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Models for the Study of the Effects of COVID-19 on Dermatological Health

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Abstract

COVID-19 and its impact on dermatological health were reviewed from theoretical and statistical frameworks in the present study. A cross-sectional and retrospective work was documented with a selection of sources indexed to Scopus, considering the period from 2019 to 2021, as well as the search by keywords. Approaches were discussed in order to outline a comprehensive model that considered the differences between the parties involved, as well as their relationships in a risk context. The proposal contributes to the state of the question in terms of the prediction of contingencies derived from the probability and affectation of dermatological health.

Keywords: COVID-19; Dermatological Health; Disease; Model

Introduction

COVID-19´s illness, first known as nCov-19, is the most important affection on human health in actual days; which threaten most of the body homeostasis´ scopes, as the dermatological issues. Whilst the COVID-19-associated cutaneous manifestations have been increasingly reported, their exact incidence has yet to be estimated, their pathophysiological mechanisms are largely unknown, and the role, direct or indirect, of SARSCoV-2 in their pathogenesis is still debated [1].

In the COVID-19 era, dermatological diseases have been limited to associated cases. Thus, one indicator of COVID-19 was a rash or hives [2]. At the beginning of the pandemic, the symptoms shared with other diseases such as the influence led to the need to identify the most frequent and common symptoms. The rash or urticaria was a symptom from which the contagion and disease by the SARS CoV-2 coronavirus was inferred.

In this scenario of lack of information and unhealthy conditions, hives or rash were considered as symptoms of COVID-19 in young people more than in adults and the elderly [3]. The importance of associating this symptom with the pandemic consisted in that from visible symptoms massive contagions or community transmission of the coronavirus would be anticipated. In an environment of scarce information and imprecise data, dermatological diseases emerged as the visible part of the pandemic, although limited to the youth sector.

Consequently, the proposals for the description and explanation of the effects of the pandemic on dermatological health were more visible at the beginning. In this context, the objective of this work was to specify a model for the study of the potential effects of dermatological contagion of the pandemic whenever it was possible to associate urticaria or rash with COVID-19.

What is the community transmission model of the pandemic closest to symptoms of urticaria or rash in students at a public university in central Mexico?

The premise that guides this work suggests that dermatological health is embedded in the pandemic through the dissemination of cases, inhibiting a prevention campaign [4]. In this sense, hives or rash may not be indicators of COVID-19 but are associated with the pandemic as a social amplification of risks. Thus, the equation that best explains this case of disseminated misinformation in students who believed they had COVID-19 from hives or rash will be: 1) the formulation that includes the influence of the media; 2) the equation that relates the informative variables with the findings of the community transmission of COVID-19; 3) the model that explains the effect of fake news on youth audiences.

Multiple skin manifestations have been described in patients with confirmed or suspected severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) infection; including morbilliform rash; urticaria; pernio-like, acral lesions; livedo-like, vascular lesions; and vesicular, varicella-like eruptions Feldman SR, et al. and Mohseni Afshar Z, et al. [5,6] were reported the histopathological examination of COVID-19-related cutaneous lesions, where they can be seen some dermatologic affections like: maculopapular eruptions, varicella-like papulovesicular exanthems, urticarial lesions, papulovesicular exanthema, acral chilblain-like lesions, livedoid lesions (livedo reticularis/racemosa-like pattern), purpuric "vasculitic" pattern, pityriasis rosea-like lesions, Kawasaki-like lesions, subcutaneous lesions and pustular lesions.

Theory of Dermatological Health

The theoretical frameworks that explain the community transmission of COVID-19, particularly those theories that anticipate the effects of the pandemic on dermatological health suggest: 1) the media can influence the decisions and actions of audiences; 2) hives and rash are associated with COVID-19 through testimonials rather than research; 3) the dissemination of personalized reports on dermatological health associated with COVID-19 amplified the pandemic.

The theory of risk amplification suggests that the pandemic is represented by the information available in the media rather than on social networks [7]. In this sense, dermatological health is an area affected by the health crisis. The testimonials that were promoted on electronic networks amplified the perception of the risk of the users of Facebook, Twitter, Instagram, YouTube, Tok-Tok and WhatsApp. As cases of urticaria or rash are disseminated on the networks, the perception of risk emerges that associates these symptoms with COVID-19. As young people are those who deal with cases of dermatological health linked to the pandemic, the use of the devices is intensifying. Exposure to risks in young people can be seen from the intensive use of mobile devices.

From the perspective of the social networks framing, the pandemic is a multidimensional phenomenon, but guided by the leaders of Facebook, Twitter, Instagram, YouTube or Tik Tok compared to opinion leaders, communicators and columnists. In the case of the cases of hives or rash that were associated with COVID-19, the framing reduced this question to a symptom [8]. Consequently, the pandemic was visible during the convergence of scarce information about the cor] onavirus and the proliferation of cases of dermatological affectation.

The amplification and framing of risks that associated dermatological health with COVID-19 can coexist. The dual-stream perspective warns that social media can spread cases of rashes and hives, while reducing symptoms of reddening of the skin or itching of the skin. In both cases, the dual flow emerges when opinions underlie both amplification and framing of risk.

Studies of Dermatological Contamination

Based on the amplification of the risk, the informative framing and the double flow of communication, studies of dermatological health associated with the pandemic have established: 1) the prevalence of cases of urticaria and rash over other cases of symptoms associated with COVID -19 as oxygenation in the blood; 2) the amplification of the risk in coexistence with the informative framework and the double communication between the interested parties; 3) dermatological health as a representation of the pandemic in Internet users.

In the context of the pandemic, studies on the prevalence of urticaria and rash as indicators of COVID-19 are scarce, but before the pandemic, there are studies in which symptoms are associated with diseases. This is the case of cancer, which is associated with various symptoms that Internet users have spread on electronic networks as risk factors. Most common are solutions for cancer or any other terminal and fatal disease. In fact, as the symptoms are frequent, they are linked to diseases. The more lethal and common the diseases, the greater the association with remedies or preventive strategies. In the case of the pandemic, the novelty is that the health ministry's oversaw spreading its low lethality [9]. In addition, the ministers of health also disseminated opinions that the pandemic would affect a low percentage of the population. Or else, the control of the health crisis based on strategies of confinement and distancing, followed by immunization and deconfinement. The studies warn that these public health strategies reflect the scarcity of scientific information on the pandemic.

Regarding the incidence of testimony disseminated on social networks regarding the representation of COVID-19 in Internet users, the studies suggest that Facebook is more influential than Twitter when it comes to legitimizing a health policy or strategy [10]. Consequently, testimonials will affect the decisions and actions of audiences more if they are reproduced on Twitter with a preventive orientation against their dissemination on Facebook as evidence of public health.

In the nineties, the studies that demonstrated the incidence of communication with images versus discourses were classic [11]. Since then, research has been consistent in clarifying that images have a greater impact than data, but it is narratives that allow an image of deteriorated or consolidated health. COVID-19 is a disease that does not have a representation. Even the coronavirus is considered invisible, but deadly. The association of hives or rash with COVID-19 represents a representation of the pandemic. Studies on immunization suggest that SARS CoV-2 is closely associated with vaccines as an image of the public administration of the pandemic, communication and risk management.

Mathematical Models of Public Health

This section includes the equations developed to explain the dissemination of testimonials on social networks, as well as the representation of COVID-19 as a contextual problem [12]. In allusion to the narratives that the coronavirus is an instrument of manipulation of Internet users, the models suggest that it is an integral problem beyond dermatological health.

In this way, the theory of risk amplification is complemented by the exponential growth of infections model by stating that the pandemic is immeasurable, unpredictable and uncontrollable once it exceeds a threshold of risk permissible for the community [13]. In the same sense, the logistic model would be associated with the amplification of risk when the testimonials disseminated on social networks exceed the official conferences. The growth of cases of urticaria and rash associated with COVID-19 from social networks would warn of a phenomenon that can be explained from the logistics function.

However, both exponential and logistic function models when associated with risk amplification limit their explanation of the parties involved [14]. The predator and prey model reveal a competition for the scarcity of information. In this way, Internet users are prey to predators or influencers who reduce the pandemic to somatic symptoms. The commensalism model is associated with the theory of framing since, mediately, bullies or aggressors spread dermatological health as a preamble to COVID-19. The reduction of the pandemic to testimonials about COVID-19 conditions is a media frame that affects the decision and action of the Internet user.

Exponential Function Model

In the family of models that explain complexity, the exponential function attempts to predict the increase in cases in the short term. In this sense, the few testimonies related to dermatological affectations by COVID-19 would favor a complex quantitative phenomenon. the exponential function would be a first approximation to the emergence of a community transmission problem that is disseminated on social networks. Sureda PY, et al. [15] suggested that the first question to be resolved in the analysis of the exponential function is the relationship between operative invariants and representation systems. In the learning of knowledge disseminated in social networks, the exponential function is a representation of the immediate future.

Miatello R, et al. [16] Suggested graph of a function that satisfies the differential equation = $\frac{dp}{dt} = kP$, were: P = Population (dependent variable), t = Time (independent variable) and k = constant of proportionality (parameter). Enter the rate of population growth and its size. The population growth rate P is the derivative $\frac{dp}{dt}$ Since it is proportional to the population, it is expressed as the product kP. In this way: $\frac{dp}{dt} = kP, o'P' = kPo'$

$$\frac{dp}{dt} = kP \text{ for some constant k}$$

$$\frac{dp}{dt} = 0 \text{ if P = 0}$$

P (t) = 0. Consequently, k> 0 and (Pt $_0$)> 0, at time t = t $_0$ and the population is growing. P (t) becomes larger, so it

$\frac{dp}{dt}$ increases [17]. From the exponential function, the diffusion of cases of dermatological effects by COVID-19 would be considered as a field of representation in the learning of the pandemic.

Logistic Function Model

Onwubu SC, et al. [18] warns that the logistic function is used to predict the reconfiguration of processes, considering a prolonged exposure to risks. Tsoularis A, et al. [19] points out that exponential growth reaches a saturation point, allowing it to be anticipated from a logistic function. Thus, the exponential function precedes the logistic function, and this precedes an inflection distribution. The complexity to be explained is that the distribution relaxes, and the exponential function can no longer predict its growth, but the logistic function adjusts to this trend. Therefore: t = time (independent variable), P = Population (dependent variable), k = coefficient of the growth rate for small populations (parameter), N (it will be called bearing capacity) and P (t) grows if $P(t) < N$ P (t) <N, if P (t)> N $P(t) > N$ is decreasing.

$\frac{dp}{dt} \approx$ in this second model if P> N. $\frac{dp}{dt} < 0$.

$\frac{dp}{dt} = kp$ we add "something" close to 1, if P is small

$\frac{dp}{dt} = k$ (Something)

P (something) $= \left(1 - \frac{P}{N}\right) P'(t) = KP\left(1 - \frac{P}{N}\right)$

P(t) it is the internauts population, K is the growth coefficient of the population. N they are the conditions (carrying capacity) of the school in which the children interact. P internauts.

$$\frac{dp}{dt} = k(1 - \frac{P}{N})\,\mathrm{P}$$

Hosmer DW, et al. [20] note that the logistic regression model is suitable for establishing peer influence. It means then that the prediction of the incidence of cases presented as a trend of dermatological contamination by COVID-19 can at least be described from the logistical function and thus explain the incidence of the networks that disseminated testimonials among young people.

Prey-Predator Model

Abdulghafour AS, et al. [21] suggested that the predator versus prey model includes healthy prey and prey infected and vulnerable to the predator. That is, unlike the exponential and logistical function that explains the trend and saturation of testimonials disseminated on networks, the predator and prey model distinguish between persuaded Internet users in relation to Internet users who disseminate and process the testimonials. In other words, the effects of COVID-19 on dermatological health in adolescents and young people can be explained from the predator and prey function. In consequence:

$$\frac{ds}{dt} = \alpha S - \beta SP$$

$$\frac{dp}{dt} = \delta SP - \Upsilon P$$

P is the number of children employed, *S* is the number of children susceptible to being infected by lice, $\frac{dp}{dt}$ and $\frac{ds}{dt}$ represent the growth of the two populations over time, *t* represents time; α, β, γ and δ are parameters that represent the interactions, *α:* Coefficient of the growth rate, *β:* proportionality constant, *ϒ:* Coefficient of the reduction ratio of carriers and *δ:* proportionality constant [22].

Propose that the specialized predator promotes a redistribution of the relationship with the prey regardless of whether it is infected or not. In other words, the generalist predator that seeks its survival is more prone to a risky scenario. In contrast, the specialized predator is rather suitable in an equilibrium scenario. Therefore, the dissemination of testimonials on networks obeys a stable scenario in which influencers are specialized predators compared to general Internet users who emerged from the pandemic.

Model of Disease Spread

Smieszek T, et al. [23] warns that community transmission of a contagion is not constant. In this sense, the exponential, logistic and predator prey functions do not allow us to observe the variations that inhibit the pandemic. The community transmission model proposes a heterogeneity and intensity of cases. The testimonials disseminated on social networks have a differential impact on Internet users. Influencers follow diffusion strategies that are not constant and promote non-homogeneous effects with discontinuous intensities. Therefore: (S) influencers, (Z) internauts, (ζ). population, (R) social network, (β) parameter. $S' = \Pi - \beta SZ - \delta S$

$$Z = \beta SZ + \zeta R - \alpha SZ$$

$$R' = \delta S + \alpha SZ - \zeta R$$

(βN) network influencers, N is the total internauts, (Y / N) probabilities that a random contact (βN) (S / N) Z = βSZ Karlsson CJ, et al. [24]warn that containing the spread of a disease comes at a cost to the parties involved. The speed with which the information is disseminated determines the decision and action to spread or avoid contagion. Therefore, the dissemination of testimonials regarding the effects of COVID-19 on local dermatological health depends on access to information and the processing of data in prevention strategies.

Complex Contagion Model

Demonstrated that the spread of specific cases leads to the increase in more cases. As the pandemic intensified, its effects on dermatological health also increased. These relationships varied based on emotions. The exponential function, logistics, predator prey and community transmission had not included the difference between the official propagation systems versus emergent or collateral events. In the basic transmission model, the comparison of other processes adjacent to the pandemic was seen as a differential covariate.

Z / N probability random contact

(αN) (Z / N) S = αSZ

S´ + Z´ + R´ = Π

S + Z + R →

As t → ∞, if Π ≠ 0. Hence, S → ∞,

Π = δ = 0.

Adjusting the differential equations equal to 0 we have:

-βSZ = 0

= 0

αSZ βSZ + ζR - αSZ - ζR = 0

From the first equation, we have either of the two S = 0 or Z = 0. So, this follows the form S = 0 with this we get the pietistic equilibrium.

(S, Z, R) = (0, Z, 0)

When Z = 0, we have the lice-free equilibrium.

(S, Z, R) = (N, 0, 0)

These equilibrium points show that, regardless of their stability.

$$J = \begin{pmatrix} -\beta Z & -\beta S & 0 \\ \beta Z - \alpha Z & \beta S - \alpha S & \zeta \\ \alpha Z & \alpha S & -\zeta \end{pmatrix}$$

$$\mathrm{J(N,0,0)} = \begin{pmatrix} 0 & -\beta N & 0 \\ 0 & \beta N - \alpha N & \zeta \\ 0 & \alpha N & -\zeta \end{pmatrix}$$

$$\det.(\mathrm{J} - \lambda I) = -\lambda\{\lambda^2 + [\zeta - (\beta - \alpha)N]\lambda - \beta\zeta N\}$$

$$\mathrm{J}(0, Z, 0) = \begin{pmatrix} -\beta Z & 0 & 0 \\ \beta Z - \alpha Z & 0 & \zeta \\ \alpha Z & 0 & -\zeta \end{pmatrix}$$

$$\det.(\mathrm{J} - \lambda I) = -\lambda(-\beta Z - \lambda)(-\zeta - \lambda)$$

We will refer to this as the SIZR model. The model is given by

$$s' = \Pi - \beta SZ - \delta S$$

$$I' = \beta SZ - \rho I - \delta I$$

$$Z' = \rho I + \zeta R - \alpha SZ$$

$$R' = \delta S + \delta I + \alpha SZ - \zeta R$$

If Π ≠ 0, a short period of time and therefore Π = δ = 0. When we set the previous equations to 0, we obtain either S = 0 or Z = 0 from the first equation. It follows once more from our analysis of the basic model that we achieve equilibrium:

$$Z = 0 \Rightarrow \mathrm{(S, I, Z, R) = (N, 0, 0, 0)}$$

$$\mathrm{S} = 0 \Rightarrow \mathrm{(S, I, Z, R)} = (0, 0, Z, 0)$$

$$Z = 0 \Rightarrow (S, I, Z, R) = (N, 0, 0, 0)$$

$$J = \begin{bmatrix} -\beta Z & 0 & -\beta S & 0 \\ \beta Z & -\rho & \beta S & 0 \\ -\alpha Z & \rho & -\alpha S & \zeta \\ \alpha Z & 0 & \alpha S & -\zeta \end{bmatrix}$$

$$\det(\mathrm{J(N,0,0,0)} - \lambda\,\mathrm{I}) = \det \begin{bmatrix} -\lambda & 0 & -\beta N & 0 \\ 0 & -\rho-\lambda & \beta N & 0 \\ 0 & \rho & -\alpha N - \lambda & \zeta \\ 0 & 0 & \alpha N & -\zeta-\lambda \end{bmatrix}$$

$$= -\lambda \det \begin{bmatrix} -\rho-\lambda & \beta N & 0 \\ \rho & -\alpha N - \lambda & \zeta \\ 0 & \alpha N & -\zeta-\lambda \end{bmatrix}$$

$$= -\lambda[-\lambda^3 - (\rho + \zeta + \alpha N)\lambda^2 - (\rho\alpha\,\mathrm{N} + \rho\zeta - \rho\beta\,\mathrm{N})\lambda + \rho\zeta\beta\,\mathrm{N}$$

Where: > 0, first we have: it has an eigenvalue with a positive

$$\det(\mathrm{J}(0,0,Z,0) - \lambda\,\mathrm{I}) = \det \begin{bmatrix} -\beta Z - \lambda & 0 & 0 & 0 \\ \beta Z & -\rho-\lambda & 0 & 0 \\ -\alpha Z & \rho & -\lambda & \zeta \\ \alpha Z & 0 & 0 & -\zeta-\lambda \end{bmatrix}$$

The eigenvalues are therefore λ = 0, -βz, -ρ.

Sprague DA, et al. [25] distinguishes between a basic and a complex contagion. The explanation for lagging cases is the difference between basic spread versus a complex structure of contagions. Influencers asymmetrically affect Internet users, causing heterogeneous effects.

Dermatological Effect Model

Buster KJ, et al. [26] warn that in the face of the pandemic, dermatological health professionals when reconverting themselves for COVID-19 care led to a shortage and low quality of service. They also show that the scarcity and unhealthy situation differentially affected the groups based on their age, income and race. The effects of COVID-19 on dermatological health generated more differences between the groups. The exponential and logistic functions did not account for these asymmetries because they focused on the homogeneity and symmetry of the relationships between influencers and Internet users.

$$S' = \Pi - \beta SZ - \delta S + cZ$$
$$I' = \beta SZ - \rho I - \delta I$$
$$Z' = \rho I + \zeta R - \alpha SZ - cZ$$
$$R' = \delta S + \delta I + \alpha SZ - \zeta R$$

, we now have the possibility that an endemic equilibrium (S, I, Z, R) satisfies:

$$-\beta SZ + cZ = 0$$
$$\beta SZ - \rho I = 0$$
$$\rho I + \zeta R - \alpha SZ - cZ = 0$$
$$\alpha SZ - \zeta R = 0$$

$$(S, I, Z, R) = \left(\frac{c}{\beta}, \frac{c}{\rho} Z, Z, \frac{\alpha c}{\zeta\beta} Z\right)$$

$$J = \begin{bmatrix} \beta Z & 0 & -\beta S + c & 0 \\ \beta Z & -\rho & \beta S & 0 \\ -\alpha Z & \rho & -\alpha S - c & \zeta \\ \alpha Z & 0 & \alpha S & -\zeta \end{bmatrix}$$

$$\det(J(S, I, Z, R) - \lambda I) = \det \begin{bmatrix} \beta Z & 0 & 0 & 0 \\ \beta Z & -\rho & c & 0 \\ -\alpha Z & \rho & -\frac{\alpha c}{\beta} - c & \zeta \\ \alpha Z & 0 & \frac{\alpha c}{\beta} & -\zeta \end{bmatrix}$$

$$= -(\beta Z - \lambda) \det \begin{bmatrix} -\rho & c & 0 \\ \rho & -\frac{\alpha c}{\beta} - c & \zeta \\ 0 & \frac{\alpha c}{\beta} & -\zeta \end{bmatrix}$$

$$= -(\beta Z - \lambda)\left\{-\lambda\left[\lambda^2 + \left(\rho + \frac{\alpha c}{\beta} + c + \zeta\right)\lambda + \frac{\zeta\alpha c}{\beta} + \frac{\rho\alpha c}{\beta} + \rho\zeta + c\zeta\right]\right\}$$

$$S' = \Pi - \beta SZ - \delta S \quad t \neq t_n$$

$$Z = \beta SZ + \zeta R - \alpha SZ \quad t \neq t_n$$

$$R' = \delta S + \alpha SZ - \zeta R \quad t \neq t_n$$

The predator prey function noted differences, but not due to the socioeconomic and educational conditions of the parties involved. The community transmission function, basic and complex explained constant or covariable contagions, but the model of dermatological effects found that the pandemic affects the interested parties asymmetrically.

Discussion

The contribution of this work to the state of the question lies in the review and discussion of models for the study of the effect of COVID-19 on dermatological health. Based on considering that dermatological health is the product of the surrounding information in the media and social networks, the models that dermatological science has proposed to explain the incidence of COVID-19 in Internet users were traced. The works that allowed the discussion of the influence of testimonials disseminated on YouTube, Facebook, Twitter, Instagram, Tik-Tok and WhatsApp were reviewed. The content of the testimonials included cases in which influencers indicated that the hives or rash emerged at the same time as other symptoms associated with COVID-19. The dissemination of these testimonials was analyzed from models under theoretical assumptions of risk amplification, informative framing and double informative flow.

In relation to the theories that explain the influence of the pandemic on dermatological health through information trends in social networks, the present work corroborates the assumptions. The models explain the impact of testimonials on perceived dermatological health. The theory of risk amplification shares with the exponential, logistics, predator prey and community transmission function the emergence of influencers in electronic networks during the pandemic. The perspective of the media framing combines with the logistical function the breaking point that can be established from the informational or distributive saturation. The double flow approximation coincides with the predator prey function in terms of the zero-sum interaction.

The community transmission function, antecedent to the complex function and effects on dermatological health, is consistent with the theory of risk amplification in terms of the asymmetry between the parties in the face of the pandemic. The differences between influencers and Internet users regarding the impact of the pandemic on their dermatological health reveal the emergence of a contagion. The basic and complex function showed that these differences correspond to sociodemographic, economic or cultural factors. The amplification of risk in this sense warns that in uncertain scenarios, risks impact the interested parties asymmetrically.

The research lines concerning the prediction of self-care in the face of the pandemic and based on the information disseminated on social networks will allow anticipating risk scenarios. The explanation of the differences between influencers and Internet users in the face of the pandemic will allow building a public agenda. The topics and axes of discussion related to the effects of anemia on dermatological health will guide the public agenda towards governance [27-30].

Conclusion

Facing SARS-COV-2 (new coronavirus) has been challenged the humanity. That virus which primary was identified as severe acute respiratory problem, added other health's problems like those in the dermatologic scope. Different models to explain impact on perceived dermatological health´s issues, provide correlated information which states informational or distributive saturation as well as zero-sum interaction. Shown model help on the prediction of self-care, when facing the pandemic scenario, collaborating on the pathway by public scope.

The effects of the pandemic on dermatological health have been explained from theoretical, conceptual and empirical frameworks. From the relationship between influencers and Internet users, the phenomenon is considered emergent. That is, the risks associated with COVID-19 are assumed as probable if they are disseminated by influencers and are directed at Internet users with a sociodemographic, economic and cultural profile oriented to the intensive use of social networks. Theoretical approaches when linked to statistical models allow the explanation of the phenomenon. Study lines related to the integration of theories and models will anticipate risk scenarios.

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