

COVID-19 in Saudi Arabia: Real Data and Simulation for Impact Prediction - A Case Study

Md Taufiq Nasseef^{1,*}, and Kottakkaran Sooppy Nisar^{1,2}

¹ Department of Mathematics, College of Science and Humanities in Al Kharj, Prince Sattam bin Abdulaziz University, Saudi Arabia

² Saveetha School of Engineering, SIMATS, Chennai, India

Received: 30 Dec. 2023, Revised: 25 Feb. 2024, Accepted: 28 Feb. 2024

Published online: 1 May 2024

Abstract: The start of the COVID-19 pandemic in early 2020 has caused trouble all over the world. This contagious disease is mostly spread by people, and it spreads much faster than other flu viruses that have been found before. Although vaccines have been discovered and are functional, it will still be the greatest challenge to conquer this disease. To effectively respond to this unprecedented crisis and save human lives from other infectious diseases in the future, it is crucial to better understand how the virus is transmitted from one host to another and how future zones of contagion can be anticipated. Several waves of infection have hit nations worldwide for almost the last four years, and governments have implemented necessary measures to tackle the spread of the virus. However, mathematical modeling has emerged as a powerful tool to inform decision-making, allowing for the prediction of COVID-19's effects. In this research article, we investigate the impact of COVID-19 in Saudi Arabia using the three most commonly used mathematical models: the classic SIR (Susceptible-Infected-Recovered) model, the extended SEIR (Susceptible-Exposed-Infected-Recovered) model, and the advanced fractional-order models using freely available real recorded data for research. By incorporating actual data from Saudi Arabia and utilizing three simulation techniques, we strive to provide valuable insights into the dynamics of the pandemic and aid in the formulation of effective strategies to control its spread in Saudi Arabia.

Keywords: coronavirus, Fractional-order model, SIR model, SEIR model, Mathematical modeling, epidemic dynamics, simulation, prediction.

1 Introduction

The global repercussions of the COVID-19 outbreak have been profound, prompting swift and decisive actions worldwide to alleviate its impact and safeguard public health. As of December 19, 2023, the confirmed global cases have reached a staggering 699,783,027, resulting in 6,957,647 deaths and 671,187,956 recoveries (source: <https://www.worldometers.info/coronavirus/>). These numbers continue to escalate exponentially with each passing day. Notably, Saudi Arabia has reported 841,469 confirmed cases, with 9,646 fatalities, until December 12, 2023; however, comprehensive data on recovered cases is currently unavailable. The urgency of the situation underscores the critical need for sustained global efforts to curb the spread and mitigate the consequences of this ongoing public health crisis.

In this ongoing battle against the coronavirus pandemic since early 2020, recent developments underscore the dynamic nature of the global health landscape, including Saudi Arabia [1–22]. Vaccination campaigns have made substantial strides, with booster shots playing a pivotal role in bolstering immunity [18]. However, the emergence of new variants necessitates the continuous adaptation of public health strategies. Some regions have witnessed fluctuations in case numbers, emphasizing the importance of sustained vigilance. Ongoing research endeavors focus on antiviral treatments and the development of new vaccines. Saudi Arabia, like many nations, has faced the challenges posed by this highly contagious virus [18]. To effectively respond to the pandemic and make informed decisions, policymakers and public health authorities require accurate and timely information regarding the spread and likely outcomes of the disease [4, 16].

* Corresponding author e-mail: m.nasseef@psau.edu.sa

Mathematical modeling has proven instrumental in providing such insights, enabling the prediction of the impact of COVID-19 based on real data and simulation techniques. By employing mathematical models, we can enhance our understanding of the transmission dynamics of COVID-19 [23–25]. The SIR model, a classic compartmental model in epidemiology, classifies individuals within a population into three distinct compartments: susceptible (S), infected (I), and recovered (R). The SIR model assumes that individuals transition directly from the susceptible state to the infected state and eventually recover, thereby acquiring immunity. By incorporating real data on the number of cases, hospitalizations, and recoveries in Saudi Arabia [1, 8, 10, 13, 26], we can calibrate the SIR model to the country's specific circumstances and estimate important epidemiological parameters. These parameters, including the basic reproduction number (R_0) and the effective reproduction number (R_t), provide valuable insights into the contagiousness of the virus and the impact of control measures. However, the SIR model does not account for the possibility of an exposed (E) state, where individuals become infectious after an incubation period. The extended SEIR model addresses this limitation by introducing an additional compartment, representing individuals in the exposed state before progressing to the infectious stage [8, 9, 14, 15, 18]. By incorporating real data from Saudi Arabia and extending the SIR model to the SEIR framework, we can capture more realistic disease dynamics, thereby improving predictions and informing public health interventions. Furthermore, the use of fractional-order models offers an alternative approach to understanding the spread of COVID-19 in Saudi Arabia [8, 9, 14, 15, 18]. Fractional-order calculus provides a mathematical framework to describe complex systems with memory and non-local dependencies. Fractional-order models can capture the long-lasting effects and non-exponential decay present in infectious diseases. By incorporating fractional-order dynamics into our models, we can account for variations in individual susceptibility, immune response, and infection/recovery times, thus enhancing the accuracy of our predictions and enabling a better understanding of COVID-19's impact [7, 27].

To achieve reliable predictions and provide actionable insights, the integration of real data and simulation techniques is crucial. By utilizing real-time epidemiological data from Saudi Arabia [28], including reported cases, testing rates, hospitalizations, and mortality rates, we can effectively calibrate and validate the mathematical models. Simulation-based approaches allow us to explore various scenarios and intervention strategies, assess their potential impact, and guide decision-makers in devising appropriate measures to manage the spread of the virus. The ability to simulate different scenarios provides a valuable tool to evaluate the effectiveness of various control measures under specific

conditions in Saudi Arabia, thus supporting evidence-based decision-making [4, 9, 24, 29].

In this research article, we present a comprehensive analysis of the impact of COVID-19 in Saudi Arabia. Our investigation begins with a global overview, examining the cumulative confirmed and death cases of COVID-19 based on recorded real data. Subsequently, we focus on nine neighboring countries of Saudi Arabia, alongside Saudi Arabia itself, to delve into the temporal dynamics of the Middle East region using recorded real data (Fig. 1 A). To gain a deeper understanding of the situation in Saudi Arabia, we employ three mathematical models, encompassing the classic SIR model, the extended SEIR model, and advanced fractional-order models. Through the integration of real data and simulation techniques, our objective is to enhance our comprehension of the COVID-19 pandemic in Saudi Arabia, predict its impact, and contribute valuable insights for the formulation of informed public health strategies. We aim to equip policymakers, healthcare professionals, and the general public with the necessary tools to effectively control the spread of the virus and mitigate its adverse effects on the population.

2 Methods:

2.1 Data Collection:

Epidemiological data for this study were primarily sourced from the COVID-19 data repository provided by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University. The data, accessible at <https://coronavirus.jhu.edu/region/>, was retrieved on 9 March 2023. This repository is widely recognized for its comprehensive and up-to-date information on confirmed cases, recoveries, and fatalities globally. Supplementary data were obtained from the World Health Organization (WHO) website, available at <https://covid19.who.int/data>, and accessed on 9 March 2023. The WHO provides a global perspective on COVID-19 statistics, contributing valuable insights to enhance the comprehensiveness of our dataset [28]. To supplement the epidemiological dataset, additional information was sourced from Our World in Data, accessible at <https://ourworldindata.org/>. This resource provides a broader context for the COVID-19 pandemic, including data on testing rates, vaccination efforts, and other relevant factors. The data retrieved from Our World in Data was also accessed on 9 March 2023.

Data included in the analysis were confined to the specified time frame, up to March 9, 2023, to ensure relevance and consistency across all datasets. This time frame aligns with the latest available information at the time of data retrieval. The data utilized in this study is publicly available and does not involve any personally identifiable information. As such, ethical approval was

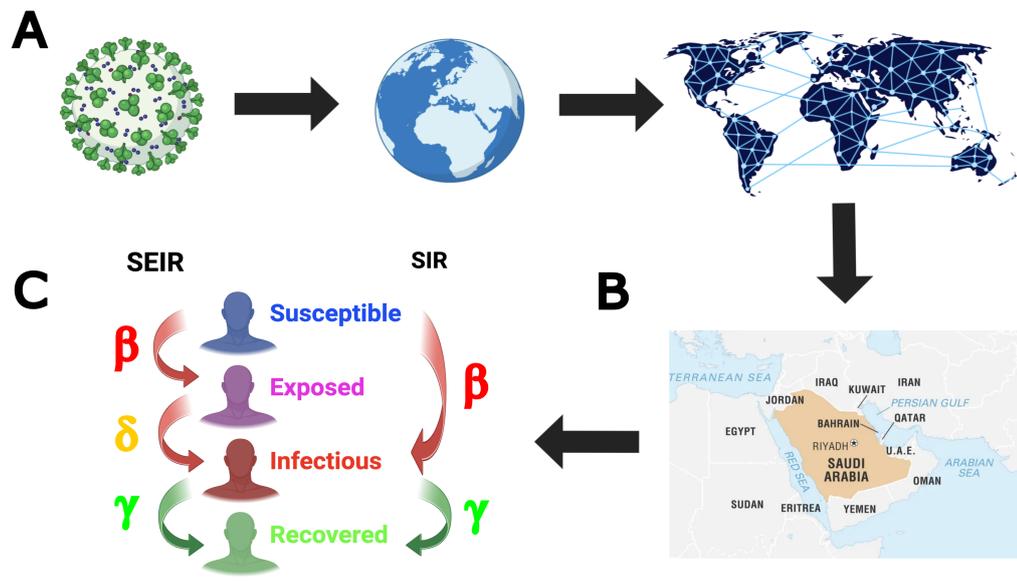


Fig. 1: Comprehensive Schematic Representation of Corona Virus, Primary Target and Mathematical Models. This figure provides a visual overview of the Corona virus life cycle, emphasizes our primary research focus on a specific country, and outlines the mathematical models employed for computational analysis. (A) Corona Virus Life Cycle: Illustration depicting the life cycle of the coronavirus, from its initial appearance to its global spread. (B) Primary Target Country for Research: Identification of the primary target country (Saudi Arabia & nine neighboring countries), crucial for data sources in our research. (C) Flow Chart of Mathematical Models: Representative flow chart outlining the computation analysis using SIR (Susceptible-Infectious-Recovered) (Right) and SEIR (Susceptible-Exposed-Infectious-Recovered) (Left) mathematical models. [β = Infection Rate; γ = Incubation Rate; δ = Recovery Rate]

not required for this research. This methodology section outlines the systematic collection of epidemiological data from reputable sources, ensuring the reliability and integrity of the dataset for subsequent analyses. Adjustments can be made based on specific details and methodologies employed in our research.

2.2 Mathematical Models:

2.2.1 Model 1: SIR model

The classic Susceptible Infectious Recovered (SIR) (Fig. 1 C(right)) model was employed to simulate the spread of COVID-19 in Saudi Arabia. The model consists of a system of ordinary differential equations (ODEs) representing the dynamics of the epidemic. The equations are formulated as follows:

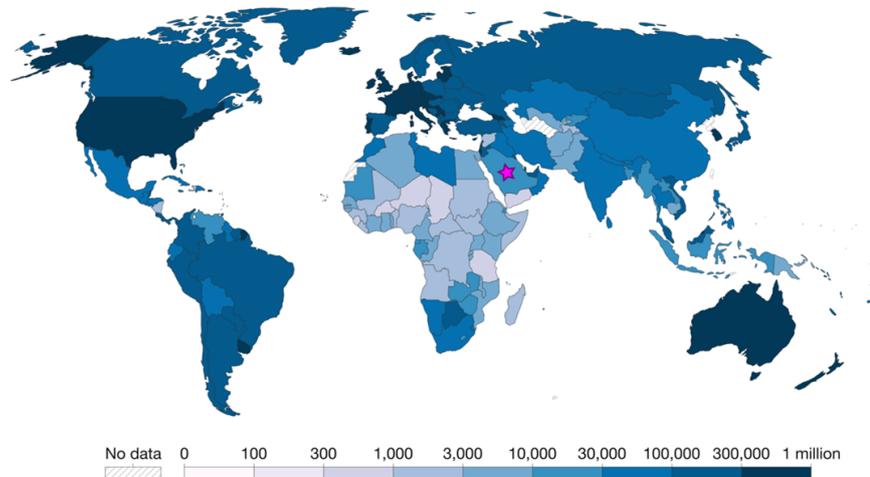
$$\begin{aligned} \frac{dS(t)}{dt} &= -\beta \frac{I(s)S(t)}{N} \\ \frac{dI(t)}{dt} &= \beta \frac{I(s)S(t)}{N} - \gamma I(t) \\ \frac{dR(t)}{dt} &= \gamma I(t) \end{aligned} \tag{1}$$

where S represent the susceptible population; I represent the infectious population; R represent the recovered population; β is the transmission rate; γ is the recovery rate; N is the total population of Saudi Arabia [1, 8, 26].

The model parameters (β and γ) were calibrated using optimization techniques to minimize the difference between the simulated data and the observed epidemiological data for Saudi Arabia. This step ensured that the SIR model accurately captured the dynamics of COVID-19 transmission in the region. The system of ODEs was numerically solved using appropriate numerical integration methods, such as the Runge-Kutta algorithm [8, 23, 26]. The solutions provided a time-dependent profile of susceptible, infectious, and recovered individuals throughout the simulation period [1, 8, 23, 26].

To assess the robustness of the SIR model, sensitivity analysis was conducted by varying key parameters within plausible ranges. This analysis gauged the impact of parameter fluctuations on the model outcomes and identified parameters with significant influence. The validity of the SIR model was evaluated by comparing the simulated results with the actual epidemiological data for Saudi Arabia. Quantitative metrics such as Mean Squared

A Cumulative confirmed cases



B Cumulative death cases

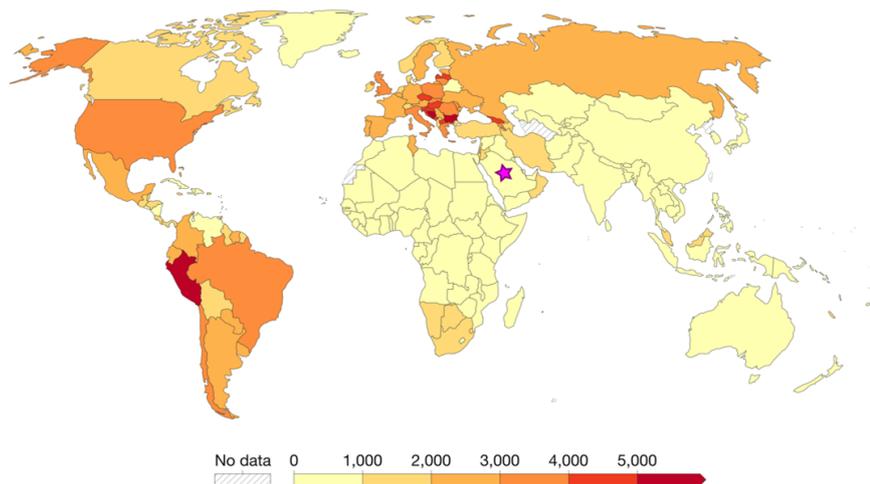


Fig. 2: Cumulative Global View of Coronavirus Infections Overlaying a World Map. (A) Confirmed Cases: Representation of the cumulative confirmed cases of the coronavirus overlaid on a world map. The blue-light blue areas indicate reported cumulative confirmed cases in different regions, with acknowledgment of the possibility that limited testing may result in an underestimation of the true number. (B) Death Cases: Representation of the cumulative confirmed deaths due to the coronavirus overlaid on a world map. The red-yellow areas denote reported cumulative death cases in various regions. It is important to note that due to diverse protocols and challenges in attributing the cause of death, the reported figures may not entirely capture the true impact of COVID-19. The color bar accompanying each panel provides a scale representing the number of individuals per million population. The pink star highlights the location of the target country, Saudi Arabia. [Data source: WHO COVID-19 Dashboard.]

Error (MSE) and Root Mean Squared Error (RMSE) were utilized to quantify the model's goodness-of-fit [1, 8, 23, 26].

The temporal validity of the SIR model was assessed by comparing short-term and long-term predictions against subsequent observed data, ensuring the model's

predictive accuracy over different time intervals. This comprehensive methodology outlines the steps taken in formulating, calibrating, and validating the SIR model for simulating the spread of COVID-19 in Saudi Arabia. Adjustments can be made based on specific details and methodologies employed in your research [23].

2.2.2 Model 2: SEIR Model

We employed the Susceptible Exposed Infectious Recovered (SEIR) (Fig. 1 C (left)) compartmental model to simulate the spread of COVID-19 in Saudi Arabia. The SEIR model extends the SIR model by introducing an exposed (E) compartment, representing individuals who have been exposed to the virus but are not yet infectious. The ordinary differential equations governing the model are given by:

$$\begin{aligned}\frac{dS(t)}{dt} &= -\beta \frac{I(s)S(t)}{N} \\ \frac{dE(t)}{dt} &= \beta \frac{I(s)S(t)}{N} - \sigma E \\ \frac{dI(t)}{dt} &= \sigma I(t) - \gamma I(t) \\ \frac{dR(t)}{dt} &= \gamma I(t)\end{aligned}\quad (2)$$

Where S represent the number of susceptible populations; E represent the exposed populations; I represent the infectious populations; R represent the recovered populations; β is the transmission rate; γ is the recovery rate; σ is the rate of progression from exposed to infectious and N is the total population of Saudi Arabia [14, 15, 18, 23].

Model parameters (β , σ , and γ) were estimated using maximum likelihood estimation based on the observed COVID-19 case data. Sensitivity analyses were conducted to assess the robustness of the model to variations in parameter values. The SEIR model was calibrated to the observed epidemiological data for Saudi Arabia by adjusting initial conditions and parameters to minimize the difference between model predictions and actual case counts. Validation of the SEIR model was performed using a separate time period or dataset not used in the calibration process. Model predictions were compared to observed data to evaluate the model's predictive accuracy [14, 15, 18, 23].

2.2.3 Model 3: Fractional SIR Model

A fractional-order differential equation (FDE) was employed to extend the classical SIR model to capture the dynamics of COVID-19 transmission. The fractional derivatives were incorporated to account for memory effects and long-range interactions in the epidemic system. The fractional SIR model is represented by the following equations:

$$\begin{aligned}\frac{d^\alpha S(t)}{dt^\alpha} &= -\beta \frac{I(s)S(t)}{N} \\ \frac{d^\alpha I(t)}{dt^\alpha} &= \beta \frac{I(s)S(t)}{N} - \gamma I(t) \\ \frac{d^\alpha R(t)}{dt^\alpha} &= \gamma I(t)\end{aligned}\quad (3)$$

Where $\frac{d^\alpha}{dt^\alpha}$ indicates the fractional derivative with order α ; $S(t)$, $I(t)$, and $R(t)$ represent the susceptible, infectious, and recovered populations, respectively; β is the transmission rate; γ is the recovery rate; N is the total population in Saudi Arabia [7, 27].

To find the optimal values for model parameters (α , β , γ), an optimization algorithm was employed. The parameter estimation process involved minimizing the difference between the simulated fractional model output and the actual epidemiological data for Saudi Arabia. The Grunwald-Letnikov discretization was applied to obtain the numerical solution of the fractional model. Simulations were conducted to project the dynamics of the epidemic over time. A sensitivity analysis was performed to assess the impact of variations in the fractional order (α) and other key parameters on the model outcomes. This analysis supported insights into the robustness and stability of the fractional SIR model (Fig. 5 C) [7, 27].

In the implementation of the SIR model, MATLAB was employed utilizing the "fitVirusCV19v3" tool developed by Joshua McGee (2023), accessible on MATLAB Central File Exchange (<https://www.mathworks.com/matlabcentral/fileexchange/74676-fitviruscv19v3-covid-19-sir-model>). This tool facilitated the modeling of the COVID-19 SIR (Susceptible-Infectious-Recovered) dynamics. For the SEIR model, we utilized the tool developed by Cheynet, E., titled "Generalized SEIR Epidemic Model (Fitting and Computation)," available on Zenodo (2020) with the doi:10.5281/ZENODO.3911854. This tool provided a comprehensive framework for fitting and computing the Generalized SEIR Epidemic Model. In the context of simulation models, custom scripts were crafted to facilitate the simulations. These scripts were developed in-house to meet the specific requirements of our research, ensuring flexibility and adaptability in the simulation process.

3 Results:

3.1 Current COVID-19 Situation in Saudi Arabia and Global Overview:

To project the trajectory and culmination of the coronavirus epidemic worldwide, spanning from January 2020 to March 2023, three distinct curve types were theoretically considered, such as the number of infected individuals, recovered individuals, and deaths attributable to the pandemic. Utilizing data sourced from the World Health Organization, the daily infection rate of real-world data emerged as a crucial factor, albeit challenging due to its inherent unreliability. This unreliability stems from the significant influence of fluctuating daily test numbers. It is well established that reported infection rates are notably lower than the actual global infection numbers,

underscoring the impact of varying testing capacities across regions. This complicated real-life situation is shown in Figure 2, which is made up of two-color maps that show the total number of confirmed coronavirus cases (top panel) and deaths linked to them (bottom panel) around the world from January 22, 2020, to March 9, 2023. The data comes from COVID-19 records kept by Johns Hopkins University. Notably, Saudi Arabia (marked with a pink star) exhibits a cumulative confirmed case range of 10,000 to 30,000 per million people, while the confirmed death cases remain comparatively low, ranging from 0 to 1000 per million. This emphasizes the nuanced nature of the pandemic's impact across different regions, necessitating a thorough examination of various contributing factors for a comprehensive understanding.

3.2 Temporal Analysis of COVID-19 in Saudi Arabia and Neighboring Regions:

Our subsequent investigation delves into the timeline dynamics of coronavirus cases, specifically focusing on both confirmed and death cases per week. With Saudi Arabia as our primary focal point, we have deliberately chosen nine neighboring countries—Jordan, Iraq, Kuwait, Qatar, United Arab Emirates, Oman, Yemen, Sudan, and Egypt—for a comprehensive analysis. This selection is based on the geographical proximity and established communication and transportation ties with Saudi Arabia. Figure 3 provides a visual representation of the cumulative temporal confirmed coronavirus cases (top panel) and associated death cases (bottom panel) across these ten Middle Eastern countries from January 22, 2020, to March 9, 2023, utilizing COVID-19 recorded data from Johns Hopkins University. Notably, Saudi Arabia, highlighted in solid red, consistently occupies a lower-middle position in both cumulative confirmed (top panel) and death (bottom panel) cases throughout the observed timeline. This comparative analysis sheds light on the relative standing of Saudi Arabia in the regional context, emphasizing the need for nuanced interpretation considering the multifaceted factors influencing the pandemic's trajectory.

3.3 SIR Model Application: Real Data Analysis, Prediction, and Simulation for COVID-19 in Saudi Arabia:

The simulation of the COVID-19 pandemic in Saudi Arabia using the SIR model has yielded highly informative results. By calibrating the model with real-world data (Fig. 4 panel B) obtained from the COVID-19 data repository maintained by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University until March 9, 2023, key epidemiological parameters were successfully estimated

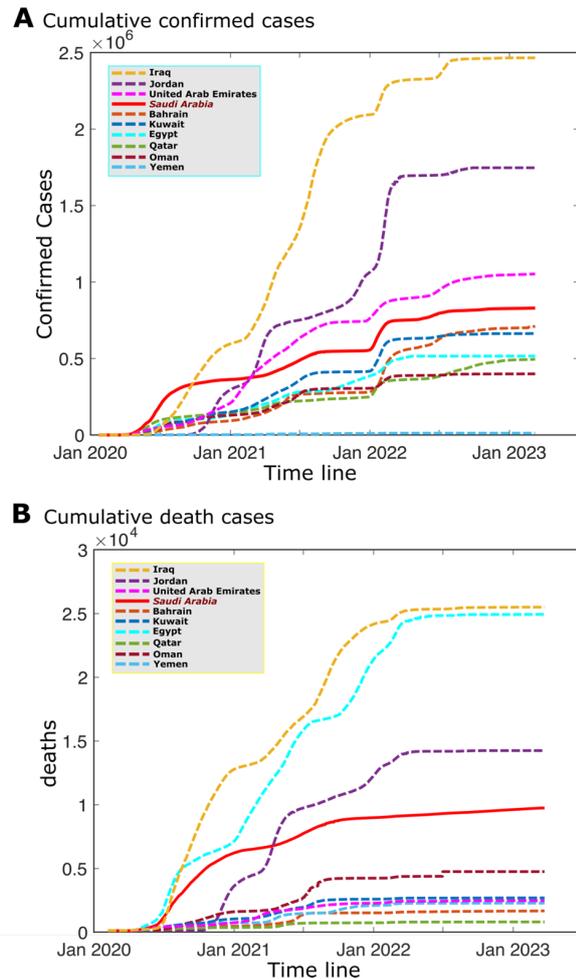


Fig. 3: Cumulative Timeline of Coronavirus Infections in Saudi Arabia and Neighboring Countries. (A) Confirmed Cases: Solid red line represents the reported cumulative confirmed cases in Saudi Arabia. Dashed lines in various colors depict the cumulative confirmed cases in nine neighboring countries of Saudi Arabia. Due to limited testing, the actual number of cases may exceed the reported figures. (B) Death Cases: Solid red line signifies the cumulative confirmed deaths in Saudi Arabia. Dashed lines in various colors show the cumulative confirmed deaths in nine neighboring countries. Owing to diverse protocols and challenges in attributing the cause of death, the reported death cases may not fully reflect the true impact of COVID-19. [Data source: WHO COVID-19 Dashboard.]

(Fig. 4 panels A and C). The transmission rate (β) and recovery rate (γ) was found to be 0.027 per day and 0.007 per day, respectively, resulting in a calculated basic reproduction number (R_0) of 3.81. This R_0 value suggests a high level of contagion, indicating that, on average, each

infected individual could potentially transmit the virus to three others. Additionally, other significant model parameters were considered, such as the initial size of the susceptible population (N) at 736,180, the total recovered population (C_{end}) at 718,399, the final number of susceptible individuals remaining (S_{end}) at 17,782, and the root mean squared error (RMSE) at 143,080. These findings provide a comprehensive understanding of the epidemiological dynamics of COVID-19 in Saudi Arabia, offering valuable insights for public health planning and intervention strategies.

Encouragingly, the model's performance was assessed by comparing its outputs with real-world data on confirmed cases, recovered individuals, and deaths. Remarkably, the simulated curves closely mirrored the observed trends, demonstrating the model's proficiency in capturing the nuanced dynamics of the pandemic. This alignment between simulated and actual data underscores the reliability of the SIR model in replicating and predicting the course of the COVID-19 outbreak in Saudi Arabia, further enhancing the utility of this modeling approach for informing public health decisions and preparedness measures.

3.4 Comparative Analysis of Coronavirus Simulation Models in Saudi Arabia:

The SIR model simulations for the spread of COVID-19 in Saudi Arabia yielded insightful results. The model, calibrated with real-world data from the COVID-19 data repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University until 9th March 2023, provided a detailed representation of the epidemic dynamics. The key epidemiological parameters estimated from the SIR model include the transmission rate (0.027), recovery rate (0.007), and basic reproduction number (3.81). These parameters are crucial for understanding the dynamics of virus transmission in the Saudi Arabian context (Fig. 5 panel A).

The SEIR model, incorporating an additional compartment for exposed individuals, was compared with the SIR model to assess its efficacy in capturing the intricacies of the COVID-19 spread (Fig. 5 panels A & B). Comparative analysis involved examining the fit of the model to real-world data and evaluating its ability to project future trends. Sensitivity analysis was conducted to explore the impact of variations in model parameters on the simulation outcomes. This analysis aimed to identify the parameters that significantly influence the model's predictions and assess the robustness of the SEIR model.

The fractional model, designed to account for non-integer order derivatives, was implemented to investigate whether fractional calculus improves the accuracy of COVID-19 predictions. Results from the fractional model were compared with those from the

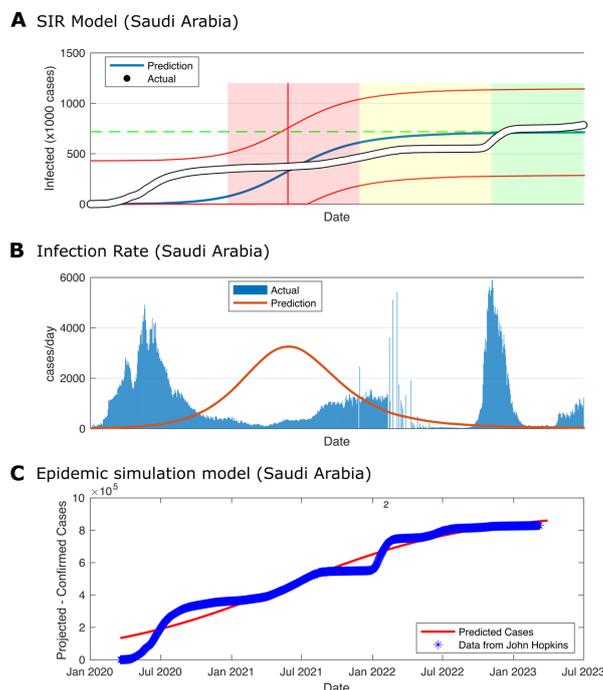


Fig. 4: Comprehensive Timeline Analysis and Model Comparison for Coronavirus Confirmed Cases in Saudi Arabia. (A) SIR model: Solid black curve represents the reported cumulative confirmed infected cases in Saudi Arabia. The blue curve represents the root mean of SIR prediction models. The red curve on top and bottom of root mean shows the square error. (B) Infection rate: the blue bars show the confirmed infected cases per day in Saudi Arabia. Solid red curve represents the prediction of confirmed infected cases per day in Saudi Arabia. (C) Epidemic simulation model: the blue star shows the cumulative confirmed infected cases per day in Saudi Arabia. Solid red curve represents the projection of cumulative confirmed infected cases per day in Saudi Arabia. [Data source: John Hopkins.]

traditional SIR and SEIR models (Fig. 5 panel A, B & C). A comparative evaluation of the fractional model against the classical models provided the most prospective insights into the potential advantages of fractional differential calculus in modeling complex epidemiological systems.

4 Discussion:

In this research paper, we conducted a comprehensive analysis of the COVID-19 pandemic, focusing on both global and regional perspectives with a special emphasis on Saudi Arabia. Utilizing theoretical considerations and real-world data, we projected the trajectory of the

epidemic globally and highlighted the challenges associated with daily infection rates. Our temporal analysis for Saudi Arabia and neighboring regions provided valuable insights into the relative standing of the country in the regional context. Subsequently, we applied the SIR model for real data analysis, prediction, and simulation specific to Saudi Arabia. The model, calibrated with data until March 9, 2023, successfully estimated key epidemiological parameters, indicating a high level of contagion. Encouragingly, the model's performance was validated by comparing its outputs with actual data, demonstrating its reliability in capturing the nuanced dynamics of the pandemic. Furthermore, we conducted a comparative analysis of coronavirus simulation models, exploring the efficacy of the SEIR model and a fractional model in improving prediction accuracy. This research contributes valuable insights for public health planning and intervention strategies in the ongoing battle against the COVID-19 pandemic.

Our research presents a comprehensive and nuanced analysis of the COVID-19 pandemic in Saudi Arabia and globally, employing a multi-faceted approach encompassing theoretical projections, temporal dynamics, and advanced epidemiological modeling. By considering three distinct curve types for infected, recovered, and deceased individuals, we address the complex real-world scenario, emphasizing the impact of varying testing capacities on reported infection rates. The temporal analysis of COVID-19 in Saudi Arabia and neighboring regions offers a unique perspective, highlighting the country's relative standing in the Middle East. The application of the SIR model for real data analysis, prediction, and simulation yields key epidemiological parameters and provides valuable insights for public health planning [8, 10, 26]. Notably, the model's exceptional performance is evidenced by its close alignment with real-world data, showcasing its reliability in capturing the pandemic's dynamics. Furthermore, our comparative analysis of simulation models, including SEIR and fractional models, contributes to the evolving understanding of COVID-19 transmission, with potential implications for enhanced predictive accuracy and public health decision-making [23].

While the SIR, SEIR, and fractional SIR models offer valuable tools for understanding the dynamics of COVID-19 transmission, each model comes with inherent limitations [23]. The SIR model, assuming constant parameters and homogeneity in the population, oversimplifies the complex and dynamic nature of real-world scenarios [8, 10, 26]. The SEIR model, while introducing an exposed compartment, may still struggle to capture variations in latent periods and fails to account for factors like age structure and mobility [8, 9, 14, 18]. Additionally, both SIR and SEIR models assume the same susceptibility and infectivity across the entire population, disregarding potential heterogeneity. The fractional SIR model, incorporating fractional calculus, aims to enhance the models' flexibility, yet its practical utility remains

underexplored, and the interpretation of fractional-order parameters poses challenges [7, 27].

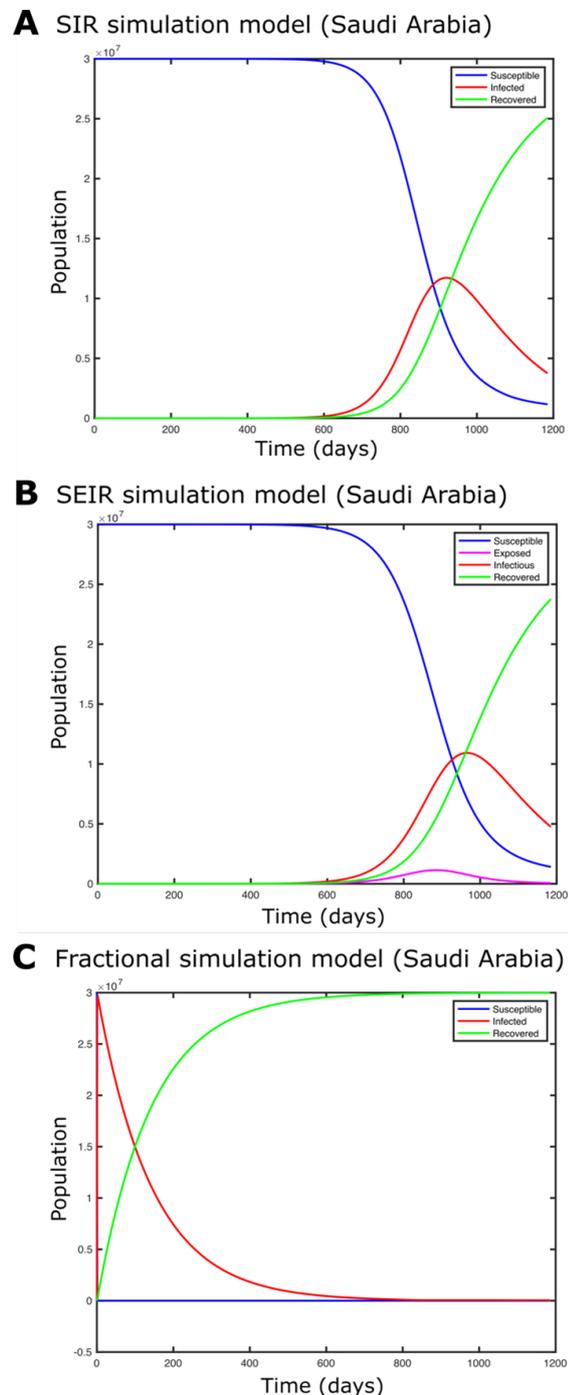


Fig. 5: Model Comparison for Coronavirus simulation in Saudi Arabia. (A) SIR simulation model. (B) SEIR simulation model. (C) Fractional simulation model: the blue, magenta, red and green curve illustrates Susceptible, Exposed, Infected and Recovered model respectively.

Furthermore, all models heavily rely on accurate and timely data, which, given the uncertainties and reporting variations associated with COVID-19, can impact the reliability of predictions. These limitations underscore the need for a cautious interpretation of model outputs and highlight the importance of integrating additional factors and refinements to enhance the models' applicability in the evolving landscape of the pandemic.

Building on the insights gained from our comprehensive analysis of the COVID-19 pandemic, both globally and in Saudi Arabia, several avenues for future research emerge. Firstly, considering the limitations of current models, there is a need to explore more sophisticated modeling approaches that account for population heterogeneity, age structure, and varying susceptibility. Incorporating real-time mobility data and dynamic parameters could enhance the accuracy of predictions [23–25]. Secondly, investigating the impact of public health interventions, vaccination campaigns, and socio-economic factors on the trajectory of the pandemic could provide valuable insights for effective policy formulation. Thirdly, advanced techniques, such as machine learning and decision support systems, can be applied to enhance the analytical capabilities of the study [20, 23, 30]. Furthermore, exploring the interplay between different virus variants and their potential influence on transmission dynamics and severity warrants attention. Lastly, delving into the psychological and social aspects of the pandemic, including the public's perception of risks, adherence to preventive measures, and the mental health implications, could contribute to a holistic understanding of the ongoing crisis. However, it can be explored whether repetitive attacks of this virus impact in gene [31, 32] or brain structure / function / connectivity [33–35]. By addressing these research gaps, future studies can provide more nuanced and actionable insights to guide public health strategies and preparedness measures in the face of evolving challenges.

5 Conclusion:

In conclusion, our comprehensive analysis of the COVID-19 pandemic has provided valuable insights into its global and regional dynamics, with a particular focus on Saudi Arabia. By employing theoretical considerations and real-world data, we projected the trajectory of the epidemic and emphasized the challenges associated with daily infection rates, acknowledging the nuances introduced by varying testing capacities. The application of the SIR model for real data analysis and simulation in Saudi Arabia yielded key epidemiological parameters, demonstrating a high level of contagion. The model's exceptional performance, validated against actual data, underscores its reliability in capturing the pandemic's nuanced dynamics. Additionally, our comparative analysis of simulation models, including the SEIR and fractional models, contributes to the evolving

understanding of COVID-19 transmission. However, it is crucial to recognize the inherent limitations of these models, emphasizing the need for caution in interpreting outputs. Looking forward, future research should explore more sophisticated modeling approaches, investigate the impact of interventions and socio-economic factors, and delve into the psychological and social aspects of the pandemic to guide informed public health strategies in the evolving landscape of the crisis.

Statements and Declaration:

Contribution of Authorship

Methodology, MTN; Software, MTN, KSN; Validation, MTN, KSN; Formal analysis, MTN; Investigation, MTN, KSN; Resources, MTN; Writing—original draft, MTN, KSN; Writing—review & editing, MTN, KSN. All authors have read and agreed to the published version of the manuscript.

Acknowledgments

The authors extend their appreciation to Prince Sattam bin Abdulaziz University for funding this research work through the project number (PSAU/2023/01/25700).

Data Availability Statement

All the data used in this paper are freely available for research on the website of the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU) (<https://coronavirus.jhu.edu/region/>, accessed on 9 March 2023), on the World Health Organization (WHO) website (<https://covid19.who.int/data>, accessed on 9 March 2023) and our world in data (<https://ourworldindata.org/>).

Conflicts of Interest

The authors declare no conflict of interest.

References

- [1] K. A. Abuhasel, M. Khadr and M. M. Alquraish, Analyzing and forecasting covid-19 pandemic in the kingdom of saudi arabia using arima and sir models, *Computational intelligence* **38**(3) (2022) 770–783.
- [2] Y. Alharbi, A. Alqahtani, O. Albalawi and M. Bakouri, Epidemiological modeling of covid-19 in saudi arabia: Spread projection, awareness, and impact of treatment, *Applied Sciences* **10**(17) (2020) p. 5895.

- [3] N. Alotaibi, Statistical and deterministic analysis of covid-19 spread in saudi arabia, *Results in Physics* **28** (2021) p. 104578.
- [4] H. Alrasheed, A. Althnian, H. Kurdi, H. Al-Mgren and S. Alharbi, Covid-19 spread in saudi arabia: modeling, simulation and analysis, *International Journal of Environmental Research and Public Health* **17**(21) (2020) p. 7744.
- [5] F. S. Alshammari *et al.*, A mathematical model to investigate the transmission of covid-19 in the kingdom of saudi arabia, *Computational and Mathematical Methods in Medicine* **2020** (2020).
- [6] M. Bachar, M. A. Khamsi and M. Bounkhel, A mathematical model for the spread of covid-19 and control mechanisms in saudi arabia, *Advances in Difference Equations* **2021**(1) (2021) p. 253.
- [7] Y.-M. Chu, A. Ali, M. A. Khan, S. Islam and S. Ullah, Dynamics of fractional order covid-19 model with a case study of saudi arabia, *Results in Physics* **21** (2021) p. 103787.
- [8] C. A. D. Durai, A. Begum, J. Jebaseeli and A. Sabahath, Covid-19 pandemic, predictions and control in saudi arabia using sir-f and age-structured seir model, *The Journal of supercomputing* **78**(5) (2022) 7341–7353.
- [9] S. Khan, Visual data analysis and simulation prediction for covid-19 in saudi arabia using seir prediction model., *International Journal of Online & Biomedical Engineering* **17**(8) (2021).
- [10] H. Khoj and A. F. Mujallad, Epidemic situation and forecasting if covid-19 in saudi arabia using sir model, *medRxiv* (2020) 2020–05.
- [11] M. M. Mansour, M. A. Farsi, S. M. Mohamed and E. M. Abd Elrazik, Modeling the covid-19 pandemic dynamics in egypt and saudi arabia, *Mathematics* **9**(8) (2021) p. 827.
- [12] I. A. Mohamed, A. B. Aissa, L. F. Hussein, A. I. Taloba and T. Kallel, Withdrawn: A new model for epidemic prediction: Covid-19 in kingdom saudi arabia case study, *Materials Today. Proceedings* (2021).
- [13] A. F. Mujallad and H. Khoj, Epidemic situation and forecasting of covid-19 in saudi arabia using the sir model, *medRxiv* (2020).
- [14] H. M. Youssef, N. A. Alghamdi, M. A. Ezzat, A. A. El-Bary and A. M. Shawky, A modified seir model applied to the data of covid-19 spread in saudi arabia, *AIP advances* **10**(12) (2020).
- [15] H. M. Youssef, N. A. Alghamdi, M. A. Ezzat, A. A. El-Bary and A. M. Shawky, A new dynamical modeling seir with global analysis applied to the real data of spreading covid-19 in saudi arabia, *Math. Biosci. Eng* **17**(6) (2020) 7018–7044.
- [16] R. Zreiq, S. Kamel, S. Boubaker, A. A. Al-Shammari, F. D. Algahtani and F. Alshammari, Generalized richards model for predicting covid-19 dynamics in saudi arabia based on particle swarm optimization algorithm, *AIMS Public Health* **7**(4) (2020) p. 828.
- [17] Q. Li, X. Guan, P. Wu, X. Wang, L. Zhou, Y. Tong, R. Ren, K. S. Leung, E. H. Lau, J. Y. Wong *et al.*, Early transmission dynamics in wuhan, china, of novel coronavirus–infected pneumonia, *New England journal of medicine* **382**(13) (2020) 1199–1207.
- [18] R. Ghostine, M. Gharamti, S. Hassrouny and I. Hoteit, An extended seir model with vaccination for forecasting the covid-19 pandemic in saudi arabia using an ensemble kalman filter, *Mathematics* **9**(6) (2021) p. 636.
- [19] O. A. Omar, Y. Alnafisah, R. A. Elbarkouky and H. M. Ahmed, Covid-19 deterministic and stochastic modelling with optimized daily vaccinations in saudi arabia, *Results in Physics* **28** (2021) p. 104629.
- [20] S. N. Shimul, A. Alradie-Mohamed, R. Kabir, A. Al-Mohaimed and I. Mahmud, Effect of easing lockdown and restriction measures on covid-19 epidemic projection: A case study of saudi arabia, *PLoS One* **16**(9) (2021) p. e0256958.
- [21] H. Youssef, N. Alghamdi, M. A. Ezzat, A. A. El-Bary and A. M. Shawky, Study on the seiqr model and applying the epidemiological rates of covid-19 epidemic spread in saudi arabia, *Infectious Disease Modelling* **6** (2021) 678–692.
- [22] H. M. Youssef, N. Alghamdi, M. A. Ezzat, A. A. El-Bary and A. M. Shawky, A proposed modified seiqr epidemic model to analyze the covid-19 spreading in saudi arabia, *Alexandria Engineering Journal* **61**(3) (2022) 2456–2470.
- [23] A. AlArjani, M. T. Nasseef, S. M. Kamal, B. S. Rao, M. Mahmud and M. S. Uddin, Application of mathematical modeling in prediction of covid-19 transmission dynamics, *Arabian Journal for Science and Engineering* **47**(8) (2022) 10163–10186.
- [24] B. Ivorra, M. R. Ferrández, M. Vela-Pérez and A. M. Ramos, Mathematical modeling of the spread of the coronavirus disease 2019 (covid-19) taking into account the undetected infections. the case of china, *Communications in nonlinear science and numerical simulation* **88** (2020) p. 105303.
- [25] F. Ndairou, I. Area, J. J. Nieto and D. F. Torres, Mathematical modeling of covid-19 transmission dynamics with a case study of wuhan, *Chaos, Solitons & Fractals* **135** (2020) p. 109846.
- [26] I. Cooper, A. Mondal and C. G. Antonopoulos, A sir model assumption for the spread of covid-19 in different communities (2020).
- [27] K. Furati, I. Sarumi and A. Khaliq, Fractional model for the spread of covid-19 subject to government intervention and public perception, *Applied mathematical modelling* **95** (2021) 89–105.
- [28] Organization wh. middle east respiratory syndrome coronavirus (mers-cov) (2016).
- [29] A. B. Hassanat, S. Mnasri, M. A. Aseeri, K. Alhazmi, O. Cheikhrouhou, G. Altarawneh, M. Alrashidi, A. S. Tarawneh, K. S. Almohammadi and H. Almoamari, A simulation model for forecasting covid-19 pandemic spread: Analytical results based on the current saudi covid-19 data, *Sustainability* **13**(9) (2021) p. 4888.
- [30] M. S. Kaiser, K. T. Lwin, M. Mahmud, D. Hajjalizadeh, T. Chaipimonplin, A. Sarhan and M. A. Hossain, Advances in crowd analysis for urban applications through urban event detection, *IEEE Transactions on Intelligent Transportation Systems* **19**(10) (2017) 3092–3112.
- [31] P. Charbogne, O. Gardon, E. Martín-García, H. L. Keyworth, A. Matsui, A. E. Mechling, T. Bienert, T. Nasseef, A. Robé, L. Moquin *et al.*, Mu opioid receptors in gamma-aminobutyric acidergic forebrain neurons moderate motivation for heroin and palatable food, *Biological psychiatry* **81**(9) (2017) 778–788.
- [32] A. T. Ehrlich, G. Maroteaux, A. Robe, L. Venteo, M. T. Nasseef, L. C. van Kempen, N. Mechawar, G. Turecki,

- E. Darcq and B. L. Kieffer, Expression map of 78 brain-expressed mouse orphan gpcrs provides a translational resource for neuropsychiatric research, *Communications Biology* **1**(1) (2018) p. 102.
- [33] M. T. Nasseef, G. A. Devenyi, A. E. Mechling, L.-A. Harsan, M. M. Chakravarty, B. L. Kieffer and E. Darcq, Deformation-based morphometry mri reveals brain structural modifications in living mu opioid receptor knockout mice, *Frontiers in psychiatry* **9** (2018) p. 411712.
- [34] M. T. Nasseef, J. P. Singh, A. T. Ehrlich, M. McNicholas, D. W. Park, W. Ma, P. Kulkarni, B. L. Kieffer and E. Darcq, Oxycodone-mediated activation of the mu opioid receptor reduces whole brain functional connectivity in mice, *ACS Pharmacology & Translational Science* **2**(4) (2019) 264–274.
- [35] M. T. Nasseef, W. Ma, J. P. Singh, N. Dozono, K. Lançon, P. Séguéla, E. Darcq, H. Ueda and B. L. Kieffer, Chronic generalized pain disrupts whole brain functional connectivity in mice, *Brain imaging and behavior* (2021) 1–11.
-