could also have lower adherence to medication or recommended behavior that could explain the differences. Future studies will need to analyze the causality of this relationship in greater detail.

Regarding the general context, Chile is a high-income country according to The World Bank data, as are the countries of the studies reviewed in this discussion (The World Bank, n.d.). The income level of the country has been associated to diabetes prevalence and diabetes-related complication risk (American Diabetes Association, 2017; World Health Organization, 2016). This condition, in addition to the demographic characteristics of the population, allows us to compare our results with previous literature. However, in our particular setting, patients belong to the lowest income population, which may be related to higher risk of diabetes-related complications (Bird, Lemstra, Rogers, & Moraros, 2015). Because of that, even when relative differences presented in each work are comparable with our results, one should be cautious with absolute comparisons between metrics.

Among the strengths of our study is the size of the population, which is comparable with sample size in related work, and the fact that medical decisions are based on a protocol based on HbA1c test results, which allows comparing patients with similar evolution assuming similar treatments. At the same time, the fact that a common protocol is being followed can also be considered as a weakness of this study, because patients are treated under particular conditions that might limit the universality of the results. Another limitation of this study is that it only considered HbA1c measurements as an outcome with which to segment the patients. More thorough analysis should consider other variables, e.g. blood pressure, cholesterol, weight, BMI, which were not available for our study. Also, we considered the last 12-24 months of data for each patient, without considering the time of diagnosis. Although most patients had already been under treatment for some time, some patients might have been recently diagnosed, and healthcare professionals might be willing to try different courses of action with patients who had been previously unsuccessful, even if the guidelines and health programs establish similar actions for all patients, according to the last HbA1c test result.

Our results show that, as expected from previous research, physician continuity of care is related to patient evolution, but also that nurse continuity of care has a similar relevance. Even though dietitians are too few to evaluate the impact of their continuity, patients who adhere to nutritional treatment have better outcomes. These results may help healthcare centers with little resources and high physician turnover to focus their protocols and guidelines towards maintaining nurse continuity and improving adherence to nutritional treatmnt.

5.5. Conclusions

Our study shows that there is an association between the continuity of care provided by physicians and nurses and the evolution of diabetic patients, as well as a relationship between dietitian visit adherence and evolution. Those results are interesting, particularly for nurses and dietitians, for whom there are not enough previous quantitative studies. The applied methodology allows to conclude that variables are related, but we cannot evaluate causality of the results. Further studies should focus on a specific intervention to assess causality.

Primary healthcare centers with little resources and high physician turnover, in line with the development of smart city services and aiming to maintain patient-centered policies, may focus their protocols and guidelines towards maintaining nurse continuity and increasing adherence to nutritional treatment.

6. MULTIDISCIPLINARY TEAM COLLABORATION NETWORKS IN DIABETES CARE: IMPLICATIONS FOR PATIENT OUTCOMES

6.1. Introduction

Multidisciplinary teams working collaboratively in diabetes care achieved better outcomes than those that were not multidisciplinary (Counsell et al., 2007). Previous work has shown significantly decreased results in HbA1c in collaborative treatments (Borgermans et al., 2009; Conca et al., 2018; Maislos & Weisman, 2004; Wishah et al., 2015), as well as improved results in low-density lipoprotein cholesterol (LDL-C) (Borgermans et al., 2009), body mass index (BMI) (Borgermans et al., 2009) and as blood pressure (Bosch et al., 2008). Other outcomes associated with collaboration have been length of stay, hospitalization cost, and readmission in diabetes-related conditions (Uddin & Hossain, 2012). In qualitative analysis, a collaborative approach also has shown to be related to improved patient knowledge about medications and diabetes, improved adherence to medication and diabetes self-care (Wishah et al., 2015), as well as better quality of care as perceived by the patients (L. H. Cheong et al., 2013). The most frequently used clinical outcomes to evaluate the effects of multidisciplinary collaboration in diabetic patients are HbA1c levels, systolic blood pressure, cholesterol levels, and weight (Ong et al., 2018; Schepman et al., 2013).

In this chapter we show how SNA techniques can be used to model multidisciplinary collaboration in order to analyze the relationship between different aspects of the collaboration and the clinical progression of patients with diabetes. Our model allows collaboration networks to be built considering its multidisciplinarity nature and the changes in the structure of teams over time.

6.2. Methods

Even though there have been several studies focusing on collaboration in healthcare, multidisciplinary collaboration has mostly been studied qualitatively. There is a lack of studies based on data analysis regarding how collaboration relates to clinical outcomes in the treatment of diabetes in primary care settings, where multidisciplinary collaboration is particularly important. The importance of continuity of care for patients with chronic conditions has also been well established for physicians and in some cases for other disciplines, but the concept of team continuity and how it changes over time has not been deeply studied. These aspects have generated the following research questions that guide our work:

- Can we quantitatively measure multidisciplinary collaboration and continuity of the care team?
- Are multidisciplinary collaboration and continuity of the care team associated with patient's progression in T2DM treatment?

In order to answer these questions, we used information from cardiovascular periodic appointments (CVPA) to model collaboration between professionals as a social network. Well-known metrics from graph theory, as well as ad-hoc metrics, were used to quantitatively compare collaboration and team continuity with patients' outcome. As measure of patient outcome, we used the progression of HbA1c, defined as a categorical variable (well-controlled, improved, worsened, moderately decompensated and highly decompensated).

The work presented in this chapter has two main contributions: (1) the proposal of a method to create collaboration networks that represent temporal variations in teams, and (2) the definition of metrics that can be used to measure aspects of collaboration such as collaboration network continuity.

This section describes the research methodology used in this study in detail. First, we describe the setting of the study, followed by the patients' inclusion and exclusion criteria, and how the progression segments were defined. Then, we describe how team collaboration networks are created, the existing SNA metrics we used, and the new SNA metrics we propose in this work.

6.2.1. Subjects

For our analysis, we used electronic medical record (EMR) data captured between 2012 and 2016. We considered patients diagnosed with T2DM as those identified by the International

Classification of Primary Care-2 [ICPC-2] code “T90”. For each patient we considered a timeframe of 12 to 24 months, during which they had at least two HbA1c test results in order to assess the progression of the patient. This timeframe is similar to other related studies (Gulliford et al., 2007; Pollack et al., 2016; Younge et al., 2012). When patients had more than 24 months of data, we used the last 24 for our analysis. Patients were filtered by adherence to the treatment (Alvarez et al., 2018; Conca et al., 2018), i.e. only those patients where the blood test periodicity and visits per year was over the minimum considered acceptable in the centers (Conca et al., 2018).

Patients were segmented according to the progression of their HbA1C test results during the studied timeframe. We used a definition used in previous studies, dividing the subjects into the following categories: stable, moderately decompensated, highly decompensated, and improved (Alvarez et al., 2018; Conca et al., 2018). We added a fifth segment of worsened patients, representing those patients in the moderately decompensated segment who had a first test result under 7% and whose progression had an increasing slope. The resulting categories are the following:

Improved: patients with a HbA1c initial value greater or equal to 7%, and a final value under 7%, or those that start the treatment with a HbA1c result greater or equal to 9%, and end with a result lower than 9%. In both cases, we only included those patients with a decreasing progression slope.

Worsened: patients with a first HbA1c test result lower than 7%, and a final value one greater than 7%, and having an increasing progression slope.

Stable: Well-controlled patients with an average HbA1c lower than 7% and at most one result between 7% and 9%, and that not belong to the previous segments.

Moderately decompensated: poorly controlled patients with each of their HbA1c test results lower than 9%, and that not belong to the previous groups.

Highly decompensated: poorly controlled patients with at least one HbA1c test result over 9%, and that are not in the Improved group.

Data used in our analysis were extracted from the EMR and lab results. We only considered appointments marked as Cardiovascular Periodic Appointment (CVPA), given by general practitioners or family physicians (GP/FP), nurses (N) and dietitian (D). As an example, Fig. 1 shows the HbA1c test results progression of the patients, each belonging to a different segment.

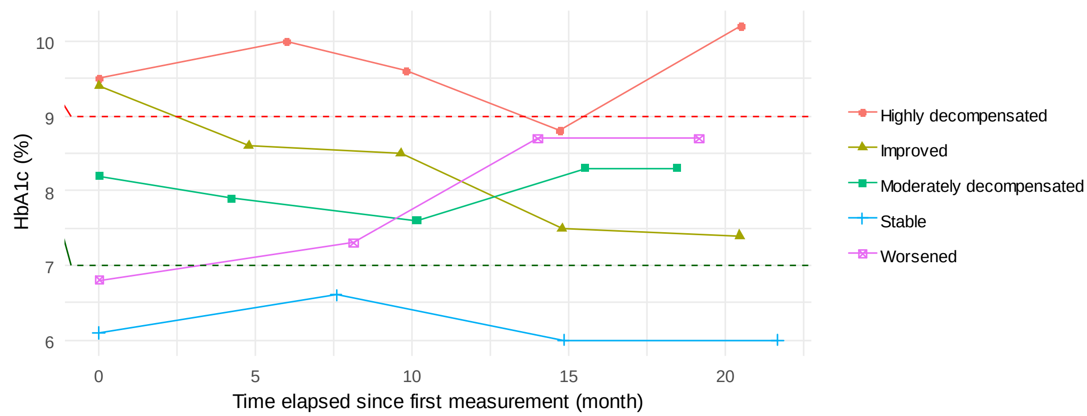


Figure 12. Example of HbA1c progression for 5 real patients, each one belonging to a different segment.

6.2.2. Definition of T2DM care team

We conducted a series of interviews in the three primary healthcare centers involved in the study, in order to understand what a "team" was in the context of T2DM treatment in these centers. We interviewed 5 healthcare professionals from different disciplines individually and also conducted 3 sessions of group interviews, one per center, totaling 33 professionals from different disciplines. The interviewees were asked how teams collaborate daily, how information is shared between them, and how teams change over time.

Teams have formal collaborative activities (e.g., meetings, case management, collaborative creation of intervention plans, shared medical appointments) and informal activities that happen spontaneously on a daily basis (e.g., hallway conversations and instant message chats). These collaborative activities are consistent with those found in the literature on collaboration in primary healthcare (Saint-Pierre, Herskovic, & Sepúlveda, 2018).

Information about patients is mainly transmitted through the use of EMR, and they are rigorous in filling all the information and forms in the system. Although not every case is treated in an explicit collaborative manner, each individual within the patient's network influences the behavior of their connections, generating homogeneity in the way the patients are treated, and in the spreading of ideas and practices (Fattore et al., 2009). As a result of our qualitative work, we defined a care team as "the group of physicians, nurses and dietitians who belong to the same clinical practice and work collaboratively in the care of the same patient during a certain period of time".

6.2.3. Team collaboration networks

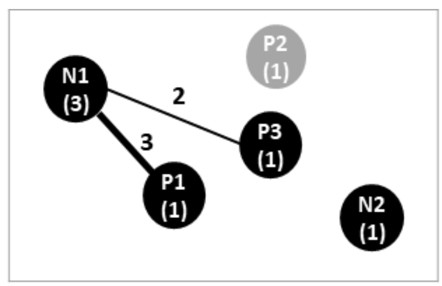
Based on the information gathered qualitatively and our review of the literature, we propose building team collaboration networks based on SNA techniques. Each network represents the group of professionals who treated a particular patient in a period of time, and how they are connected to each other.

A team collaboration network was built for each patient, considering the professionals that were part of their treatment. In each network, represented as a graph, two professionals are connected if and only if, they were part of the same practice during the time period in which the patient was treated. The more appointments a patient has with the same team, the stronger the connection between the professionals in the patient's network. Conversely, when a patient is treated by a new professional, and all the previous professionals are no longer in the clinical practice, there is a complete breakdown in the management continuity (and therefore, in the transmission of the clinical and contextual knowledge). In the process of constructing each patient network, we used the date of the visits recorded in the EMR system to verify whether two professionals had been part of the same team at the moment of each attention.

An example of the creation process of the team collaboration network is shown in Fig. 2. The patient in this example had 7 CVPA with 5 different healthcare professionals in the time period. The professionals belong to 2 clinical practices: black and gray. In the first 3 visits (a, b and c), the patient was treated by N1 and P1 in the black practice. In that moment, only those two professionals were part of the care team, since the other 3 had not started working in the center yet. The fourth visit (d) was to P2 in the gray practice. In the following two visits (e and f), the patient met N1 and P3 in the black practice, but P1 is no longer part of the team. At last, the patient met N2, who was a new member of the team, at the black practice, and none of the previous treating professionals were part of the team anymore. So N2 is not connected with any other professional of the black practice.

In the previous example, there are two isolated professionals: N2 from the black practice, and P2 from the gray practice. Although one of them belongs to a different practice than the others, for the purpose of our analysis, we will consider three different teams that treat the patient, independently of the practice each one belongs to. Therefore, in the following analysis we do not consider the practice of the professional, but how they are structured around the patient's treatment. For the network construction, professionals were numbered independently for each patient, i.e. the first appointment with a GP/FP will be with professional P1.

	Date (m/d/y)	Practice	Professional
a	9/12/2014	Black	Nurse 1 (N1)
b	11/04/2014	Black	Physician 1 (P1)
c	12/02/2014	Black	Nurse 1 (N1)
d	04/20/2015	Grey	Physician 2 (P2)
e	10/04/2015	Black	Nurse 1 (N1)
f	12/27/2016	Black	Physician 3 (P3)
g	03/03/2017	Black	Nurse 2 (N2)



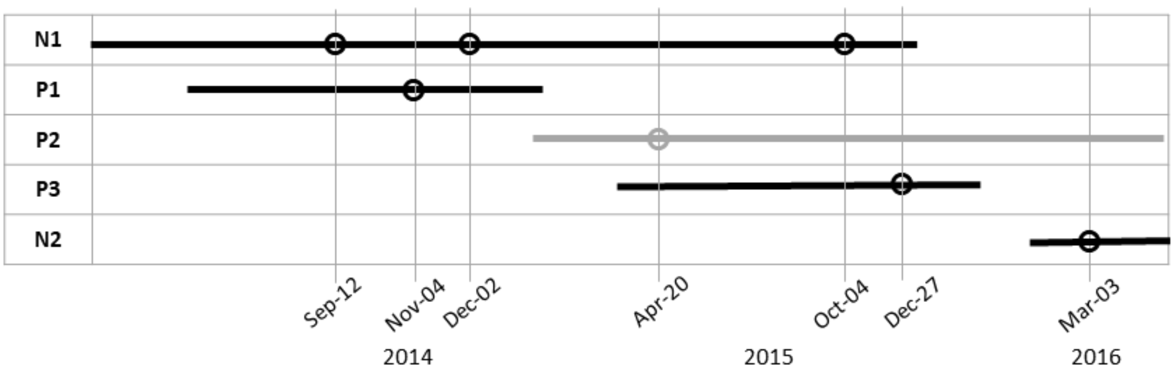


Figure 13. Example of the creation of a team collaboration network.

Formally, we define a team collaboration network of a patient i as an undirected graph $G = \{V, E\}$. The set V corresponds to the set of tuples (v, w_v), where v represents each provider and w_v the number of CVPA provided by them, and the set E is the set of tuples $(j, k, w_{j,k})$, where j and k are two different providers, and $w_{j,k}$ is the number of times both of them work collaboratively in the treatment of the patient i. Each provider v belongs to a subset V_d that groups all the providers of discipline d, with $V = \bigcup_d V_d$.

A graph G is called *connected*, if all its nodes are linked, either directly or through other nodes, i.e., there are no unreachable nodes. A graph that is not connected is called disconnected. Each subset of connected nodes in a disconnected graph is called a component. By definition, a connected graph will have just one component, whereas a disconnected graph could have as many components as nodes. Fig. 3 shows the networks constructed for 4 real patients from our study. Each node v represents one professional (P, N or D) and is labeled with its weight w_v. Edges are labeled with $w_{j,k}$. Colors of the nodes represent different teams, that can or cannot be part of the same practice.

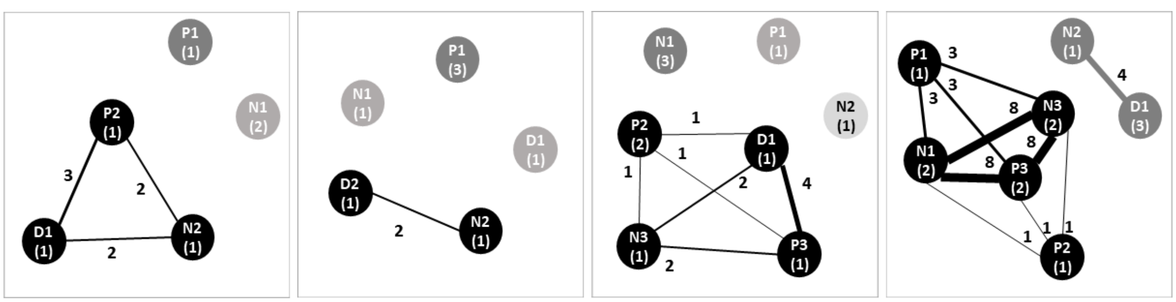


Figure 14. Example of team networks constructed for 4 real patients.

6.2.4. Collaboration network metrics and indexes

The created networks reveal how teams interacted during the treatment. We computed network metrics based on graph theory for each network (Durugbo et al., 2011). We also created new metrics to measure other aspects of team continuity and collaboration.

SNA metrics

a) Density

Density is a measure of how connected the group of professionals that have treated the patient is. A completely connected network, i.e., with density equal to 1, indicates that the patient was treated by only one team, where each pair of professionals worked on the same practice at the time of at least one patient visit. On the other hand, a network with density equal to 0 indicates that the patient was treated by professionals who were never part of the same team. A denser network can be interpreted as a more cohesive team (Kadushin, 2011). In a denser network, information can flow quickly between team members, and social processes may result in positive intentions to use new information in daily practice (M.P. et al., 2015). Density (δ) is calculated as follows:

$$\delta = \frac{2\ |E|}{|V|\ (|V| - 1)}$$

Where $|E|$ is the number of edges present in the network, and $|V|$ the number of nodes or professionals in the patient's treatment. Notice that $|V|\ (|V| - 1)/2$ corresponds to the maximum number of possible connections in an undirected graph of $|V|$ nodes.

b) Betweenness centrality for valued graphs

Centrality metrics in SNA consider the connections in a graph as channels of communication linking the group members with one another (Leavitt, 1951). In particular, *betweenness centrality* is based on the assumption that information is passed from one person to another only along the shortest paths linking them, i.e. the least number of edges and intermediate nodes required to connect each other. People in between others' path of communication can facilitate or inhibit the communication of others and are, therefore, in a position to mediate the access of others to information, power, prestige or influence (Freeman, Borgatti, & White, 1991). In our model, each edge has a value $w_{j,k}$, that reflects the number of interactions between two nodes related to the patient's treatment. So, if we understand the edges as channels of communication linking pairs of people, then the value of the connection determines the capacity of the channel linking them, or the maximum amount of information that can be passed between them (Freeman et al., 1991).

Betweenness centrality for valued graphs is computed for each node in the network, and is defined as follows:

$$B_{v_i} = \frac{\sum_j \sum_{k>j} m_{j,k}(v_i)}{\sum_j \sum_{k>j} m_{j,k}}$$

Where $j, k \neq i$; $m_{j,k}$ corresponds to the maximum flow of information between nodes v_j y v_k through every path connecting them; and $m_{j,k}(v_i)$ corresponds to how much of this information passes through v_i. This metric reaches values from 0 to 1, representing the proportion of the information that flows in the network and where v_i is involved.

As a graph-level centrality metric, we identified the node with highest B_{v_i}, and measured how far the other nodes are from it, to see whether information is centered on one central node. The graph betweenness centrality used in our analysis is defined as follows:

$$B = \frac{\sum_i [\max(B_{v_i}) - B_{v_i}]}{|V| - 1}$$

The values reached for this metric are in a range from 0 to 1. The 1 value is obtained when there is a central node and every other node is connected to each other through it and not directly (star shape).

Proposed metrics

c) Interdisciplinary Collaboration

Our model links together professionals from different disciplines who intervene in a patient's treatment. The goal of the *interdisciplinary collaboration* metric is to understand how two disciplines collaborate, without considering the number of healthcare professionals that participate in each. We define the interdisciplinary collaboration metric as the ratio between the number of times that professionals from both disciplines participated in the same team, over the total number of visits. This metric reflects the intensity of the collaboration between both disciplines. Formally, this metric is calculated as the sum of the value $w_{i,j}$ of the edges connecting providers from those disciplines, over the total potential links. The values of this metric are between 0 and 1, where the maximum value is reached when the providers of those two disciplines were part of the team in each patient visit. Interdisciplinary collaboration is defined as follows:

$$IC_{M-M'} = \frac{\sum_{i,j \in M \times M'} w_{i,j}}{Q\ |V_M||V_{M'}|}$$

Where M and M' are different disciplines, i and j are two providers from M y M', respectively; $w_{i,j}$ the number of times professionals v_i and v_j where part of the same team; V_My $V_{M'}$ the subsets of providers from both disciplines; and Q the total number of visits.

d) Total collaboration

The *total collaboration* metric seeks to measure how much the professionals of a team collaborated among them in the treatment of a patient, measured as the proportion of times in which the professionals worked together in a team without considering the discipline they belong to, over the total of potential connections. When all the treating professionals have been part of the same team during all the visits of the patient, a maximum total collaboration equal to 1 is obtained. On the contrary, if none of the professionals was part of the same team during the whole treatment, the total collaboration is equal to 0. This metric is similar to the density metric but considers the weight of the edges. The total collaboration metric is described as:

$$Total\ Collaboration = \frac{2\sum_i \sum_{j>i} w_{i,j}}{Q|V|(|V|-1)}$$

Where $w_{i,j}$ corresponds to the number of times professionals v_i and v_j were part of the same team, V to the set of providers involved in the treatment, and Q to the total visits of the patient.

e) Team Continuity

In the proposed model, each component of the graph is considered to be a different team, thus, a connected graph in a patient's treatment reflects that every involved professional was part of the same care team. In practice, this means that, between two consecutive visits of the patient, at least one of the treating professionals remained on the team. By maintaining the continuity of a team, we assume that the way the patient's treatment is handled is consistent between visits. Thus, a completely connected graph shows that the collaboration was maintained between all the patient's visits, being treated by only one team. Disconnected graphs are obtained when either a patient had to visit a provider from another practice, or when the completed team changed between any two consecutive visits. A completely disconnected graph has as many teams as professionals in the treatment of the patient. Thus, the *team continuity* metric is defined as follows:

$$Team\ Continuity = \frac{|V| - S}{|V| - 1}$$

Where S is the number of connected components in the graph.

This metric reaches values between 0 and 1, where 0 is obtained in a network where every node is isolated, and 1 in patients treated by only one care team.

f) Concentration

The team continuity metric evaluates how distributed treatment is among different teams, without considering the number of professionals in the team. Alternatively, the *concentration* metric evaluates the size of the largest team that treated the patient, in comparison to the total number of providers. Therefore, a patient treated by two teams may have the same team continuity regardless of how these teams are organized (e.g. two teams that are the same size, or a large team and one isolated professional) but will have different concentration. Formally, we define concentration as the proportion of providers who are connected in the largest component of the network. It is computed as follows:

$$C = \frac{\max_{j \in V}(S_j)}{|V|}$$

Where S_j is the number of providers in the j^{th} team involved in the patient's treatment.

g) Multidisciplinary collaboration

We considered as *multidisciplinary collaboration* the existence of professionals from each of the three disciplines inside the care team. Greater multidisciplinary collaboration is achieved when professionals of the three disciplines are on the same team in more visits of the patient. The maximum multidisciplinary collaboration is then reached when the professionals of the three disciplines are part of the same team during all visits. This concept can be observed in the network as connected triads of nodes from different disciplines. In order to measure how multidisciplinary a treatment is, we consider the weight of the edges of these triangles in the graph, over the case in which all professionals collaborate at the time of all visits. This metric is described as:

$$MC = \frac{\sum_{i,j,k \in P \times NxD} \min(w_{i,j}, w_{i,k}, w_{k,j})}{Q\ |V_{\mathcal{P}}|\ |V_{\mathcal{N}}|\ |V_{\mathcal{D}}|}$$

Where $V_{\mathcal{P}}$, $V_{\mathcal{N}}$ and $V_{\mathcal{D}}$ correspond to the subsets of physicians, nurses and dietitians who are involved in the patient's treatment.

6.2.5. Descriptive variables of the population

The following descriptive variables of the population were considered: age, gender, years living with diabetes, Chronic Illness with Complexity index (CIC) and Diabetes Complications Severity Index (DCSI). The CIC index contains information regarding nondiabetes physical illness complexity (including cancers, gastrointestinal, musculoskeletal, and pulmonary diseases), diabetes-related complexity, and mental illness/substance abuse complexity (Meduru et al., 2000). The DCSI consists of scores (no (0), some (1), or severe (2) abnormality) from 7 categories of complications: cardiovascular complications, nephropathy, retinopathy, peripheral vascular disease, stroke, neuropathy, and metabolic disorders (Utilization et al., 2013).

6.2.6. Statistical analysis

The normality of the metrics and the descriptive variables of the population was tested through the Shapiro-Wilk test, establishing significance with a p-value lower than 0.05. All of the tested variables were not normally distributed, so in our results we include the median, minimum and maximum value of each one. The Kruskal-Wallis test was used to study association between the descriptive variables and the patient progression segment.

All of the metrics used to measure aspects of collaboration are defined in the (0,1) interval, so they are, by definition, not normally distributed. However, since we wanted to identify differences in collaboration between the evolution segments, and we had enough data, we applied a two-tailed Student's t-test between each pair of segments. This analysis is shown in Tables II and III.

Finally, to analyze correlation between collaboration metrics and number of visits, we compared groups of patients with similar number of visits using a two-tailed Student's t-test.

This study used the R software (version 3.5.1) for statistical analysis, with the igraph and sna libraries.

6.3. RESULTS

6.3.1. Population characteristics

From a total of 3,369 patients diagnosed with T2DM, 2,962 had at least 2 HbA1c test results; from them, only 1,836 had an acceptable adherence to the HbA1c test frequency protocol; and from them, 1,424 patients had at least 12 months of data. Finally, considering compliance with the visit frequency protocol, a set of 974 patients was left, who were divided in the 5 previously defined segments.

Table 23 shows a characterization of the population by segment. Women were between 49% and 70% of the population for each segment with a higher proportion of women in highly decompensated patients, and a lower proportion in worsened patients (p-value 0.019). Average age of patients was 63, with a significant lower value in highly decompensated, and significant higher value in stable and moderately decompensated patients (p-value <0.01).

Average years living with diabetes has significant differences among segments (p-value < 0.01), with a lower value in stable patients, and higher in highly decompensated and improved patients. CIC index do not shows association with patient segments, while DCSI score shows a higher value in patients from the highly decompensated segment (p-value 0.02), with a median of 1. This score reaches values between 0 and 13, so the difference is not clinically relevant..

Table 23: Characterization of study population.

	Stable	**Worsened**	**Highly decompensated**	**Moderately decompensated**	**Improved**	**POPULATION**	**p-value Kruskal-Wallis test**
Patients	270 (28%)	91 (9%)	257 (26%)	153 (16%)	203 (21%)	**974 (100%)**	
General characteristics							
Female *[n (%)]*	168 (62%)	45 (49%)	179 (70%)	94 (61%)	119 (59%)	**605 (62%)**	0.019
Age *[med (min,max)]*	66 (34,95)	62 (36,88)	60 (30,94)	66 (36,93)	64 (33,89)	**63 (30,95)**	0.000
Years living with T2DM *[med (min,max)]*	4 (1,12)	5 (1,20)	8 (1,26)	7 (1,22)	8 (1,20)	**7 (1,26)**	0.000
DCSI score *[med (min,max)]*	0 (0,6)	0 (0,5)	1 (0,8)	0 (0,7)	0 (0,7)	**0 (0,8)**	0.018
CIC index *[med (min,max)]*	1 (0,5)	1 (0,4)	1 (0,5)	1 (0,5)	1 (0,5)	**1 (0,5)**	0.286
Number of visits							
Total of visits *[med (min,max)]*	8 (5,15)	8 (5,45)	11 (5,77)	8 (5,33)	9 (5,89)	**8 (5,89)**	0.000
Physicians *[med (min,max)]*	4 (0,8)	4 (0,9)	5 (0,13)	4 (1,10)	5 (0,14)	**4 (0,14)**	0.000
Nurses *[med (min,max)]*	2 (0,9)	3 (0,35)	4 (0,73)	3 (0,26)	3 (0,77)	**3 (0,77)**	0.000
Dietitians *[med (min,max)]*	1 (0,7)	1 (0,4)	1 (0,5)	1 (0,8)	1 (0,6)	**1 (0,8)**	0.238
Number of providers							
Total of providers *[med (min,max)]*	6 (2,12)	6 (2,15)	7 (2,16)	6 (3,14)	6 (2,17)	**6 (2,17)**	0.001
Physicians *[med (min,max)]*	3 (0,7)	3 (0,8)	4 (0,8)	3 (1,7)	3 (0,9)	**3 (0,9)**	0.006
Nurses *[med (min,max)]*	2 (0,5)	2 (0,8)	3 (0,8)	2 (0,8)	2 (0,8)	**2 (0,8)**	0.000
Dietitians *[med (min,max)]*	1 (0,3)	1 (0,2)	1 (0,3)	1 (0,3)	1 (0,2)	**1 (0,3)**	0.257
HbA1c test results							
First *[med (min,max)]*	6.1 (4.6,6.9)	6.4 (5.6,6.9)	8.9 (4.2,16.4)	7.5 (6.3,8.9)	9.2 (7.0,16.1)	**7.4 (4.6,16.4)**	0.000
Last *[med (min,max)]*	6.0 (4.9,6.9)	7.5 (7.0,17.4)	9.7 (5.4,15.3)	7.5 (5.7,8.8)	6.8 (4.5,8,9)	**7.2 (4.5,17.4)**	0.000
Last – First *[med (min,max)]*	0.0 (-1.6,1.2)	1.2 (0.1,11.2)	0.3 (-7.0,5,7)	0.0 (-1.9,1.5)	-1.8 (-8.6,-0.2)	**-0.1 (-8.6,11.2)**	0.000

T2DM: Type 2 Diabetes Mellitus. CIC: Chronic Illness with Complexity index. DCSI: Diabetes Complications Severity Index. A Shapiro–Wilk test for normality was applied to the variables obtained that all distributions were non-normal. Variables are described with median value, accompanied by the minimum (min) and maximum (max) values. A Kruskal-Wallis test was used to assess the dependence between each variable and the segmentation. Statistical significance was established as p-value < 0.05.

Regarding the number of visits, the Kruskal-Wallis statistical test shows an association between progression segments and the number of visits to: all providers, only physicians and only nurses (p-value < 0.01 in every case). The highest values in those variables are obtained in highly decompensated patients, while the lowest values are from the stable (well-controlled) segment. The number of dietitian visits, however, does not show an association to the segments.

In terms of the number of different professionals involved in the treatment, we also found an association between progression segments and the number of providers for: all providers, only physicians and only nurses (p-value < 0.01 in every case). Highly decompensated patients had a higher number of total professionals, physicians and nurses. The number of dietitians visited by the patients, however, does not show an association to the segments.

By construction, segments are associated with first and last HbA1c test result, as well as the HbA1c last – first result (p-value < 0.01 in each variable).

6.3.2. Results by segment of evolution

Table 24 displays the mean of the metrics computed for each team collaboration network, by segment and total population. Table 25 shows the p-value of the student's t-test for the comparison of two means, for pairs of segments.

Table 24: Average of metrics computed for each patients' network, by segment.

	Stable	Worsened	Highly decompensated	Moderately decompensated	Improved	POPULATION
Density	0.41	0.36	0.36	0.37	0.39	0.38
Betweenness	0.19	0.18	0.16	0.16	0.17	0.17
IC P-N	0.21	0.18	0.17	0.18	0.21	0.19
IC P-D	0.12	0.05	0.06	0.08	0.08	0.08
IC N-D	0.10	0.04	0.05	0.07	0.06	0.07
Total collaboration	0.20	0.17	0.16	0.16	0.18	0.18
Team continuity	0.67	0.62	0.66	0.65	0.66	0.66
Concentration	0.64	0.61	0.60	0.60	0.62	0.62
Multidisciplinary collaboration	0.05	0.02	0.02	0.03	0.03	0.03

P-N: physician-nurse; P-D: physician-dietitian; N-D: nurse-dietitian

Density mean in the networks was 0.38, i.e., for each patient, a 38% of the professionals involved in the treatment coincided in at least one visit. Comparison between segment pairs for this variable showed that there is a statistically significant difference between patients in the stable segment (well-controlled patients), with a denser network (p-value 0.03). The betweenness centrality metric, which reflects the extent to which the information is concentrated in a central professional, did not show differences between any segment and the population.

Table 25. T-student test p-value for mean comparison between each pair of segments

	S / W	S / HD	S / MD	S / I	W / HD	W / MD	W / I	HD / MD	HD / I	MD / I
Density	0.03	0.01	0.02	0.21	0.73	0.74	0.20	0.97	0.17	0.26
Betweenness	0.58	0.06	0.11	0.15	0.36	0.44	0.53	0.90	0.83	0.93
IC P-N	0.18	0.00	0.04	0.61	0.49	0.82	0.32	0.59	0.03	0.13
IC P-D	0.00	0.00	0.01	0.02	0.39	0.12	0.06	0.36	0.19	0.74
IC N-D	0.00	0.00	0.07	0.01	0.41	0.10	0.23	0.26	0.60	0.53
Total collaboration	0.09	0.00	0.02	0.12	0.80	0.88	0.52	0.92	0.22	0.34
Team continuity	0.01	0.45	0.19	0.58	0.07	0.22	0.05	0.53	0.87	0.45
Concentration	0.08	0.00	0.01	0.08	0.55	0.66	0.68	0.89	0.18	0.30
Multidisciplinary collaboration	0.00	0.00	0.06	0.04	0.42	0.10	0.09	0.27	0.24	0.99

P-N: physician-nurse; P-D: physician-dietitian; N-D: nurse-dietitian
S: Stable; W: Worsened; HD: Highly decompensated; MD: Moderately decopensated; I: Improved.

Regarding interdisciplinary collaboration metrics, in the physician-nurse dyad, the comparison by pairs of segments shows significative differences between stable segment and both, highly and moderately decompensated segments, with higher collaboration in well-controlled patients (p-value <0.01 and 0.04 respectively), and between highly decompensated and improved segments (p-value 0.03). In the physician-dietitian dyad we found significant differences between segments, with a higher value in stable patients than worsened (p-value <0.01). highly decompensated (p-value <0.01), moderately decompensated (p-value 0.01) and improved (p-value 0.02) patients. in the nurse-dietitian collaboration t-student test show similar differences to physician-dietitian collaboration, with higher collaboration in stable segment than worsened patients (p-value < 0.01), highly decompensated (p-value <0.01), moderately decompensated (p-value 0.07) and improved patients (p-value 0.02). Total collaboration in patients' treatment had a higher value in stable patients than both highly and moderately decompensated (p-value <0.00 and 0.02 respectively). The team continuity metric shows difference only between stable and worsened patients, with a higher value in stables (p-value 0.01). The concentration metric shows significant association between metric values and segmentation, showing a similar behavior than physician-dietitian collaboration, i.e. higher concentration in stable segment than the others (p-value 0.01), as well as multidisciplinary collaboration with higher value in stable patients.

To evaluate the correlation between the results and the total number of visits, we applied Student's t-test to patients with the same number of visits (6, 7, 8 or 9). Considering the high dispersion in the number of visits and number of professionals, we also repeated the analysis excluding the 10% of patients with the least frequent values in both variables. In both cases, the results followed the same trends as the results for the entire population. Specifically, we found that in almost all cases, patients belonging to the well-controlled and improved segments had higher values for density, concentration, IC P-N and total collaboration. Well-controlled patients had higher values of multidisciplinary collaboration, IC P-D and IC N-D. Worsened patients had lower values for team community and multidisciplinary collaboration. Moderately decompensated patients had lower concentration. More detailes may be found in Supplementary Material 1.

6.4. DISCUSSION

In our study, we illustrate a novel way to model and measure collaboration among healthcare providers with a data-driven approach and considering the changes in team composition over time. The construction of networks and definition of links was based on the EMR of the centers, and not based on affinity surveys as most similar studies. The interviews we made allowed us to design a dynamic model that reflects collaboration aspects that cannot be observed otherwise. Our study was developed using a sample of 974 patients with similar demographic characteristics to previous studies (C. C. Chen & Cheng, 2011; Hanafi et al., 2015; Younge et al., 2012).

This study focused on understanding whether the structure of care teams is associated with patient progression. We found several correlations in that sense. This section discusses some of the reasons behind our findings, and how our findings differ from, or agree with, previous work.

Highly decompensated patients had the highest values for total number of visits and different providers. This is a result of the treatment protocol, which establishes different periodicities of CVPA according to HbA1c test results, but also due to the high staff turnover, since a patient with many visits has an increased probability to experience changes in treating professionals between visits. The number of visits is highly correlated with total number of providers (Pearson's correlation 0.61 with p-value <0.01). There were more nurse visits for highly decompensated than for stable patients. These results can be explained because, according to the protocol, patients with HbA1c results over 9% have been prescribed insulin, which requires a higher frequency of nurse visits for usage directions and dose adjustment (Subsecretaria de Redes Asistenciales, 2010). An interesting aspect, not directly explained by the protocol, is the number of dietitian visits that should be similar to the visits to the physician and nurse but had lower values in every segment. The number of dietitian visits had no differences between segments, when they should be significantly higher in highly decompensated patients. This shows a low adherence to dietitian controls, consistent with previous studies (Alvarez et al., 2018; Saint-Pierre, Herskovic, & Sepulveda, 2018).

In SNA, links reflect communication channels, collaboration or interactions among individuals in the network (Bae et al., 2015; Benton et al., 2015; Freeman et al., 1991; Smith & Christakis, 2008). In our study, we propose that two professionals who are part of a same practice during the same time window interact because of having been co-located. This could be not enough to assure collaboration, but in the interviews, we could identify regular collaborative activities in the practices. Even when we cannot be certain that two professionals in a collaboration network collaborated in the particular case being modeled by the network, we do know that they interact and collaborate in other cases. This closeness is relevant, because in social networks there is a tendency towards similarity in socially connected nodes (Raghavan et al., 2016). In our context, this closeness reflects a coherence in the treatment provided by different professionals to a patient, since they share protocols and coordination meetings and are guided by a T2DM and Cardiovascular Diseases Program leader.

For the analysis of the patient-level networks, we calculated density and betweenness centrality. These two metrics were selected because they are the most used in healthcare context (Bae et al., 2015; Benton et al., 2015). Stable (well-controlled) patients had denser and smaller networks. This is consistent with a previous study that shows an association between lower density in physician networks and higher cost of hospitalization and readmission ratio in different hospitals (Uddin & Hossain, 2012). Unlike our study, this analysis used hospital-level networks, instead of patient-level networks.

The centrality metric (Freeman et al., 1991) did not show an association with patient progression. This is similar to a result from a previous study, in which there was no association between nurse network betweenness and length of hospital stay in a neonatology unit (J. E. Gray et al., 2010). This study, from 2010, claims to be the first application of EMR data and SNA methods to perform a quantiative assessment of healthcare teams at patient-level. Other studies that have analyzed PCC/hospital-level networks and their relationship to health outcomes have shown significant differences, e.g., of an association between higher betweenness centrality and higher hospitalization cost and readmission rate (Uddin & Hossain, 2012), fewer medical specialist visits and lower spending on imaging and tests (M. L. Barnett et al., 2012), and more medication errors (Effken et al., 2011).

Regarding the multidisciplinary nature of the care teams, we quantitatively measured the interaction between disciplines involved in the treatment of each patient. Physician-nurse collaboration, around a 20% of the total potential collaboration, was higher than physician-dietitian and nurse-dietitian interactions, which were both around 8%. This phenomenon can be explained by the lower global adherence of T2DM patients to dietitian treatment (Alvarez et al., 2018; Saint-Pierre, Herskovic, & Sepulveda, 2018). In particular, we found that a lower collaboration in the three dyads was related with patients who remain moderately and highly decompensated and/or worsened in the timeframe, whereas higher physician-dietitian and nurse-dietitian collaboration were related with patients who remain stable (well-controlled) during the whole period. These results are consistent with earlier work associated to the impact of multidisciplinary collaboration and T2DM patients (Saint-Pierre, Herskovic, & Sepúlveda, 2018). Total collaboration also showed significant differences that confirmed the association between collaboration and better progression, with a higher value in stable patients compared with the other segments' means. These results give quantitative evidence of the collaboration-progression association present in the international T2DM treatment guides (American Diabetes Association, 2017; International Diabetes Federation, 2015; World Health Organization, 2016).

Our results showed a lower team continuity in worsened patients. The concentration metric, that measures how the treatment are concentrated in a main team, independently of the total number of visits and how many teams were involved in the patient's treatment, showed significantly higher values in stable segment than the population results. Both metrics are similarly oriented towards associating team continuity with better outcomes in T2DM patients. Even though the continuity of care has been widely studied (Saint-Pierre, Herskovic, & Sepulveda, 2018), our contribution is to quantitatively measure multidisciplinary interaction and team changes over time.

Regarding the multidisciplinary nature of the treatment, the presence of three disciplines in the team at the moment of the visit was measured quantitatively, also showing a relationship with patient progression. Results showed higher multidisciplinary collaboration stable patients, and lower in worsened patients. Like the interdisciplinary collaboration, this could be explained because of the low adherence of worsened patients (Alvarez et al., 2018; Saint-Pierre, Herskovic, & Sepulveda, 2018).

When this study began, we expected to find significant differences between patients that improved versus those that remained unstable, in order to understand which components of the collaborative treatment were different between them. The significant differences that were actually found were between the patients that remained well-controlled and those who worsened during the studied time period. Patients in the worsened segment of progression had similar network metrics, i.e. similar collaboration level, to those that remained highly unstable.

6.5. CONCLUSION

This study shows a significative association between aspects of collaboration and patient progression. To show this relationsip, we used a data-driven methodology to analyze collaboration based on data from information systems, specifically electronic medical records. We proposed metrics that allow measuring collaboration and how multidisciplinary teams are, as well as their continuity over time. Because this is the first application of these metrics, values cannot be compared with previous literature, so the results are analyzed in comparison with the population mean. However, our results are consistent with previous literature and give quantitative evidence that validates findings of several previous studies.

The results are promising, since we were able to quantitatively measure collaboration with a data-driven approach. The used method provides tools to assess teams and objectively analyze their collaboration and its relationship to patient outcomes. These methods could potentially be applied to other settings in chronic diseases that require a multidisciplinary collaborative approach.

However, having applied these methods to T2DM patients under treatment in 6 clinical primary care practices located in urban areas, and which follow to the same protocol, does not allow us to extend our results about the association between metrics and progression to a more general settings. The main limitations of this study are that we worked with incomplete clinical information, only from the primary care centers, without access to information on referrals to more complex care or visits to ER; we used only one outcome metric (HbA1c), omitting other variables such as body mass index or blood pressure because they were not available in the data; and finally, data did not include medication use. However, the use of the protocol establishes the type of treatment according to the level of HbA1c, which is why we consider our segmentation as a good approximation.

7. CONCLUSION AND FUTURE WORK

7.1. Summary of Contributions

In the development of this work we made several contributions, both in the scientific and social domains.

Our systematic literature review concerning multidisciplinary collaboration in primary care provided a fully up-to-date overview about how collaboration is actually carried out by teams in primary care settings. This work also allowed us to classify collaboration by the involved disciplines, as well as by the collaborative activities used in the treatment of patients. Our intention was to relate the distinct collaboration types with the outcomes of the interventions in comparison with non-collaborative treatments, but unfortunately, the reviewed articles did not have enough information to do so.

In our case study, we noticed that most of the teams had similar collaborative activities, but the team composition was different. We tested the team composition types found in our literature review in the case study dataset and found differences between the patients treated by each type, further than the obvious patients' requirements. We concluded that, in our settings, there were team composition types associated with different kinds of patients that were consistent with the related literature.

In a first approach, we used process mining techniques to analyze our dataset. Our aim with this work was to understand whether in teams with similar collaborative activities and composition, we could find patterns of interaction that were related with the patient evolution. Considering only interactions among disciplines, without considering how many professionals were involved, we found 7 interaction patterns that differed in the structure of the handover of patient networks. We also found an association between more balanced participation of the disciplines in the treatment and better patient evolution.

Understanding that the study of the interactions between disciplines was not enough to model collaboration, we decided to include not just the disciplines, but the individual professionals participating in each patient's treatment. With this analysis, we wanted to understand how the number of different professionals and the change of treating professional between consecutive visits could impact the metabolic control of T2DM patients. Our results showed an association between higher continuity in physicians and nurses and better clinical outcomes. We also found a significant difference in the patients' evolution and the adherence to the dietitian controls, where those with lower adherence also had a worsening of their metabolic control.

Finally, considering the relevance of multidisciplinary collaboration according to the literature, and the evidence of the impact of interaction between disciplines and continuity of care in T2DM patients, we proposed a methodology to model multidisciplinary collaboration as a social network, under the concept of "continuity of care team". The difference between this approach and previous research is that we considered the variations in team composition along time. This proposal allows graphically display how the team changes and how intense the collaboration is. To our knowledge, this is the first study that measures collaboration with a data-driven approach. Objective metrics can be useful to manage human resource interactions with the aim of improving clinical outcomes and patient satisfaction and reducing costs.

7.2. Accomplishment of the objectives

We started our work with the aim of answering our research question: *"Is it possible that different multidisciplinary collaboration patterns have different clinical outcomes in patients?"*. This question led our study to test three hypotheses:

> H1) *Different collaboration patterns exist among professionals treating patients diagnosed with T2DM.*
>
> H2) *Collaboration patterns among professionals treating patients diagnosed with T2DM can be obtained from EMR data analysis.*
>
> H3) *Patients with diabetes treated according to different collaboration patterns have different clinical outcomes.*

These hypotheses were validated in our work. From the systematic literature review, we identified patterns of team compositions and activities, and tested those patterns in our dataset of T2DM patients. We found that the population treated by different team types had significant different characteristics. Those results validated H1.

Using a process mining approach over ECR data, we were able to identify different patterns related to the handoff of patients between disciplines in T2DM treatment. We expanded our analysis to the study of the professionals' relationship during the treatment using SNA techniques, considering how the teams change over time. With this work we detected several topologies in the networks of each patient. This topology could be described by several metrics. With both approaches we validated H2.

We used PM and SNA approaches to compare the patterns and its metrics with patient evolution. We did find an association between some patterns and patient evolution, consistent with the literature and with fieldwork observations. With this statistical analysis we validated H3.

At last, the general objective of this thesis, stated as *"To design a data-driven methodology that allows to measure collaboration in multidisciplinary teams treating chronic patients in primary care settings, identify collaboration patterns and analyze its relationship with clinical outcomes"* was accomplished with two different approaches, PM and SNA.

7.3. Directions for Future Work

One of the limitations of this thesis work is that the results obtained are valid only in particular settings: primary care centers in a low-income urban area, for adults diagnosed with T2DM, the proposed methodology could be applied to the treatment of any diseases that require a multidisciplinary collaborative treatment as well as in other fields. Therefore, we consider as future work two lines of research. A first line is related to the impact of our results for the treatment of T2DM patients and to validate the proposed methodology and extend the results to other chronic diseases that require multidisciplinary collaboration. A second line of research is to apply and validate the proposed methodology to model and measure collaboration in other domains, in order to improve performance in teams. Examples of other domains where this methodology could be used are collaborative learning, software development and business processes.

7.3.1. Future work related to healthcare domain and T2DM treatment

In the healthcare field in general, measuring collaboration is likely useful to improve outcomes and patient satisfaction, and according to interactions with physicians and others further work in this area would be welcomed. The following opportunities should be considered:

a) Test the proposed methodology in the treatment of other diseases.

As T2DM, other chronic diseases also require collaborative multidisciplinary treatments. Proposed methodology could be useful to understand the social dynamic of the team.

a) Test results in different settings in T2DM.

Since our results are valid only in the settings described, we recommended to apply the proposed methods to other settings in T2DM to validate the results.

b) Add other patient characterization variables that could be relevant, such as socioeconomic level, educational level and family support.

Even when in our settings the population has similar socioeconomic level and social risk, several studies show association between those variables and clinical outcomes, Future studies should control the statistical analysis by those variables.

c) Use other metrics to assess evolution in diabetic patients, such as weight, blood pressure and body mass index.

Clinical guidelines suggest the use of other health metrics to assess the condition of the diabetic patient. Those metrics are used to construct a cardiovascular risk index that be recommended to include in future studies.

d) Include in the analysis information about secondary level attention as well as emergency room visits.

One of the clinical outcomes assessed in related studies is the number of visits to emergency room, length of stay in diabetes-related hospitalization events and rate of readmission. In our work we did not have access to secondary or tertiary level of attention, limiting our analysis to primary care data. Is highly recommended to include this information in future analysis.

e) Analyze the relationship between data-driven results and qualitative results obtained from interviews and surveys.

   Our work defines metrics that are associated to patient's progressions, but we did not validate that the relationship obtained in each patient was consistent with the evaluation of the professionals involved in the treatment. We recommend assess the results with interviews or surveys in randomized cases.

7.3.2. Future work related to other domains

Multidisciplinary collaborative work is not an exclusive characteristic of healthcare domain, it can be found in several other fields such as software development, business processes, collaborative learning or data science. In those examples, multidisciplinary teams are structured around projects and team members could change in the life cycle of the project. Since current SNA methods do not consider the team variation over time, our proposal could be useful to understand team member relationships and its relationship with efficiency or productivity.

7.4. Final words to future PhD students

The present thesis is the result of 6 years of work, and it is possible that nobody ever read the full document. But maybe future PhD students do, for them I want to leave some advices:

1. Healthcare data is hard to come by due to the personal information protection laws. For this work, we were doing paper work, letters and protocols for almost 2 years to get the required data.
2. Detailed research protocols and informed consent are needed, and the times of revisions and authorizations is long. Healthcare area journals ask for those authorization before publishing.

3. Data is always messy. Healthcare data… worse. You should consider enough time to do that in your plan. For this work, cleaning data took almost a year in order to get a nice event-log.
4. It is important to understand the domain, but that is not enough. In this field it is imperative to involve a healthcare professional in the result analysis and presentation to get meaningful insights.
5. If you are not an expert in statistics, you should look for someone with experience to help you with the analysis of your results.
6. Good luck.

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9. SUPPLEMENTARY MATERIAL 1

Analysis conditioned to the number of visits	Student's t-test p-value for comparison between segments										Mean					
	Stable vs Worsened	Stable vs Highly decompensated	Stable vs Moderately decompensated	Stable vs Improved	Worsened vs Highly decompensated	Worsened vs Moderately decompensated	Worsened vs Improved	Highly decompensated vs Moderately decompensated	Highly decompensated vs Improved	Moderately decompensated vs Improved	Stable	Worsened	Highly decompensated	Moderately decompensated	Improved	POPULATION
Density																
Total population	0.030	0.010	0.020	0.210	0.730	0.740	0.200	0.970	0.170	0.260	0.41	0.36	0.36	0.37	0.39	0.38
6 visits	0.077	0.090	0.091	0.262	0.895	0.971	0.366	0.874	0.481	0.345	0.48	0.36	0.37	0.35	0.42	0.42
7 visits	0.271	0.963	0.948	0.080	0.482	0.370	0.700	0.999	0.255	0.158	0.39	0.33	0.39	0.31	0.39	0.37
8 visits	0.932	0.719	0.076	0.271	0.845	0.214	0.413	0.268	0.241	0.044	0.39	0.38	0.37	0.32	0.44	0.38
9 visits	0.072	0.329	0.635	0.490	0.306	0.367	0.414	0.805	0.958	0.874	0.41	0.32	0.36	0.37	0.38	0.38
Betweenness																
Total population	0.580	0.060	0.110	0.150	0.360	0.440	0.530	0.900	0.830	0.930	0.19	0.18	0.16	0.16	0.17	0.17
6 visits	0.789	0.026	0.723	0.371	0.101	0.906	0.598	0.136	0.273	0.703	0.22	0.20	0.12	0.19	0.17	0.18
7 visits	0.544	0.196	0.716	0.004	0.525	0.673	0.050	0.277	0.018	0.013	0.17	0.20	0.25	0.09	0.18	0.17
8 visits	0.643	0.152	0.219	0.451	0.065	0.119	0.291	0.942	0.788	0.835	0.22	0.25	0.17	0.17	0.18	0.20
9 visits	0.668	0.342	0.441	0.558	0.760	0.329	0.381	0.231	0.282	0.979	0.20	0.18	0.16	0.24	0.24	0.20
IC P-N																
Total population	0.180	-	0.040	0.610	0.490	0.820	0.320	0.590	0.030	0.130	0.21	0.18	0.17	0.18	0.21	0.19
6 visits	0.084	0.204	0.102	0.567	0.616	0.932	0.196	0.594	0.470	0.204	0.28	0.17	0.20	0.16	0.24	0.23
7 visits	0.677	0.692	0.184	0.147	1.000	0.520	0.378	0.653	0.500	0.679	0.20	0.18	0.18	0.13	0.15	0.17
8 visits	0.481	0.920	0.157	0.052	0.579	0.817	0.067	0.332	0.104	0.013	0.21	0.17	0.20	0.16	0.30	0.21
9 visits	0.629	0.389	0.672	0.976	0.226	0.942	0.635	0.254	0.332	0.688	0.20	0.23	0.15	0.20	0.22	0.19
IC P-D																
Total population	-	-	0.010	0.020	0.390	0.120	0.060	0.360	0.190	0.740	0.12	0.05	0.06	0.08	0.08	0.08
6 visits	0.124	0.003	0.034	0.369	0.250	0.626	0.594	0.521	0.069	0.271	0.12	0.06	0.02	0.04	0.08	0.08
7 visits	0.423	0.955	0.698	0.787	0.589	0.408	0.405	0.818	0.908	0.873	0.10	0.06	0.10	0.11	0.12	0.10
8 visits	0.014	0.057	0.013	0.285	0.666	0.889	0.475	0.695	0.716	0.518	0.12	0.04	0.05	0.04	0.07	0.07
9 visits	0.028	0.045	0.013	0.004	0.770	0.911	0.540	0.623	0.319	0.555	0.14	0.04	0.05	0.03	0.04	0.07
IC N-D																
Total population	-	-	0.070	0.010	0.410	0.100	0.230	0.260	0.600	0.530	0.10	0.04	0.05	0.07	0.06	0.07
6 visits	0.112	0.013	0.010	0.086	0.611	0.568	1.000	0.943	0.566	0.516	0.13	0.04	0.02	0.02	0.04	0.07
7 visits	0.087	0.824	0.842	0.223	0.197	0.239	0.651	0.726	0.309	0.417	0.07	0.02	0.08	0.03	0.06	0.06
8 visits	0.031	0.004	0.448	0.660	0.488	0.268	0.301	0.098	0.167	0.834	0.09	0.02	0.01	0.06	0.07	0.06
9 visits	0.163	0.026	0.256	0.076	0.502	0.978	0.796	0.618	0.659	0.850	0.10	0.05	0.03	0.04	0.05	0.06

Analysis conditioned to the number of visits	Student's t-test p-value for comparison between segments										Mean					
	Stable vs Worsened	Stable vs Highly decompensated	Stable vs Moderately decompensated	Stable vs Improved	Worsened vs Highly decompensated	Worsened vs Moderately decompensated	Worsened vs Improved	Highly decompensated vs Moderately decompensated	Highly decompensated vs Improved	Moderately decompensated vs Improved	Stable	Worsened	Highly decompensated	Moderately decompensated	Improved	POPULATION
Total collaboration																
Total population	0.090	-	0.020	0.120	0.800	0.880	0.520	0.920	0.220	0.340	0.20	0.17	0.16	0.16	0.18	0.18
6 visits	0.058	0.128	0.009	0.480	0.714	0.837	0.140	0.545	0.364	0.093	0.26	0.16	0.19	0.16	0.23	0.22
7 visits	0.599	0.864	0.901	0.183	0.642	0.604	0.610	0.927	0.388	0.233	0.18	0.16	0.19	0.14	0.18	0.17
8 visits	0.805	0.822	0.068	0.202	0.677	0.197	0.204	0.108	0.376	0.031	0.18	0.17	0.18	0.13	0.23	0.18
9 visits	0.303	0.382	0.475	0.169	0.443	0.717	0.798	0.876	0.510	0.809	0.20	0.14	0.17	0.15	0.16	0.17
Team continuity																
Total population	0.010	0.450	0.190	0.580	0.070	0.220	0.050	0.530	0.870	0.450	0.67	0.62	0.66	0.65	0.66	0.66
6 visits	0.098	0.071	0.030	0.228	0.796	0.693	0.482	0.907	0.330	0.188	0.69	0.59	0.56	0.55	0.63	0.63
7 visits	0.232	0.640	0.860	0.041	0.707	0.383	0.560	0.737	0.378	0.127	0.65	0.59	0.62	0.56	0.64	0.62
8 visits	0.729	0.720	0.751	0.769	0.975	0.949	0.654	0.971	0.620	0.635	0.66	0.64	0.64	0.65	0.67	0.65
9 visits	0.071	0.259	0.734	0.655	0.468	0.185	0.203	0.554	0.593	0.938	0.68	0.58	0.63	0.66	0.66	0.65
Concentration																
Total population	0.080	-	0.010	0.080	0.550	0.660	0.680	0.890	0.180	0.300	0.64	0.61	0.60	0.60	0.62	0.62
6 visits	0.263	0.007	0.084	0.277	0.256	0.584	0.839	0.541	0.118	0.399	0.71	0.65	0.58	0.62	0.66	0.66
7 visits	0.482	0.594	0.834	0.137	0.374	0.422	0.599	0.756	0.138	0.140	0.62	0.59	0.65	0.56	0.63	0.61
8 visits	0.918	0.718	0.060	0.340	0.717	0.116	0.550	0.176	0.272	0.017	0.62	0.63	0.61	0.55	0.66	0.61
9 visits	0.298	0.320	0.719	0.543	0.724	0.546	0.602	0.656	0.784	0.860	0.64	0.59	0.60	0.61	0.62	0.62
Multidisciplinary collaboration																
Total population	-	-	0.060	0.040	0.420	0.100	0.090	0.270	0.240	0.990	0.05	0.02	0.02	0.03	0.03	0.03
6 visits	0.184	NA	NA	NA	NA	NA	NA	NA	NA	NA	0.07	0.02	-	0.01	0.02	0.03
7 visits	0.108	0.781	0.960	0.648	0.261	0.232	0.376	0.851	0.593	0.675	0.03	0.01	0.04	0.02	0.03	0.03
8 visits	0.005	0.008	0.022	0.974	0.519	0.311	0.126	0.528	0.146	0.194	0.05	0.00	0.00	0.01	0.05	0.03
9 visits	0.241	0.082	0.080	0.034	0.581	0.551	0.342	0.936	0.605	0.704	0.05	0.02	0.01	0.01	0.01	0.02