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Geomarketing-Based Spatial Analysis of Pharmacies in France

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Abbreviations

AM (Assurance Maladie) - French social security system managing mandatory health insurance

API (Application Programming Interface) - Programming interface enabling data exchange between applications

APL (Accessibilité Potentielle Localisée - Localized Potential Accessibility) - Indicator measuring spatial adequacy between healthcare supply and demand

ATIH (Agence Technique de l'Information sur l'Hospitalisation - Technical Agency for Hospital Information) - French public agency for hospital information systems

CartoSanté - Institutional visualization platform for statistical data on healthcare professionals developed by ATIH

CSV (Comma-Separated Values) - Tabular data file format with comma-separated values

DREES (Direction de la Recherche, des Études, de l'Évaluation et des Statistiques - Directorate of Research, Studies, Evaluation and Statistics) - Statistical service of French social ministries

GeoJSON (Geographic JavaScript Object Notation) - Geospatial data exchange format based on JSON

GIS (Geographic Information System) - System for creating, organizing and presenting geographical data

GPS (Global Positioning System) - Satellite-based geolocation system

INSEE (Institut National de la Statistique et des Études Économiques - National Institute of Statistics and Economic Studies) - French national statistical institute

IRIS (Îlots Regroupés pour l'Information Statistique - Aggregated Units for Statistical Information) - INSEE territorial division for sub-municipal data dissemination

JSON (JavaScript Object Notation) - Lightweight data interchange format

LLM (Large Language Model) - Artificial intelligence model trained on large amounts of text

SHP (Shapefile) - File format for vector geospatial data

Glossary

Spatial Analysis - Methods for studying geographical phenomena by analyzing their distribution and interactions in space, combining statistics and geography to identify patterns and correlations.

Geomarketing Analysis - Study method combining geographical, demographic, and behavioral data to assess territorial potential for strategic decisions like retail location planning and catchment area definition.

INSEE Grid Data (200m) - Regular grid of 200-meter squares overlaid on French territory, providing homogeneous spatial analysis independent of administrative boundaries.

Voronoi Method - Spatial division technique creating zones of influence by assigning each point to the nearest establishment based on Euclidean distance.

Catchment Area - Geographical perimeter from which the majority of an establishment's clientele originates, serving as the fundamental unit for evaluating commercial potential.

La Longue Vue - Consulting firm specialized in pharmaceutical geomarketing, offering location studies and decision-support tools including "La Loupe" for pharmacy potential evaluation.

Dash - Open-source Python framework by Plotly for creating interactive web applications, combining Flask, React.js, and Plotly.js for analytical dashboard development.

1. Introduction

In France, community pharmacies play a dual role: they are both healthcare access points for primary care and local businesses subject to economic constraints. This dual nature makes their establishment a highly strategic decision. On one hand, it must guarantee equitable access to care across territories; on the other, it must ensure financial viability for the pharmacist. Two structural characteristics reinforce this tension. Firstly, reimbursed medications account for nearly 80% of the total revenue of French pharmacies [1]. This underscores the dependence on the national health system and the local patient base. Secondly, the average purchase price of a pharmacy is around €1.3 million [2], usually repaid over 12 to 15 years [3]. In this context, the siting of a pharmacy becomes a crucial decision, balancing public service objectives and economic sustainability.

However, contemporary territorial dynamics – including demographic aging, disparities in medical density, and evolving mobility patterns – further complicate this evaluation. This leads to the central research question of this work: Is it possible, using public data, to build an interactive tool that helps assess a territory's attractiveness for pharmacy location through a combined geo-demographic and medico-economic analysis?

This issue is particularly pressing for pharmacists and investors who lack a clear, synthetic, and actionable understanding of their territorial environment. Although relevant datasets exist (from INSEE, DREES, the French Health Insurance, or CartoSanté), they are fragmented, occasionally outdated, and rarely interoperable. Their analysis requires time and technical skills that many healthcare professionals do not have. Available tools, such as CartoSanté, offer basic visualization capabilities but fall short when it comes to dynamically cross-referencing demographic, economic, and territorial indicators for strategic purposes. None of the current solutions offer an operational interface tailored to pharmacy siting decisions.

This project aims to fill that gap by developing an interactive decision-support tool, based entirely on open public data, to evaluate the territorial attractiveness of pharmacy locations through a dual geo-demographic and medico-economic lens. It brings together heterogeneous datasets, structures them within a coherent analytical framework, and delivers them in a format accessible to non-specialist users.

Situated at the crossroads of public health, data science, and geomarketing, this initiative draws on multiple disciplines: public health to address accessibility and territorial balance, data science to ensure integration, analysis, and visualization of data, and geomarketing to guide commercial siting strategies in a regulated health context.

2. Methods

2.1 Data Sources and Collection Protocol

The application relies exclusively on public, open, and anonymized datasets, all accessible online from official French institutional platforms. The selection of these sources was guided by three primary criteria: their relevance for territorial analysis, their spatial granularity, and their temporal validity. The objective was to build a heterogeneous and interoperable database capable of feeding a decision-support interface for pharmacy location analysis.

2.1.1 Demographic Data

Demographic variables were sourced from INSEE (the French National Institute of Statistics and Economic Studies), particularly from three main datasets: "Évolution et structure de la population", "Couples - Familles - Ménages", and the 200-meter grid dataset (carreaux). The first two are available at multiple geographic levels (regional, departmental, communal, and IRIS) and provide information on age, sex, household composition, and family structures. The third, the grid-based dataset, offers a high-resolution spatial breakdown of the population and household counts across regular 200-meter cells covering the entire national territory.

The use of the 200-meter grid was essential for enabling high-resolution spatial analysis and overlaying with customized catchment areas. This grid-based partition, unlike administrative boundaries, provides a regular and exhaustive spatial framework, ideal for proximity calculations and influence zones.

2.1.2 Pharmacy Locations

The geographic coordinates of all French pharmacies were extracted from the official registry maintained by the Ordre National des Pharmaciens. This dataset, regularly updated and nationwide in scope, served both to represent existing pharmacy locations and to define catchment areas using the Voronoi diagram method.

2.1.3 Medical Environment

To characterize the medical context of a given location, we used data from Directorate of Research Studies, Evaluation and Statistics (DREES), notably the Localized Potential Accessibility index (APL) and from the CartoSanté platform. These datasets provide indicators such as general practitioner (GP) density, age distribution, workforce trends, and practice patterns. The data were used at the commune level, which matches the native resolution of most variables.

2.2 Preprocessing, Structuring, and Quality Control

The collected data were heterogeneous, large-scale, and often inconsistent across sources. The preprocessing aimed to standardize, harmonize, and clean the data to enable a robust territorial analysis. Files were categorized into two processing streams: "standard" datasets (commune, IRIS) and "grid-based" datasets (carreaux).

In the standard datasets, column names often included the year (e.g., `P15_POP`, `P16_POP`), which hindered cross-year merging. These were cleaned to extract the temporal component and standardized (e.g., `POP`) to enable longitudinal concatenation. In grid-based files, ID conventions varied by year. A mapping dictionary was used to rename fields (e.g., `idinspire` to `idcar_200m`), discard obsolete attributes, and enforce schema consistency. This semantic harmonization was essential for inter-annual comparability.

All transformed datasets were exported in compressed Parquet format. This choice was motivated by performance constraints observed during application testing. For instance, loading a single CSV file took 1–2 seconds on a high-end machine; aggregating five years of data resulted in delays of up to 10 seconds. For grid datasets, delays reached nearly 9 seconds per year. After conversion, all standard datasets load in under 1 second and all grid-based datasets load in approximately 4–5 seconds, significantly improving interactivity.

Each dataset underwent thorough validation: duplicate removal, type checking, and structural consistency. Geographic identifiers (e.g., INSEE codes, grid IDs) were systematically verified across years. Unstable or redundant columns were excluded, with all decisions documented in the codebase. No dataset was included without explicit typing and structural alignment. Raw files were archived automatically, ensuring complete traceability of the data transformation pipeline

2.3 Geographic Analysis Method

Once the data were preprocessed and structured, the central task was their spatial projection to produce actionable indicators for strategic decision-making. The tool is built on a multi-scale architecture that allows for territorial analysis at several levels of granularity: commune, IRIS, INSEE grid (carreaux), or catchment areas. Each level supports different analytical needs, from macro-scale insights to fine-grained local positioning.

Catchment areas were modeled using Voronoi diagrams, based on the geolocation of all pharmacies. This method was chosen for its simplicity, reproducibility, and ability to delineate continuous territories using Euclidean proximity. While it does not account for real-world travel constraints (e.g., time, physical barriers), it provides an initial, objective approximation of pharmacy influence zones. These polygons were then overlaid with the 200-meter INSEE grid, enabling direct aggregation of demographic indicators within each catchment. This transformation created a new analytical unit that is often more relevant than traditional administrative boundaries in geomarketing logic.

Such segmentation allows meaningful comparison between catchment areas: differences in size, shape, or population density can signal market saturation or, conversely, unmet needs. A small catchment encircled by other pharmacies might indicate competitive saturation, while a large, sparsely populated area without nearby pharmacies could suggest under-service.

Finally, this spatial framework was adapted to the specificities of the pharmaceutical sector. Unlike classic geomarketing models that focus primarily on purchasing power or commercial density, our approach incorporates a dual lens: demographic and medico-economic. This dual perspective is essential in a context where pharmacy viability depends on both population characteristics and the local density of medical prescribers.

2.4 Strategic Decision-Support Indicators

Geographic analysis alone does not suffice to guide pharmacy siting decisions. Spatial information must be transformed into concrete indicators that can directly inform business reasoning. These indicators are designed to serve a practical purpose: to help a pharmacist or investor objectively assess the potential of a given location.

2.4.1 Demographic Indicators

The demographic offers interactive visualizations (bar charts, heatmaps, territorial dominance graphs) that allow users to identify the salient features of an area. The interface supports guided exploration: by selecting a variable (age, socio-professional category, family structure, housing type), the user can observe dominant subgroups or relative intensities.

The demographic module focuses on variables that have direct operational impact for a pharmacy. We included age categories because each group corresponds to distinct prescription and counseling needs—from pediatric care to chronic disease management and mobility aids. Socio-professional categories serve as proxies for both purchasing power and health literacy, informing choices about product mix and communication. Household composition, whether a couple with children or a single-occupant dwelling, signals demand for family planning resources, pediatric advice or more individualized counseling services.

A pharmacist can thus identify a young dominant population, accelerated aging, or an unusually high number of large families. These signals carry strategic implications: an area populated by young adults may indicate demand for contraception, emergency care, or accessible devices. An aging population suggests chronic treatments, regular follow-up needs, and physical accessibility issues. A concentration of large families implies higher pediatric prescription volumes and demand for first-necessity products and counseling.

Key variables such as total population and household count are also tracked over time. These series are normalized using an index base (100) to compare local trends against national averages. This approach reveals deviations in demographic growth or decline, adding a strategic dimension to siting decisions.

Though indirect, these insights translate population characteristics into commercial hypotheses. They can be operationalized by any practitioner with basic business acumen.

2.4.2 Medico-Economic Indicators

The "medical environment" section is structured around three indicator groups: medical supply, healthcare consumption, and demand structure. Each addresses a specific practical question relevant to prospective pharmacy siting. The indicators focus on general practitioners (GPs), as they represent the main entry point into outpatient care and are the primary source of reimbursable prescriptions. Their activity directly impacts patient flows to pharmacies[4, 5].

Medical presence is assessed via indicators such as APL, GP density, temporal trends in GP numbers, and age distribution of physicians. The APL, developed by DREES, is a composite measure of supply-demand adequacy, accounting for provider availability, population healthcare needs (weighted by age), and geographic accessibility[6, 7]. Low APL values suggest insufficient medical coverage relative to local needs, while high scores denote good healthcare access. A territory with a low or declining APL and an aging physician base may signal structural fragility in healthcare access, posing risks for prescription-dependent pharmacy projects.

Healthcare consumption is approximated through variables like acts per doctor, acts per patient, and care utilization rates. These metrics identify high-demand zones. Over 80% of GP consultations result in a prescription, with an average of 2.9 drugs per visit[8]. Thus, medical acts serve as a proxy for prescription volume and potential pharmaceutical load. For instance, a high act-per-patient ratio in an aging area may reflect chronic disease prevalence, indicating regular pharmacy traffic.

Demand structure is assessed through dominant patient profiles, categorized by healthcare usage. A concentration of young working adults or low-income households may indicate demand for front-line advice, accessible devices, or personalized support. Conversely, an older population may require expertise in managing complex prescriptions and therapeutic follow-up.

Indicators are displayed in a structured table with color-coded tags (green, orange, red) for quick assessment: green signals favorable conditions, orange flags intermediate situations requiring attention, and red warns of unfavorable contexts or service gaps. This visual system aids rapid identification of territorial strengths and weaknesses.

A global score (0–100) summarizes all indicators into a strategic composite index. The score allocates weights across four dimensions: medical demand (40 points), GP workload (20 points), structural healthcare stress (30 points), and professional density (10 points). This is not a predictive model but a prototype based on expert-coded thresholds. It is designed for adaptability and aims to highlight areas warranting special consideration.

Finally, a Large Language Model (LLM) module generates an automated textual summary of the medical environment. Its role is to deliver a human-readable synthesis for non-technical decision-makers. This illustrates how data can be made accessible and interpretable without requiring advanced analytical skills.

2.5 Tool Design

The developed tool is built on an interactive web architecture using the Dash framework. This technology was chosen for its ability to handle dynamic visualizations, its performance on medium to large datasets, and its seamless integration with the Python ecosystem already used for upstream processing. The goal was not to create a visually sophisticated interface, but rather a clear, functional, and analysis-centered environment.

The interface consists of three main pages, organized to follow a smooth user journey: a homepage featuring an interactive map of pharmacies as an entry point, a "Demography" page for population analysis, and a "Medical Environment" page for exploring medico-economic factors. At each step, users can either select a pharmacy or input a custom address. The spatial scale of analysis (region, department, commune, IRIS, grid, or catchment area) is selected via a dropdown menu, acting as a spatial filter for all data layers.

The design prioritizes clarity and hierarchy: each interaction instantly updates maps, charts, and associated tables. Responsiveness is central to enabling seamless exploration. Interactive elements are minimal yet targeted: filters, selectors, and informative tooltips guide users through the analysis.

Technically, the architecture maintains a clear separation between processing and presentation layers. Each interface page operates as a self-contained module dedicated to a specific analysis type: demographic data, medical environment, or entry map. These pages rely on independent business logic components responsible for data processing, filtering, and structuring. This modular organization ensures both code readability and maintainability. Data operations occur in real time using optimized file formats. Datasets are converted to Parquet format to ensure rapid access to relevant data subsets. This setup reflects a simple goal: to make a large, heterogeneous data corpus accessible without losing sight of end-user usability.

3. Results

3.1 Real-World Application: Cross-Reading Demographic and Medical Environment Data

This section applies the tool to a real-world setting to illustrate its analytical capabilities in evaluating a pharmacy's local environment. The analysis centers on the "Pharmacie du Parvis Saint-Michel" located at 213 rue de Solférino in Lille (Nord), France. The area of interest corresponds to its estimated catchment area modeled using Voronoi diagrams and intersected with the INSEE grid (Figure 1).

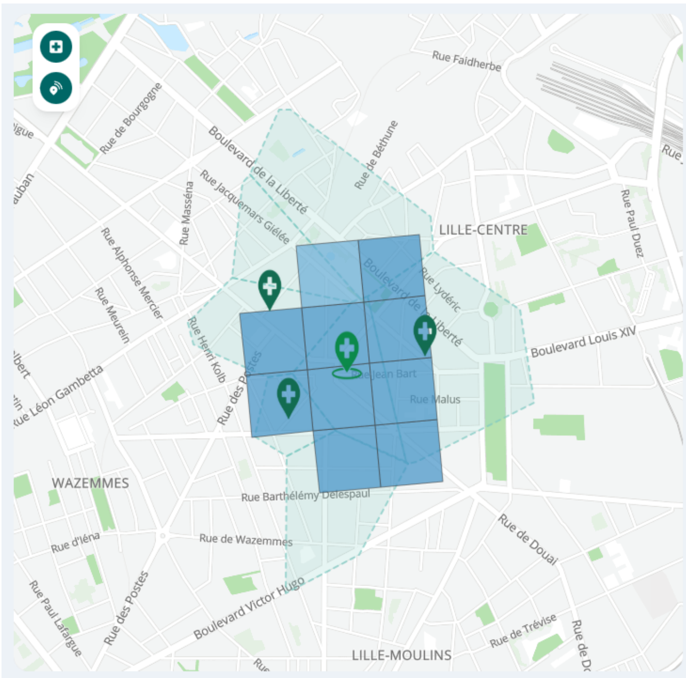

Figure 1: Analytical perimeter: estimated catchment area (green) overlaid on INSEE grid (blue), Parvis Saint-Michel Pharmacy, Lille.

In this area, the population remained stable from 2015 to 2019, both in inhabitants and households. At the IRIS level, a notable uptick appears in 2020, potentially reflecting a local residential renewal. This trend is readily observable through the base-100 visualization in the application, enabling quick interpretation without complex manipulation.

The age structure reveals a predominance of individuals aged 25–39, the dominant group in nearly all grid cells (Figure 2). This signal, highlighted via the interactive map filtered by dominant age class, reflects a youthful urban neighborhood likely attractive to middle and upper socio-professional groups. A single cell stands out with a dominant 18–24 age group, possibly indicating a student or transient housing cluster.

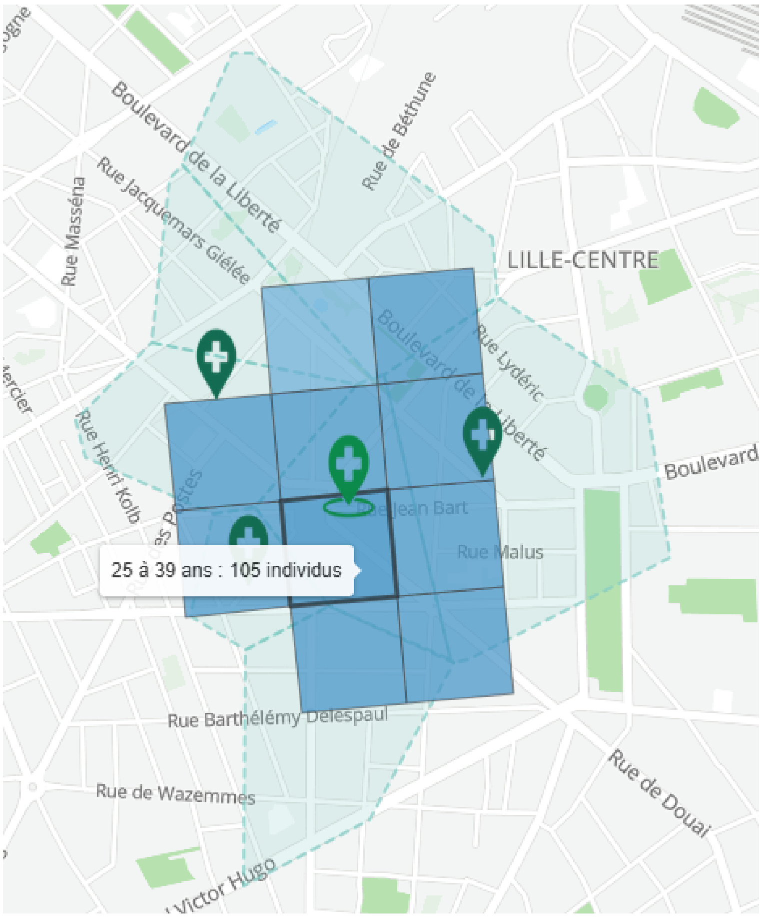

Figure 2: Dominant age class spatial distribution: predominance of 25–39-year-olds in the INSEE grid cells.

Regarding household types, the area is dominated by collective housing and small-sized units (single-person households), as seen in the dedicated filtered visualization (Figure 3). This denotes a dense, low-family urban fabric, consistent with the previously described young profile. At the IRIS level, most households are composed of families with children, without a clear size distinction. This nuance suggests that, while the area is not exclusively student- or youth-oriented, it retains a structured residential base potentially loyal to a nearby pharmacy.

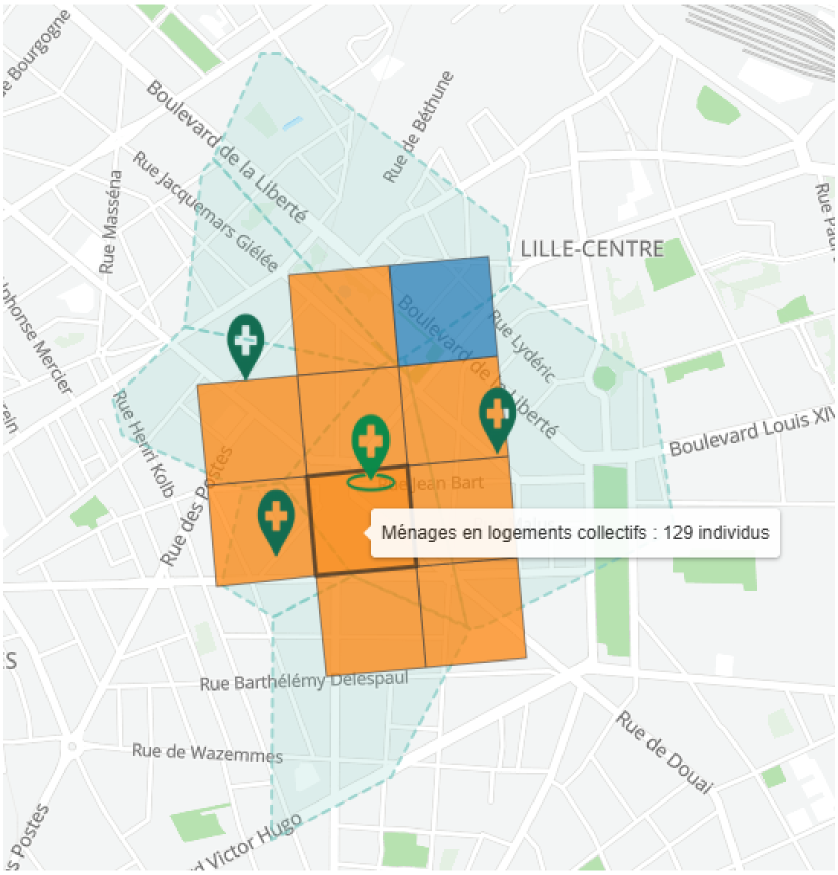

Figure 3: Household typology: predominance of collective housing within the catchment area.

In short, the demographic profile suggests a youthful urban area with a blend of established and transient populations. For a pharmacy, such a setting provides both a pool of active customers and a degree of volatility requiring targeted loyalty or service strategies.

From a medico-economic standpoint, the broader municipal context reveals more complex dynamics. The density of general practitioners (11.8 per 10,000 inhabitants) surpasses the national average [2, 9] (Figure 4). GP activity is high, with 5,327 acts per practitioner on average, and around 6.1 acts per patient. Moreover, the medical consumption typology is classified as "senior-oriented." These findings are made clear through the interactive synthesis table and the tool's built-in visual alerts.

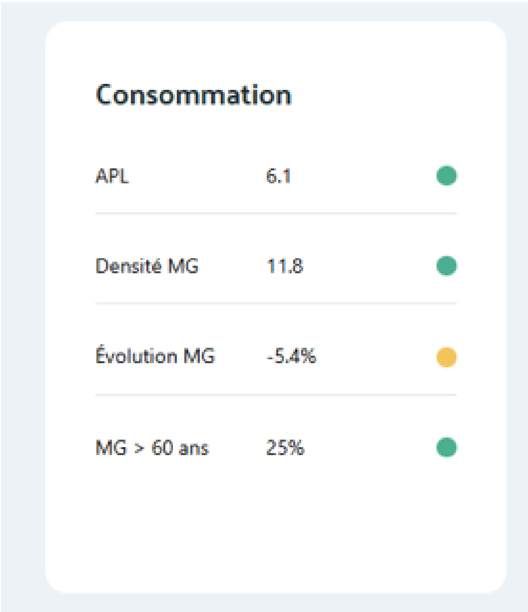

Figure 4: Summary of medico-economic indicators (City of Lille).

The divergence between the local population profile and aggregated medical consumption is explained by a scale effect: the catchment area represents only part of the city, while medical acts are recorded citywide. Thus, despite the youthful local population, the dominant patient group is older, likely originating from neighboring IRIS zones.

The number of GPs has slightly declined since 2015 (-5.4%), though Lille outperforms the national trend. The age distribution of GPs, mostly under 40, indicates renewal, even if the 60+ share (25%) warrants medium-term vigilance (Figures 5 and 6).

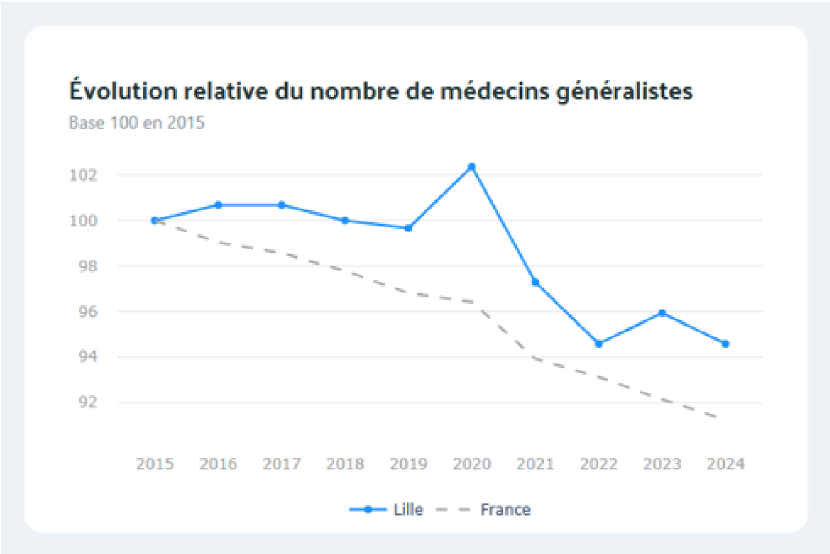

Figure 5: Relative evolution of GP numbers in Lille (2015–2024), base 100.

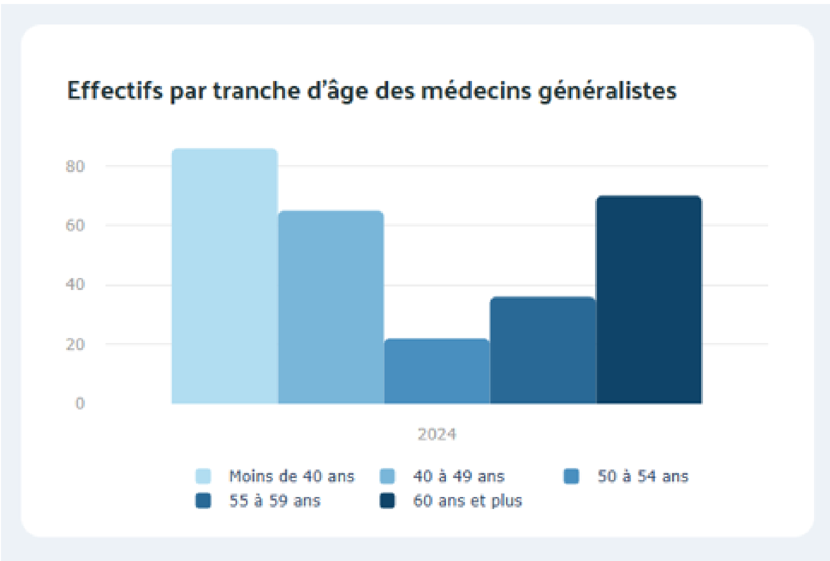

Figure 6: Age distribution of general practitioners in Lille (2024).

This dual analysis enables a more nuanced strategic view: the studied pharmacy lies in a youthful zone within a healthcare basin driven by older demand. The tool facilitates this cross-analysis by aligning maps and indicators, suggesting strategic adjustments: expanding preventive services or advice for mobile young adults, while also offering chronic disease management and home-care products for older patients.

4. Discussion

4.1 A Relevant Yet Partial Tool

The primary objective of this project was to design an interactive web application capable of supporting location analysis for community pharmacies through a geo-marketing approach based on public data. The developed tool attains this objective for the most part: it enables users to assess a given territory from two main perspectives (demographics and medical environment) and delivers insights through graphical, cartographic, and textual outputs. It targets non-expert users while supporting nuanced strategic interpretations.

The case study conducted on the Parvis Saint-Michel pharmacy in Lille illustrates the tool's ability to capture fine-grained territorial dynamics that are difficult to detect from raw data. It highlights the value of combining population profiles with healthcare indicators to identify opportunities or anticipate risks. However, the tool is not a fully-fledged siting simulator: it does not produce a unified attractiveness score or automated recommendations. Its strength lies in structuring the preliminary analysis for pharmacy siting or repositioning.

4.2 Comparison with Existing Practices and Literature

4.2.1 A Marginalized Application Area in Pharmaceutical Literature

Geomarketing applied to community pharmacies remains an underdeveloped field, especially within the French academic literature. Private consulting firms such as "La Longue Vue" have long offered proprietary zoning analyses, but their methods are often expensive, inaccessible to independent pharmacies, and lack peer-reviewed validation[10]. In contrast, a few academic studies—such as Cavallone et al. (2017), which demonstrate the utility of geomarketing for optimizing radiological services—exist, but their hospital-oriented focus limits direct transposability to community pharmacy siting[11]. This gap stands in stark contrast to other areas of public health where geospatial analysis is routinely employed to optimize service delivery.

4.2.2 A Methodological Foundation Inspired by Mature Sectors

The retail sector has long developed advanced geomarketing tools, including multi-criteria models, Geographic Information Systems (GIS), and hybrid strategies combining business expertise with large-scale data exploitation. This methodological maturity provides valuable insights, provided that these approaches are adapted to the specificities of the pharmaceutical sector[12].

Unlike traditional retail, pharmacy siting involves a dual imperative: economic viability and the continuity of public health services. The use of tools such as Voronoi diagrams, borrowed from commercial catchment modeling, demonstrates that certain principles of geomarketing can be transposed to regulated contexts—provided they are combined with robust medico-social indicators (e.g., APL, prescriber demographics, care utilization patterns).

The objective is not to replicate commercial models, but to selectively adapt their spatial and segmentation logic to the unique challenges of community healthcare delivery. This methodological hybridization represents a distinctive contribution of this work.

4.2.3 Voronoi Diagrams: A Robust but Simplified Method

The use of Voronoi diagrams in our tool offers a straightforward, transparent, and reproducible means to model service areas. Their application in public health is documented, particularly for defining ambulance or hospital catchment zones[13, 14]. However, our implementation employs unweighted Euclidean Voronoi diagrams, without accounting for transport networks or pharmacy-specific capacities. Recent developments such as Time-Travel Voronoi Diagrams (TTVD) could enhance accuracy but exceed the scope of this exploratory project.

4.2.4 Positioning and Unique Contributions

This project proposes a reproducible framework for geomarketing analysis tailored to community pharmacies. It applies structured academic methods to a sector where economic viability is intertwined with public health missions. The combined use of INSEE grid data and Voronoi-based partitioning enables precise territorial diagnostics. Furthermore, the integration of underutilized medico-economic indicators (e.g., APL, prescriber age pyramids, utilization rates) extends the tool beyond traditional geomarketing.

By relying exclusively on open public data, the tool ensures transparency and scientific replicability. This hybrid positioning—at the crossroads of data science, health geography, and siting strategy—opens concrete perspectives for improving pharmacy decision-support tools, while acknowledging functional limitations and territorial complexity.

4.3 Methodological Limitations

Despite its contributions, the application presents several limitations. The main bias stems from the Voronoi-based catchment area model, which uses Euclidean proximity and does not account for physical barriers, road networks, or actual mobility behaviors. While this method is robust for exploratory analyses and scalable across large areas, it loses precision in dense urban settings where travel times and real patient flows are key.

The use of the INSEE grid offers spatial accuracy but limits the variety of usable variables. Unlike IRIS datasets, which are richer in socio-economic dimensions, the grid data provide only basic demographic indicators. This illustrates a methodological trade-off between spatial granularity and analytical depth. Consequently, variables like household structure or socio-professional classification are not available at fine scales.

Additionally, census data quality raises reliability concerns. INSEE's renewed census relies on samples in municipalities over 10,000 inhabitants[15], increasing statistical uncertainty at smaller scales. Grid data are also subject to statistical secrecy rules, excluding tiles with fewer than 11 inhabitants[16]. This creates data voids in peri-urban or rural zones, disrupting spatial continuity.

Temporally, the tool is based on data available up to 2020. This prevents medium-term projections, despite pharmacy acquisitions typically spanning 4 to 12 years. The absence of forecasting models limits the ability to anticipate demographic or medical shifts.

The medical environment section is limited to general practitioners. This choice was based on their central role as prescribers, yet it omits other key healthcare actors such as nurses, physiotherapists, and specialists. Including them could provide a fuller picture of healthcare circuits, especially in fragmented or specialized care areas.

Finally, the lack of spatial visualization in the "medical environment" page is a gap. Unlike the demographic section, users cannot see maps of care providers. Integrating such maps (e.g., physician and pharmacy locations) would enhance the tool's exploratory capabilities.

4.4 Future Directions

Several concrete enhancements could increase the tool's added value. First, to improve the realism and analytical depth of service-area delineation, the tool could let users choose between Euclidean Voronoi diagrams and isochrone-based catchments. Indeed, isochrones customizable by transport mode and time, would yield more accurate flow representations, especially in urban settings. Furthermore, this catchment module could implement a hybrid data-layering approach—combining the spatial precision of INSEE 200 m grids with the socio-economic richness of IRIS polygons—to overcome the current trade-off between granularity and variable diversity.

Second, incorporating drug consumption data from Open Medic would allow estimation of dispensation volumes by therapeutic class at the territorial level, enriching the medico-economic analysis.

Lastly, enabling pharmacists to import internal data (sales, customer typologies) would allow for benchmarking against contextual indicators. This could support strategic adjustments: for example, a pharmacy in a family-dense area but with low pediatric sales might adapt its product offering. Conversely, high performance in a seemingly low-potential zone might reveal best practices or unique positioning. Such cross-analysis would facilitate more operational insights and support local commercial and health decision-making.

5. Conclusion

This work aimed to design an interactive decision-support tool for pharmacy location planning, by applying geomarketing principles to the healthcare sector. The developed application provides an intuitive interface centered on two strategic dimensions: demographic characteristics and the medical environment. By integrating heterogeneous public data, it enables a detailed territorial analysis to support more informed location decisions. The chosen approach offers several contributions. It leverages INSEE grid data for high-resolution spatial analysis, adapts commercial geomarketing methods to the specificities of a sector governed by both economic and public service logic, and establishes a visualization system that combines indicators, maps, and textual summaries to facilitate strategic interpretation. While limitations remain, particularly regarding temporal dimensions, the types of healthcare professionals considered, and the method for defining catchment areas, numerous development opportunities have been identified. The integration of drug consumption data, isochrone-based delimitation, or cross-referencing with internal pharmacy data offer concrete prospects for refining the tool. This project demonstrates that the valorization of public data, when structured by professional expertise, can produce useful, accessible, and reproducible tools. It represents a first step toward territorial intelligence applied to the strategic management of community pharmacies.

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Abstract

Solim Laokpezi, Tanguy Surowiec ______________________________

Analyse spatiale des pharmacies en France fondée sur le géomarketing

L'implantation d'une pharmacie constitue une décision stratégique alliant enjeux économiques et sanitaires. Ce mémoire présente un outil interactif d'aide à la décision pour évaluer l'attractivité territoriale via des données publiques. L'approche applique les principes du géomarketing au secteur officinal, croisant structure démographique et environnement médical. L'outil web permet une exploration multi-échelle basée sur les données carroyées INSEE et les indicateurs DREES. Les zones de chalandise sont modélisées par diagrammes de Voronoï superposés à une maille géographique fine. Un cas concret illustre la capacité à révéler des dynamiques locales pertinentes pour l'implantation.

Mots-clés : pharmacie, géomarketing, implantation, données publiques, zone de chalandise, analyse territoriale

Solim Laokpezi, Tanguy Surowiec ______________________________

Geomarketing-Based Spatial Analysis of Pharmacies in France

The establishment of a community pharmacy is a strategic decision combining economic viability and public health needs. This thesis presents an interactive decision-support tool for assessing territorial attractiveness using public data. The approach applies geomarketing principles to the pharmaceutical sector, combining demographic structure and healthcare environment analysis. The web-based tool enables multi-scale territorial analysis using INSEE grid data and DREES medico-economic indicators. Catchment areas are modeled through Voronoi diagrams overlaid on geographic grids to generate localized indicators. A case study demonstrates the tool's effectiveness in revealing local dynamics relevant to pharmacy location decisions.

Keywords: pharmacy; geomarketing; location analysis; public data; catchment area; territorial analysis

ANNEXE N° 1

M2 DATA SCIENCE EN SANTE
Année 2024 – 2025

Sujet de mémoire

1. Proposition du sujet

Nom et prénom de l'étudiant (e) : LAOKPEZI Solim **Sp. : DSS**

Intitulé – Thème ou sujet   Implantation officinale sur différents territoires en France Analyse cartographique 2 (Construction de l'interface Homme Machine)

Avis de votre responsable de spécialité sur le sujet de votre mémoire

Accepté ☒ Refusé ☐

Motivation :

2. Proposition du directeur de mémoire

Nom - Prénom : Djamel Zitouni	Adresse professionnelle : djamel.zitouni@univ-lille.fr Fac de pharmacie de lille Qualité/fonction : Maître de conférences laboratoire de Biomathématiques	
N° de tél : +33 (0)3 20 96 40 02	N° de fax : +33 (0)3 20 95 90 09	Mail : djamel.zitouni@univ-lille.fr
Je soussigné, ZITOUNI Djamel reconnais avoir pris connaissance des modalités de rédaction du mémoire et notamment du rôle du directeur de mémoire		Date et signature du directeur de mémoire 05/05/2025

Avis de votre responsable de spécialité sur la proposition du directeur de mémoire

Accepté ☒ Refusé ☐

Motivation :

Validation du responsable de spécialité
A Loos, le 06/06/2025

ANNEXE N° 1

M2 Data Science en Sante
Année 2024 – 2025

Sujet de mémoire

1. Proposition du sujet

Nom et prénom de l'étudiant (e) : SUROWIEC Tanguy Sp. : DSS

Intitulé – Thème ou sujet *(Facultativement, principale(s) question(s) scientifiques et/ou techniques)* Cartographie officinale en France – Interface Homme Machine (IHM)

Avis de votre responsable de spécialité sur le sujet de votre mémoire [1]

Accepté ☒ Refusé ☐

Motivation :

2. Proposition du directeur de mémoire

<table>
<tr><td>Nom - Prénom :ZITOUNI Djamel</td><td colspan="2">Adresse professionnelle : djamel.zitouni@univ-lille.fr
Fac de pharmacie de lille
Qualité/fonction : Maître de conférences laboratoire de Biomathématiques
MCU</td></tr>
<tr><td>N° de tél : +33 (0)3 20 96 40 02</td><td>N° de fax +33 (0)3 20 95 90 09</td><td>Mail :
djamel.zitouni@univ-lille.fr</td></tr>
<tr><td colspan="2">Je soussigné, ZITOUNI Djamel
reconnais avoir pris connaissance des modalités de rédaction du mémoire et notamment du rôle du directeur de mémoire</td><td>Date et signature du directeur de mémoire 05/05/2025</td></tr>
</table>

Avis de votre responsable de spécialité sur la proposition du directeur de mémoire

Accepté ☒ Refusé ☐

Motivation :

Validation du responsable de spécialité
A Loos, le 06/05/2025

[1] ***Le sujet de votre memoire n'est pas modifiable.*** *Si pour une raison dument justifiee, une modification importante devait intervenir, celle-ci doit etre validee par le responsable de specialite. Cette absence d'accord entraine systematiquement la non validation du memoire et par consequent l'impossibilite de soutenir.*

ANNEXE N° 2

M2 DATA SCIENCE EN SANTE
Année 2024 – 2025

Autorisation[2] de soutenance

1. *Informations à compléter **par l'étudiant***

Nom de l'étudiant : Tanguy SUROWIEC **Spécialité :** Data Science en Santé

Titre du mémoire : Développement d'un outil d'aide à la décision pour L'implantation officinale sur différents territoires en France basé sur une analyse cartographique : Construction de l'interface Homme-Machine

Date soutenance : jeudi 3 juillet 2025 **Heure :** 13h10

Composition du jury :

	NOM Prénom	Fonction	Entreprise	Signature
Président de jury 1er membre permanent	**GUINHOUYA Benjamin**	**Enseignant Chercheur**	**ILIS**	
2ème membre permanent	**ZITOUNI Djamel**	**Enseignant Chercheur**	**ILIS**	
3ème membre permanent	**DUFOSSEZ François**	**Médecin DIM**	**GHT Artois**	
4ème membre Membre invité	**BOUDIS Fabio**	**Data Scientist**	**CHU Lille**	

Avis de votre responsable de spécialité sur la composition du jury

Accepté ☒ Refusé ☐ Signature :

Dès réception, il vous appartient de confirmer cette décision aux membres de jury. Votre mémoire doit être délivré aux membres du jury 15 jours avant la soutenance et 1 mois avant au directeur du mémoire et au responsable de spécialité.

2. *Matériel audio - visuel à mettre à disposition :*

× Vidéo - projecteur pour présentation informatique - ☐ Ordinateur
☐ Autre (s) : précisez

✓ Autorisation de soutenir le mémoire de fin d'études

A compléter par le directeur de mémoire :
☒ **est autorisé (e) à soutenir son mémoire de fin d'études**
☐ **n'est pas autorisé à soutenir son mémoire de fin d'études**

A, Lille **, le** 20/05/2025

Nom du directeur de mémoire
Signature

Validation du responsable de spécialité
A Loos, le 30/05/2025

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[2] *L'autorisation de soutenir ci-dessus ne préjuge en aucun cas de la validation ou non de votre mémoire. Elle signifie simplement que votre directeur de mémoire estime que le travail a été réalisé en respectant les consignes données et peut être soumis aux autres de membres du jury. **Le sujet de votre mémoire n'est pas modifiable.** Si pour une raison dûment justifiée, une modification importante devait intervenir, celle-ci doit être validée par le responsable de spécialité. Cette absence d'accord entraîne systématiquement la non validation du mémoire et par conséquent l'impossibilité de soutenir.*

ANNEXE N° 2

M2 DATA SCIENCE EN SANTE
Année 2024 – 2025

Autorisation[2] de soutenance

1. *Informations à compléter **par l'étudiant***

Nom de l'étudiant : Solim LAOKPEZI **Spécialité :** Data Science en Santé

Titre du mémoire : Développement d'un outil d'aide à la décision pour L'implantation officinale sur différents territoires en France basé sur une analyse cartographique : Construction de l'interface Homme-Machine

Date soutenance : jeudi 3 juillet 2025 **Heure :** 13h10

Composition du jury :

	NOM Prénom	Fonction	Entreprise	Signature
Président de jury 1er membre permanent	**GUINHOUYA Benjamin**	**Enseignant Chercheur**	**ILIS**	
2ème membre permanent	**ZITOUNI Djamel**	**Enseignant Chercheur**	**ILIS**	
3ème membre permanent	**DUFOSSEZ François**	**Médecin DIM**	**GHT Artois**	
4ème membre Membre invité	**BOUDIS Fabio**	**Data Scientist**	**CHU Lille**	

Avis de votre responsable de spécialité sur la composition du jury

Accepté ☒ Refusé ☐ Signature :

Dès réception, il vous appartient de confirmer cette décision aux membres de jury. Votre mémoire doit être délivré aux membres du jury 15 jours avant la soutenance et 1 mois avant au directeur du mémoire et au responsable de spécialité.

2. *Matériel audio - visuel à mettre à disposition :*

× Vidéo - projecteur pour présentation informatique - ☐ Ordinateur
☐ Autre (s) : précisez

✓ Autorisation de soutenir le mémoire de fin d'études

A compléter par le directeur de mémoire :
☒ **est autorisé (e) à soutenir son mémoire de fin d'études**
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A, Lille **, le** 20/05/2025

Nom du directeur de mémoire
Signature

Validation du responsable de spécialité
A Loos, le 22/0/2025

[2] L'autorisation de soutenir ci-dessus ne préjuge en aucun cas de la validation ou non de votre mémoire. Elle signifie simplement que votre directeur de mémoire estime que le travail a été réalisé en respectant les consignes données et peut être soumis aux autres de membres du jury. **Le sujet de votre mémoire n'est pas modifiable.** Si pour une raison dûment justifiée, une modification importante devait intervenir, celle-ci doit être validée par le responsable de spécialité. Cette absence d'accord entraîne systématiquement la non validation du mémoire et par conséquent l'impossibilité de soutenir.