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Drug Shortages and Patient Reactions: Exploring the Influence of Drug Type and Individual Factors

A Study of the SOR Model

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Dissertation

presented as partial requirement for obtaining the Master Degree Program in Statistics and Information Management

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação

Universidade Nova de Lisboa

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**DRUG SHORTAGES AND PATIENT REACTIONS: EXPLORING THE
INFLUENCE OF DRUG TYPE AND INDIVIDUAL FACTORS**

A STUDY OF THE SOR MODEL

By

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Master Thesis presented as partial requirement for obtaining the Master's degree in Statistics and Information Management, with a specialization in Risk Analysis and Management

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November of 2023

STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledge the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Daniela Rotaru

Lisbon, 1st of November of 2023

ACKNOWLEDGEMENTS

Even though the present dissertation was only written by one person, there are a few people who were an essential support for its completion. And I want to use this space to specially thank them.

To my parents who worked and keep working hard to provide me with the best upbringing.

To my sister who knows how to get on my nerves the best, and is still the one I root for the most.

To my close family who even from far away can be my biggest supporters.

To my boyfriend who falls asleep when I talk about my dissertation but is the one who motivates me the most.

To my friends for being present even when I couldn't be, and a special one to Gonçalo, Beatriz and Bernardo for being my amateur advisors.

And last, but definitely not least, a big thank you to my advisor Maria Helena Baptista who always made herself available to help me, answered all my questions and guided me through the whole process.

ABSTRACT

The relation between scarcity and impulsive behavior has already been studied and proven to influence one another, and even used as a marketing technique. Hence, the purpose of this study is to focus on recent drug shortages and the buying behavior of regular pharmaceutical drug consumers, while also analyzing what factors influence panic buying tendencies, with special focus of the fear of missing out on the purchase and changes on the treatments. The model is constructed based on the Stimulus-Organism-Response (SOR) theory and hypothesis are tested with a partial least squares structural equation modelling (PLS-SEM). Data was collected through 42 surveys done to consumers who recently suffered with drug shortages of five known molecules used for diabetic treatment – dulaglutide, exenatide, liraglutide, lixisenatide and semaglutide. Based on the gathered data, the results of the study have shown that even though drug scarcity is seen as a problem and a worry, it does not trigger panic buying. And other factors such as fear of missing out and changes on the treatment also do not trigger panic buying. Nonetheless, governmental authorities and the health sector should take measures to not only manage but also avoid drug shortages, since these type of shortages have been having direct impact on the life style of the population.

KEYWORDS

Drug Shortages; Prescription Drugs; Non-prescribed Drugs; Panic Buying; SOR Model

Sustainable Development Goals (SGD):



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LIST OF ABBREVIATIONS AND ACRONYMS

ANF	Associação Nacional de Farmácias (National Association of Pharmacies)
ATC	Anatomical Therapeutic Chemical Code
AVE	Average Variance Extracted
CA	Cronbach Alpha
CB-SEM	Covariance Based Structural Equation Modeling
CEFAR	Centro de Estudos e Avaliação em Saúde (Center for Health Studies and Evaluation)
CR	Composite Reliability
DM	Diabetes Mellitus
EEA	European Economic Area
EMA	European Medicines Agency
ERP	External Reference Pricing
EU	European Union
FDA	Food and Drug Administration
FOMO	Fear of Missing Out
GDP	Gross Domestic Product
GSL	General Sales List
HMA	Heads of Medicines Agency
INFARMED	Autoridade Nacional do Medicamento e Produtos de Saúde (National Authority of Medicines and Health Products)
MAH	Marketing Authorization Holder
MNSRM	Medicamentos Não Sujeitos a Receita Médica (Non-prescription Medicines)
MSRM	Medicamentos Sujeitos a Receita Médica (Prescription Medicines)
OTC	Over-the-Counter
P	Pharmacy
PLS-SEM	Partial Least Squares Structural Equation Modelling
POM	Prescription-Only Medicine

R&D	Research and Development
SCM	Supply Chain Management
SCRM	Supply Chain Risk Management
SEM	Structural Equation Modeling
SOR	Stimulus – Organism – Response Theory
SR	Stimulus – Response Theory
SRMR	Standardized Root Mean Square Residual
WHO	World Health Organization

1. INTRODUCTION

The World Health Organization (WHO) is responsible for satisfying population needs and ensure access to basic health services, products and medicines (World Health Organization, n.d.). Medicines, in specific, help improving health conditions, and subsequently, increase population life expectancy (Dylst & Simoens, 2010). Thus, access to medicines has been gradually gaining importance, and is nowadays considered a basic human right (Hogerzeil, 2006). However, the population rise and the increase in medicine circulating in the market has been fueling drug shortages along the years. Drug shortages impact the pharmaceutical and healthcare sectors by restricting access to medicines and compromising the management of the health sector, affecting developed countries and countries in development (Hogerzeil, 2004; Shukar et al., 2021). Therefore, understanding how drug shortages emerge, develop and settle is essential to allow involved parties to be prepared for future situations.

Shortages happen when drug supply is not enough to meet the demand. The possible causes can be divided into supply-based and demand-based (Musazzi et al., 2020), in Portugal those are manufacturing restrains and fluctuations on demand, respectively (INFARMED, 2022). The supply chain of the pharmaceutical industry is composed of several stakeholders, from manufacturers to consumers (Jaberidoost et al., 2013; Singh et al., 2016), increasing the chances of possible setbacks, hindering the identification of the setback and making it more difficult to solve. Patients tend to be the most affected from all the supply chain participants (Kweder & Dill, 2013; Steinbrook, 2009), besides being affected by cost increases they are also affected by treatment delay, adverse effects and medication errors (Fox et al., 2014). Furthermore, patients seek solutions such as alternative drugs but never with guaranteed efficiency.

In moments of uncertainty, consumers tend to adopt impulsive behaviors such as impulsive purchases or panic buying (Omar et al., 2021; Rodrigues et al., 2021). And the same might happened in the case of drug shortages since it brings uncertainty in patients' life and might create emotional responses. Hence, the purpose of this study is to learn about consumer behavior when faced with drug shortages, and additionally understand what individual factors influence that behavior, such as fear of missing out on a purchase or modified treatments. Moreover, this study also intends to compare consumer behavior between shortage of prescription drugs and non-prescription drugs, as each type of drug has different levels of accessibility, regulation, and importance for consumers. Besides the difference between prescription and non-prescription drugs, it is also important to take into account what is the type of treatment a medicine provides. Therefore, the present study will be focused on a specific group of drugs which was chosen based on data about recent shortages and based on media attention. Thus, the group chosen was medicine for the treatment of diabetes. Diabetes is an incurable disease with serious consequences in case of neglect, which makes consumers highly attached to the medicine they usually consume.

Data was collected through the help of an over the phone fully structured questionnaire, and was posteriorly analyzed and interpreted. The analysis was done based on the Stimulus-Organism-Response (SOR) theory and tested with a partial least squares structural equation modelling (PLS-SEM). SOR theory is a theoretical framework highly used to study consumer behavior, and it is based on three constructs that are connected which are stimulus, organism and response (Mehrabian & Russell, 1974; G. Zhang et al., 2021). These three constructs change based on the context, in this particular study drug scarcity is the stimulus, the response is panic purchases and the organism is

patient's fear of missing out on a purchase and modified treatments. In conclusion, the goal of this study is to better understand the psychological factors that influence customer panic buying intentions when taking into account drug shortages. The objectives of the thesis will be achieved by answering the following research questions:

- (a) Do drug shortages lead to panic buying?
- (b) Does fear of missing out on a drug purchase or modified treatments triggers panic buying?
- (c) Does the type of drug (prescription or non-prescription) matter when it comes to drugs shortages emotional reactions?
- (d) What are the implications of the study for healthcare professionals and policymakers?

Literature about patient perspective on drug shortages is very little (Atif et al., 2021). And since drug shortages have been gaining increasing attention from governmental authorities, news media and healthcare professionals, the findings from this study have the potential of improving how health authorities and pharmaceutical industry manage patients, community pharmacies and hospitals in situations of shortage. Understanding consumer behavior will help the healthcare system delineate action plans, policymakers implement the necessary measures and policies, and persuade researchers to study the matter. Additionally, future studies on subpopulations, drug classes, and the long-term effects of drug shortages may be inspired by this.

2. LITERATURE REVIEW

The following sections discuss related work on literature including scarcity of products, drug shortages, panic buying, types of medicine and news media.

2.1. SCARCITY OF PRODUCTS

Products are goods which main goal is to fulfill people's needs, while scarcity is when those goods are not available, and consequently, needs are not met (Ladeira et al., 2023). Scarcity can be real or perceived, short-term in case of short supply or long-term in case of legal limitations, or at individual, macro, or community level (Hamilton et al., 2019). Scarcity can also be supply-based or demand-based. Supply-based is when a good in short supply is unable to meet demand requirements, whilst demand-based is when the available supply is incapable to meet the increasing demand (John et al., 2018).

Marketing experts can use scarcity as a marketing technique, this is what is called perceived scarcity. Marketers will limit availability of certain products which will subsequently create a false sensation of scarcity and unavailability, by applying this technique goods will be promoted, consumer demand intensified and market performance improved (Brannon & Brock, 2001; Cialdini, 1993; W. Y. Wu et al., 2012). This technique works for only a handful of situations and is unsuccessful when supply is indeed limited and products are non-conspicuous (Gierl & Huettl, 2010), such as medicine. This procedure is only viable when taking into consideration the commodity theory, which defends that a good has more value when availability decreases, correlated to the consumer need for uniqueness (Brock, 1968). Thus, scarce products are more attractive than available ones (Gierl & Huettl, 2010; Hamilton et al., 2019), creating feelings of attractiveness, desire, expensiveness, and quality among those who own them (Lynn & Bogert, 1996). These feelings are comparatively lower when consumers do not know about the unavailability (Hamilton et al., 2019).

There is a general consumer reaction to scarcity, independently of being real or perceived, which follows a four-step process where the consumer first tries to understand the shortage, followed by a moment of consideration, selection, and consumption of alternative products (Court et al., 2009). Different outcomes can result from this process which are backed by three different theories – conformance theory, reactance theory and regret theory (Ladeira et al., 2023). Conformance theory explains that once the decision is made consumers go through a period of conformance (Jones, 1984). Regret theory suggests that consumers avoid future regret by anticipating the possibility of a wrongly made choice between buying now or risking missing out on a purchase opportunity (Loomes & Sugden, 1982). Reactance theory defends that people react when feeling restricted (Brehm, 1966), this can be through impulsive purchases or panic buying, and is not likely to occur when scarce medicine has alternative options.

Any small chance of restriction felt by the consumer can often led to impulsive purchases and panic buying behavior. Impulsive buying are spontaneous purchases for an immediate feeling of satisfaction, and no thought is put into possible alternative options or future implications (Rodrigues et al., 2021), owing to the closeness and emotional bond with the desired product that leads to personal satisfaction (Li, 2015). Whereas panic buying is when consumers develop feelings of anxiety and stress triggered by the possibility of shortages, and consequently, might lead to hoarding or stockpiling (Omar et al., 2021), which can be considered rational, or not, depending on the stocked goods (Martin-Neuninger

& Ruby, 2020). Additionally, a fear of missing out can develop (John et al., 2018), or even trigger feelings of pleasure and excitement (Omar et al., 2021). Panic buying is often present during health crises, it was first documented in 1918 with the appearance of the Spanish flu, and some other examples are the 1968 Hong Kong flu and 2003 SARS outbreak (Taylor, 2021). More recently, the COVID-19 pandemic (Arafat et al., 2020; Hamilton, 2021), and the conflict between Russia and Ukraine, where anxiety and stress levels increased (Ladeira et al., 2023). Overall, there is a clear increase of panic buyers during times of uncertainty, consumers tend to over-buy various products, including medicine, since it provides them a feeling of safety. This behavior is, in most cases, instigated by news of short supply in moments of high demand which creates a sense of urgency among consumers. Hence, news media can trigger panic buying and rise public anxiety (Taylor, 2021). A survey made in Canada and the USA to more than six thousand adults during the early stages of COVID-19 concluded that 20% of the studied population was stockpiling on prescription drugs and 13% on cold and flu medicine, which was equivalent to a stock up for a two-week supply (Taylor et al., 2020). Stockpiling on vaccines and medicine is a preparation method in case of an emergency (Arafat et al., 2020). Possible strategies to adopt by authorities to overcome thoughtless purchases are production of extra stock, limit on bulk buying and promote media downplay of their coverage (Taylor, 2021).

Purchases should always be done responsibly, independently if a shortage is faced or not. Alternatively to what has been said above, there are also studies defending that product scarcity encourages careful decision making (Brannon & Brock, 2001; Ladeira et al., 2023), since it obligates consumers to efficiently allocate available resources to satisfy their own needs (Shi et al., 2020).

The panic generated around certain products will end up affecting consumers the most. The economy theory defends that as products get scarcer prices increase (W. Y. Wu et al., 2012), which creates a false feeling of high quality of the scarce products (Cialdini, 1993; Rao & Monroe, 1989), whilst creating skepticism for the alternative options (Hamilton et al., 2019). News reports about scarce products can also be an instigator to price appreciation. Therefore, today's scarcity is a predictor of tomorrow's price increase on products (Lynn & Bogert, 1996). It is in these moments of stress that suppliers take advantage of the poor economic decisions made by consumers (John et al., 2018; Ladeira et al., 2023), those who forget about the already acquired knowledge and follow purchase behaviors of other consumers (Gierl & Huettl, 2010; Worchel et al., 1975). Product shortages increases the willingness to pay, increases the probability of choosing unfamiliar brands and impacts consumers' decisions (Ladeira et al., 2023).

2.2. DRUG SHORTAGES

2.2.1. Definition

There are several definitions for drug shortages depending on the organization or health authority who wrote it and what conditions and elements they had into account, such as level of supply, permanent or temporary discontinuation, time frame with a variance of 20 days and typology (De Weerd, Simoens, Casteels, et al., 2015). The various possible definitions create the first challenge to understand what a drug shortage is and if indeed exists (Fox et al., 2014). Finding an universal definition is important to avoid miscommunication and misinterpretations. The first step in addressing drug shortages is to agree on an accepted and common definition (Shuman et al., 2020). By having a uniform definition international comparison will be facilitated, corrective measures can be taken and

communication between involved parties eased (De Weerd, Simoens, Casteels, et al., 2015). By 2018, only a few group of countries had a set definition (Bochenek et al., 2018).

Finally, in 2019, the European Medicines Agency (EMA) together with the Heads of Medicines Agency (HMA) joined forces to create an uniform definition for the European Economic Area (EEA) with the main goal of facilitating communication and coordination between the involved parties when it came to drug shortages (Musazzi et al., 2020). At national level Portugal has its own definition - "A disruption in drug supply is temporary or permanent unavailability, potential or real... In the context of community pharmacies, it is considered missing when it is verified the infeasibility of satisfying a prescription for a period exceeding 12 hours after its presentation." (INFARMED, 2022).

2.2.2. Pharmaceutical Supply Chain

Supply chain is a network composed of various collaborative organizations – suppliers, manufacturers, distributors, and retailers – that together follow a set of processes from the acquisition of raw materials to the delivery of the final products to customers (Aldrighetti et al., 2019). The pharmaceutical industry has a complex supply chain, besides the already enumerated involved organizations there are also wholesalers, information service providers, customers, and regulatory agencies (Jaberidoost et al., 2013; Singh et al., 2016), and the process involves the discovery, development and manufacturing of drugs and medications (Shah, 2004).

Population growth and introduction of new drugs in the market increases exchange of resources and information and implementation of processes and operations (Koh et al., 2003). This unpredictability of the surrounding environment will inevitably increase the chances of risk, which are daily occurrences, and each business has a different exposure and preparedness to them depending on the implemented risk management processes (Wang & Jie, 2020). Risks in the pharmaceutical industry can affect people's life and waste important resources, the most common risks are supplier and regulatory risks (Jaberidoost et al., 2013), for example, a simple delay of raw material distribution will affect delivery to customers, which will consequently affect the cash flow and sales (Wang & Jie, 2020).

To ensure a business is prepared to face risks it is important to have a good supply chain management (SCM) to manage activities, reduce costs, create value (Jaberidoost et al., 2013; Wang & Jie, 2020) and create an efficient flow of information and goods between the involved parties (Kaufmann et al., 2005). The success of a well implemented SCM depends on good communication, support from executive positions, data collection and analysis, education on supply chain and measure of costs and performance (McKone-Sweet et al., 2005). Complementarily, it is also vital to have a good supply chain risk management (SCRM) to prepare businesses for any risk regardless of complexity, financial costs, and high consumption of non-financial resources (Hoon Kwak & Dixon, 2008; Wang & Jie, 2020; Wieland, 2013). Full mitigation of risks and setbacks is not an easy task. Businesses need to be prepared for the common risks, but also the not so common ones, such as natural disasters or epidemics (Grifa et al., 2020). The most recent epidemic was COVID-19 which affected business efficiency and performance independently on their risk preparedness (Chowdhury et al., 2021; Sherman, 2020), especially the healthcare sector where demand for personal protective equipment and ventilators increased (Shuman et al., 2020).

The objective of a supply chain is a seamless flow of goods, services, and information between all involved stakeholders to meet the market needs, thus demand must be effectively and accurately

conveyed. In this specific area, pharmaceutical companies are more challenging since drugs are prescribed by physicians and consumed by patients who have little control over their choice (Pedroso & Nakano, 2009).

2.2.3. Causes

Drug shortages originate when there is a deficiency in drug supply to those who require access to treatments in due time (Pauwels et al., 2015). The first documented drug shortage date back to 1920 with the shortage of insulin, thenceforth shortages have been increasing due to population and marketed drugs increase (Shukar et al., 2021). Nowadays, it is named by the WHO as a “complex global challenge” (Gray & Manasse, 2012).

Any part of the supply chain can be responsible for a shortage (Heiskanen et al., 2015), and in most cases it is difficult to identify the cause (De Oliveira et al., 2011), which can be either supply-based or demand-based (Musazzi et al., 2020) or the mismatch between both. Literature identifies different causes for drug shortages but the most common supply-based causes are manufacturing problems, business decisions, natural disasters, scarcity of raw materials and regulatory issues, and demand-based causes are fluctuating demand, parallel market and price and reimbursement policies (Bochenek et al., 2018; Tyler & Mark, 2002; Ventola, 2011). According to Portuguese authorities, drug shortages in Portuguese pharmacies are mostly caused by factory constraints and increased demand (INFARMED, 2022).

Manufacturers are responsible for the discovery, development, production and distribution of drugs, any disruption on this phase of the supply chain will create volatility on the whole process (Duong et al., 2019). Identification and resolution of any disruption is essential, and it can be done by implementing production and availability policies (Khan, 2019), for example, the just-in-time inventory approach will help produce only the necessary stock and find an equilibrium between cost and inventory quantity (Fox et al., 2014), and not hold buffer stock (Hedman, 2016). Manufacturing problems are rarely admitted and real reasons are often left in the open (Fox & Tyler, 2013), not allowing external entities to tackle the problem accordingly and in a timely manner (McKenna, 2011).

Business decisions can be voluntary recalls or production discontinuation. Recalls are based on safety reasons, for example, errors on the leaflet or on the packaging (De Weerd, Simoens, Hombroeckx, et al., 2015), while discontinuation is a strategic business decision based on profit, patent expiration, market competition and expected demand (De Oliveira et al., 2011). Generic drugs (explained in more detail on chapter 2.3.2.) are an example of production discontinuation because of their low margin, therefore not financially appealing for businesses (Duong et al., 2019; Kweder & Dill, 2013; Metzger et al., 2012), which either leads to cost and drug price increase (Singh et al., 2016). With no support these risks end up being neglected (Wang & Jie, 2020; Wieland, 2013).

Causes for drug shortages have always been mostly operational, but with time natural disasters have gained territory and nowadays are highly mentioned as a possible cause, such as the occurrence of a hurricane, earthquake or flood can damage manufacturing facilities and cause temporary or even permanent shut-downs (Aldrighetti et al., 2019; Hoffman, 2012; Ventola, 2011). Big geopolitical events and epidemics can also affect manufacturing facilities and delay production, for example Brexit or Covid-19 (Govindan et al., 2020; Musazzi et al., 2020).

Drug demand can be unpredictable or seasonal, or artificial when supply decreases (De Oliveira et al., 2011). Abnormal fluctuations in demand can lead to panic buying, uncertainty about the future and stockpiling and hoarding behavior. This happens because consumers feel pressured and threatened about the possibility of losing the opportunity of buying a desired product, therefore the high demand will lead to uncertainty followed by price increase (Chowdhury et al., 2021; Yuen et al., 2020). Stockpiling and hoarding happens when consumers purchase a product in higher quantities than needed in order to avoid facing a shortage, meet consumer or institution needs and avoid future higher costs, although it might seem a solution it creates an artificial shortfall (Tyler & Mark, 2002). It is viewed by consumers and retailers as a solution to guarantee supply availability, prevent future shortages, secure on-time delivery and avert profit loss (Chopra & Sodhi, 2004), but the short drug shelf-life and the poor assessment of the stocked inventory might originate unnecessary large inventories, loss of stock, expired products, unavailable medicine, high storage costs and delivery delay (Aldrighetti et al., 2019; Duong et al., 2019). During the initial stages of Covid-19 the increasing volume of demand and sales created a feeling of fear and unfamiliarity between consumers, so, to avoid panic purchases authorities intervened by implementing: a) quantity restrictions on over-the-counter (OTC) medicines, b) pharmacies could not dispense six month renewal prescription and c) permission for pharmacies to deliver prescription-only medicine (detailed explanation on chapter 2.3.1.) to people at home (Romano et al., 2021).

Parallel trade is a non-traditional type of demand where products are imported from countries at lower prices and sold into secondary high-price markets without authorization (Bart, 2008; Bochenek et al., 2018). The European Union (EU) is propitious to parallel trading due to their free movement of people and goods policy. Supply quotas can be implemented to avoid parallel trading and ensure access, but they are not able to foresee the unexpected increase in demand (De Weerd, Simoens, Hombroeckx, et al., 2015; Pauwels et al., 2014), therefore reducing medicine prices is not always the solution, as it might create more problems (De Weerd, Simoens, Hombroeckx, et al., 2015).

Pricing and reimbursement policies are used by healthcare authorities to ensure affordable access to medicines, safeguarding citizens from financial distress, generate savings and control costs (Vogler et al., 2017; World Health Organization, 2004), but these can also affect the availability of drugs (Huys & Simoens, 2013). The pricing of a medicine is done in most European countries based on a practice called external price referencing (EPR) which is when a country sets the price of a medicine according to the price from another country, by doing so policy-makers can have a benchmark (Vogler et al., 2017). The main contribution of this practice is lower drug prices and creation of savings for the stakeholders (Vogler et al., 2020). This practice is not mandatory, and each country had their own methods of pricing such as internal price referencing, which can have disadvantages. Internal price referencing is similar to ERP but at national level, price of a medicine is defined based on comparable medicines in the same country, for example this practice is common for generics (Vogler et al., 2020). Allowing each national authority to negotiate the charged prices based on their gross domestic product (GDP) and willingness to pay will create price differences between countries, which can lead to parallel trading or unavailability of drugs because of the low gain margin, encouraging manufacturers to focus on more profitable markets (De Weerd, Simoens, Hombroeckx, et al., 2015). In countries where is practiced lower prices or the market is smaller it was found that there is a higher chance of drug unavailability and longer launch delays (Espin et al., 2011). Therefore, it is important to do a regular revision to pricing procedures to avoid shortages.

Reimbursement policies is a mechanism implemented at national level to safeguard patients from a high healthcare cost with medicine (Paris et al., 2016). Marketing Authorization Holders (MAH) are profit or non-profit organizations with marketing authorizations from EMA, and they are responsible for the commercialization and marketing of a specific medical product inside the EU. To apply for a reimbursement policy each MAH must first submit their request, followed by a decision-making process where expert committees, and eventually public authorities and stakeholders participate to decide about the reimbursement status and to what extent will the drug be funded by the national authorities. Their decisions are based on therapeutic value, medical necessity, safety, cost-efficiency and budget impact (Vogler et al., 2018). But similarly, to the pricing policies each country has their own reimbursement policies (WHO, 2018), which means that the price of the same medicinal product may vary significantly around Europe (Musazzi et al., 2020).

2.2.4. Affected Stakeholders

Drug shortages are a public health problem in an increasing number of countries. Independently of the economic power of a country, geographical position, or health care system, both developed and in development countries are affected by drug shortages and their price increase (Bochenek et al., 2018; Hedman, 2016; Hogerzeil, 2004; Lucero-Prisno et al., 2020), turning it into a globalized phenomenon (Walker et al., 2017). Countries in development are more likely to face drug shortages when compared to countries financially stable. Besides not having a good management, financial support, a stable healthcare system or research and development (R&D) investments, countries in development also face drug smuggling, licensing of products, local manufacturing shortages and lodging governmental taxes (Atif et al., 2019; Khan, 2019; Shukar et al., 2021). Lebanon is an example of a country highly propitious to shortages, they were expected to face one of the biggest shortages in 2021 due to their economic state and poor valuation of the currency, which was worsen with the 2019 pandemic and 2020 Beirut explosion (Das, 2021).

Pharmaceutical companies are different from manufacturing companies since their highest investments are intellectual capital, marketing efforts and R&D (Pedroso & Nakano, 2009), which require comparatively higher financial investments and longer approval periods to guarantee profitability, quality, safety, and efficiency of the product, however market entry is still not guaranteed (Levis & Papageorgiou, 2004).

The main stakeholders affected by drug shortages are pharmaceutical industry, pharmacies, hospitals, patients, health insurers, wholesalers, and the competent authorities (Huys & Simoens, 2013; Kruijtbosch et al., 2022), being patients the most harmed (Kweder & Dill, 2013; Steinbrook, 2009). Decisions made by patients after being affected by a drug shortage can be made on their own, by contacting a physician for a new prescription, search on the internet, ask family and friends or delaying treatment (Atif et al., 2021). Possible consequences they might endure are treatment delay, expenses increase, cancellation and reallocation of appointments, adverse effects, medication errors and, in worst cases, patient death (Fox et al., 2014; Kweder & Dill, 2013; McLaughlin et al., 2013; Metzger et al., 2012). In 2019, a survey about this topic was conducted in Portuguese community pharmacies and more than 20 thousand patients answered, from these more than a half had experienced drug shortages in a 12 month period, 20% had to contact their physician to change their prescription, 5.7% interrupted treatment and it was estimated that an additional physician appointment costed patients between 2.1 and 4.4 million euros (Romano et al., 2022).

When a pharmacy order is not received is when it is first noticed a possible drug shortage, making it extremely difficult to establish a successful management approach. At this stage pharmacists act by collaborating with other pharmacies, contacting manufacturers and informing physicians (Pauwels et al., 2015). Pharmacists' and physicians' job is to mitigate shortages and minimize the number of patients affected by guaranteeing continuous delivery of drugs while always providing efficient service. The consequences are workload increase, operational cost growth and prolonged hospital stays (Badreldin & Atallah, 2021; Huys & Simoens, 2013; Shaban et al., 2018), which consume resources such as time, information, financial and human (E. Chen et al., 2021; Tyler & Mark, 2002; Yang et al., 2016). In a 2011 study it was concluded that pharmacists spent on average 9 hours per week dealing with drug shortage topics (Kaakeh et al., 2011). Pharmacists need to provide efficient services to guarantee optimal outcomes for patients. This can be done by identifying and reporting OTC drug unavailability, guarantee appropriate drug therapy, judge the quality of alternative treatments, contact other involved parties, and find solutions for patients (Kruijtbosch et al., 2022; Liu et al., 2020). Additionally, community pharmacies should educate patients and manage stockpiling (Romano et al., 2021). Hospitals are also responsible for managing stockpiling, finding alternative drugs, and making difficult decisions in critical situations (Hantel et al., 2019). Any delay, cancellation or transfer of an appointment or treatment affects hospital efficient performance (Pauwels et al., 2015).

Governmental authorities must find solutions for the short term and guarantee them for the long term. Drug shortages make it hard for governmental authorities to fulfill their obligations towards patients and society, as their duty is to promote equity, minimize harm and provide benefit (Bochenek et al., 2018). Similarly, to pharmacies and hospitals, governments also must investigate shortages but at a national and international level, find replacement products internally or alternatives in other markets, work with manufacturers and wholesalers, find new suppliers and communicate with other authorities (Tyler & Mark, 2002).

2.2.5. Solutions

Management of drug shortages has been on the table for European organizations for a long time (European Medicines Agency, 2011). In 2001, EU directive 2001/83/EC was implemented establishing that governmental authorities are responsible for the continuous supply of drugs, and suppliers are obligated to inform about permanent or temporary cessation of drug production with a notice period of two months to prevent patients being deprived from new and innovative drugs (Directive 2001/83/EC, 2001). In the USA, the Food and Drug Administration (FDA) has defined the notice period for manufacturers as six months, but only in cases the produced drug is single-sourced and is medically necessary (Ventola, 2011). Having a time window allows authorities to have time to search for alternative drugs. In the USA in 2010 early notice prevented 38 drug shortages (De Weerd, Simoens, Hombroeckx, et al., 2015; Ventola, 2011). Nonetheless, authorities should avoid reaching this point at all costs, to do so there should be posterior work done such as implementing short and long-term policies to soften drug shortages impact, incentivize low profit drugs, list potential drugs with shortage risk, encourage communication between authorities and implement a reporting system (Badreldin & Atallah, 2021; Khan, 2019; Mayer, 2012; Tyler & Mark, 2002). High volumes of information and drugs are shared between the involved participants thus to guarantee a good flow it is necessary investments in good communication channels and the assembly of a taskforce (Badreldin & Atallah, 2021; Shuman et al., 2020).

The possibility of resorting to alternative drugs is one of the first solutions for governmental authorities, hospitals, pharmacies, and patients. Alternative drugs can be the solution to guarantee a patient need is met, but it might not achieve the expected effectiveness, safety levels might decrease, and consequences already enumerated might persist, such as medication errors that can cause overdose and even underdose, and disease progression originating adverse effects on patients (Badreldin & Atallah, 2021; McKenna, 2011; Pauwels et al., 2015). Besides the health concerns it might arise, there is also the possibility of medication hoarding, therefore it is important to optimize utilization of the available supply (Quadri et al., 2015). A survey answered by anesthesiologists in the USA concluded that 92% of shortages were solved by resorting to alternative drugs (Bochenek et al., 2018). Searching for alternative drugs is time consuming because of the time spent searching for new alternative drugs and cost consuming because of the operating costs of importation and the price discrepancy from the original to the alternative drug (Kruijtbosch et al., 2022). Often generic drugs are the alternative solution for drug shortages (Atif et al., 2021), but there are also cases where alternative drugs cannot be a solution, for example chemotherapy medicine and antibiotics (Gatesman & Smith, 2011).

In 2016, the WHO enumerated different approaches to combat drug shortages – prioritize measures with a risk-based approach, communication between stakeholders at all levels, efficient supply chain management, fair access to medicines, fair price for buyers and suppliers, collection of the regulatory best practices, harmonization of reporting systems and a global reporting mechanism (Hedman, 2016).

In Portugal, in 2019, a decret law was published where the obligations of each participant in the pharmaceutical supply chain were clarified, for instance wholesalers have to guarantee minimum stock, shortage notification within 24 hours after shortage notice by all stakeholders and identification of shortage based on a 3 level risk (low for drugs with generic, average for drugs with limited substitute and high for drugs with no substitute) (Presidência do Conselho de Ministros, 2019; Romano et al., 2022). The levels of risks are also measured based on the existence of other similar drugs or with the same active substance, dose, methods of administration, drug market share, shortage duration, existent stocks and impact to the patient (INFARMED, 2022).

Suggestions to prevent and manage drug shortages found on literature are the implementation of therapeutic replacement protocols in pharmacies where doses, dosage forms, packing size and respective equivalents would be defined, making it easier for pharmacists and physicians to deal with a shortage and the National Health System workload would be eased (Romano et al., 2022). Pharmacies and hospitals should forecast possible shortages and identify critical drugs and respective alternatives, and subsequently take measures of conservation and adding inventory (Kweder & Dill, 2013; Yang et al., 2016).

There is not a right approach to control and manage drug shortages and what works for a national authority or organization might not work with another, thus organizations must be prepared for the possible consequences and keep in mind a shortage can occur even if all the measures were applied.

2.2.6. Drug Scarcity in Portugal

In Portugal, when health issues occur the responsibility is divided between multiple authorities. In case of a shortage, the key parties are the Ministry of Health and Infarmed (National Authority of Medicines and Health Products), while at European level it is EMA. The Ministry of Health should be responsible

for monitoring and coordinating efforts between ministries, agencies, and organizations to address pharmaceutical shortages, while Infarmed should regulate medicines and healthcare products by identifying the causes of a shortage, collaborating with other stakeholders and mitigate the impact. Each entity has their own responsibility, but it is crucial the collaboration and communication between all.

In collaboration with *Centro de Estudos e Avaliação em Saúde* (CEFAR) from *Associação Nacional de Farmácias* (ANF) data about monthly unfulfilled customer orders between 2019 and 2020 in Portugal was shared. The respective datasets had information about the number of unfulfilled orders, district where it was registered, pharmacy where deficiency was noted, drug in dearth and respective information, for example, name, dose, MAH, and Anatomical Therapeutic Chemical Code (ATC) group. ATC is a classification system with five levels created in 2004 to ease healthcare professionals' job by dividing each active substance into different groups according to the system they act on and their therapeutic, pharmacological and chemical properties. Each drug in the market has an ATC denomination which allows the healthcare professionals to easily access the medicine they need for a specific case or disease.

[Graph 1](#) from Appendix section represents unfulfilled orders of drugs during 2019 which were the highest from May to September. And only in January and March of 2020 those amounts were again reached ([Graph 2](#) from Appendix section). Between 2019 and 2020, the highest number of unfulfilled orders was 10 876 420 in March of 2020, which is when Covid-19 was first detected in Portugal, therefore the sudden increase of unfulfilled orders might be related to panic buying behavior of the population when faced with an abnormal situation. Regardless of the pandemic, the following months had a constant decrease of unfulfilled orders.

When comparing unfulfilled orders of prescribed (identified as MSRM in the graph) and non-prescribed (identified as MNSRM in the graph) drugs there is a clear difference, prescribed drugs have higher levels of unfulfilled orders when compared with OTC drugs ([Graph 1](#) and [Graph 2](#) from Appendix section). Therefore, it is expected to have more people affected by prescribed drugs shortages.

When looking at these unfulfilled orders by the active substance of each medicine, three groups stand out – ATC A which is focused on gastrointestinal tract and metabolism medicines, ATC C dedicated to cardiovascular system medicines and ATC N for medicines involving the nervous system, 11 509 213 un, 18 857 696 un and 24 124 273 unfulfilled orders, respectively ([Graph 3](#) from Appendix section). Specifically for non-prescribed drugs, the biggest ATC group with unfulfilled orders is ATC A with more than 2 million unfulfilled orders ([Graph 4](#) from Appendix section). For prescribed drugs, the ATC group with more unfulfilled orders in ATC N ([Graph 5](#) from Appendix section).

For each of the three ATC groups with highest number of unfulfilled orders, the two sub-groups with the highest shortages are C09 (Agent Acting on the Renin-angiotensin System), C10 (Lipid Modifying Agents), N05 (Psycholeptics) and N06 (Psychoanaleptics) ([Table 2](#)).

Table 1 Unfulfilled orders by ATC group in 2020. Source: CEFAR

ATC	Unfulfilled Orders	ATC	Unfulfilled Orders
A	11 509 213	L	95 343
B	2 094 571	M	3 940 115
C	18 857 696	N	24 124 273
D	3 723 953	P	525 658
G	4 833 660	R	5 048 671
H	412 835	S	2 697 317
J	2 922 128	V	4 619

Table 2 Unfulfilled orders by ATC subgroup A, C and N in 2020. Source: CEFAR

ATC A	Unfulfilled Orders	ATC C	Unfulfilled Orders	ATC N	Unfulfilled Orders
A01	399 856	C01	1 388 393	N01	3 294
A02	3 212 218	C02	75 601	N02	3 628 407
A03	497 065	C03	1 709 055	N03	2 257 869
A04	17 497	C04	102 463	N04	446 342
A05	189 151	C05	428 873	N05	10 826 718
A07	332 527	C07	1 650 270	N06	6 384 635
A08	22 242	C08	1 252 564	N07	576 666
A09	120 800	C09	10 230 125		
A10	4 599 449	C10	2 020 352		
A11	920 526				
A12	199 960				
A13	5 737				
A14	1 076				
A15	2 883				
A16	1 145				

When comparing shortages by district, the differences between 2019 and 2020 are very minimal. In both years the districts with the highest numbers are Lisboa with 17 225 508 unfulfilled orders, followed by Porto with 11 097 715 unfulfilled orders and finally Setúbal with 7 461 199, which are also the districts with the highest population density in Portugal ([Graph 6](#) and [Graph 7](#) from Appendix section).

A report published by Infarmed in February of 2022 called Medicines Availability Management (in Portuguese *Gestão da Disponibilidade de Medicamentos*) has shown that there has been an improvement in the early notice of possible shortages within the established two-month period, more than 50% of the notices were done within the expected period. Early notice is highly advantageous for national authorities since it allows for early mitigation measures, such as providing exceptional use authorizations (in Portuguese *Autorização de Utilização Excepcional*) and prohibiting exportation of critical drugs through parallel trading.

2.3. TYPES OF MEDICINE

2.3.1. Prescription Drugs and Non-Prescription Drugs

Pharmaceutical drugs can be divided into two groups: prescription drugs and non-prescription drugs. Prescription drugs, also known as Prescription-Only Medicine (POM), can only be prescribed by authorized healthcare professionals, and supplied by pharmacies, and cannot be advertised. Whereas, non-prescription drugs, also known as OTC medicines, can be sub-divided into two groups Pharmacy (P) and General Sales List (GSL). Both do not need doctor authorization but while P medicine can only be sold in pharmacies and under supervision, GSL medicine can be sold by authorized retailers depending on the medicine quantity and medication strength and if it does not need pharmaceutical supervision (Keen, 1994).

In 1992, the European Community published a Directive for medicine classification (92/26/EEC) stating that member states have the obligation to review the status of prescription drugs every five years and change it to non-prescription drugs if it is safe without medical supervision, if there is no chance it could be used incorrectly, if it does not need additional investigation or it does not need to be administrated by injection (Directive 92/26/EEC, 1992), since then non-prescription drugs that enter the pharmaceutical market tend to be in a higher number and range than prescription drugs (Bradley & Bond, 1995). Additionally, advertisement of OTC drugs also increases their use (Major & Vincze, 2010), allowing the creation of new businesses (Blenkinsopp & Bradley, 1996).

Non-prescription drugs have been increasingly used as self-medication (Major & Vincze, 2010), with the aim of improving health, preventing diseases, limiting illness, and restoring health after an illness or injury (Stearns et al., 2000). In 2010, a study revealed that 75% of the studied population in pharmacies in Budapest and other provincial towns were regular users of non-prescription drugs for self-medication purposes (Major & Vincze, 2010). Consumers consider OTC drugs harmless and often underestimate the potential risks (Ylä-Rautio et al., 2020). A Swedish study, made in 2017, concluded that 7% of the respondents agreed that OTC drugs are completely harmless regardless of how they are being used (Westerlund et al., 2017), therefore it is important to promote high safety levels of OTC drugs while not over imposing restrictions to those who use them correctly (Major & Vincze, 2010). Self-medication brings a higher level of responsibility to consumers, a complete use of pharmacists' clinical skills avoiding unnecessary doctor appointments, increase access to medicine, encourage

freedom in decision making and reduce costs related to prescription drugs (C. M. Hughes et al., 2001). The pharmaceutical industry benefits highly of the public access to medicine and other products, since it protects against generic competition and existing prescription brands might be promoted (Blenkinsopp & Bradley, 1996; C. M. Hughes et al., 2001). Pharmacists benefit from a more fulfilling role, increases therapeutic options, increasing contact with patients and enhances their professional status (C. M. Hughes et al., 2001). Self-medication clearly has benefits for consumers, healthcare professionals, pharmaceutical industry, and governments.

However, the easy access to non-prescription drugs needs to be controlled as it will persuade consumers to find drug treatments for every problem, which might hide serious diagnoses and delay treatment (C. M. Hughes, 2003). There is also the chance of abuse and mishandling of medication by taking higher doses or for a longer time than recommended or not even using it for medical purposes, increasing the probability of adverse effects (G. F. Hughes et al., 1999). These behaviors are understood as of poor importance given to their own self-care and health (Blenkinsopp & Bradley, 1996).

Even though pharmacist's skills will be used fully and save up doctor's time spent in appointments, their contact with the patients is still very superficial and their knowledge is incomparable to a doctor (Major & Vincze, 2010). Hence, the consumer preference for doctors instead of pharmacists (Kendrick & Bayne, 1982). Nevertheless, patients should have an open conversation with pharmacists and communicate what medication they are, and were, taking (C. M. Hughes, 2003). While pharmacists save up doctors' time, doctors still have some concerns because of the reduced contact with patients, possible incorrect diagnoses by patients or pharmacists of a medical condition and inappropriate use of non-prescription drugs (C. M. Hughes et al., 2001). Finally, governments benefit from shifting their responsibility and cost to consumers (Blenkinsopp & Bradley, 1996).

2.3.2. Generic Drugs

The ageing of the population, increase in prices, introduction of newer and more expensive medicine and the rise in chronic conditions have been triggers to find newer and more effective medicines by developing the generic medicine market (Dylst & Simoens, 2010). Generic medicines are substitutes for original already authorized medicines, which are called reference medicine. It should have the same active substance, the same dose and treat the same disease but the appearance, packaging, name and inactive substances can be different. The authorization of generic drugs is based on the data from the already authorized medicine where quality, safety and efficiency should be the same (European Medicines Agency, n.d.-a), but the price is comparatively lower (Simoens & De Coster, 2006). Hence, by adopting generic drugs into a market, health authorities will guarantee access to affordable medicines and pharmaceutical expenditure will be under control (Dylst & Simoens, 2010). The competitive prices stipulated by generic medicines will force the original medicines, their direct competitor, to develop cost effective medicines and reduce prices. This allows customers to increase their savings (Simoens & De Coster, 2006). Developing countries tend to be a fierce competition to developed countries because of the low prices practiced on medicines, consequence of the low labor, low production costs and weak laws (Dylst & Simoens, 2010). Generic drugs can only enter the market after the 10-year exclusivity period of the reference medicine expires (European Medicines Agency, n.d.-a).

In a 2017 survey, made in Saudi Arabia, it was determined that generic drugs are more propitious than brand drugs to go scarce (AlRuthia et al., 2017). Low priced generic drugs, or even low-priced drugs in

general are at a 60% to 72% higher risk for shortages when compared to medium and high-priced drugs (Dave et al., 2018). Consequently, drug shortages of low-priced drugs are associated to the increase in drug prices. Besides the increase in drug prices, patients are also faced with increasing costs related to therapy changes and management of shortages, ensuing a dramatic impact on patient care. Some solutions are finding alternative drugs, and better manage and allocate stock (Fox & Tyler, 2017). Low-priced drugs tend to be more at risk because of their low profit margins, and manufacturers might opt for the more profitable drugs within their portfolio (Dave et al., 2018).

Possible solutions are the early announcement by manufacturers about disruptions and possible shortages, change outdated processes and resource to importation (Dave et al., 2018). High costs associated to drugs are a setback for many patients, which will avoid using prescribed drugs. Access to generic drugs increases the adherence and improves patient health outcomes (Briesacher et al., 2009).

2.4. NEWS MEDIA

News media is a tool used by people to become informed (Holbert, 2005; Strömbäck et al., 2020), by transporting the most recent information and opinions from professionals to consumers (Doms & Morin, 2004). This can be in the form of newspaper, broadcast news or online news. A requirement for these news media is to be unbiased and trustworthy, allowing each person to freely formulate their own opinion and make their own decisions (Kovach & Rosenstiel, 2001; Strömbäck, 2005; Strömbäck et al., 2020).

A good communication is based on trust (Warner-Søderholm et al., 2018). But, over the years, trust in news media has been decreasing and becoming more fragile (Strömbäck et al., 2020). Nevertheless, news media still has a big impact on population intentions, plans, knowledge, beliefs, and opinions, but not on their direct actions (Van Dijk, 1995). According to Gerbner et al. (1986) cultivation theory, those who are heavy viewers of television do not develop a critic spirit towards what is viewed, influencing the viewers attitudes.

There has been a natural transaction from the traditional sources of information, such as newspaper and television broadcast, to digital and social media where information is instant, of easy access and part of the day-to-day of many people (Warner-Søderholm et al., 2018). The modern sources of information are the direct competitors to the traditional news (Strömbäck et al., 2020).

At the turn of the century, there was a natural switch from saying mass communication to saying media communication, with the goal of removing the idea of “mass-ness” from communication and to provide a more individualized experience to the consumers (Turow, 1992). Nonetheless, the word mass is still a good adjective to understand how vast the spread of information onto an audience is, independently of their personal and geographical characteristics (Chaffee & Metzger, 2001).

Carroll et al. (1994) and Souleles (2004) have studied the relation between sentiment and consumption which can be influenced by the news media and their way of delivering the information to the consumers. Generally, optimistic expectations lead to increase in spendings (Doms & Morin, 2004). Or in contrast, when media portraits, in a sensational way, that people are excessively buying it could provide a threatening perception and create panic, which could escalate to a global crisis (Arafat et al., 2020). Measures such as prohibiting publishing sensational photos of empty shelves, provide adequate information, identify fake news, and reduce fear should be implemented (Arafat et al., 2021). Although

consumers sentiments are affected by the media, these are affected for a short period of time (Doms & Morin, 2004).

The increasing attention, from media and political entities, given to evolving drug shortages result in an increase of demand (Badreldin & Atallah, 2021). Drug shortages are continuously reported through newsletters, anecdotes and claims from patients, doctors, pharmacists, and hospitals (Huys & Simoens, 2013). News media coverage contributes to drug shortages through hoarding by patients and stockpiling by institutions. Hoarding and stockpiling will deprive patients who really need those drugs to not have access to them.

Based on the available data and news reports it is possible to make some conclusions regarding the relation between news reports and unfulfilled orders. When analyzing the data about the unfulfilled shortages during a certain time frame where news about shortages are also published, it can be seen an increase of unfulfilled orders. Some examples of this tendency are Ben-U-Ron, Hydrocortisone, Tafixyl and Victan, which are represented in [Graph 8](#), [Graph 9](#), [Graph 10](#) and [Graph 11](#), respectively, in the Appendix section. On each graph it will be possible to see the evolution of unfulfilled orders during a specific period, and represented by a red line will be the day, or days, news reports about the shortage were published.

Ben-U-Ron is a popular medicine used to relieve pain and decrease fever. Between the end of 2019 and the beginning of 2020 Portuguese pharmacies struggled to fulfill orders. In December of 2019 it is when it was first noticed a slight increase with around 100000 unfulfilled orders. By the very end of the same month news reports were publicized about this drug decreasing in supply, which led to a significant increase of 400000 unfulfilled orders in January of 2020. Later on, a new wave of news reports in the middle of March of 2020 were made leading once again to a significant increase of 600000 unfulfilled orders, which decreased on the following months.

Hydrocortisone, a steroid medicine, is another example on how news reports can be a driving force to the increase of unfulfilled orders. In February of 2019, it was when it was first noticed a small increase in unfulfilled orders, reaching a little more than 10000 unfulfilled orders. But by the month of March these values have reached the 45000 mark, which is coincidentally the month when two different news reports waves were verified. From April onwards there has been a decrease in unfulfilled orders.

Tafixyl is a medicine used for prevention and treatment of heavy bleeding, consumed mainly by young females. Before any news report about Tafixyl shortages, this medicine has been affected by small amounts of unfulfilled orders, reaching a maximum of 250 unfulfilled orders. Once news were published at the beginning of the month of October of 2020, unfulfilled orders more than duplicated reaching almost 1500 unfulfilled orders in the same month. And even surpassing this amount in the next two months.

Lastly, Victan a medicine used for anxiety. This medicine has been noticing an increase of unfulfilled orders since April of 2020 to July of 2020, going from close to 200000 unfulfilled orders to more than 500000, and the month it noticed the highest amount of unfulfilled orders was also the month news reports about this shortage were published. From July onwards there has been a constant decrease.

3. CONCEPTUAL MODEL AND HYPOTHESIS DEVELOPMENT

The Stimulus-Organism-Response (SOR) theory was popularized by Robert S. Woodworth in 1929, it is an adaptation from the initial Stimulus-Response (SR) approach (Chan et al., 2017). It was later theoretically extended by Mehrabian and Russell (1974). Afterwards, Jacoby (2002) noticed that the stimulus has different responses depending on the organism, therefore he added the organism to the framework to mediate the relationship between stimulus and response (Ming et al., 2021). The SOR model is characterized as a psychological framework connecting external stimuli, personal traits, and behavior, hence it will be possible to understand how individuals with different characteristics behave when they are affected by external stimuli (Mehrabian & Russell, 1974; Y. L. Wu & Li, 2018).

Stimulus (S) are the external adversities that affect the internal state of an organism positively or negatively. Any changes on the environment will affect the organism (O) which represents the individual and their internal state (cognition, feelings, and emotion), and it is the bridge between the reactor and the reaction. Response or reaction (R) is the behavior adopted once the final action initiated by the stimulus (Eroglu et al., 2001; Islam et al., 2021; Kamboj et al., 2018; G. Zhang et al., 2021).

Since 1929 the SOR model has been used as a theory for diverse studies to explain the relationship between scarcity and panic purchases (C.-C. Chen & Yao, 2018; Lin et al., 2023; Ming et al., 2021). For example, J. Zhang et al. (2022) and J. J. Zhang et al. (2021) used the SOR model to study the impact of protective equipment shortage on the consumer behavior and identified fear of missing out (organism) as a type of emotion that is aroused by scarcity and can influence impulsive purchases. Similarly, Islam et al. (2021) also used the SOR model to study the relation between scarcity and impulsive purchases, while using Covid-19 as a stimulus. A final example is Karim et al. (2021) which published a study about the influence of website and marketing stimulus on impulsive purchases, using perceived enjoyment as the organism.

Based on the above-mentioned academic research this theory seems fit to be applied to the present study which tries to understand consumer behavior towards drug shortages. More specifically, the assumption that drug shortages (stimulus) create feelings of panic buying (response) through fear of missing out on a purchase and delayed or changed treatment (organism). To the best of our knowledge there does not exist any research done about drug shortages in specific.

When facing scarcity consumers have one of two options, either buy immediately or miss out on the purchase opportunity (Shi et al., 2020). Independently of the outcome, it creates different feelings on consumers, being fear of missing out one of them (Hodkinson, 2019), influencing decision making and behavior. Fear of missing out is an emotion which appears when consumers develop anxiety about a possible missed chance or missed experience (Abel et al., 2016; J. J. Zhang et al., 2021). Which might later develop to panic purchases induced by the external environment or personal emotions. On this specific study fear of missing out (FOMO) is used in the context as fear of missing the chance to buy a medical drug. By using it as a variable on the model, it is expected to help identify its role in the relationship between scarcity and panic buying.

H1: Scarcity of prescription drugs is positively related to fear of missing out.

H3: Fear of missing out a prescription drug is positively related to panic buying.

H6: Scarcity of non-prescription drugs is positively related to fear of missing out.

H8: Fear of missing out a non-prescription drug is positively related to panic buying.

A shortage implicitly means an increasing difficulty to access the needed drug, which can be in the form of a postponed treatment, time taken to contact a healthcare provider and selection of possible alternative drugs. When patients encounter these delays, it might create feelings of anxiousness and consumers participate in panic purchases due to their need to obtain the necessary medications. This impulsiveness puts aside any reasoning when making decisions, and consumers might buy drugs that are not medically required or alternative drugs that are not even appropriate. By doing this analysis, it will be possible to understand how this variable influences the effect of shortages on panic purchases.

H2: Scarcity of prescription drugs is positively related to modified treatment.

H4: For prescription drugs, modified treatment is positively related to panic buying.

H7: Scarcity of non-prescription drugs is positively related to modified treatment.

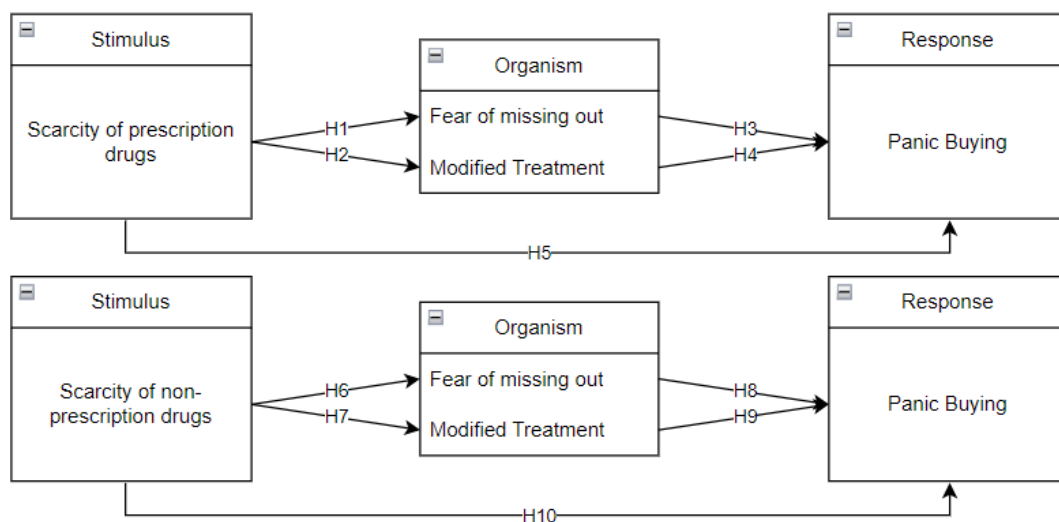
H9: For non-prescription drugs, modified treatment is positively related to panic buying.

Based on the situation of external environmental stimuli impacting internal psychological perception, this study adopts the SOR theory to explore the relationship between drug shortages and panic buying. This study examines whether when consumers' stimuli are satisfied, consumers will accept and form a panic buy or not. The research framework consists of three parts, the influence of stimuli (S), including drug shortages, which in turn influences internal psychological changes (O), the variable is fear of missing out and modified treatments, to generate purchase panic buying behavior (R).

H5: Scarcity of prescription drugs is positively related to panic buying.

H10: Scarcity of non-prescription drugs is positively related to panic buying.

Figure 1 Conceptual Model
Source: Own creation based on the SOR model



4. METHODOLOGY

4.1. RESEARCH DESIGN AND SAMPLING

The present study is a quantitative research based on observations of a particular group through a questionnaire to analyze their behavior towards scarcity of drugs and panic buying. In the end, the collected data is validated and analyzed using statistical methods such as descriptive and exploratory analysis. Once data is analyzed and cleaned, the purposed hypothesis can be tested. On this particular study, the independent variable is scarcity, fear of missing out and modified treatment, and the dependent variable is panic buying.

The purpose of the study is to explore the panic buying tendencies of pharmaceutical drug's consumers and analyze how fear of missing out and modified treatment play out on consumer's actions. Also, identify the role of different emotions in the relationship between scarcity and panic buying. We expect to understand how people emotionally respond to an unpredictable scarcity and how they engage with the environment around them.

The data used for this study is both secondary and primary. Data about shortages, sales and medicine was retrieved by CEFAR and later provided through a signed confidentiality contract. While the data used to study the hypothesis is primary and retrieved through voluntary survey from a non-probability sampling more specifically a convenience sample. This is a convenience sample because the data was collected from two pharmacies selected by CEFAR, who subsequently, provided a list of regular consumers of drugs belonging to ATC group A10BJ (Peptides analogous to Glucagon-1), and from this list only those who accepted being interviewed were interviewed on specific days.

The data will be analyzed using R, SPSS and Smart-PLS. R was used to do a statistical analysis to the secondary data, study the covariance of the variables and any other complementary analysis (R Core Team, 2021). SPSS is used for any additional statistical analysis, to complement the analysis done in R (IBM Corp., 2021). Smart-PLS is used to test and verify the fit of the research model by studying the reliability and validity, and test the hypothesis and relationships between the variables by applying PLS-SEM (Ringle, Sven, et al., 2022).

Structural equation modeling (SEM) is used to measure the latent variables of a model, but also the cause-effect relationship between them (Babin et al., 2008; Hair et al., 2021). This method is divided into two approaches: covariance-based (CB-SEM), and partial least squares (PLS-SEM), the latter is the one chosen for this study based on the nonnormal data distribution and the small sample size (Hair et al., 2014). PLS-SEM was first developed by Wold (1982) and later improved by Lohmöller (1989), and it is a technique similar to a multiple regression analysis (Hair et al., 2011), which can be applied in a variety of disciplines such as marketing, strategic management, information systems management, operations management, and accounting (Hair et al., 2014). The analysis of the data is divided into two parts and each part has a set of metrics to evaluate the model. First, the measurement model where indicators, constructs and the relationship between both is studied, and secondly the structural model that focus on the relationship between constructs (Hair et al., 2011, 2016).

4.2. DATA COLLECTION

The target population are consumers of drugs that fall under ATC group A10BJ, which covers five molecules - dulaglutide, exenatide, liraglutide, lixisenatide and semaglutide. Additionally, the population needs to be composed of regular users, which makes this population highly specific. The choice behind this ATC group was done based on an interview with two pharmacy directors from pharmacies in Lisbon and reinforced by recent news.

With the help of CEFAR two pharmacies in Lisbon agreed to participate on the present study, composed of a first meeting with the pharmacy director and a second part to interview pharmacy customers. The study was first presented and explained, followed by a debate of ideas about scarce molecules and medicines, and different ways to deliver the survey.

Pharmacy directors mentioned that, in 2023, the molecules showing higher levels of scarcity were three molecules focused on diabetes treatment (semaglutide, liraglutide and dulaglutide) and two focused on cardiac treatments (bisoprolol and propranolol). By performing further analysis on recent national and international news, it was found that medicines used for diabetes treatment have gained a lot of media attention and reactions from consumers over the last year, therefore the respective ATC group was chosen for this study – ATC group A10BJ. The increased media attention on this specific molecules started by the end of 2022 with a tweet publication from Elon Musk, an influential figure referring that one of his methods of weight loss was Wegovy - a medicine used for obesity - and Ozempic - a medicine used for diabetes treatment, and both have semaglutide as the active ingredient (Musk, 2022a, 2022b). Since then, the demand for these drugs increased in the USA (Thompson, 2022), and consequently, in Europe. In the EU, in the beginning of 2022, Wegovy has been approved by the EMA, but it is still not commercialized in many European countries (European Medicines Agency, n.d.-b), leaving Ozempic as an off-label solution for obesity treatment (Ordem dos Médicos, 2022). This has been highly affecting diabetes patients since Ozempic is one of the most common and preferred methods of treatment, and its high use has been leading to shortages (Barreto, 2023).

The main consumers of diabetes medicine are middle-aged and older population, thus they are also the most propitious to suffer from drug shortages. Because of this restriction, online surveys would hardly be answered and collected data wouldn't be the most accurate, hence doing a questionnaire over the phone or face-to-face would be the most precise way. Additionally, research is done to a very specific group of medicine consumers who have experienced shortages at similar times and dealt with the same setbacks. This highly filters the target population focusing only on consumers with a very specific experience which justifies the small sample size of this study. Potential limitations to such a small sample size are the generalization of the findings and how those findings can hardly be applied to a larger population.

As mentioned, the characteristics of the population require face-to-face or over the phone questionnaires, therefore the best location to do them would be at pharmacies, where consumers are mostly found. In an initial meeting with the pharmacy director it was agreed the most efficient way to perform the questionnaires would be over the phone, since each pharmacy keeps records of customers who have faced shortages with their respective phone numbers. In order to guarantee the shared information is under compliance guidelines every interview was done on the pharmacy premises, using a telephone from the pharmacy, and no personal information was shared with the interviewer or the

interviewee. The surveys were conducted at two different locations, hence it is expected to have various answers from two different IP addresses.

The survey itself was constructed using a popular survey maker tool Qualtrics (*Qualtrics, 2020*). It has six demographic questions, and it is divided into two parts with a total of 30 items, the first part is dedicated to prescription drugs and the second part to non-prescription drugs. There is a total of four variables for each part – drug shortages, panic buying, fear of missing out and modified treatment. The questionnaire was written in Portuguese and answering it was completely voluntary. The questionnaire was ethically approved before any interview and respondents were presented with this information ([Annex B](#)).

A pre-test was conducted before reaching the final version of the questionnaire to ensure the good understanding and clarity of the questions and statements. The pre-test sample was composed of six respondents from the target population. Comments and questions raised were considered and necessary changes were made to have a more perceptible questionnaire. For example, statement D2 was changed from “The medicine will run out soon or is sold out” to “I am afraid that the medicine will run out again in the future”, or statement IB1 from “When I'm prescribed the medicine, I buy it straight away” to “The scarcity of the medicine pushes me to buy in a timely manner”.

4.3. MEASUREMENT

The study gathered 42 responses through an over the phone questionnaire to test the research model. It was conducted at two previously selected pharmacies in Lisbon, the selection of the pharmacies was done with the help of CEFAR that selected and made the first contact with the pharmacies. The average time spent for each questionnaire was approximately 11 minutes, and they were made in the following days 3, 4 and 12 of October of 2023 at Pharmacy Holon Campo Grande and 13 and 19 of October of 2023 at Pharmacy Alto do Lumiar. All the responses were considered valid since it was done in the presence of the student.

The measures of this questionnaire were adopted from prior studies and adapted to fit the present study, and others were made based on the literature review about the subject. It is composed by a total of 30 items, 15 items dedicated to prescription drugs and the other 15 to non-prescription drugs. Scarcity of medical products is measured by adapting 3 items from W. Y. Wu et al. (2012) which have an appropriate reliability of 0.7 where respondents had to provide their level of agreement towards the statements about scarcity of medical protective products. The rest of the measures are done based on literature review.

The items presented on this study were measured using a five-point Likert scale with “Agree–Disagree” anchor statements, where 1 represents totally disagree and 5 represents totally agree (Dawes, 2008).

5. EMPIRICAL STUDY

5.1. DESCRIPTIVE STATISTICS

On [table 3](#) it is represented the demographic profile of the 42 respondents of this study. The sample population is composed of 66,7% female respondents and 33,3% male respondents. As predicted, most respondents are higher than 64 years old, which translates into 35,7%, followed by 45-54 years old (26,2%) and 55-64 years old (16,7%). Population between 18 and 24 years old is not represented on this study, meanwhile the population younger than 45 years old altogether represents 21,4%. Regarding education, the higher percentage belongs to basic school and bachelor's degree with 33,3% each, secondary school and master's degree with the same proportion of 11,9% each, PhD with 7,1%, and there was only one interviewee that preferred not to answer. Most participants tend to avoid the question about their income, therefore 23,8% preferred not to answer, followed by the population with an income lower than 800€ and population with income higher than 2000€ with 23,8% each, participants with an income between 800€ and 1200€ with 11,9%, between 1200€ and 1600€ with also 11,9%, and between 1600€ and 2000€ with 4,8%. Regarding occupation, most respondents are employed with 64,3%, followed by the population who is retired with 30,9%, and finally, 4,8% who are unemployed.

It is also important to differentiate what the medicine is used for. As previously mentioned, the molecules studied are for the treatment of diabetes, but also used to treat obesity. From the participants on this study 92,9% consume the medicine to treat diabetes and 7,1% to treat obesity, there were also 3 respondents who mentioned they used the medicine for both treatments even though their main goal was the diabetes treatment.

Table 3 Demographic profile of respondents
Source: Based on the primary data collected

Demographic Profile	Scale	Frequency (n)	Percentage (%)
Gender	Female	28	66,7
	Male	14	33,3
	Other/Prefer not to answer	0	-
Age (years old)	18-24	0	-
	25-34	3	7,1
	35-44	6	14,3
	45-54	11	26,2
	55-64	7	16,7
	Above 64	15	35,7
	Prefer not to answer	0	-
Education	Basic School	14	33,3

	Secondary School	5	11,9
	Bachelor Degree	14	33,3
	Master Degree	5	11,9
	PhD	3	7,1
	Prefer not to answer	1	2,4
Income	Less than 800€	10	23,8
	Between 800€ and 1200€	5	11,9
	Between 1200€ and 1600€	5	11,9
	Between 1600€ and 2000€	2	4,8
	More than 2000€	10	23,8
	Prefer not to answer	10	23,8
Occupation	Employed	27	64,3
	Unemployed	2	4,8
	Retired	13	30,9
	Student	0	-
	Other/Prefer not to answer	0	-
Purpose	Diabetes	39	92,9
	Obesity	3	7,1

Note: The sum of some percentages on the table might not equal 100% due to rounding.

Before proceeding with further analysis it is important to mention that from the total population only three respondents had experienced shortages of non-prescribed medicines, therefore an analysis of non-prescribed drug shortages is not done, and the study will only be focused on prescribed drug shortages.

Based on the analysis of the mean and weighted average it is possible to study the perception of the respondents to the questions. For example, respondents had a high perception of the small supply of the drug in study, and about the possibility of this shortage to continue in the future. The levels of anxiety related to the shortage were also well perceived, same as the chances of visiting more than one pharmacy until the needed medicine was found. Regarding panic purchases, respondents had the tendency to buy as soon as they could, and keep a stock of medicine at home if possible. The rest of the items are viewed by the respondents as low perception, such as items related to modified treatment.

Table 4 Consumer perception of drug scarcity
Source: Based on the primary data collected

ID	Question	Mean	St. Deviation	Perception
D1	The supply of the medicine is small.	4.64	0.58	High
D2	I am afraid the medicine will run out again in the future.	4.24	0.73	High
D3	Many people buy this medicine.	2.71	1.42	Low
F1	I feel anxious about the possibility of not being able to buy medicine.	4.12	0.94	High
F2	News of drug shortages may influence me to buy.	3.57	1.23	Low
F3	I am willing to visit more than one pharmacy until I find the medicine I need.	4.36	1.08	High
T1	I am upset about postponing a treatment.	3.50	1.02	Low
T2	I contact a health professional immediately for advice.	3.26	1.25	Low
T3	I am willing to consider alternative medicines recommended by a healthcare professional.	3.26	1.25	Low
T4	I am willing to pay the difference if the alternative medication is more expensive.	3.43	0.89	Low
T5	I faced adverse effects due to the delay or change in treatment.	3.33	1.28	Low
IB1	The scarcity of the medicine pushes me to buy in good time.	4.24	0.69	High
IB2	Even if I don't need it, I like having the medicine at home.	3.79	1.18	High
IB3	I buy the full amount I was prescribed on my first trip to the pharmacy.	3.55	1.25	Low

Note: Weighted average = Sum of all means / Number of items = 52/14 = 3,71 Decision: If mean is higher than weighted average than item has a high perception

The study of the outliers was conducted for all four constructs, but there was no sufficient reasoning for the removal of any of the responses. Construct scarcity had two outliers which weren't worried about future shortages. Construct modified treatment had one outlier that wasn't bothered by the delay of treatment, and did not take any measures, such as contacting a health professional or getting informed about alternative drugs. Construct FOMO and panic purchases had the same outlier which did not feel affected by shortage news, did not have feelings of anxiety or visited more pharmacies to find the needed medication, and subsequently, did not have the need to buy in-time, have medicine stocked up at home or buy all quantity prescribed.

5.2. MEASUREMENT MODEL

The measurement model can either be formative or reflective depending on the relation between the indicators and latent construct. In this particular study the indicators are reflective, since changes on the constructs will influence how the indicators behave (Hair et al., 2011), and the removal of an indicator will not change the construct purpose. For example, construct scarcity influences how respondents feel about short supply and possible future shortages, not the other way around. Therefore, the model will be represented with arrows pointing from the latent variable to the indicator variables.

The measurement model studies the quality of the constructs and the relationship between constructs and respective indicators, and also determines what indicators to use for construct measurement (Hair et al., 2014, 2021). The quality of the outer model will be measured by an assessment of the outer loadings and by calculating the reliability and validity of the constructs (Hair et al., 2021). All the results done on this model are presented on [Table 5](#) and [Table 6](#). Also, details about indicators and constructs can be found in [Annex A](#).

The analysis of the demographic characteristics verified that there was a disparity between how respondents older than 64 years old reacted to the shortage versus respondents younger than 64 years old. Therefore, the following analysis was done based on the comparison between both populations, which is composed by 15 respondents older than 64 years old and 27 respondents younger than 64 years old.

Figure 2 Measurement model for the respondents older than 64 years old
Source: Based on the primary data collected

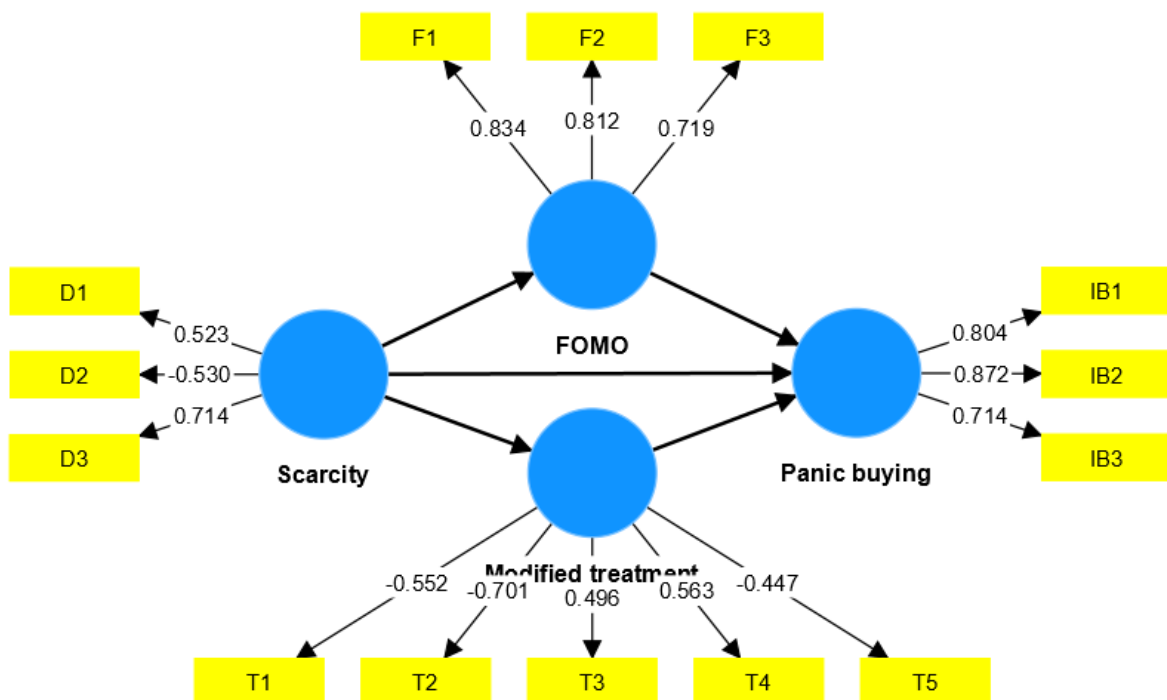
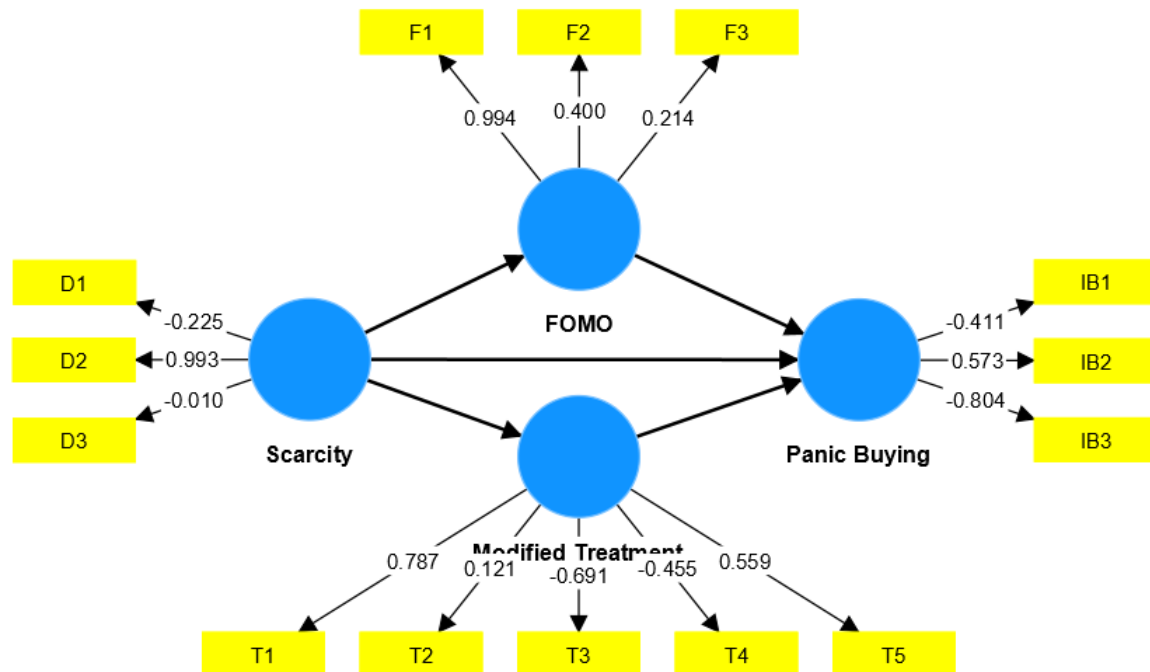


Figure 3 Measurement model for the respondents younger than 64 years old
 Source: Based on the primary data collected



Outer loadings estimate the relationship between the latent variable and the indicators, and higher the outer loading higher the contribution of the indicator for the construct. A reliable outer loading should be higher than 0.7, although an outer loading between 0.4 and 0.7 is also acceptable but it should be considered how it affects the overall reliability and convergent validity before eliminating (Gentle et al., 2010; Hair et al., 2016). Negative loadings or loadings lower than 0.4 should be deleted (Hair et al., 2011). Outer loadings for the two populations are represented on [Figure 2](#) and [Figure 3](#).

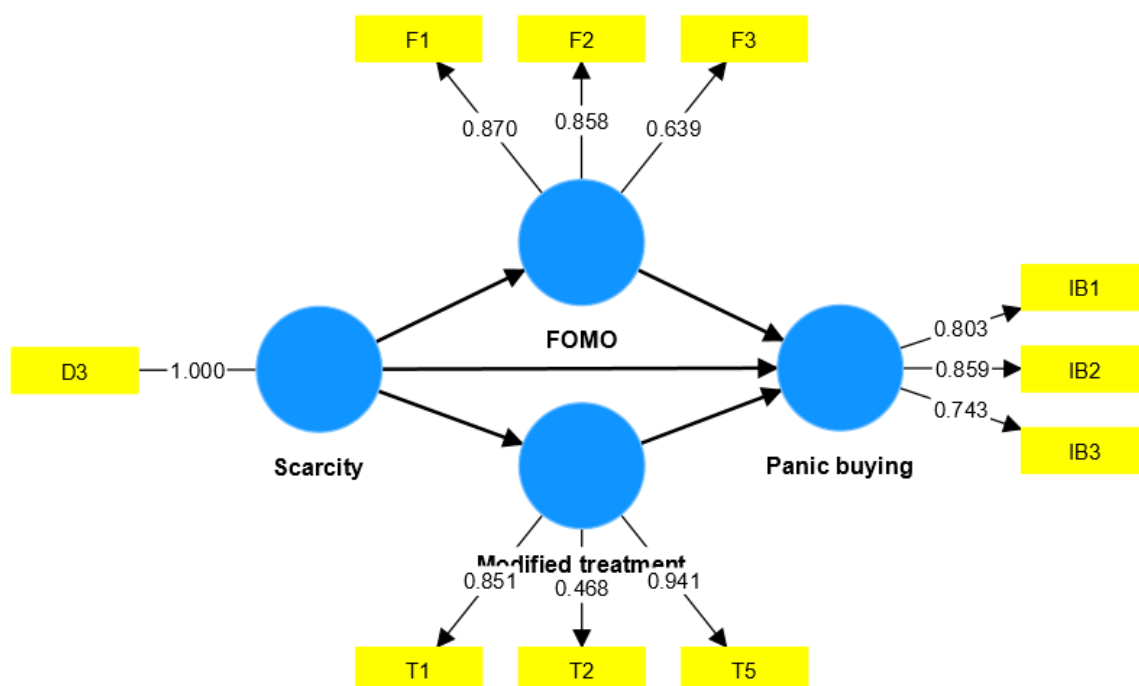
The first step is to delete any negative loadings and outer loadings lower than 0.4. The structural model for the respondents older than 64 years old ([Figure 2](#)) has one negative loading (D2) on construct scarcity and three negative loadings (T1, T2 and T5) on construct modified treatment. Negative loadings are not necessarily bad for the model, they represent negative loads which measure opposite poles of the construct (Distefano et al., 2009). Indicator D2 which has a negative loading refers to statement “I am worried the medicine might get scarce in the future” which respondents mainly responded “Strongly disagree” and “Disagree”, since they are not particularly worried about future shortages when they are currently going through a shortage, therefore item D2 was deleted. For construct modified treatment the approach for the deletion was somewhat different in order to avoid deleting more items than needed. Since this construct has three negative loadings and two positive loadings that measure different poles of the construct, it was chosen to delete the two positive loadings referring to statements about alternative drugs. This not only turned the initial negative outer loadings into positive outer loadings, but it also highly improved the quality of the model. For this particular model there are no loadings lower than 0.4.

Next step, is the analysis of outer loadings between 0.4 and 0.7, which are D1 and F3. Each variable was removed sequentially starting from the lowest, and each time quality measures were analyzed. The removal of an indicator was only done if model quality was improved. Starting with D1, its removal

improved the model, specially the quality of construct scarcity, therefore its removal was kept. Followed by the removal of F3, which improved the quality of the construct FOMO but not enough to justify the deletion of an item. Because of the deletion of item D1, a new outer loading (T2) was below 0.7 and above 0.4, and its removal would only decrease the quality of the model therefore it was kept. In conclusion, items removed were D1, D2, T3 and T4, as represented on [Figure 4](#).

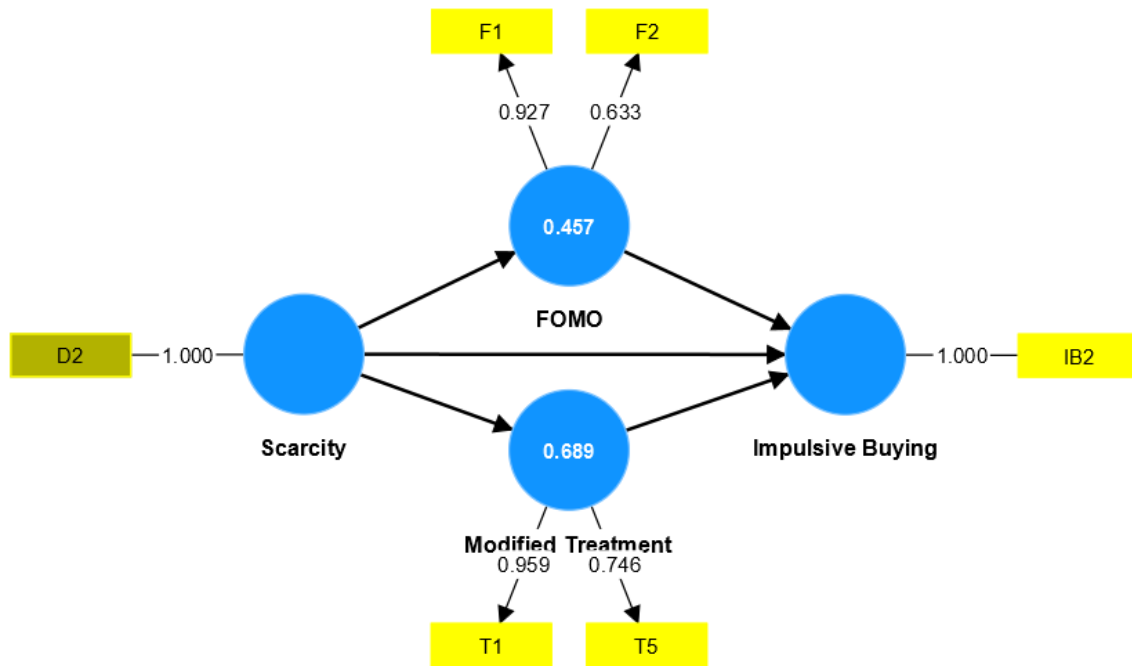
By making the necessary modifications, the model ends up with construct scarcity with only one item, which means that the relation between construct and indicator will always be one and there will be no variability, hence the criteria for the assessment of measurement models is not applicable for this specific relation (Hair et al., 2016).

Figure 4 Measurement model for the respondents older than 64 years old after the analysis
Source: Based on the primary data collected



Indicators and constructs of the measurement model of respondents younger than 64 years old ([Figure 3](#)) follow a different path and vary a lot from how the respondents older than 64 years old behave. On this model there are six items with negative loadings (D1, D3, T3, T4, IB1 and IB3) and one item with an outer loading lower than 0.4 (F3) which were all deleted. Next, the analysis of the items with outer loading between 0.4 and 0.7 is done from the lowest to the highest – T2 and F2. The removal of T2 does improve the model quality, while the removal of F2 it does not. Regardless of any further removals or analysis the model does not improve quality and each construct is left with very few indicators, therefore the analysis of this model will not be further done.

Figure 5 Measurement model for the respondents younger than 64 years old after the analysis.
 Source: Based on the primary data collected



The reliability measures the stability and consistency of the constructs using the Cronbach's alpha (CA) and the composite reliability (CR), which are considered good when above 0.7, and any value below 0.6 lacks reliability, and between 0.6 and 0.7 is acceptable (Nunnally & Bernstein, 1994). For the first model for population older than 64 years old, the CA varies from 0.702 and 0.773, and CR ranging from 0.733 to 0.804, which means that the constructs are reliable and consistent.

The validity of the constructs is divided into convergent validity and discriminant validity which are measured by calculating the average variance extracted (AVE) and the Fornell-Larcker criterion, respectively. A good AVE needs to measure at least 0.5 to indicate a good convergent validity, which means that the construct is able to explain at least half of the variance of the indicators (Chin, 1998; Hair et al., 2014). And an AVE lower than 0.5 means that error variance exceeds explained variance. While the Fornell-Larcker criterion measures if the latent variable shares more variation with the assigned indicators or other latent variables, and it is established when the square root of AVE is greater than the correlation with all other constructs (Fornell & Larcker, 1981). On the first model AVE values are higher than 0.5 which means the model has an acceptable convergent validity and more than 50% of the constructs variance is due to its indicators. And for all the constructs the square root of AVE is greater than the correlation of the other constructs, hence discrimination validity is established. The results are an adequate fit for the measurement model.

Table 5 Measurement model results
Source: Based on the primary data collected

Construct	Cronbach's alpha	Composite reliability	AVE
FOMO	0.702	0.733	0.634
Modified treatment	0.773	0.804	0.610
Panic Buying	0.734	0.767	0.645

Table 6 Discriminant validity assessment using Fornell Larcker criterion
Source: Based on the primary data collected

Construct	FOMO	Modified Treatment	Panic Buying	Scarcity
FOMO	0.796			
Modified Treatment	0.435	0.781		
Panic Buying	0.582	-0.110	0.803	
Scarcity	-0.456	-0.498	-0.268	1.000

5.3. STRUCTURAL MODEL

After the assessment of the measurement model, it is time to analyze the relationship between constructs by assessing the model quality, test the hypothesis and the relationship between the exogenous and endogenous constructs. All of this is done using a PLS-SEM model to obtain parameters that best predict the endogenous construct (Hair et al., 2014), also called the dependent variable which is in this case panic buying. The model quality is measured based on the ability to measure the endogenous constructs by measuring the path coefficients (*Beta*), coefficient of determination (*R-square*) and the effect size (*f-square*) (Chin, 1998; Hair et al., 2016; Memon & Rahman, 2014).

The structural relationships are studied by analyzing the path coefficients and their significance levels, which is done by the analysis of the *t*-values and their strength. This test is done by performing a non-parametric bootstrapping technique (Chin, 1998), generating 5000 samples of size 42, which were used to compute *t*-values and the significance of the path coefficients. For the test it was adopted a two-tailed test with a significance level of 0,05 with a *t*-value of 1.96 (Hair et al., 2011). The bootstrapping technique creates several subsamples drawn at random from the original dataset, and to ensure stability and statistic precision the number of subsamples should be large ranging from 1000 to 10000, hence for this study a subsample of 5000 was chosen (Becker et al., 2023).

Path coefficients, also called β , indicate the strength of an effect from variables to endogenous latent variables. As represented on [table 7](#), it is possible to conclude that modified treatment and scarcity are negative predictors of panic buying, while FOMO is a positive predictor of panic buying.

H1 evaluates whether scarcity is positively correlated with FOMO, and based on the results there is no correlation and scarcity does not have a significant association with FOMO ($\beta = -0.456$, $t = 0.993$, $p = 0.321$), hence, H1 is not supported. H2 evaluates if scarcity is positively correlated with modified treatment, and the results reveal that there is no relation ($\beta = -0.498$, $t = 1.781$, $p = 0.075$), hence H2 is not supported. H3 measures if FOMO is positively correlated with panic buying, and based on the results the hypothesis is not supported ($\beta = 0.717$, $t = 1.361$, $p = 0.174$). H4 measures if modified treatment is positively correlated to panic buying, which based on the results it is not ($\beta = -0.521$, $t = 1.030$, $p = 0.303$), and therefore H4 is not supported. Finally, H5 measures if scarcity is positively correlated with panic buying, and the results say otherwise ($\beta = -0.201$, $t = 0.406$, $p = 0.684$), hence H5 is not supported. From all the hypothesis presented none have a significant association, as represented in [table 7](#).

Table 7 Path coefficients. Source: Based on the primary data collected

Hypothesis	Relationship	Path coefficient	Std. Dev.	T statistic	p-value	Supported
H1	Scarcity → FOMO	-0.456	0.459	0.993	0.321	No
H2	Scarcity → Modified Treatment	-0.498	0.280	1.781	0.075	No
H3	FOMO → Panic Buying	0.717	0.527	1.361	0.174	No
H4	Modified Treatment → Panic Buying	-0.521	0.506	1.030	0.303	No
H5	Scarcity → Panic Buying	-0.201	0.495	0.406	0.684	No

The model fit will be tested by calculating R-square of the endogenous construct. R-square is a statistical measure which represents the amount of variance in the endogenous constructs (dependent variable) explained by the other constructs (independent variables) and the result provides information about the predictive accuracy of the model and the goodness of fit (Hair et al., 2014). R-square varies between 0 and 1, and its interpretation depends on different literature. According to Chin (1998), the model fit is moderate since it is higher than 0.33 but lower than 0.67. In other words, panic buying is being explained 52,8% by scarcity, modified treatment and FOMO and the model exploratory power is moderate.

Table 8 R-square and R-square adjusted. Source: Based on the primary data collected

	R-square	R-square adjusted
Panic Buying	0.528	0.399

F-square measures how R-square and how the endogenous variables behave when an exogenous variable (independent variable) is removed from the model. According to Cohen (1988), an f-square

higher than 0.02 is small, higher than 0.15 is medium and higher than 0.35 is large. The model from this study has an *f*-square that ranges from 0.058 (small) for construct scarcity on construct panic buying to 0.799 (large) for construct FOMO on construct panic buying. Since all results are higher than 0.02 than the removal of a specific variable will influence the variability of R-square, for example, the removal of construct scarcity influencing FOMO will have a moderate impact on the R-square.

Table 9 *f*-square. Source: Based on the primary data collected

Construct	FOMO	Modified Treatment	Panic Buying	Scarcity
FOMO			0.799	
Modified Treatment			0.402	
Panic Buying				
Scarcity	0.262	0.330	0.058	

The standardized root mean square residual (SRMR) is the discrepancy between the observed correlation and the predicted correlation which allows measuring the model fit. The saturated model considers the correlation between all constructs, whereas the estimated model considers the model structure and is based on a total effect scheme. Literature is not clear on what model to analyze, thus both models were taken into account (Ringle, Wende, et al., 2022). According to Hu & Bentler (1988) a good fit has values lower than 0.10, or even 0.08. Based on the results presented on [table 10](#) the model is not a good fit as the SRMR is higher than 0.10.

Table 10 Standardized Root Mean Square Residual. Source: Based on the primary data collected

	Saturated model	Estimated model
SRMR	0.152	0.181

6. DISCUSSION

The purpose of this study is to understand the impact of drug shortages in consumers, and ultimately, if drug shortages impact consumers to adopt panic buying behavior. While also analyzing if factors such as fear of missing out on a purchase or the possibility of modifying a treatment are taken into account.

The impact of prescription drug shortages and non-prescription drugs shortages is very distinct. Proof of that is the number of consumers who have experienced shortage of non-prescription drugs. From the total number of responses – 42 – there were only three responses reporting their experience with non-prescription drugs shortages, which translates into 7% of the total sample. Concluding that the Portuguese population has experienced more shortages on prescription drugs than non-prescription drugs, therefore the impact is more meaningful and might create more emotional reactions. Even further, non-prescription drugs tend to have more alternative options such as generics, which means people tend to have a quick solution avoiding the need of searching for new medicines or delaying treatment, and even making panic purchases.

When it comes to what triggers panic purchases – if it is the scarcity itself or if there are other factors, such as FOMO or modified treatment – the results have shown that fear of missing out does not play an important role in the relationship between scarcity and panic buying. Which means that drug scarcity does not impact consumers need to buy a medicine because of the fear of not being able to have it, which in turn would trigger their panic buying behavior. The results have also shown that the possibility of having a delayed or a different treatment also does not impact the consumer behavior, and people do not tend to panic buy when those possibilities appear. Which means people do not tend to be worried about how those changes will impact their life and health. Lastly, based on the results scarcity itself is also not a trigger on consumer panic behavior, therefore only the fact that a drug might be in shortage does not provoke panic purchases.

Even though, the results show no relation between scarcity and panic buying, this can be justified by the low perception of possible future consequences, and not because people are not affected by medicines in shortage, specially medicines they consume regularly. A study made to the Portuguese population about health literacy has concluded that 61% of the total sample has a poor and problematic level of health literacy (Pedro et al., 2016). Having a low health literacy translates into poor decisions regarding health on the daily basis, poor control over the capacity of gathering information and over the health status, low capacity of taking the medicine correctly and on-time, and difficulty interpreting a leaflet (Huizinga et al., 2009; Lee & Kim, 2009).

In the case of *Diabetes Mellitus* (DM), there are two types – Type 1 and Type 2. In the case of type 1 diabetes, patients need to take insulin regularly since their body can't produce it itself and it is necessary for their survival. While for diabetes type 2 the body still produces insulin but is not able to use it. The ATC group studied on this dissertation are diabetes medicine used for the treatment of type 2 diabetes, which comparatively to type 1 diabetes is not so severe as patients don't suffer immediate consequences in case of postponed treatment, but might suffer consequences in the long run if not correctly medicated, and most patients might not be aware of this (Jacobson et al., 1994). Due to the characteristics of type 2 diabetes, patients with low health literacy will not take seriously the

modification or postponement of treatments and the respective consequences, which makes diabetes one of the most affected diseases by low health literacy (Huizinga et al., 2009; Pedro et al., 2016).

During the questionnaire, many respondents shared their experience about how they dealt with shortages. A popular medicine in shortage is Ozempic administrated weekly and the respective alternative is Trulicity which is also administrated weekly but in higher doses, even though the difference between both is minimal a few of the interviewed Ozempic consumers acknowledged how they would rather postpone and wait for the its availability since it is the medicine they are used to consume, rather than change to Trulicity. In these cases, consumers are clearly not aware of the consequences diabetes can have if not treated correctly and on-time. Therefore, the poor knowledge might lead to higher chances of hospitalization, poor adherence and missing doses, and increasing severity of the chronic disease (Dewalt et al., 2004).

In the last years in Portugal, health literacy has been growing importance and is increasingly promoted among the population with the goal of improving the health system and the population health, reduce health related costs, more knowledge among the population, lower use of health services and creation new health policies (Pedro et al., 2016). Having a good social support and health system implemented by health authorities would also help implementing health literacy in the population (Lee & Kim, 2009), specifically older population which tend to be the most affected (Pedro et al., 2016).

In conclusion, scarcity of medicines might not trigger panic purchases, not because consumers are not affected by shortages, but rather because the population is not aware of the consequences.

7. CONCLUSIONS AND FUTURE WORKS

This study raised questions about the lack of theoretical framework in drug shortages studies that explore consumer behavior associated with panic purchases. Drug shortages have been a raising problem for the population, and panic purchases behavior has been noticed on the population on other different situations. Therefore, studying the relation between both is important to not only enrich the literature about the topic but also start the conversation on how to prevent and resolve these problems. Prevention of drug shortages is done by governmental authorities and health organizations, hence it is important to study of the lack of solutions and prevention for drug shortages affect the population.

Important limitations to point out and consider for future researches are the following. The sample size was of 42 observations, even though it was a highly selected group it would be beneficial to expand the sample size to achieve more accurate results. Additionally, it would also be interesting to better distribute the age group and study the behavior of younger populations to see if it reacts the same to drug scarcity or not. Another found limitation is the molecules used for this study which were only 5 focused on the treatment of diabetes. In future works, it would be important to study other molecules and medicines with focus on different treatments. Finally, this study is only focused on FOMO and modified treatment as individual factors that might influence the panic purchases, and it would be important to study other factors and analyze how it influences the population behavior.

Nonetheless, this study is important as it opens new paths to study the impact of drug scarcity on the population, and eventually laws and new measures might be taken to prevent panic purchases and avoid drug scarcity.

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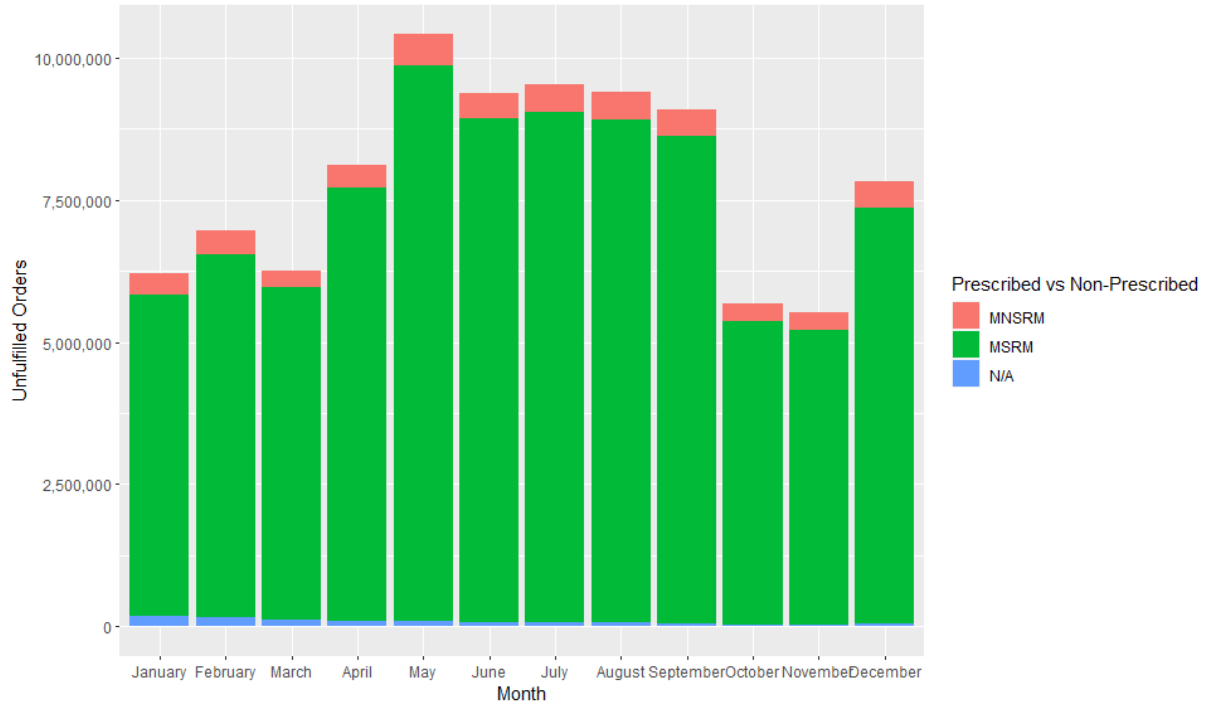
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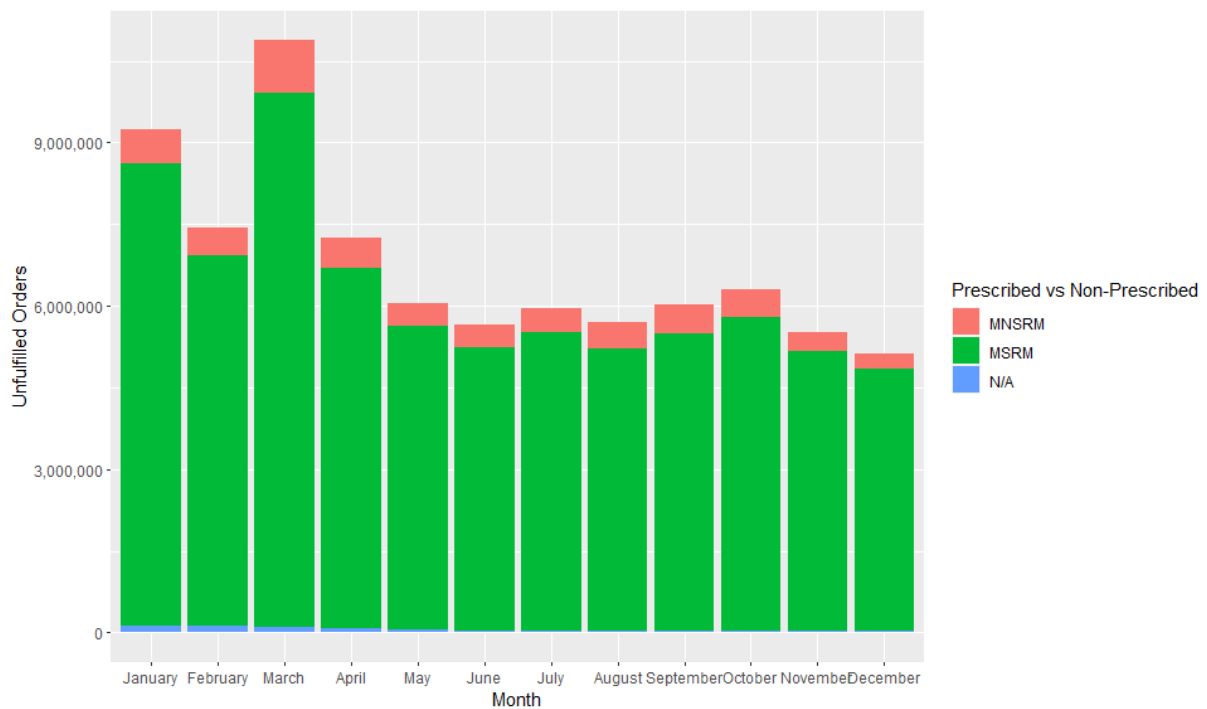
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APPENDIX A

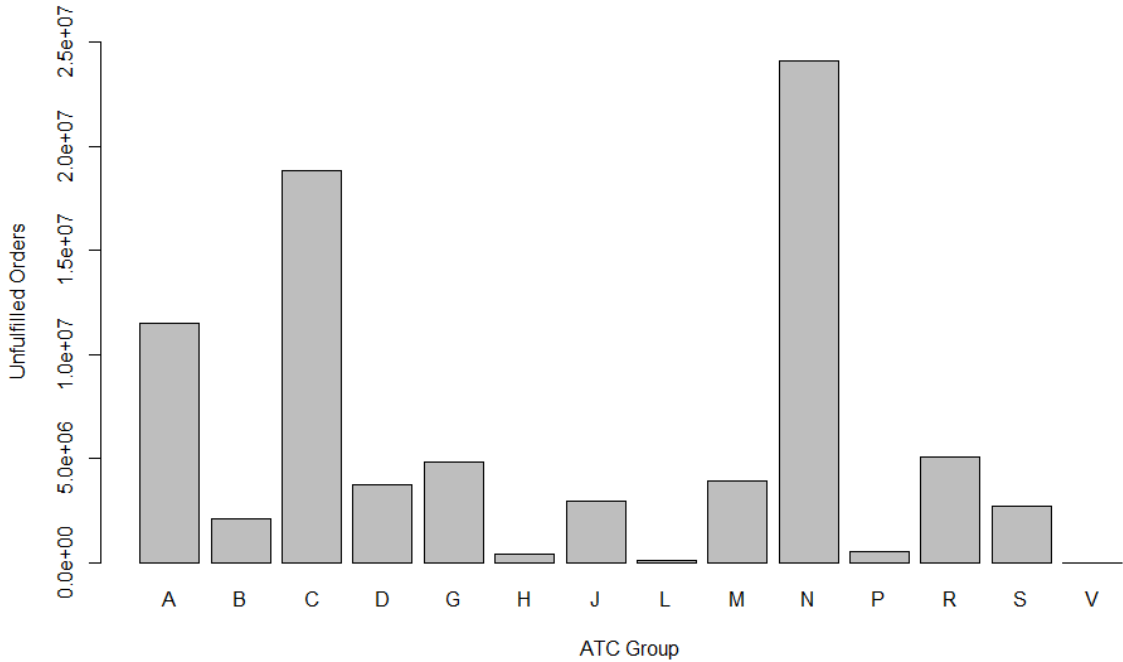
Graph 1 Histogram representation of unfulfilled orders of prescribed (MSRM) and non-prescribed (MNSRM) drugs in 2019 in Portugal. Source: CEFAR



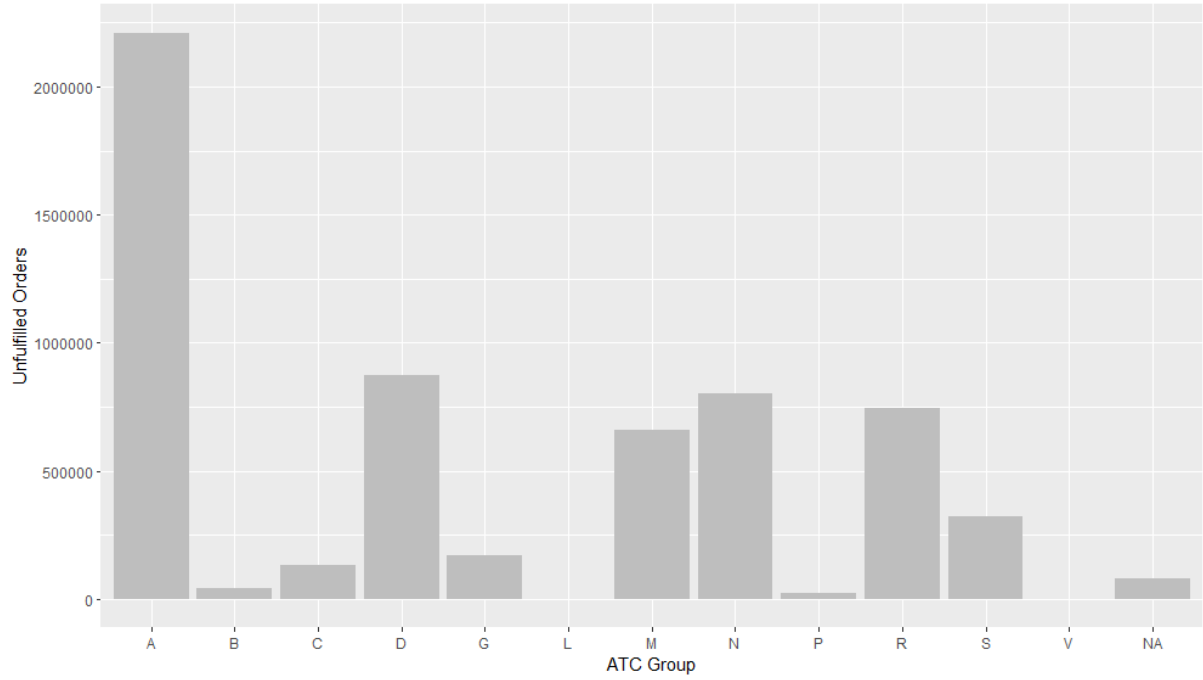
Graph 2 Histogram representation of unfulfilled orders of prescribed (MSRM) and non-prescribed (MNSRM) drugs in 2020 in Portugal. Source: CEFAR



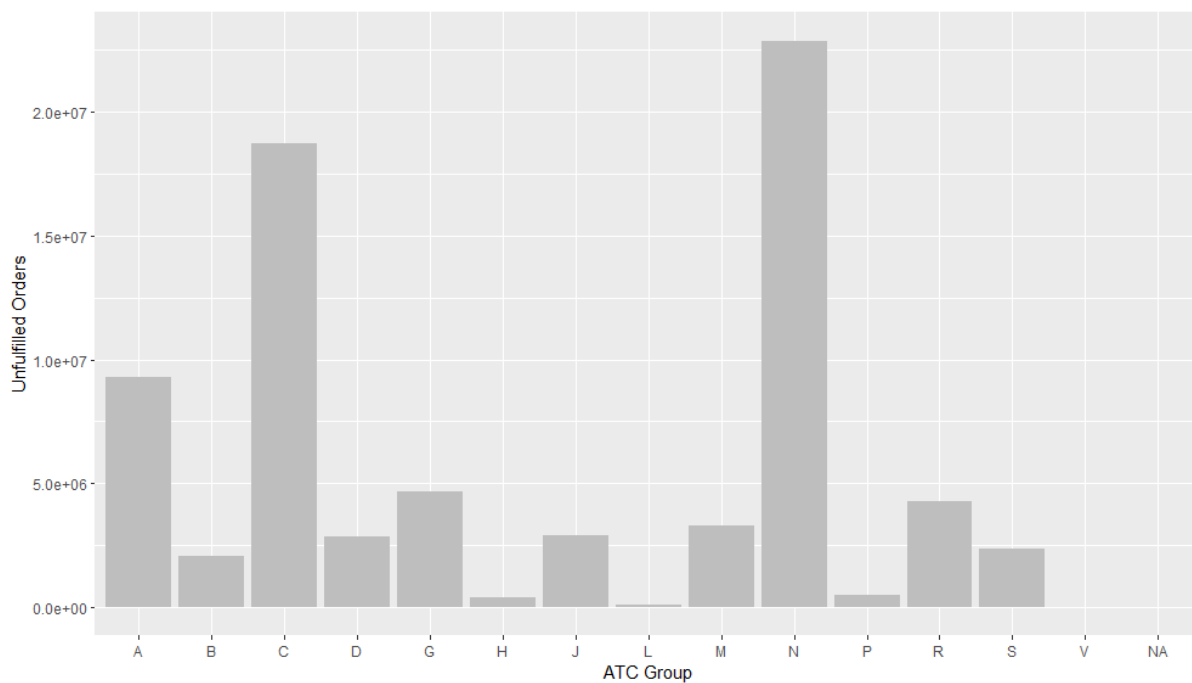
Graph 3 Histogram representation of unfulfilled orders by ATC group in 2020 in Portugal. Source: CEFAR



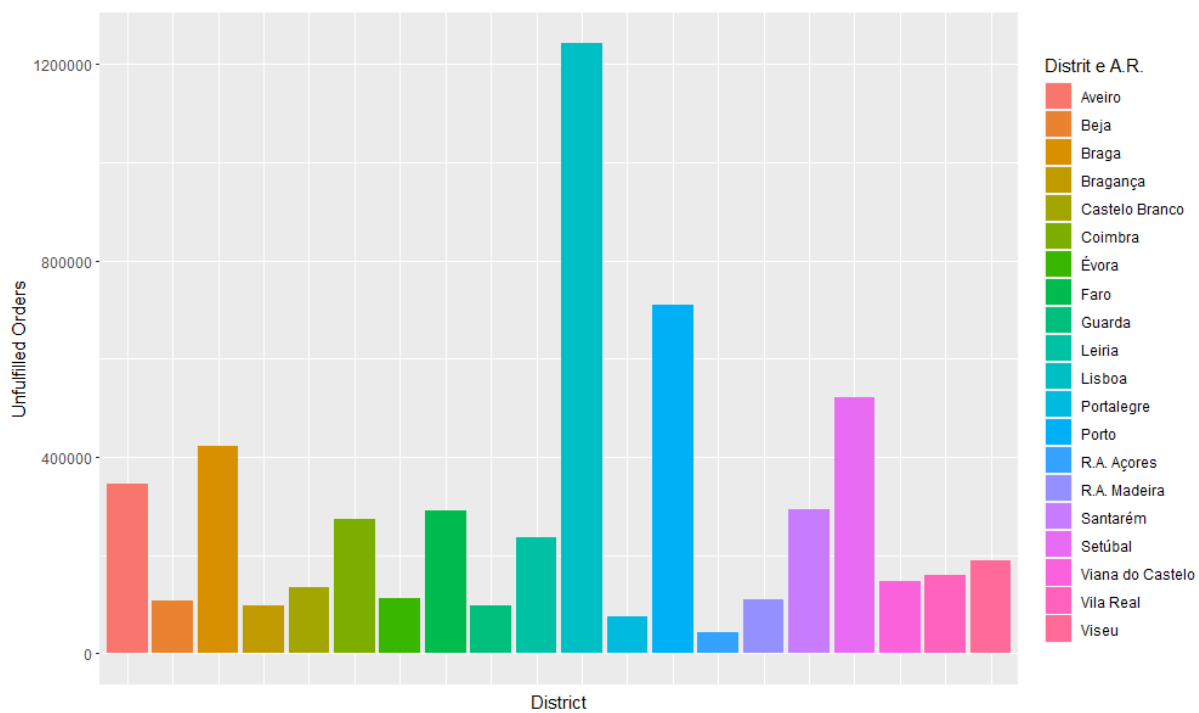
Graph 4 Histogram representation of unfulfilled orders for non-prescribed drugs by ATC group in 2020, in Portugal. Source: CEFAR



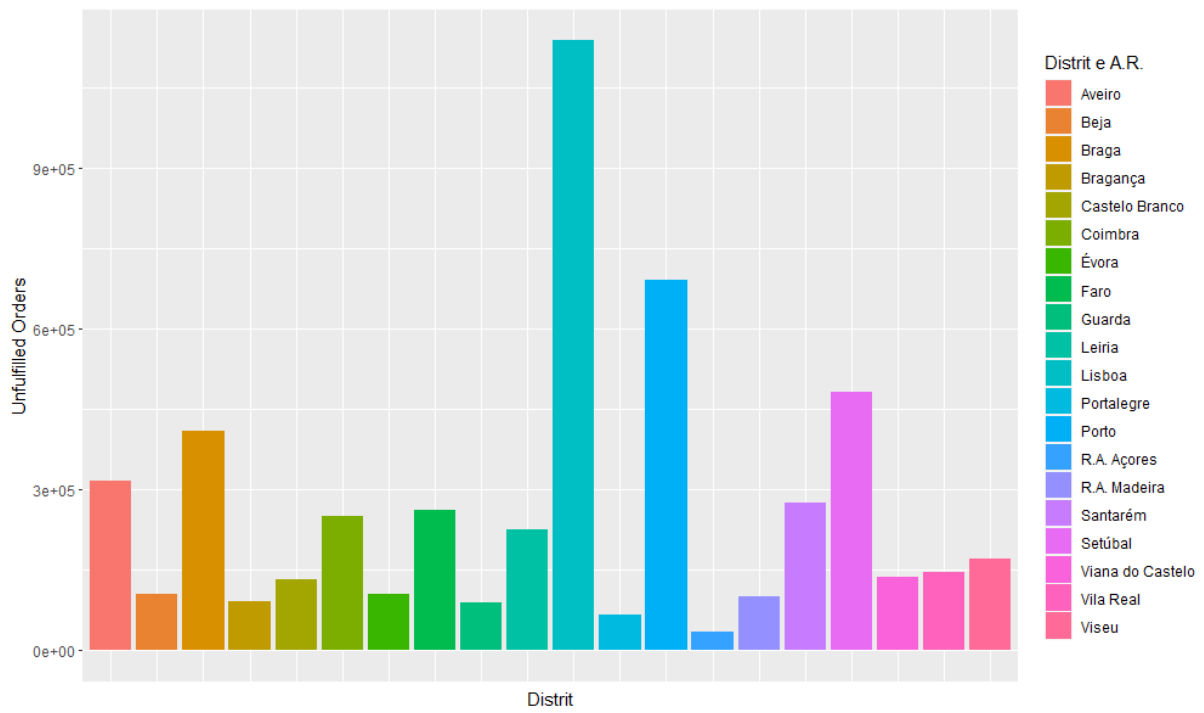
Graph 5 Histogram representation of unfulfilled orders for prescribed drugs by ATC group in 2020, in Portugal. Source: CEFAR



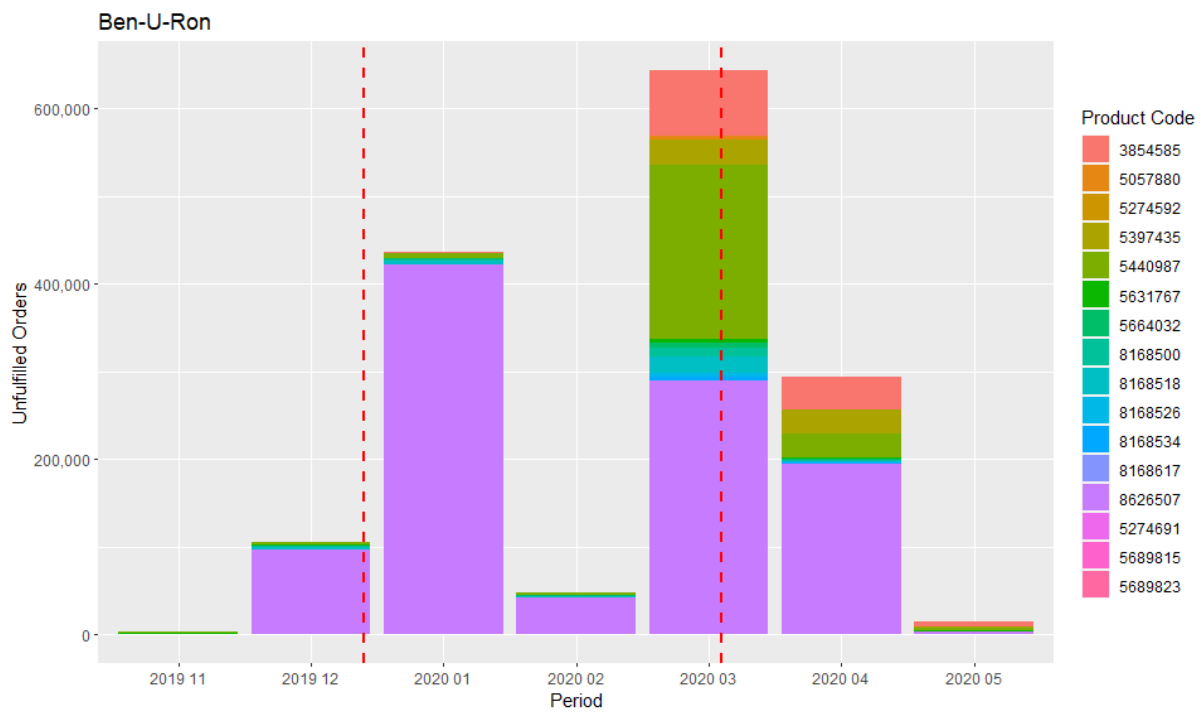
Graph 6 Histogram for unfulfilled orders by district in 2019. Source: CEFAR



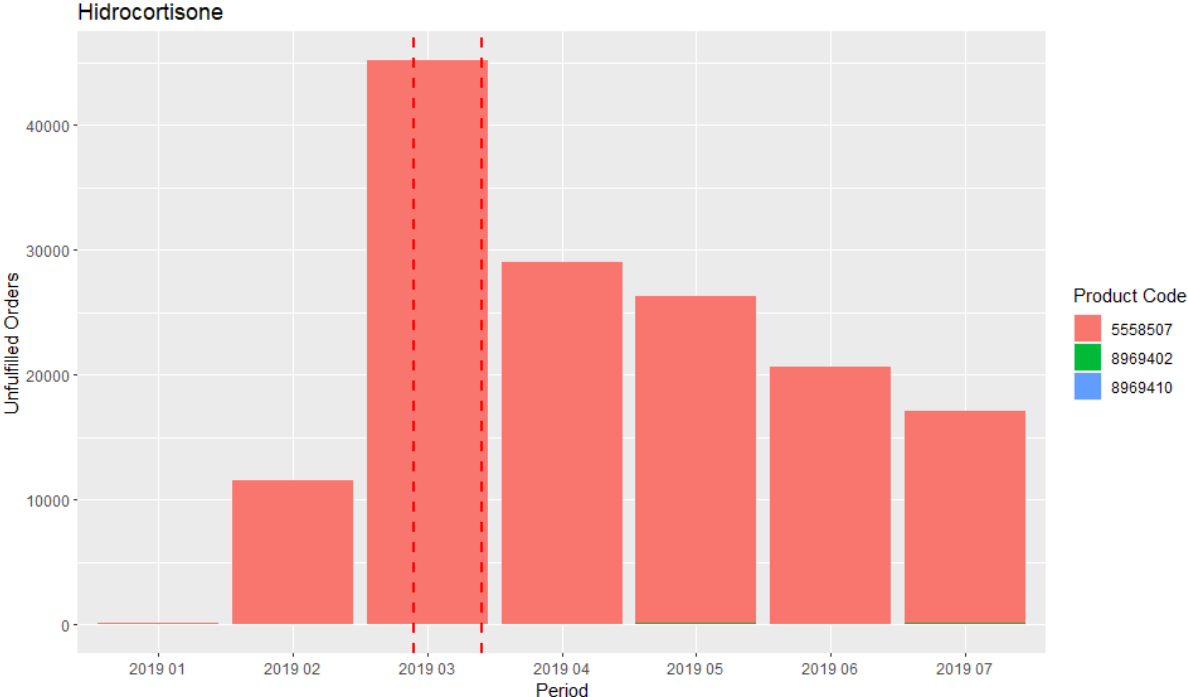
Graph 7 Histogram for unfulfilled orders by district in 2020. Source: CEFAR



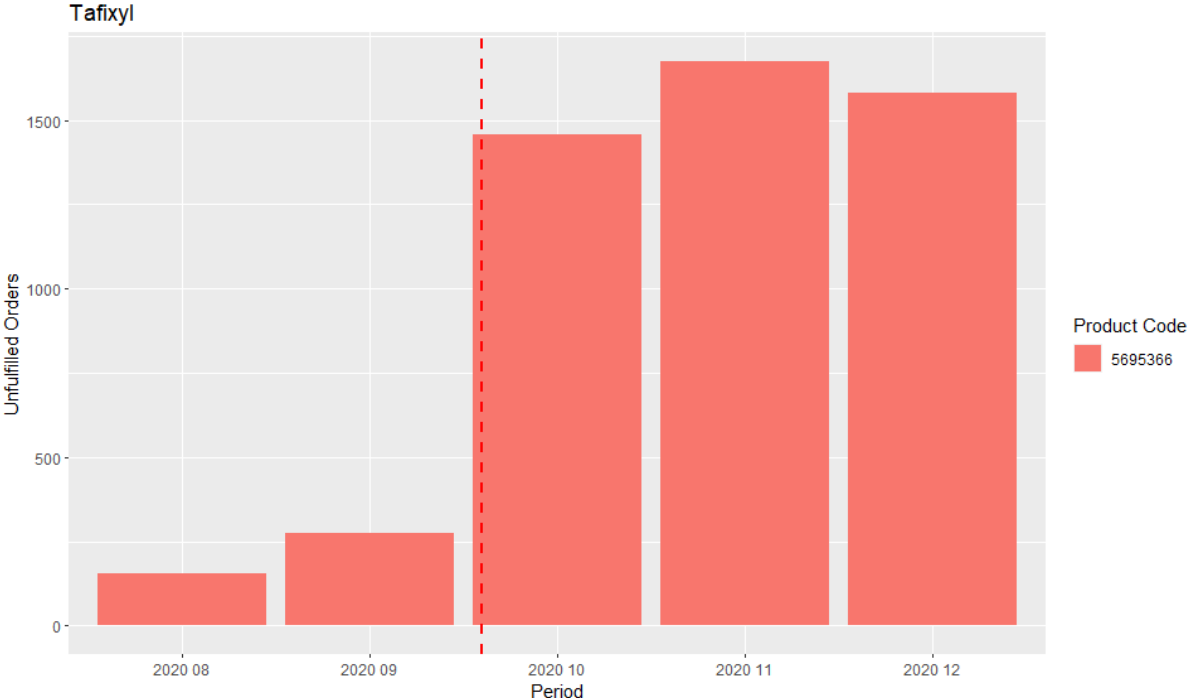
Graph 8 Histogram representation of unfulfilled orders for Ben-U-Ron between November of 2019 and May of 2020. Source: CEFAR



Graph 9 Histogram representation of unfulfilled orders for Hidrocortisone between January of 2019 and July of 2019. Source: CEFAR



Graph 10 Histogram representation of unfulfilled orders for Tafixyl between August of 2020 and December of 2020. Source: CEFAR



Graph 11 Histogram representation of unfulfilled orders for Victan between April of 2020 and September of 2020. Source: CEFAR



ANNEXES

Annex A Survey

Construct	ID	Indicators	Scale
Demographic Characteristics	Age	Select your age	18-24; 25-34; 35-44; 45-54; 55-64; Above 64; Prefer not to answer
	Gender	Select your gender	Female; Male; Other; Prefer not to answer
	Education	Select your education level	Basic School; Secondary School; Bachelor's Degree; Master's Degree; PhD; I cannot read and/or write; Prefer not to answer
	Income	Select your monthly income	Less than 800€; Between 800€ and 1200€; Between 1200€ and 1600€; Between 1600€ and 2000€; More than 2000€; Prefer not to answer
	Professional situation	Select your professional situation	Employed; Unemployed; Retired; Student; Other; Prefer not to answer
	Pharmacy	Select the pharmacy	Pharmacy Holon Campo Grande; Pharmacy Alto do Lumiar
	Drug purpose	Select the drug purpose	Diabetes; Obesity
Scarcity (MSRM)	D1	The supply of the medicine is small.	Five point scale 1 = strongly disagree to 5 = strongly agree; Prefer not to answer
	D2	I am afraid the medicine will run out again in the future.	
	D3	Many people buy this medicine.	
FOMO	F1	I feel anxious about the possibility of not being able to buy medicine.	Five point scale 1 = strongly disagree to 5 = strongly agree; Prefer not to answer
	F2	News of drug shortages may influence me to buy.	
	F3	I am willing to visit more than one pharmacy until I find the medicine I need.	
Modified treatments	T1	I am upset about postponing a treatment.	

	T2	I contact a health professional immediately for advice.	
	T3	I am willing to consider alternative medicines recommended by a healthcare professional.	Five point scale 1 = strongly disagree to 5 = strongly agree; Prefer not to answer
	T4	I am willing to pay the difference if the alternative medication is more expensive.	
	T5	I faced adverse effects due to the delay or change in treatment.	
Panic Buying	IB1	The scarcity of the medicine pushes me to buy in good time.	Five point scale 1 = strongly disagree to 5 = strongly agree; Prefer not to answer
	IB2	Even if I don't need it, I like having the medicine at home.	
	IB3	I buy the full amount I was prescribed on my first trip to the pharmacy.	
Scarcity (MNSRM)	MNSRM	Have you ever experienced a shortage of non-prescribed drugs?	Yes; No
	D4	The supply of the medicine is small.	Five point scale 1 = strongly disagree to 5 = strongly agree; Prefer not to answer
	D5	I am afraid the medicine will run out again in the future.	
	D6	Many people buy this medicine.	
FOMO	F4	I feel anxious about the possibility of not being able to buy medicine.	Five point scale 1 = strongly disagree to 5 = strongly agree; Prefer not to answer
	F5	News of drug shortages may influence me to buy.	
	F6	I am willing to visit more than one pharmacy until I find the medicine I need.	
Modified treatments	T6	I am upset about postponing a treatment.	
	T7	I contact a health professional immediately for advice.	Five point scale 1 = strongly disagree to 5 = strongly agree; Prefer not to answer
	T8	I am willing to consider alternative medicines recommended by a healthcare professional.	
	T9	I am willing to pay the difference if the alternative medication is more expensive.	
	T10	I faced adverse effects due to the delay or change in treatment.	
Panic Buying	IB4	The scarcity of the medicine pushes me to buy in good time.	Five point scale 1 = strongly disagree to 5 = strongly agree; Prefer not to answer
	IB5	Even if I don't need it, I like having the medicine at home.	
	IB6	I buy the full amount I was prescribed on my first trip to the pharmacy.	

Annex B Ethics Approval

RE: NOVA IMS | Ethics Committee - NEED REVIEW

Ethics Committee <ethicscommittee@novaims.unl.pt>

qua, 30/08/2023 11:57

Para: Daniela Rotaru <m20210289@novaims.unl.pt>; Maria Helena Miranda Flores Baptista <mhbaptista@novaims.unl.pt>
Cc: Ethics Committee <ethicscommittee@novaims.unl.pt>

Dear Daniela Rotaru,

Dear Professor Marie Helena Baptista,

Thank you for filling in the Research Ethics Checklist. After reviewing your request, you can proceed with the study but we suggest not to include people under 18 in your data collection (as it was mentioned in your reply, that the study could be undertaken without the participation of this age group). As such, please find below the approval from the Ethics Committee.

This is to certify that

Project No.: **STAT2023-7-314997**

Project Title: **Drug Shortages and Patient Reactions: Exploring the Influence of Drug Type and Individual Factors**

Principal Researcher: **Daniela Rotaru**

according to the regulations of the Ethics Committee of NOVA IMS and MagIC Research Center this project was considered to meet the requirements of the NOVA IMS Internal Review Board, being considered **APPROVED** on 30/8/2023.

It is the Principal Researcher's responsibility to ensure that all researchers and stakeholders associated with this project are aware of the conditions of approval and which documents have been approved.

The Principal Researcher is required to notify the Ethics Committee, via amendment or progress report, of

- Any significant change to the project and the reason for that change;
- Any unforeseen events or unexpected developments that merit notification;
- The inability of the Principal Researcher to continue in that role or any other change in research personnel involved in the project.

Lisbon, 30/8/2023

NOVA IMS Ethics Committee

ethicscommittee@novaims.unl.pt

Cristina Oliveira

Gestora executiva do centro de investigação MagIC | *Executive manager of the Information Management Research Center (MagIC)*

Vice-chair of BESTPRAC - EARMA Thematic Group

Team member of RM Roadmap - Co-creating the future of Research Management (<https://rmroadmap.eu/>)

<https://orcid.org/0000-0002-0887-7961>

Annex C R Code

#Graph 1 Histogram representation of unfulfilled orders of prescribed (MSRM) and non-prescribed (MNSRM) drugs in 2019 in Portugal

```
all_data_2019 <- bind_rows(
  PERIODO_2019_01 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo="January"),
  PERIODO_2019_02 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo="February"),
  PERIODO_2019_03 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo="March"),
  PERIODO_2019_04 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo="April"),
  PERIODO_2019_05 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo="May"),
  PERIODO_2019_06 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo="June"),
  PERIODO_2019_07 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo="July"),
  PERIODO_2019_08 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo="August"),
  PERIODO_2019_09 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo="September"),
  PERIODO_2019_10 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo="October"),
  PERIODO_2019_11 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo="November"),
  PERIODO_2019_12 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo="December"))

colnames(all_data_2019)[colnames(all_data_2019) == "codigo_produto"] <- "cod_prod"
merged_data <- left_join(all_data_2019, data_2019 %>% select(cod_prod, Class_Dis), by =
  "cod_prod") %>% mutate(Class_Dis = ifelse(is.na(Class_Dis), "N/A", Class_Dis))
merged_data$periodo <- factor(merged_data$periodo, levels = c("January", "February", "March",
  "April", "May", "June", "July", "August", "September", "October", "November", "December"))
merged_data$Class_Dis <- recode(merged_data$Class_Dis, "MNSRM-EF" = "MNSRM", "MSRM
especial" = "MSRM", "MSRM especial e restrita - Alínea b)" = "MSRM",
  "MSRM especial e restrita - Alínea c)" = "MSRM",
  "MSRM restrita" = "MSRM", "MSRM restrita - Alínea a)" = "MSRM",
  "MSRM restrita - Alínea b)" = "MSRM", "MSRM restrita - Alínea c)" = "MSRM")

ggplot(merged_data, aes(fill=Class_Dis, y=qt_falta, x=periodo)) +
  geom_bar(position="stack", stat="identity") +
  labs(x = "Month", y = "Unfulfilled Orders", fill = "Prescribed vs Non-Prescribed",
  caption = "") + scale_y_continuous(labels = scales::comma)
```

#Graph 2 Histogram representation of unfulfilled orders of prescribed (MSRM) and non-prescribed (MNSRM) drugs in 2020 in Portugal

```
all_data_2020 <- bind_rows(
  PERIODO_2020_01 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo = "January"),
  PERIODO_2020_02 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo = "February"),
  PERIODO_2020_03 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo = "March"),
  PERIODO_2020_04 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo = "April"),
  PERIODO_2020_05 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo = "May"),
  PERIODO_2020_06 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo = "June"),
  PERIODO_2020_07 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo = "July"),
  PERIODO_2020_08 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo = "August"),
  PERIODO_2020_09 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo = "September"),
  PERIODO_2020_10 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo = "October"),
  PERIODO_2020_11 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo = "November"),
  PERIODO_2020_12 %>% select(periodo, codigo_produto, qt_falta) %>% mutate(periodo = "December"))
```

```
colnames(all_data_2020)[colnames(all_data_2020) == "codigo_produto"] <- "cod_prod"
merged_data <- left_join(all_data_2020, data_2020 %>% select(cod_prod, CLASS_DISPENSA), by =
"cod_prod") %>%
  mutate(CLASS_DISPENSA = ifelse(is.na(CLASS_DISPENSA), "N/A", CLASS_DISPENSA))
merged_data$periodo <- factor(merged_data$periodo, levels = c("January", "February", "March",
"April", "May", "June", "July", "August", "September", "October", "November", "December"))
merged_data$CLASS_DISPENSA <- recode(merged_data$CLASS_DISPENSA, "MNSRM-EF" =
"MNSRM", "MSRM restrita" = "MSRM", "MSRM restrita - Alínea a)" = "MSRM", "MSRM restrita -
Alínea b)" = "MSRM", "MSRM restrita - Alínea c)" = "MSRM")
```

```
ggplot(merged_data, aes(fill=CLASS_DISPENSA, y=qt_falta, x=periodo)) +
  geom_bar(position="stack", stat="identity") +
  labs(x = "Month", y = "Unfulfilled Orders", fill = "Prescribed vs Non-Prescribed",
  caption = "") + scale_y_continuous(labels = scales::comma)
```

#Graph 3 Histogram representation of unfulfilled orders by ATC group in 2020 in Portugal

#Table 1 Unfulfilled orders by ATC group in 2020

```
df1 <- read_excel("Análise Faltas + Media/Dados Falta de medicamentos 2019-
20/20201202_Meds_Nova_IMS.xlsx")
df2 = data.frame(df1$cod_prod, df1$ATC_COD_1)
colnames(df2)[1] = "codigo_produto"
```

```

df2 <- df2 %>%
  add_column(ATC = (str_extract(df2$df1.ATC_COD_1, "[aA-zZ]+")))
table(df2$ATC)

faltas20 <-
rbind(PERODO_2020_01,PERODO_2020_02,PERODO_2020_03,PERODO_2020_04,PERODO_2020_
_05,PERODO_2020_06,PERODO_2020_07,PERODO_2020_08,PERODO_2020_09,PERODO_2020_1
0,PERODO_2020_11,PERODO_2020_12)
faltas20 = data.frame(faltas20$codigo_produto,faltas20$qt_falta)
colnames(faltas20)[1] ="codigo_produto"
colnames(faltas20)[2] ="qt_falta"
faltas20.1 = merge(faltas20, df2, by.x= "codigo_produto", all.x = TRUE)
faltasporATC <- aggregate(qt_falta ~ ATC, data=faltas20.1, sum)
faltasporATC[order(faltasporATC$qt_falta),]
barplot(faltasporATC$qt_falta, names.arg = faltasporATC$ATC, col = "grey",
  xlab = "ATC Group", ylab = "Unfulfilled Orders", ylim=c(0,25000000), main = "")

```

#Table 2 Unfulfilled orders by ATC subgroup A, C and N in 2020

```

df1 <- read_excel("Análise Faltas + Media/Dados Falta de medicamentos 2019-
20/20201202_Meds_Nova_IMS.xlsx")
df2 = data.frame(df1$cod_prod,df1$ATC_COD_1)
colnames(df2)[1] ="codigo_produto"

df2 <- df2 %>%
  add_column(ATC = str_sub(df2$df1.ATC_COD_1, 1, 3))
table(df2$ATC)

faltas20 <-
rbind(PERODO_2020_01,PERODO_2020_02,PERODO_2020_03,PERODO_2020_04,PERODO_2020_
_05,PERODO_2020_06,PERODO_2020_07,PERODO_2020_08,PERODO_2020_09,PERODO_2020_1
0,PERODO_2020_11,PERODO_2020_12)
faltas20 = data.frame(faltas20$codigo_produto,faltas20$qt_falta)
colnames(faltas20)[1] ="codigo_produto"
colnames(faltas20)[2] ="qt_falta"
faltas20.1 = merge(faltas20, df2, by.x= "codigo_produto", all.x = TRUE)
faltasporATC <- aggregate(qt_falta ~ ATC, data=faltas20.1, sum)
barplot(faltasporATC$qt_falta, names.arg = faltasporATC$ATC, col = "grey", xlab = "ATC", ylab =
"Unfulfilled Orders", main = "Barplot: Total Quantity by ATC")

```

```

plot <- ggplot(data = faltasporATC, aes(x = ATC, y = qt_falta)) +
  geom_bar(stat = "identity", fill = "grey") +
  labs(x = "ATC", y = "Unfulfilled Orders", title = "")
ggplotly(plot)
barplot(subset(faltasporATC, ATC %in% c('N','N01','N02','N03','N04','N05','N06','N07'))$qt_falta,
  names.arg = subset(faltasporATC, ATC %in% c('N','N01','N02','N03','N04','N05','N06','N07'))$ATC,
  col = "grey", xlab = "ATC", ylab = "Unfulfilled Orders",
  main = "")
filter(faltasporATC, ATC %in% c('N','N01','N02','N03','N04','N05','N06','N07'))
barplot(subset(faltasporATC, ATC %in%
c('C','C01','C02','C03','C04','C05','C06','C07','C08','C09','C10'))$qt_falta,
  names.arg = subset(faltasporATC, ATC %in% c('C','C01','C02','C03','C04','C05','C06','C07','C08',
  'C09','C10'))$ATC, col = "grey", xlab = "ATC", ylab = "Unfulfilled Orders", main = "")
filter(faltasporATC, ATC %in% c('C','C01','C02','C03','C04','C05','C06','C07','C08','C09','C10'))

barplot(subset(faltasporATC, ATC %in%
c('A01','A02','A03','A04','A05','A06','A07','A08','A09','A10','A11','A12','A13','A14','A15','A16'))$qt_falt
a, names.arg = subset(faltasporATC, ATC %in% c('A01','A02','A03','A04','A05','A06','A07',
  'A08','A09','A10','A11','A12','A13','A14','A15','A16'))$ATC,
  col = "grey", xlab = "ATC", ylab = "Unfulfilled Orders",
  main = "", ylim = c(0,5000000))
filter(faltasporATC, ATC %in% c('A01','A02','A03','A04','A05','A06','A07',
  'A08','A09','A10','A11','A12','A13','A14','A15','A16'))

```

#Graph 6 Histogram for unfulfilled orders by district in 2019

```

all_data_2019_districts <- bind_rows(
  PERIODO_2019_01 %>% select(farm, distrito, qt_falta),
  PERIODO_2019_02 %>% select(farm, distrito, qt_falta),
  PERIODO_2019_03 %>% select(farm, distrito, qt_falta),
  PERIODO_2019_04 %>% select(farm, distrito, qt_falta),
  PERIODO_2019_05 %>% select(farm, distrito, qt_falta),
  PERIODO_2019_06 %>% select(farm, distrito, qt_falta),
  PERIODO_2019_07 %>% select(farm, distrito, qt_falta),
  PERIODO_2019_08 %>% select(farm, distrito, qt_falta),
  PERIODO_2019_09 %>% select(farm, distrito, qt_falta),
  PERIODO_2019_10 %>% select(farm, distrito, qt_falta),
  PERIODO_2019_11 %>% select(farm, distrito, qt_falta),
  PERIODO_2019_12 %>% select(farm, distrito, qt_falta))

```

```

ggplot(all_data_2019_districts, aes(distrito)) + geom_bar(aes(fill = as.factor(distrito))) +
  scale_fill_discrete(name="Distrit e A.R.",
    labels=c("Aveiro", "Beja", "Braga", "Bragança", "Castelo
Branco", "Coimbra", "Évora", "Faro", "Guarda", "Leiria", "Lisboa", "Portalegre",
    "Porto", "R.A. Açores", "R.A. Madeira", "Santarém", "Setúbal", "Viana do
Castelo", "Vila Real", "Viseu")) +
  theme(axis.text.x= element_blank(),axis.ticks.x=element_blank()) +
  labs(x= "District",y= "Unfulfilled Orders")

```

```

pie(table(all_data_2019_districts$distrito),
  main = "Unfulfilled Orders by District and A.R.")

```

#Graph 7 Histogram for unfulfilled orders by district in 2020

```

all_data_2020_districts <- bind_rows(
  PERIODO_2020_01 %>% select(farm, distrito, qt_falta),
  PERIODO_2020_02 %>% select(farm, distrito, qt_falta),
  PERIODO_2020_03 %>% select(farm, distrito, qt_falta),
  PERIODO_2020_04 %>% select(farm, distrito, qt_falta),
  PERIODO_2020_05 %>% select(farm, distrito, qt_falta),
  PERIODO_2020_06 %>% select(farm, distrito, qt_falta),
  PERIODO_2020_07 %>% select(farm, distrito, qt_falta),
  PERIODO_2020_08 %>% select(farm, distrito, qt_falta),
  PERIODO_2020_09 %>% select(farm, distrito, qt_falta),
  PERIODO_2020_10 %>% select(farm, distrito, qt_falta),
  PERIODO_2020_11 %>% select(farm, distrito, qt_falta),
  PERIODO_2020_12 %>% select(farm, distrito, qt_falta))

```

```

ggplot(all_data_2020_districts, aes(distrito)) + geom_bar(aes(fill = as.factor(distrito))) +
  scale_fill_discrete(name="Distrit e A.R.",
    labels=c("Aveiro", "Beja", "Braga", "Bragança", "Castelo
Branco", "Coimbra", "Évora", "Faro", "Guarda", "Leiria", "Lisboa", "Portalegre",
    "Porto", "R.A. Açores", "R.A. Madeira", "Santarém", "Setúbal", "Viana do
Castelo", "Vila Real", "Viseu")) +
  theme(axis.text.x= element_blank(),axis.ticks.x=element_blank()) +
  labs(x= "Distrit",y= "Unfulfilled Orders")

```

```

pie(table(all_data_2020_districts$distrito),
  main = "Unfulfilled Orders by District and A.R.")

```

#Graph 4 Histogram representation of unfulfilled orders for non-prescribed drugs by ATC group in 2020 in Portugal

```
all_data_MNSRM_MSRM_2020 <- bind_rows(
  PERIODO_2020_01 %>% select(codigo_produto, qt_falta),
  PERIODO_2020_02 %>% select(codigo_produto, qt_falta),
  PERIODO_2020_03 %>% select(codigo_produto, qt_falta),
  PERIODO_2020_04 %>% select(codigo_produto, qt_falta),
  PERIODO_2020_05 %>% select(codigo_produto, qt_falta),
  PERIODO_2020_06 %>% select(codigo_produto, qt_falta),
  PERIODO_2020_07 %>% select(codigo_produto, qt_falta),
  PERIODO_2020_08 %>% select(codigo_produto, qt_falta),
  PERIODO_2020_09 %>% select(codigo_produto, qt_falta),
  PERIODO_2020_10 %>% select(codigo_produto, qt_falta),
  PERIODO_2020_11 %>% select(codigo_produto, qt_falta),
  PERIODO_2020_12 %>% select(codigo_produto, qt_falta))

colnames(all_data_MNSRM_MSRM_2020)[colnames(all_data_MNSRM_MSRM_2020) ==
"codigo_produto"] <- "cod_prod"
merged_data_MNSRM_MSRM_2020 <- left_join(all_data_MNSRM_MSRM_2020, data_2020 %>%
select(cod_prod, CLASS_DISPENSA, ATC_COD_1), by = "cod_prod") %>%
  mutate(CLASS_DISPENSA = ifelse(is.na(CLASS_DISPENSA), "N/A", CLASS_DISPENSA))
tapply(merged_data_MNSRM_MSRM_2020$qt_falta,
merged_data_MNSRM_MSRM_2020$CLASS_DISPENSA, sum)
tapply(merged_data_MNSRM_MSRM_2020$qt_falta,
merged_data_MNSRM_MSRM_2020$ATC_COD_1, sum)
merged_data_MNSRM_2020 <- merged_data_MNSRM_MSRM_2020 %>%
  filter(CLASS_DISPENSA %in% c("MNSRM", "MNSRM-EF"))
merged_data_MNSRM_2020 <- merged_data_MNSRM_2020 %>%
  add_column(ATC = (str_extract(merged_data_MNSRM_2020$ATC_COD_1, "[aA-zZ]+")))
ggplot(merged_data_MNSRM_2020, aes(x = ATC, y = qt_falta)) +
  geom_bar(stat = "identity", fill = "grey") +
  labs(x = "ATC Group", y = "Unfulfilled Orders", title = "")
tapply(merged_data_MNSRM_2020$qt_falta, merged_data_MNSRM_2020$ATC_COD_1, sum)
```

#Graph 5 Histogram representation of unfulfilled orders for prescribed drugs by ATC group in 2020 in Portugal

```
merged_data_MSRM_2020 <- merged_data_MNSRM_MSRM_2020 %>%
  filter(CLASS_DISPENSA %in% c("MSRM", "MSRM restrita", "MSRM restrita - Alínea a)",
    "MSRM restrita - Alínea a)", "MSRM restrita - Alínea b)",
    "MSRM restrita - Alínea c"))

merged_data_MSRM_2020 <- merged_data_MSRM_2020 %>%
  add_column(ATC = (str_extract(merged_data_MSRM_2020$ATC_COD_1, "[aA-zZ]+")))
ggplot(merged_data_MSRM_2020, aes(x = ATC, y = qt_falta)) +
  geom_bar(stat = "identity", fill = "grey") +
  labs(x = "ATC Group", y = "Unfulfilled Orders", title = "")
```

#Graph 8 Histogram representation of unfulfilled orders for Ben-U-Ron between November of 2019 and May of 2020

```
df1 <- data.frame(PERIODO_2019_09$CFT_COD1, PERIODO_2019_09$qt_falta)
df2 <- df1 %>% group_by(PERIODO_2019_09.CFT_COD1) %>%
  summarize(PERIODO_2019_09.qt_falta = sum(PERIODO_2019_09.qt_falta))
df3 <- df2 %>%
  filter(str_detect(PERIODO_2019_09.CFT_COD1, '^5'))
ggplot(df2, aes(PERIODO_2019_09.CFT_COD1)) + geom_bar(aes(fill =
as.factor(PERIODO_2019_09.CFT_COD1))) +
  scale_fill_discrete(name="CFT",
    labels=c("5", "5.1", "5.1.1", "5.1.2", "5.1.3.1", "5.1.3.2", "5.1.3.3", "5.1.4", "5.1.5", "5.1.6", "5.2",
    "5.2.1", "5.2.2", "5.2.3")) +
  theme(axis.text.x= element_blank(), axis.ticks.x=element_blank()) +
  labs(x= "CFT", y= "Número de Medicamentos Indisponíveis")

pie(table(df3$PERIODO_2019_09.CFT_COD1),
  main = "Indisponibilidade por Distrito")
summary(df2)
as.data.frame(df2)

head(sort(df2$PERIODO_2019_08.qt_falta, decreasing=TRUE), n=50)
head(arrange(df2, desc(df2$PERIODO_2019_01.qt_falta)), n=50)
as.data.frame(head(df2[order(df2$PERIODO_2019_08.qt_falta, decreasing= T),], n = 50))
```

```

BENURON112019 <- PERIODO_2019_11 %>% group_by(codigo_producto) %>%
  summarize(qt_falta = sum(qt_falta)) %>%
  filter(codigo_producto %in%
c('8168500','8168518','8168526','8168534','8626507','8168617','3854585','5274691',
      '5274592','5057880','5057989','9168617','5440888','5440987','5441084','5344189',
      '5700984','5397427','5397435','5397443','5355078','5633953','5633961','5633870',
      '5633904','5633946','5633920','5633938','5633912','5473863','5473871','5473905',
      '5473913','5473921','5631742','5631767','5631759','5664024','5664032','5664040',
      '5673256','5689823','5713979','5689815')) %>%
  mutate(periodeo="2019 11",.before = codigo_producto)
as.data.frame(BENURON112019)
sum(BENURON112019$qt_falta)
BENURON122019 <- PERIODO_2019_12 %>% group_by(codigo_producto) %>%
  summarize(qt_falta = sum(qt_falta)) %>%
  filter(codigo_producto %in%
c('8168500','8168518','8168526','8168534','8626507','8168617','3854585','5274691',
      '5274592','5057880','5057989','9168617','5440888','5440987','5441084','5344189',
      '5700984','5397427','5397435','5397443','5355078','5633953','5633961','5633870',
      '5633904','5633946','5633920','5633938','5633912','5473863','5473871','5473905',
      '5473913','5473921','5631742','5631767','5631759','5664024','5664032','5664040',
      '5673256','5689823','5713979','5689815')) %>%
  mutate(periodeo="2019 12",.before = codigo_producto)
as.data.frame(BENURON122019)
sum(BENURON122019$qt_falta)
BENURON012020 <- PERIODO_2020_01 %>% group_by(codigo_producto) %>%
  summarize(qt_falta = sum(qt_falta)) %>%
  filter(codigo_producto %in%
c('8168500','8168518','8168526','8168534','8626507','8168617','3854585','5274691',
      '5274592','5057880','5057989','9168617','5440888','5440987','5441084','5344189',
      '5700984','5397427','5397435','5397443','5355078','5633953','5633961','5633870',
      '5633904','5633946','5633920','5633938','5633912','5473863','5473871','5473905',
      '5473913','5473921','5631742','5631767','5631759','5664024','5664032','5664040',
      '5673256','5689823','5713979','5689815')) %>%
  mutate(periodeo="2020 01",.before = codigo_producto)
as.data.frame(BENURON012020)
sum(BENURON012020$qt_falta)
BENURON022020 <- PERIODO_2020_02 %>% group_by(codigo_producto) %>%
  summarize(qt_falta = sum(qt_falta)) %>%
  filter(codigo_producto %in%
c('8168500','8168518','8168526','8168534','8626507','8168617','3854585','5274691',

```

```

'5274592','5057880','5057989','9168617','5440888','5440987','5441084','5344189',
'5700984','5397427','5397435','5397443','5355078','5633953','5633961','5633870',
'5633904','5633946','5633920','5633938','5633912','5473863','5473871','5473905',
'5473913','5473921','5631742','5631767','5631759','5664024','5664032','5664040',
'5673256','5689823','5713979','5689815')) %>%
mutate(perodo="2020 02",.before = codigo_producto)
as.data.frame(BENURON022020)
sum(BENURON022020$qt_falta)
BENURON032020 <- PERIODO_2020_03 %>% group_by(codigo_producto) %>%
summarize(qt_falta = sum(qt_falta)) %>%
filter(codigo_producto %in%
c('8168500','8168518','8168526','8168534','8626507','8168617','3854585','5274691',
'5274592','5057880','5057989','9168617','5440888','5440987','5441084','5344189',
'5700984','5397427','5397435','5397443','5355078','5633953','5633961','5633870',
'5633904','5633946','5633920','5633938','5633912','5473863','5473871','5473905',
'5473913','5473921','5631742','5631767','5631759','5664024','5664032','5664040',
'5673256','5689823','5713979','5689815')) %>%
mutate(perodo="2020 03",.before = codigo_producto)
as.data.frame(BENURON032020)
sum(BENURON032020$qt_falta)
BENURON042020 <- PERIODO_2020_04 %>% group_by(codigo_producto) %>%
summarize(qt_falta = sum(qt_falta)) %>%
filter(codigo_producto %in%
c('8168500','8168518','8168526','8168534','8626507','8168617','3854585','5274691',
'5274592','5057880','5057989','9168617','5440888','5440987','5441084','5344189',
'5700984','5397427','5397435','5397443','5355078','5633953','5633961','5633870',
'5633904','5633946','5633920','5633938','5633912','5473863','5473871','5473905',
'5473913','5473921','5631742','5631767','5631759','5664024','5664032','5664040',
'5673256','5689823','5713979','5689815')) %>%
mutate(perodo="2020 04",.before = codigo_producto)
as.data.frame(BENURON042020)
sum(BENURON042020$qt_falta)
BENURON052020 <- PERIODO_2020_05 %>% group_by(codigo_producto) %>%
summarize(qt_falta = sum(qt_falta)) %>%
filter(codigo_producto %in%
c('8168500','8168518','8168526','8168534','8626507','8168617','3854585','5274691',
'5274592','5057880','5057989','9168617','5440888','5440987','5441084','5344189',
'5700984','5397427','5397435','5397443','5355078','5633953','5633961','5633870',
'5633904','5633946','5633920','5633938','5633912','5473863','5473871','5473905',
'5473913','5473921','5631742','5631767','5631759','5664024','5664032','5664040',

```

```

      '5673256','5689823','5713979','5689815')) %>%
  mutate(periodo="2020 05",.before = codigo_producto)
as.data.frame(BENURON052020)
sum(BENURON052020$qt_falta)
BENURON112019$codigo_producto <- as.factor(BENURON112019$codigo_producto)
BENURON122019$codigo_producto <- as.factor(BENURON122019$codigo_producto)
BENURON012020$codigo_producto <- as.factor(BENURON012020$codigo_producto)
BENURON022020$codigo_producto <- as.factor(BENURON022020$codigo_producto)
BENURON032020$codigo_producto <- as.factor(BENURON032020$codigo_producto)
BENURON042020$codigo_producto <- as.factor(BENURON042020$codigo_producto)
BENURON052020$codigo_producto <- as.factor(BENURON052020$codigo_producto)
BENURON <-
rbind(BENURON112019,BENURON122019,BENURON012020,BENURON022020,BENURON032020,BE
NURON042020,BENURON052020)
as.data.frame(BENURON)
B <- ggplot(BENURON, aes(fill=codigo_producto, y=qt_falta, x=periodo)) +
  geom_bar(position="stack", stat="identity") +
  labs(x = "Period", y = "Unfulfilled Orders", fill = "Product Code",
  title = "Ben-U-Ron",
  caption = "") +
  geom_vline(xintercept=2.4, linetype="dashed",color = "red", size=1) +
  geom_vline(xintercept=5.1, linetype="dashed",color = "red", size=1) +
  scale_y_continuous(labels = label_comma())
ggplotly(B)

```

#Graph 9 Histogram representation of unfulfilled orders for Hidrocortisone between January of 2019 and July of 2019

```

HIDROCORTISONA012019 <- PERIODO_2019_01 %>% group_by(codigo_producto) %>%
  summarize(qt_falta = sum(qt_falta)) %>%
  filter(codigo_producto %in%
c('8969402','8969410','3487287','3487386','3487089','3487188','5380555','5550736',
      '5558507','7988303','7988279','7988311','5752803','5752779','5801634')) %>%
  mutate(periodo="2019 01",.before = codigo_producto)
as.data.frame(HIDROCORTISONA012019)
sum(HIDROCORTISONA012019$qt_falta)
HIDROCORTISONA022019 <- PERIODO_2019_02 %>% group_by(codigo_producto) %>%
  summarize(qt_falta = sum(qt_falta)) %>%
  filter(codigo_producto %in%
c('8969402','8969410','3487287','3487386','3487089','3487188','5380555','5550736',

```

```

      '5558507','7988303','7988279','7988311','5752803','5752779','5801634')) %>%
mutate(periode="2019 02",.before = codigo_producto)
as.data.frame(HIDROCORTISONA022019)
sum(HIDROCORTISONA022019$qt_falta)
HIDROCORTISONA032019 <- PERIODO_2019_03 %>% group_by(codigo_producto) %>%
  summarize(qt_falta = sum(qt_falta)) %>%
  filter(codigo_producto %in%
c('8969402','8969410','3487287','3487386','3487089','3487188','5380555','5550736',
      '5558507','7988303','7988279','7988311','5752803','5752779','5801634')) %>%
mutate(periode="2019 03",.before = codigo_producto)
as.data.frame(HIDROCORTISONA032019)
sum(HIDROCORTISONA032019$qt_falta)
HIDROCORTISONA042019 <- PERIODO_2019_04 %>% group_by(codigo_producto) %>%
  summarize(qt_falta = sum(qt_falta)) %>%
  filter(codigo_producto %in%
c('8969402','8969410','3487287','3487386','3487089','3487188','5380555','5550736',
      '5558507','7988303','7988279','7988311','5752803','5752779','5801634')) %>%
mutate(periode="2019 04",.before = codigo_producto)
as.data.frame(HIDROCORTISONA042019)
sum(HIDROCORTISONA042019$qt_falta)
HIDROCORTISONA052019 <- PERIODO_2019_05 %>% group_by(codigo_producto) %>%
  summarize(qt_falta = sum(qt_falta)) %>%
  filter(codigo_producto %in%
c('8969402','8969410','3487287','3487386','3487089','3487188','5380555','5550736',
      '5558507','7988303','7988279','7988311','5752803','5752779','5801634')) %>%
mutate(periode="2019 05",.before = codigo_producto)
as.data.frame(HIDROCORTISONA052019)
sum(HIDROCORTISONA052019$qt_falta)
HIDROCORTISONA062019 <- PERIODO_2019_06 %>% group_by(codigo_producto) %>%
  summarize(qt_falta = sum(qt_falta)) %>%
  filter(codigo_producto %in%
c('8969402','8969410','3487287','3487386','3487089','3487188','5380555','5550736',
      '5558507','7988303','7988279','7988311','5752803','5752779','5801634')) %>%
mutate(periode="2019 06",.before = codigo_producto)
as.data.frame(HIDROCORTISONA062019)
sum(HIDROCORTISONA062019$qt_falta)
HIDROCORTISONA072019 <- PERIODO_2019_07 %>% group_by(codigo_producto) %>%
  summarize(qt_falta = sum(qt_falta)) %>%
  filter(codigo_producto %in%
c('8969402','8969410','3487287','3487386','3487089','3487188','5380555','5550736',

```

```

'5558507','7988303','7988279','7988311','5752803','5752779','5801634')) %>%
  mutate(periode="2019 07",.before = codigo_producto)
as.data.frame(HIDROCORTISONA072019)
sum(HIDROCORTISONA072019$qt_falta)
HIDROCORTISONA012019$codigo_producto <- as.factor(HIDROCORTISONA012019$codigo_producto)
HIDROCORTISONA022019$codigo_producto <- as.factor(HIDROCORTISONA022019$codigo_producto)
HIDROCORTISONA032019$codigo_producto <- as.factor(HIDROCORTISONA032019$codigo_producto)
HIDROCORTISONA042019$codigo_producto <- as.factor(HIDROCORTISONA042019$codigo_producto)
HIDROCORTISONA052019$codigo_producto <- as.factor(HIDROCORTISONA052019$codigo_producto)
HIDROCORTISONA062019$codigo_producto <- as.factor(HIDROCORTISONA062019$codigo_producto)
HIDROCORTISONA072019$codigo_producto <- as.factor(HIDROCORTISONA072019$codigo_producto)
HIDROCORTISONA <-
rbind(HIDROCORTISONA012019,HIDROCORTISONA022019,HIDROCORTISONA032019,HIDROCORTISO
NA042019,
      HIDROCORTISONA052019,HIDROCORTISONA062019,HIDROCORTISONA072019)
as.data.frame(HIDROCORTISONA)

H <- ggplot(HIDROCORTISONA, aes(fill=codigo_producto, y=qt_falta, x=periode)) +
  geom_bar(position="stack", stat="identity") +
  labs(x = "Period", y = "Unfulfilled Orders", fill = "Product Code",
       title = "Hidrocortisone",
       caption = "") +
  geom_vline(xintercept=3.4, linetype="dashed",color = "red", size=1) +
  geom_vline(xintercept=2.9, linetype="dashed",color = "red", size=1)
ggplotly(H)

```

#Graph 10 Histogram representation of unfulfilled orders for Tafixyl between August of 2020 and December of 2020

```

TAFIXYL082020 <- PERIODO_2020_08 %>% group_by(codigo_producto) %>%
  summarize(qt_falta = sum(qt_falta)) %>%
  filter(codigo_producto %in%
c('5639026','5639034','5647730','5647748','5647755','5647763','5695358',
  '5695366','5695374','5695408','5695416','5695424','5695432','5695440',
  '5734215','5734223','5734231','5734249','5734256','5734264','5734272',
  '5734306')) %>%
  mutate(periode="2020 08",.before = codigo_producto)
as.data.frame(TAFIXYL082020)
sum(TAFIXYL082020$qt_falta)
TAFIXYL092020 <- PERIODO_2020_09 %>% group_by(codigo_producto) %>%

```

```

summarize(qt_falta = sum(qt_falta)) %>%
filter(codigo_produto %in%
c('5639026','5639034','5647730','5647748','5647755','5647763','5695358',
    '5695366','5695374','5695408','5695416','5695424','5695432','5695440',
    '5734215','5734223','5734231','5734249','5734256','5734264','5734272',
    '5734306')) %>%

mutate(periodeo="2020 09",.before = codigo_produto)
as.data.frame(TAFIXYL092020)
sum(TAFIXYL092020$qt_falta)
TAFIXYL102020 <- PERIODO_2020_10 %>% group_by(codigo_produto) %>%
summarize(qt_falta = sum(qt_falta)) %>%
filter(codigo_produto %in%
c('5639026','5639034','5647730','5647748','5647755','5647763','5695358',
    '5695366','5695374','5695408','5695416','5695424','5695432','5695440',
    '5734215','5734223','5734231','5734249','5734256','5734264','5734272',
    '5734306')) %>%

mutate(periodeo="2020 10",.before = codigo_produto)

as.data.frame(TAFIXYL102020)
sum(TAFIXYL102020$qt_falta)
TAFIXYL112020 <- PERIODO_2020_11 %>% group_by(codigo_produto) %>%
summarize(qt_falta = sum(qt_falta)) %>%
filter(codigo_produto %in%
c('5639026','5639034','5647730','5647748','5647755','5647763','5695358',
    '5695366','5695374','5695408','5695416','5695424','5695432','5695440',
    '5734215','5734223','5734231','5734249','5734256','5734264','5734272',
    '5734306')) %>%

mutate(periodeo="2020 11",.before = codigo_produto)
as.data.frame(TAFIXYL112020)
sum(TAFIXYL112020$qt_falta)
TAFIXYL122020 <- PERIODO_2020_12 %>% group_by(codigo_produto) %>%
summarize(qt_falta = sum(qt_falta)) %>%
filter(codigo_produto %in%
c('5639026','5639034','5647730','5647748','5647755','5647763','5695358',
    '5695366','5695374','5695408','5695416','5695424','5695432','5695440',
    '5734215','5734223','5734231','5734249','5734256','5734264','5734272',
    '5734306')) %>%

mutate(periodeo="2020 12",.before = codigo_produto)
as.data.frame(TAFIXYL122020)
sum(TAFIXYL122020$qt_falta)

```

```

TAFIXYL082020$codigo_producto <- as.factor(TAFIXYL082020$codigo_producto)
TAFIXYL092020$codigo_producto <- as.factor(TAFIXYL092020$codigo_producto)
TAFIXYL102020$codigo_producto <- as.factor(TAFIXYL102020$codigo_producto)
TAFIXYL112020$codigo_producto <- as.factor(TAFIXYL112020$codigo_producto)
TAFIXYL122020$codigo_producto <- as.factor(TAFIXYL122020$codigo_producto)
TAFIXYL <- rbind(TAFIXYL082020,TAFIXYL092020,TAFIXYL102020,TAFIXYL112020,TAFIXYL122020)
as.data.frame(TAFIXYL)
T <- ggplot(TAFIXYL, aes(fill=codigo_producto, y=qt_falta, x=periodo)) +
  geom_bar(position="stack", stat="identity") +
  labs(x = "Period", y = "Unfulfilled Orders", fill = "Product Code",
       title = "Tafixyl",
       caption = "") +
  geom_vline(xintercept=2.6, linetype="dashed",color = "red", size=1)
ggplotly(T)

```

#Graph 11 Histogram representation of unfulfilled orders for Victan between April of 2020 and September of 2020

```

VICTAN042020 <- PERIODO_2020_04 %>% group_by(codigo_producto) %>%
  summarize(qt_falta = sum(qt_falta)) %>%
  filter(codigo_producto %in% c('4511796','4511895','9626028','9626036','5475090')) %>%
  mutate(periodo="2020 04",.before = codigo_producto)
as.data.frame(VICTAN042020)
sum(VICTAN042020$qt_falta)
VICTAN052020 <- PERIODO_2020_05 %>% group_by(codigo_producto) %>%
  summarize(qt_falta = sum(qt_falta)) %>%
  filter(codigo_producto %in% c('4511796','4511895','9626028','9626036','5475090')) %>%
  mutate(periodo="2020 05",.before = codigo_producto)
as.data.frame(VICTAN052020)
sum(VICTAN052020$qt_falta)
VICTAN062020 <- PERIODO_2020_06 %>% group_by(codigo_producto) %>%
  summarize(qt_falta = sum(qt_falta)) %>%
  filter(codigo_producto %in% c('4511796','4511895','9626028','9626036','5475090')) %>%
  mutate(periodo="2020 06",.before = codigo_producto)
as.data.frame(VICTAN062020)
sum(VICTAN062020$qt_falta)
VICTAN072020 <- PERIODO_2020_07 %>% group_by(codigo_producto) %>%
  summarize(qt_falta = sum(qt_falta)) %>%
  filter(codigo_producto %in% c('4511796','4511895','9626028','9626036','5475090')) %>%
  mutate(periodo="2020 07",.before = codigo_producto)

```

```

as.data.frame(VICTAN072020)
sum(VICTAN072020$qt_falta)
VICTAN082020 <- PERIODO_2020_08 %>% group_by(codigo_producto) %>%
  summarize(qt_falta = sum(qt_falta)) %>%
  filter(codigo_producto %in% c('4511796','4511895','9626028','9626036','5475090')) %>%
  mutate(periodeo="2020 08",.before = codigo_producto)
as.data.frame(VICTAN082020)
sum(VICTAN082020$qt_falta)
VICTAN092020 <- PERIODO_2020_09 %>% group_by(codigo_producto) %>%
  summarize(qt_falta = sum(qt_falta)) %>%
  filter(codigo_producto %in% c('4511796','4511895','9626028','9626036','5475090')) %>%
  mutate(periodeo="2020 09",.before = codigo_producto)
as.data.frame(VICTAN092020)
sum(VICTAN092020$qt_falta)
VICTAN042020$codigo_producto <- as.factor(VICTAN042020$codigo_producto)
VICTAN052020$codigo_producto <- as.factor(VICTAN052020$codigo_producto)
VICTAN062020$codigo_producto <- as.factor(VICTAN062020$codigo_producto)
VICTAN072020$codigo_producto <- as.factor(VICTAN072020$codigo_producto)
VICTAN082020$codigo_producto <- as.factor(VICTAN082020$codigo_producto)
VICTAN092020$codigo_producto <- as.factor(VICTAN092020$codigo_producto)
VICTAN <-
rbind(VICTAN042020,VICTAN052020,VICTAN062020,VICTAN072020,VICTAN082020,VICTAN092020)
as.data.frame(VICTAN)
V <- ggplot(VICTAN, aes(fill=codigo_producto, y=qt_falta, x=periodeo)) +
  geom_bar(position="stack", stat="identity") +
  labs(x = "Period", y = "Unfulfilled Orders", fill = "Product Code",
       title = "Victan",
       caption = "") +
  geom_vline(xintercept=4.3, linetype="dashed",color = "red", size=1)
ggplotly(V)

```