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Is The Logistic Growth Model The Best-Suited Mathematical Model To Use In Epidemics? A Literature Review

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Abstract:
Mathematical and statistical models are used to model pandemics, providing information about disease dissemination and aiding in policy planning. Logistic growth models are best for predicting pandemic trajectory and infection size, with a peak time arising from control efforts.
This study utilized secondary sources to gather and analyze data. Mathematical models have been applied in various fields, including psychology, economics, education, and humanities, to control the spread of epidemics and predict their consequences. The COVID-19 pandemic has led to the use of logistic growth models for predicting outcomes and proposing preventative and control measures.
The accuracy of models is crucial for government interventions, long-term decisions, and future planning. The study suggests that the logistic growth model, also known as the Verhulst-Pearl equation, can effectively model pandemics, accurately reflecting cases and deaths, enabling the development of interventions and health systems for improved clinical management of infected individuals.
Key Words: *Logistic Model, Mathematical Models, Pandemic, Epidemiology*

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I. Introduction

Various mathematical and statistical models have attempted to model pandemics with varying accuracy and reliability (Roda et al., 2020). Statistical and mathematical modeling of the supplied data might provide significant information about the disease's dissemination and thus aid in planning various actions to control the spread of the epidemic (Sen & Sen, 2021).

Models have been employed by mathematical epidemiologists to address a wide series of policy concerns, and their usage has been widespread throughout pandemics (Adiga et al., 2020). The techniques that can be used to model and estimate epidemic cases include the Susceptible, Infection and Recover (SIR) model, the Susceptible, Exposed, Infection and Recover (SEIR) model, the Susceptible, Infected, Recovered, Dead (SIRD) model. Additionally, because the epidemic's growth is exponential, agents-based models and curve-fitting approaches are used alongside logistic growth models (Mackolil & Mahanthesh, 2020; Sen & Sen, 2021; Bhatnagar et al., 2020). Furthermore, the Auto-Regressive Integrating Moving Average (ARIMA) model was also used to predict the total number of vaccinated persons which is a novel approach in vaccine research (Cihan, 2021).

According to Kartono et al. (2021), a logistic growth model is best used for predicting a pandemic’s trajectory since it gives a better prediction for a shorter period with greater accuracy. In addition, the logistic growth model can be used to calculate the infection's ultimate size and peak time (Pell et al., 2018). This population biology-based model proposes a first exponential development phase that peaks when more situations arise from continued efforts at control and newly learned human behaviors (Aviv-Sharon & Aharoni, 2020).

The Concept Of Mathematical Modeling

According to Schank and Twardy (2009), the language of models was first used by late-nineteenth-century physicists. Although mathematical modeling did not become a significant research approach until the twentieth century's second decade, its roots can be traced back to the mid-nineteenth century. Models express our beliefs about how the world works (Lawson & Marion, 2008).

A model can be defined as a representation of actual circumstances utilizing symbols to solve complicated problems (D’Ambrosio, 2009; Dundar et al., 2012). Dundar et al. (2012) noted that there is a difference between the terms 'model' and 'modeling'. A model is regarded as the product that is formed as a result of modeling, while modeling is related to the procedure. A mathematical model is a mathematical framework that describes known phenomena or predicts future events by expressing variables and their relationships (Eykhoff, 1974 as cited in Porgo et al., 2019). In addition, mathematical modeling is defined as a combination of methodologies, instruments, and formulas that are adaptable to specific fields and answer research questions (Chubb & Jacobsen, 2009; Porgo et al., 2019).

According to Dundar et al. (2012), the process of mathematical modeling entails uncovering relationships, executing mathematical analyses, obtaining results, and interpreting the model. Additionally, Rodgers (2010) asserted that mathematical modeling provides a natural framework for researchers to conceptualize, think about, and carry out studies. Moreover, D'Ambrosio (2009) noted that the application of mathematical models of reality is dependent on knowledge of facts and phenomena, as well as the observable behaviour of real objects and systems, which are normally expressed by laws, which are mostly derived empirically.

According to Shmueli (2010), modeling is an effective technique for generating and testing hypotheses, as these models rely on data rather than subjecting them to observation (Hutson & Correll, 2018). Since models are only approximations of actual behavior, they can help reformulate hypotheses and even formulate new ones, laying the groundwork for new theories that are better suited to dealing with research questions (D'Ambrosio, 2009). Furthermore, many models have been developed to make predictions based on some kind of optimal fit parameter (Dawes, 2001).

Porgo et al. (2019) have claimed that mathematical models and statistical models have similar applications. Statistical modeling is becoming more common in modern mathematical modeling investigations. Additionally, statistical models are considered a type of mathematical model that is frequently used to link model output to data utilizing a statistical paradigm in complicated mathematical modeling research (Porgo et al., 2019).

The Logistic Model

In the case of epidemics, the logistic differential equation applied to COVID-19 is as follows:

$$\boldsymbol{\frac{dC}{dt} = rC(1 - \frac{C}{K})}$$

where C is the total number of cases,

$r > 0$, denotes the infection rate or the slope of the curve C.

t is the time

$K > 0$, is the final epidemic size, the maximum value of the curve

According to the logistic model, as C approaches the epidemic's final size, the relative growth rate $\frac{dC}{dt}$ declines.

The Logistic differential equation can be solved by:

$$\frac{dC}{dt} = rC\left(1 - \frac{C}{K}\right)$$

Separating the variables

$$\frac{dC}{dt} \cdot dt = rC\left(1 - \frac{C}{K}\right) \cdot dt$$

$$dC = rC\left(1 - \frac{C}{K}\right) dt$$

$$\frac{1}{C(1 - \frac{C}{K})} dC = r\,dt$$

$$\frac{1}{C(K - \frac{C}{K})} dC = r\,dt$$

$$C\left(\frac{K}{K} - C\right) dC = rdt$$

Using partial fractions and then taking the integral of both sides

$$\int C\left(\frac{K}{K} - C\right) dC = \int r\,dt$$

$$\int \frac{1}{C} dC + \int \frac{1}{K - C}\, dC = \int r\,dt$$

$$\ln|C| - \ln|K - C| = rt + A_1$$

$$\ln\left|\frac{C}{(K - C)}\right| = rt + A_1$$

Taking the exponent of both sides

$$\frac{C}{K-C} = e^{rt} \cdot e^{(A)}$$

$$\frac{C}{K-C} = Ae^{rt}$$

Taking the reciprocal of both sides

$$\frac{K-C}{C} = \frac{1}{Ae^{rt}}$$

$$\frac{K-C}{C} = Ae^{-rt}$$

Multiplying both sides by C

$$K - C = AC\, e^{-rt}$$

$$K = C + AC\, e^{-rt}$$

Factoring C on RHS

$$K = (1 + Ae^{-rt})C$$

$$\boldsymbol{C = \frac{K}{1 + Ae^{-rt}}}$$

$$\boldsymbol{Using\ the\ initial\ condition\ C(0) > 0, it\ is\ obtained\ that}\ A = \frac{K - C_0}{C_0}$$

Characteristics Of The Logistic Growth Model

The following can be considered when studying the logistic growth model:

- *When the infectious phase first begins, the curve C behaves like a natural growth (exponential)* $C \approx C_0e^{kt}$
- *The number of cases tends to follow the Weibull function when t is large:*
  $C = L(1 - e^{-k(t-t_0)})$.
- *When the derivative of the growth rate* $\frac{dC}{dt}$ *equals 0, it reaches its maximum value., that is,* $\frac{d^2C}{dt^2} = 0$
- *From the previous condition, the growth rate (peak) is at its highest when* $t_p = \frac{ln(A)}{r}$ *where the number of cases equals to* $C_p = \frac{L}{2}$ *and a growth rate* $\left(\frac{dC}{dt}\right)_p = \frac{kL}{4}$
- *The calculation of the rate of infection's doubling time is as follows:*
  Doubling time $= \frac{ln2}{k} - \frac{1}{k} ln\left(\frac{1}{A} - e^{-kt}\right) - t$
- *Moreover, the epidemic's peak marks a shift in the number of cases of infection that have been reported cumulatively through time.*
- *When* $r > 0$, *the outcome of the growth curves will take on a sigmoid shape, exhibiting asymptotic behavior. The population will always remain constant at the original value* $C(0)$*in the scenario when* $r = 0$ *because there is no intrinsic growth rate. However, the mostly used particular case is* $r > 0$, *which is assumed in this study.*

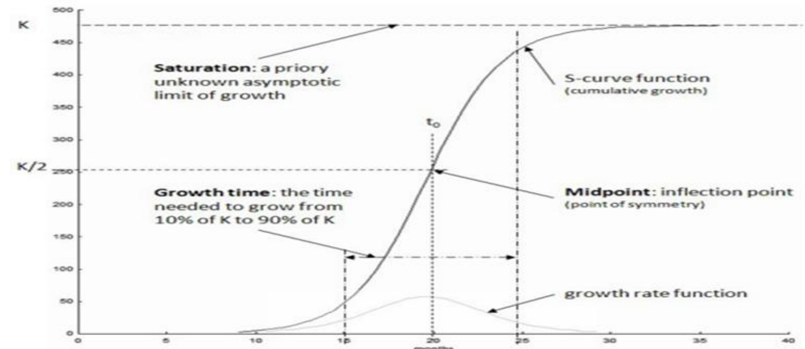

Figure 1-an illustration of a basic logistic S-curve with three parameters: midpoint, growth time, and saturation.

Assumptions of the model

The following are assumptions when using the Logistic Growth Equation.

- *Every individual at every density is comparable, so every new person slows the real rate of increase by the same percentage.*
- *The rate of growth and carrying capacity are fixed constants.*

In a pandemic scenario, herd immunity—which states that an individual can only get sick once before becoming immune—is assumed. Additionally, it is anticipated that there will be no births, deaths, or migrations. Furthermore, it is expected that the virus reproduction rate will not change in response to virus modifications or preventive actions. (Balak et al., 2021).

Understanding the Logistic Model

The logistic function was pioneered by Belgian mathematician Pierre-François Verhulst. This function has become one of the most important tools, with applications in domains as diverse as statistics, economics, and epidemiology (Cramer, 2004). Shen (2020) indicated that the logistic function has been used to represent population increase in an area, studying the growth rate of bacteria, and has even been employed in economics and finance decision-making processes.

Population growth was first modeled by the Malthusian or exponential model. According to this model, population growth is proportionate to population size (Stewart, 2012). The differential equation that follows can be used to illustrate the exponential model.

$$\boldsymbol{y(t) = Y_0 e^{rt}} \qquad (1)$$

where r is the proportional growth rate parameter, Y_0 is the initial population size, and $y(t)$ is the population time at the time, t.

Because population increase is unlimited, the exponential model is rarely applied to population expansion. By developing the logistic growth model, which takes population increase into account until a maximum capacity is achieved, Verhulst thereby enhanced the exponential model (Stewart, 2012). Therefore, according to Pelinovsky et al. (2020), the most basic model available for explaining population expansion is the logistic growth model.

The logistic growth model modified with variation in parameters applied in various areas of study is a type of phenomenological model. Bürger et al. (2019) established that phenomenological models are effective for describing the trajectory of epidemics. This is because they provide an easy mathematical form that can be solved in many circumstances, as defined by ordinary differential equations (ODEs).

The Logistic differential equation is

$$\boldsymbol{\frac{dP}{dt} = rP(1 - \frac{P}{K})} \qquad (2)$$

Where, $\frac{dP}{dt}$, is the first derivative which denotes the instantaneous rate of change of the population as a function of time, where K stands for carrying capacity, P for population size, and r for growth rate.

The following questions will be investigated in this study:

1. In what areas of study are mathematical models applied?
2. How can the Logistic Model be applied to Epidemiology?
3. Which other Mathematical models are used in the study of epidemics?
4. How accurate are the models that are used in the study of epidemics?

II. Material And Methods

Making decisions requires gathering and analyzing data (Ajayi, 2017). Secondary sources were used in this investigation. Secondary sources provide perspectives from other scholars who either deduce or explain specifics from sources. Secondary sources are used by skilled researchers (Streefkerk, 2022). Carrying out comprehensive evaluations to offer a synopsis of findings from qualitative and quantitative research (Krull and Duart, 2017). To review papers, the researcher used a five-stage process which included: selecting terms to pursue, opening the exploration, refining it, gathering data, and assessing the data (Febriani and Churiyah, 2022).

81 results were found after a thorough search utilizing inclusion and exclusion criteria. From these results, the publication date was noted as well as the title and author and the data from the abstract and methodology retrieved. The data analysis involved identifying trends and gaps using a systematic methodology, ensuring the research articles address the study's challenges and inquiries (Snyder, 2019, as cited in Aisyah and Afrizal, 2022).

The research population in a study includes secondary sources like expert academic writings and journals (Asiamah, 2017). These sources are retrieved from databases like Google Scholar, SAGE, ProQuest, Taylor & Francis, and other search engines. The articles represent recent empirical findings or systematic reviews of past studies, written by objective writers.

Researchers need to develop inclusion and exclusion criteria based on the study questions, which should also form the basis for the search terms, according to Xiao and Watson (2019). Following the initial search, 129 articles were discovered. A more targeted search that used the inclusion-exclusion criteria produced 99 articles.

Using the abstracts from the publications, a secondary review was carried out, and 81 papers were selected for gathering and analyzing data. Data was taken from the 81 papers and organized into subheadings by the researchers. The researchers documented the methodology, principal findings, and conclusions of each investigation. After that, information was gathered and examined to address the research questions. The investigation's goals led to the establishment of the following criteria for the enhanced search.

Table 3.1 outlines the criteria for a narrower search.

Criterion	Inclusion Criteria	Exclusion Criteria
Research Population	The study topic serves as the foundation for all scholarly academic works.	Articles that are not scholarly or are opinion-based.
Language	English.	Other languages.
Level of Education	both postgraduate and graduate	Undergraduate.
Research Design	Combining qualitative and quantitative methods.	Unclear research techniques.
Availability	Complete publications regarding the research topic are accessible.	Articles with incomplete accessibility.

The study sample, consisting of a subset of the general population, is used to draw population-level inferences after reviewing abstracts, titles, and inclusion-exclusion standards (Mujere, 2016). This desktop research used secondary data from peer-reviewed journals, university studies, educational reports, and books. The selection process considered publication date, author credentials, reliability, depth of discussion, and data significance. While these methods offer benefits like efficacy, quick analysis, cost-effectiveness, and convenience (McLaughlan, 2022).

This research used scientific literature and peer-reviewed journal papers to verify its validity. Over 90% of the articles were peer-reviewed, ensuring the validity of the conclusions. The review process ensured the work was supported by facts. The study also analyzed the journal's indexing, listing in leading databases, and its impact factor. The articles were thoroughly examined for objectivity and lack of bias, ensuring they were not biased. The authors' credentials and educational history were verified, and the research was verified through cross-references and additional reliable sources. Only articles with a reference page and acknowledged citations were used.
The study confirmed the accuracy and dependability of the data by examining publications and reliable sources. The reliability of the instrument was evaluated by assessing the writer's qualifications, subject knowledge, accuracy, references, biases, and relevance to the research. Factors like sample size, response rate, questionnaire design, and data processing techniques also impacted the data's dependability.

III. Results And Discussion

In what areas of study are mathematical models applied?

Mathematical models have been applied in many areas of study. These models have been employed to address problems daily in the areas of psychology, physical, biological, and social sciences, economics, education, and humanities (Rodgers, 2010; Tinsley & Brown, 2000; Shmueli, 2010). Additionally, mathematical modeling has been used by several researchers in the field of epidemiology. These models can be used to decipher patterns of infectious diseases and design policies to contain them (Singh & Singh, 2020). Mathematical methods have been used to explore the transmission of contagious diseases dating back to at least Daniel Bernoulli's investigation on smallpox in 1760 (Boyce et al., 2020).

Many studies have revealed that mathematical models have been successfully adopted to control the spread of epidemics and predict their consequences (Siettos & Russo, 2013; Pelinovsky et al., 2020). Siettos and Russo (2013) emphasized that mathematical modeling plays a critical role in forecasting, analyzing, and controlling future outbreaks of transmittable diseases. Additionally, Chowell et al. (2016) acknowledged the use of mathematical models in developing potential strategies by studying and comprehending the patterns of infectious disease transmission. Furthermore, mathematical modeling has the potential to improve the scientific method and function as a medium for informing policymakers of findings (Chubb & Jacobsen, 2009).

In what way are Mathematical models classified?

Mathematical models can be categorized as either deterministic or stochastic (Vytla et al., 2021). Deterministic models are models that disregard random variation fluctuation and, as a result, always anticipate the same result from the same initial point (Lawson & Marion, 2008). The stochastic model, on the other hand, is more statistical with probability distributions describing the parameters, variables, and changes in variables (Porgo et al., 2019; Lawson & Marion, 2008).

Under the umbrella of mathematical models, commonly used statistical models include methods for time series analysis, regression analysis, autoregressive modeling, Hidden-Markov modeling, and spatial modeling.

Agent-based simulations, SIR models, stochastic models, and Markov chain models are examples of mathematical or mechanistic models. In addition, models based on empirical or machine learning include web-based data mining and surveillance networks (Vytla et al., 2021; Siettos & Russo, 2013). Furthermore, other statistical models that represent population growth in the field of epidemiology include the Exponential model, the Richard growth model, the logistic growth model, and the generalized growth model (Gnanvi et al., 2021).

How can the Logistic Model be applied to Epidemiology?

When studying epidemics, the logistic growth model is a helpful resource (Mackolil & Mahanthesh, 2020). This model is employed when the total infected population is considered, as well as being able to capture an outbreak's temporal variations, such as the turning point, this is the point in time at which the pace of accumulation starts to decline. (Liu et al., 2015). The model of Logistic Growth clarifies the exponential growth in the number of disease cases at the beginning of the disease outbreak and trends toward a consistent value at the end of the outbreak (Pelinovsky et al., 2020). The logistic growth model is well-known for its ability to accurately describe the real data progression of numerous epidemic outbreaks. This model accurately simulates an outbreak in a small community and uses a deterministic model solution (Kartono et al., 2021).

Numerous disease outbreaks have previously been modeled using logistic models. This type of phenomenological modeling technique is considered a more robust and significantly simpler approach since it does not entail making assumptions about the transmission method (Reddy et al., 2020). When it came to epidemics like the West African Ebola outbreak in 2014, the logistic model was employed (Chowell et al., 2014; Pell et al., 2018). Moreover, the Zika virus, dengue, influenza virus (H1N1), and severe acute respiratory syndrome (SARS) were among the other epidemics for which the Logistic Growth Model was applied (Chowell et al., 2019; Wang et al., 2012; Sebrango-Rodríguez et al., 2017).

However, even though logistic models can be used to analyze present epidemics by studying past epidemics, they may not always be helpful. This is due to the impact of the intensity of the virus, the preventative measures to control the spread, and the population density, among other factors (Pelinovsky et al., 2020). Understanding the variability of the model's parameters and how it affects the anticipated results is critical for making long-term predictions.

With the novel coronavirus 2019 outbreak, mathematicians and statisticians have utilized models to predict the outcome and propose preventative and control measures for the epidemic (Zhao et al., 2021). Zhang (2021) said that for the healthcare industry to understand the COVID-19 pandemic's trajectory and take appropriate action, a strong prediction model is needed.

In many instances, the exponential growth model has been used to comprehend and analyze pandemics. This is because epidemiologists have used this model in previous epidemics and have found it fits well for the beginning period of the epidemic. However, for the later stages, researchers pointed out that the logistic growth model can be considered to analyze pandemics (Singh & Singh, 2020; Malavika et al.,2021).

The Logistic Models with various modifications were employed by several researchers to model the novel coronavirus pandemic (Malavika et al., 2021; Jain et al., 2020; Chen et al., 2020; Mackolil & Mahanthesh, 2020). The Logistic models involve several important parameters that aid in modeling the curve accurately. These parameters include the growth rate at an early stage of the infection, the extent of the epidemic in the end, the total number of cases at a given moment in time, the growth stall, and the infection tipping point (Jain et al., 2020).

Malavika et al. (2021) confirmed the use of the logistic growth model for the COVID-19 pandemic since it is subjected to increasing growth at first, and subsequently decreasing growth, as it approaches the maximum. Jain et al. (2020) asserted that the formulation of a logistic growth model is more useful than using the exponential model, as it can reveal the rise and fall in the number of cases around the inflection point.

The COVID-19 situation was evaluated using the logistic growth model for several countries, including Brazil, China, India, and the United States of America (Malavika et al., 2021; Jain et al., 2020; Mackolil & Mahanthesh, 2020; Wu et al., 2020; Shen, 2020; Chen et al., 2020). Malavika et al. (2021) evaluated the COVID-19 outbreak in India by utilizing the logistic growth curve model to forecast new cases during the short run. The results from their study projected that the cumulative COVID-19 cases were modeled precisely onto the observed cases. A similar study conducted by Jain et al. (2020), focused on extrapolating accessible data also for India to build models in the early stage of the epidemic growth. The Logistic Growth model in their study represented an optimistic situation.

Additionally, Jain et al. (2020) utilized two other growth models to estimate the rise in the total number of cases, the daily growth rate in confirmed cases, and the daily increase in cases. In their investigation, they used the logistic model's expansions, generalized logistic growth, and generalized growth. The findings suggested that these two models showed pessimistic results. Meanwhile, Pelinovsky et al. (2020) noted in their study that the predicted number of the overall COVID-19 case count using the generalized logistic model was slightly greater than the simple logistic model. Also, the convergence to the maximum capacity took a longer time.

Furthermore, Chen et al. (2020) examined the dynamics of the coronavirus's spread in the United States of America by assessing the applicability of a five-parameter logistic growth model. The findings of this study showed that the data fit this logistic growth model reasonably, with a growth rate suggested to be doubling every four days. Furthermore, Shen (2020) investigated the logistic growth model's applicability and its implications for assessing the COVID-19 pandemic in China. Shen (2020) indicated that there was a good fit between the data and the logistic growth model.

The Logistic model is a useful model for making short-term predictions (Roda et al., 2020; Reddy et al., 2020; Kartono et al., 2021). Reddy et al. (2020) used a three- and four-parameter logistic model for short-term predicting in South Africa and contrasted their estimates with the data seen over the studied period. For a maximum of 10 days, the model was shown to generate trustworthy and accurate projections. In comparison to Richard's model, the three- and four-parameter logistic growth models produced more accurate findings for the cumulative cases and fatalities.

Furthermore, the COVID-19 pandemic's end and the number of persons afflicted by it under the current conditions were predicted using the logistic growth model, a prediction model (Mackolil & Mahanthesh, 2020; Kartona et al., 2021). Mackolil and Mahanthesh (2020) conducted a study in India and chose three states based on the number of individuals afflicted and the disease's spread. The Logistic Growth model was used to divide based on the type and rate of infection growth, the pandemic was divided into five stages. Furthermore, the high coefficients of determination , R^2, for the logistic models for the three states showed that the fitted models are accurate.

In addition, the logistic growth models were not only used to predict COVID-19-related cases but were also applied to modeling COVID-19 deaths (Triambak et al., 2021). The power-law logistic model was employed for fatalities in three waves of the infectious COVID-19 disease in South Africa. The findings have shown that the model was consistent with the data. Triambak et al. (2021) suggested that this model can be implemented in other nations to forecast cases and deaths not only from the coronavirus pandemic but an epidemic in general.

Therefore, the Logistic models have been successfully used by many researchers, since they agreed with the available data for the COVID-19 pandemic (Pelinovsky et al., 2020). Numerous studies revealed that, when compared to other models, the Logistic model suited the data the best.

Which other Mathematical models are used in the study of Epidemics?

According to Chubb and Jacobsen (2009), models used in epidemiology refine each other and based on the results from the models, epidemiologists can have a better understanding of population health and make predictions. Mathematical modeling in the study of epidemics generally comprises three categories: Mechanistic State models, Empirical Learning models, and statistically based techniques (Vytla et al., 2021).

Based on these three categories of mathematical models the commonly used models to study infectious diseases include the compartmental models: Susceptible-Infected-Recovered (SIR) model, Susceptible-Infected-Recovered-Deceased (SIRD), Susceptible-Exposed-Infected-Recovered (SEIR) models, and the Auto-Regressive Integrated Moving Average (ARIMA) models.

Basic mechanistic mathematical models grounded in biological principles are known as compartmental models (Yadav & Akhter, 2021). The most frequently used compartmental model in the study of epidemics is the SIR model. A mathematical model known as the SIR model simulates the spread of an epidemic by employing a system of time-dependent differential equations (Mackolil & Mahanthesh, 2020). Popovici et al. (2019) expressed that, according to their infectious status, individuals are categorized as Susceptible (S), Infectious (I), or Recovered (R) in the SIR model, a compartmental technique that tracks population sizes over time. Mackolil and Mahanthesh (2020) noted that the compartments into which the population is separated form the basis for the differential equations. The SIR model, as well as modified SIR models, were employed by researchers to model the Ebola outbreak (Khaleque & Sen, 2017) and AIDS (Zackary et al., 2016). Recently, the SIR models with variations of parameters were utilized to model the coronavirus pandemic (Malavika et al., 2021; Mackolil & Mahanthesh, 2020).

The coronavirus's excessive number of active cases and peak times have been predicted using the SIR model. But until the data was examined, it was found that the model predicted a higher number of active cases than what was shown (Malavika et al., 2021). It was mentioned that the SIR model's outcomes can be used to organize interventions and set up the nation's health systems for more effective clinical care of infected patients.

With an additional parameter, the Susceptible-Infected-Recovered-Deceased (SIRD) model and its modifications is another compartmental model that was used to model the COVID-19 pandemic (Shringi et al., 2021; Martínez, 2021; Sen & Sen, 2021). Sen and Sen (2021) highlighted that this technique is distinctive in that it can explain the active, recovered, and dead population, all at the same time. While there are researchers that use all the compartments, the Susceptible, Exposed, Infected, Recovered, Dead (SEIRD) model (ŠUšteršič et al., 2021; Ala'raj et al., 2021), others leave out the Dead compartment and utilize the SEIR model (López & Rodó, 2020; Saikia et al., 2021).

Additionally, the ARIMA model is a statistical method that relies on data rather than theory that was successfully used for epidemic outbreaks in the past such as SARS, influenza, and Hepatitis A (Earnest et al., 2005; He & Tao, 2018; Guan, 2004). ARIMA models are also being used to study the present COVID-19 pandemic, with great results (Anne & Jeeva, 2020; Perone, 2020; Chaurasia & Pal, 2020; Zhang, 2021).

How accurate are the models that are used in the study of epidemics?

Aviv-Sharon and Aharoni (2020) noted in their study that the accuracy of models in the study of epidemics is important for government interventions, and making long-term decisions concerning testing and facilities for COVID-19. Additionally, the accuracy of models is important in planning for the future. Planning involves acquiring the number of vaccine doses needed for the population, hospital beds, and medical equipment and making decisions to take necessary measures to control and help bring the pandemic to an end (Lewis & al Mannai, 2021).

However, several factors could influence the accuracy of models. Moran et al. (2016) stated that the accuracy and uncertainty of predictions are determined by the assumptions, data availability, and data quality. These factors were emphasized by researchers who studied the COVID-19 pandemic.

Jain et al. (2020) noted that the accuracy of the results is related to the quantity of the data sample obtained. Additionally, limited data can be a constraint to the accurate modeling of the growth of the coronavirus in its early stages. Thus, differences would have an impact on the actual and predicted results. Moreover, external factors can result in misreporting of actual cases (Jain et al., 2020). Additionally, making wrong assumptions in the process of modeling affects the accuracy of forecasting. Many models assume homogeneity, which means that everyone has an equal chance of mixing with and infecting one another. This is an assumption that overlooks the reality of exposure and coordination (Ioannidis et al., 2020).

Moreover, the lack of data is a serious concern for modelers (Roda et al., 2020). Singh and Singh (2020) argued that the lack of reliable data makes correct parameter estimation challenging, and some parameters may only be able to be estimated with a range of values. Additionally, Malavika et al. (2021) found that unreported cases that impact the reliability of data would affect the accuracy of models. Furthermore, external factors also might have resulted in the misreporting of actual cases.

IV. Conclusion

In this study, it can be concluded that pandemics should be modeled using the logistic growth model. When dealing with growth issues, the logistic growth model—also referred to as the Verhulst-Pearl equation—is typically employed. This study revealed that the logistic growth model's short-term estimates closely match the number of cases and deaths recorded. The logistic growth model is a useful tool for studying epidemics, and accurately describing the progression of disease cases. It has been used to model numerous disease outbreaks, including the Ebola outbreak, Zika virus, SARS, and COVID-19. The model has been used in various countries, including Brazil, China, India, and the United States of America, to evaluate the situation. Thus, the logistic model results should be used to build interventions and prepare health systems for better clinical management of infected people in the country.