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Review article

An epidemiological model of SIR in a nanotechnological innovation environment

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A R T I C L E I N F O

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A B S T R A C T

Today, when nanotechnological innovation, in particular, faces stringent regulations, the question arises concerning a tool that can quantify individual interventions and thus complement current knowledge in the diffusion theory of innovation. This paper examines the complex nature of innovation diffusion in a rapidly evolving technological environment. The research presents current knowledge in the field linking diffusion of innovation theory and the basic epidemiological model of SIR (Susceptible, Infected, Recovered). Epidemiological models, originally developed to study the spread of infectious diseases, offer intriguing parallels to innovation diffusion due to shared characteristics in propagation dynamics. Integrating the SIR epidemiological model into the current theoretical framework allows the SIR model to be considered as a tool capable of filling current gaps in the literature. Nanotechnological innovations are chosen because of their significant impact on society, which faces unique market entry challenges. Within the framework of high interdisciplinarity, nanotechnologies, like viruses, tend to 'mutate' into different industries where their 'infectivity' varies. The case of nanotechnology serves to illustrate the usefulness of the proposed model and shows how factors that influence the spread of viruses can similarly affect the adoption of technological innovations. Similar characteristics in the propagation framework between innovations and viruses can serve as one of many arguments for the use of the SIR model in this field. Using an integrative review, aspects that have the potential to add to the SIR model in the current literature are identified. By combining epidemiological findings with innovation theory, the paper contributes to a richer and more integrated understanding of the phenomena of diffusion of nanotechnological innovations. The motivation is to open a debate regarding the ability of the epidemiological model of SIR to reveal the impact of interventions affecting the diffusion of innovations.

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1. Introduction

In an ever-evolving environment of technological progress, understanding the mechanisms behind the diffusion of innovation remains a key challenge for both researchers and industry practitioners. Traditional theories in the diffusion of innovation, such as the diffusion theory proposed by Rogers or the Bass model, have laid a solid foundation for examining how new ideas and technologies permeate society. These models emphasize the role of individual and system attributes in the processes of diffusion of innovation but contain assumptions that distance these theories from the real world. In an attempt to eliminate these limitations, this paper explores the use of the SIR (Susceptible, Infected, Recovered) epidemiological model in the diffusion of technological innovations. According to the Web of Science database, only six publications have explored the use of this mathematical model SIR in conjunction with innovation.

The SIR model, introduced by Kermack and McKendrick in 1927, is a deterministic mathematical framework used to predict the spread of disease in populations by categorizing individuals into three compartments: susceptible, infected, and recovered [1]. Individuals transition between these compartments based on interactions and transmission rates, with recovery providing immunity. The model operates through a system of nonlinear differential equations that account for transmission and recovery rates. A key output of the SIR model is the reproduction number R_0, which helps assess disease transmissibility and the effectiveness of control measures over time.

At the core of our discourse is the claim that innovation diffusion is strikingly similar to the dynamics of virus transmission in a population. According to Rogers, the way in which a particular innovation spreads in a society depends on both the environment and the characteristics of the innovation itself [2]. Thus, it is crucial to consider the characteristics of viruses and innovations, which may share basic attributes in the context of diffusion in society. This parallel invites analyses of individual technological innovations that may find similarities with the behavior of some viruses. With this conceptual framework, it is possible to synthesize existing research findings to create a new theoretical model reflecting the complexity of the phenomena under investigation.

The selected area of innovation under investigation from an epidemiological perspective is nanotechnology, a field that is characterized by rapid progress and significant potential for societal impact but is burdened by unique challenges that have impeded its widespread adoption [3]. Nanotechnology is an ideal example of information dissemination subject to external interference due to its wide applicability in various fields and the obstacles it encounters due to specific physical phenomena [4].

By linking the epidemiological model and innovation theory elements, the paper aims to contribute to a more dynamic and comprehensive understanding of how innovation diffuses in different contexts and settings. It suggests that adopting the SIR model in the field of technological innovation not only addresses some of the gaps left by traditional diffusion theories but also offers a robust tool for assessing the impacts associated with adopting regulatory frameworks and other interventions in the innovation environment. In doing so, this paper seeks to pave new avenues for research and practical application in efforts to guide and support the diffusion of innovation in today's complex and interconnected world. This paper aims to contribute to the diffusion of nanotechnology innovations with a new perspective based on similar diffusion aspects of innovations and viruses. Using the following research questions, fundamental theoretical currents and ideas will be introduced to compare the standard features of innovations and viruses.

RQ1. How can the reproduction number (R_0) derived from the basic SIR model be used to evaluate the effectiveness of different intervention strategies in controlling the spread of infectious diseases?

RQ2. What are the key factors determining the infectivity of viruses, and how do these factors affect the overall dynamics of transmission among human populations?

RQ3. What are the key factors influencing the dynamics of virus transmission?

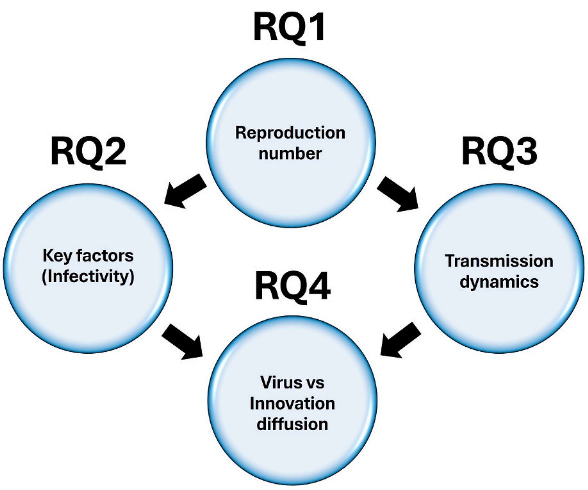

Fig. 1. Interdependencies among the research questions.

RQ4. What are the similarities and differences between the diffusion of innovation and the spread of viruses, and how can this knowledge be used to improve innovation adoption strategies?

The interdependencies among the research questions (Fig. 1) are structured to reflect insights derived from integrating the SIR model with innovation diffusion theory, particularly in the context of nanotechnological innovations.

RQ1, which focuses on the R_0 and its use in evaluating intervention strategies, forms the foundation of this framework. It can provide the quantitative basis for understanding propagation dynamics, including key parameters such as transmission and recovery rates. Building on this, RQ2 explores the factors determining infectivity, linking directly to the variables that influence R_0 in the SIR model. This relationship emphasizes how specific characteristics of viruses and innovations affect their spread.

Similarly, RQ3 delves into the broader transmission dynamics by examining how changes in the SIR groups shape propagation patterns. This provides a nuanced understanding of the temporal dynamics of diffusion.

Finally, RQ4 integrates the findings from the previous research questions to draw parallels between the spread of viruses and the diffusion of innovations. It highlights how the SIR model, originally developed for epidemiology, can be adapted to analyze the diffusion of technological innovations like nanotechnology.

2. Methodology

This paper uses the integrative review method to examine the existing literature on the use of the SIR model in innovation. The integrative review method was selected based on its ability to go beyond a mere literature review. Using this tool, the available literature on a given topic can be merged to create new theoretical frameworks that bring new insights to the issue [5–7]. The integrative review is appropriate for cases where existing research is dispersed across several areas [8]. This particular case concerns the application of the SIR model in the field of technological innovation, which is not well covered in terms of literature. This paper is based on four areas of literature reviewed: the theory of diffusion of innovation, the SIR model, viral diffusion, and literature linking the SIR model and diffusion of innovation.

2.1. Study selection

In exploring the intersection between innovation diffusion and epidemiological modeling, this study identifies a set of key terms designed to bridge these two fields. By employing descriptive analysis from scientific databases, relevant literature was meticulously selected to ensure alignment with the research objectives. The primary focus rests on utilizing the SIR (Susceptible-Infected-Recovered) model to draw parallels between the spread of innovations and viral behaviors underpinned by deductive thematic analysis. Keywords and prompts were determined based on the main objective of the article and the research questions. The research keywords were also chosen based on the intention to connect the diffusion of innovations with the epidemiological model of SIR. These terms were applied in the following generators: Web of Science, Elicit, and Scite. The selection of databases was based on their relevance within the research community. The search was performed manually, and relevance to the aim and research was selected as the main criteria for study inclusion. Duplicate documents were excluded.

Deductive thematic analysis was chosen to identify similarities in the propagation between innovations and viruses, which can be used to reveal the shortcomings of theories compared to real-world processes. Similarly, analogies in behavioral patterns can be identified, which, based on a collection and synthesis of existing theories, provide insights into the underlying causes, triggers, or conditions that lead to the same behavior [6,9–11].

The identification of analogous properties can serve as an additional argument for using the SIR model in the diffusion of innovation, where it has the potential to complement the shortcomings of Rogers' theory and Bass model. The shortcomings of diffusion theories have been critically analysed by individual authors considering the complexities of innovation and environmental issues. The paper is based on the assumption that each innovation diffuses based on its unique characteristics while being subject to its environment [12]. From this perspective, the characteristics of viruses and the attributes that affect their diffusion were examined.

Due to the different characteristics of each innovation, the field of nanotechnology was chosen as it is interdisciplinary and meets the prerequisite of a horizontal technology that can spread across disciplines. This characteristic tends to create new innovations that spread at different speeds and are often 'contagious' to other susceptible groups, thus fulfilling the similarities with the mutation of a virus.

2.2. Conceptual frameworks

The conceptual framework method was chosen based on its ability to introduce readers to key concepts and their relationship to the research. Conceptual frameworks enable the definition of key concepts and identify gaps in the literature, and by linking empirical findings, theories and models extend [13,14]. Based on a literature search containing each theory and a review of articles linking the SIR model to innovation, it is possible to identify overlapping theoretical frameworks. The SIR model is selected from the position of a basic epidemiological tool used to predict the spread of viruses and evaluate external interventions. The Bass model and Rogers theory are in turn selected based on their position in mainstream theories of the spread of innovation.

The literature search was conducted in December 2024, using the following aggregators: Web of Science, Elicit and Scite. In the field of SIR model associated with innovation, the query contained the following keywords: (model OR modelling) AND (spread OR diffusion) AND (innovation) AND ("SIR model" OR "Susceptible-Infected-Recovered"). The prompt used in the Elicite and Scite aggregators was chosen as follows: "What are the applications of the SIR model in modelling the diffusion of innovation?" From the 37 publications generated, the 11 most relevant papers were selected and summarized in Table (1) below.

The literature review addressing the issue of viral spread was conducted using the Web of Science database and the aggregators Scite and Elicite. The literature review was conducted with the aim of comprehensively investigating the factors influencing viral spread and their impact on the dynamics of transmission in the human population. The process began with a literature search and manual reference checks, which, after removing duplicates, yielded a total of 12,405 articles. The search strategy used a created query containing the keywords: (virus OR disease) AND (spread OR diffusion) AND (attributes OR factors) AND (impact OR effect).

Two targeted calls were used in parallel to further guide the survey: the first call asked: "What are the main factors influencing viral infectivity, and how do these factors affect the overall dynamics of transmission in the human population?" The second call sought to clarify: "What are the critical determinants influencing the dynamics of viral transmission?" These prompts helped narrow the focus of the review and ensure that the selected literature addressed the complexity of viral transmission.

After initial screening, six duplicate articles were removed from the 62 articles from Elicite and Scite, and the 50 articles with the highest frequency of keywords were selected from the WoS database. Ultimately, 106 articles were selected for a detailed full-text review. During this phase, a content assessment was conducted to determine the relevance and quality of the findings presented. As a result, 26 articles were identified as meeting the inclusion criteria and providing valuable insights related to research questions RQ2 and RQ3. The integrative review was reported following the PRISMA guidelines (Fig. 2).

Table 1
The major issue in the literature on the fusion of innovation diffusion and the SIR model.

Author name	Main issues addressed
Zhou (2018) [65]	Design of a model for investigating the propagation of dynamic phenomena on complex networks based on the SIR model. Computations suggest that the proposed model is a feasible economic method for controlled dynamics propagation and supports potential applications in the form of diffusion of innovation or marketing communication.
Mandl (2023) [66]	The article deals with the criticism of Bass model, which, according to Mandel, does not address the situation where not all potential adopters actually adopt the innovation. The SIR model is proposed to solve the problem. The paper mainly deals with the impact of group size, which affects the level of adoption of a given information. The level of concentration of the susceptible and the size of the group in which the potential adopters are located are important for the diffusion of the innovation.
Ota and Mizutani, (2020) [67]	Design of a model that combines the SIR model with Rogers diffusion theory. Ota and Mizutani assume that there is a time lag of innovation adoption based on diffusion theory and, therefore, include five Rogers groups in the SIR model that adopt innovations at different time horizons.
Wang et al., (2017) [68]	Wang discusses the impact of network structure on the diffusion of information and innovation. In this paper, a network consisting of 50 nodes and 141 links was tested using the SIR model. Several times, a different node was chosen as the initial source of infection, which led to a different infection rate. Wang argues that in addition to the structure of the network, the characteristics of individual nodes also affect the spread.
Evangelatos and Carayannis, (2014) [69]	In their article Innovation Diffusion, Evangelatos and Carayannis address the issue of innovation diffusion from an epidemiological perspective. Their description of innovation diffusion is one of the least modified in terms of the epidemiological model. A patent is viewed as a virus that is transmitted by citations.
Carayannis and Evangelatos, (2014) [64]	In another article, firms are described as susceptible hosts and knowledge as a virus. Within the SIR model, "S" shows hosts, "I" shows infected hosts that cite the patent, and "R" reflects firms that have failed and are no longer in the group. In the SIR model, the growth rate of infected firms is analogous to the strength of infection, which represents how quickly susceptible firms acquire new knowledge.
Soheili et al., (2017) [70]	This paper explores the application of the SIR model to the dissemination of ideas in the science and technology communities. Based on Goffman and Nevil's theory, it highlights the parallels between disease transmission and the diffusion of scientific concepts and technological advances. Mathematical models are used to determine the feasibility of the SIR model in the context of innovation diffusion. These suggest that the SIR model can be an effective tool for understanding the diffusion of innovation.
Iacopini, (2021) [71]	Iacopini focuses on the development of network models that address the dynamics of idea adoption. He relates the SIR model to the Barabási-Albert graph, which deals with propagation in terms of neighboring nodes. Iacopini also draws on empirical observations where the introduction of novelties (innovations) is positively correlated with the emergence of others.
Jiang and Luo, (2004) [72]	Jiang focuses on how technology diffusion in enterprise clusters can be likened to the spread of infectious diseases, employing the SIR model to analyze this process. The study investigates the impact of alternative technologies and the dynamics between competing technologies on diffusion. It concludes that technology diffusion is sustainable when the total diffusion rates are higher than the combined rates of alternative technology acceptance and enterprise bankruptcy, with competing technologies' proportions changing exponentially based on their diffusion success rates.
Li et al., (2020) [73]	Lie identifies influential spreaders in complex networks to manage the spread of diseases, information, innovations, and behaviors. The research presents the adaptive weighted link model (AWLM), a semi-local-information-based algorithm that efficiently classifies links among second-order neighbors and adapts weights based on local topology. Empirical analyses using the Susceptible-Infected-Recovered (SIR) model show that the AWLM consistently outperforms established methods, showcasing its effectiveness in understanding innovations and disease dynamics.
Yang et al., (2020) [74]	Yang abstracts real-world systems into complex networks to promote the spread of information, such as commercial messages, vaccination guidance, innovations, and political movements. The study presents an edge-based approach that quantifies the potential influence of adding latent edges to enhance information spreading dynamics, utilizing the Susceptible-Infected-Recovered (SIR) model. Numerical simulations demonstrate that this strategy outperforms several static methods, providing insights into optimizing network structures for more effective information dissemination and inspiring further research into edge-based promotional strategies for various spreading dynamics.

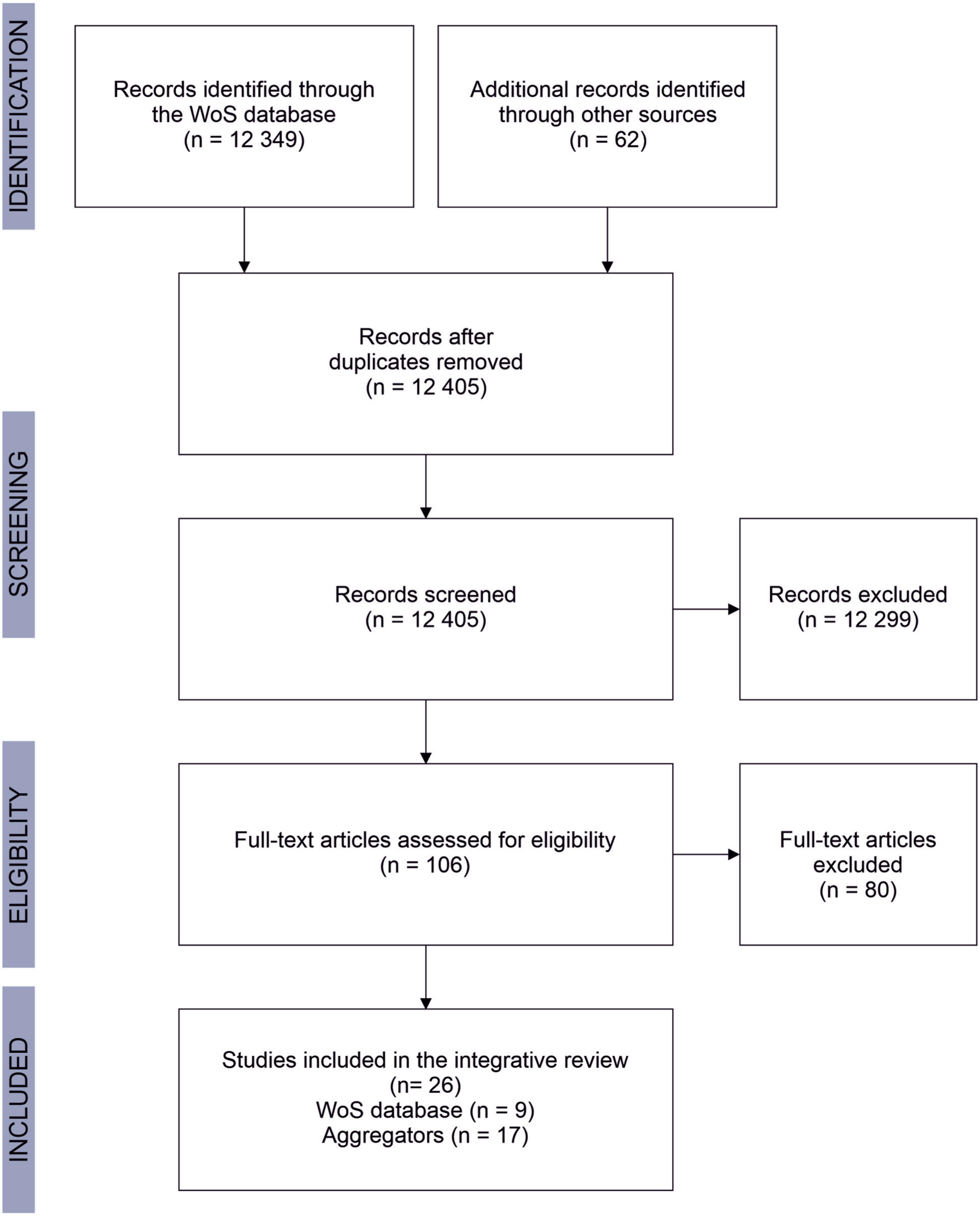

Fig. 2. Prisma diagram demonstrating search strategy.

3. Results

This chapter outlines the application of the SIR model in the field of innovation and emphasizes the significance of the reproduction number R_0. It examines factors that influence the spread of viruses, including the virus's infectivity, the susceptibility of individuals to infection, and the environmental conditions that facilitate viral transmission. The chapter then compares the spread of viruses with the dissemination of innovations, demonstrating that both processes share similarities and can be modeled using analogous frameworks. Based on this comparison, the integration of the SIR model into the study of innovation diffusion is explored, highlighting its potential to predict how innovations spread in a manner similar to infectious diseases. Various studies that illustrate the adaptability of the SIR model in innovation contexts are reviewed, and key factors influencing the spread of innovations are discussed. Additionally, the chapter examines nanotechnology as an example of an innovation that exhibits characteristics analogous to viral spread. The discussion further addresses how the regulatory environment, technological maturity, and prevailing trends affect the speed and manner of innovation adoption. The selected chapters are framed by specific research questions that provide a structured approach to exploring the topics discussed. Each chapter addresses these questions, offering insights and findings contributing to a deeper understanding of the researched issue.

RQ1. How can the reproduction number R_0 derived from the basic SIR model be used to evaluate the effectiveness of different intervention strategies in controlling the spread of infectious diseases?

3.1. SIR model

The SIR model was first introduced by Kermack and McKendrick in 1927 as a mathematical model with the ability to predict the spread of disease in a population [1]. It is a deterministic model formulated using differential equations, which in its basic version is in a setting of three different groups (compartments). The compartments are referred to by the phase the groups represent [15].

In the model, individuals move between these compartments based on their interactions and the aggressiveness of the virus. Individuals can thus become infected through contact with an infectious group at a certain transmission rate. If an individual becomes infected, the individual moves from the susceptible group to the infectious group until either recovery or death. In the event of recovery, he moves from the infectious group "I" to the recovered group "R", which is immune to the virus and cannot become infected again [16].

The basic SIR model assumes that the population is free of any spatial, social, or demographic heterogeneity. At the same time, the total population size remains constant throughout the epidemic. All individuals in the population have the same level of susceptibility. Infection occurs through contact between individuals. Once recovered, lifelong immunity is acquired that will not allow reinfection [17].

The SIR model can be extended to include population heterogeneity and assess the effects of individual interventions on disease spread. By integrating factors such as age, location, and behavior within a population, researchers can adapt the model to more accurately reflect the different characteristics present in the real world. This improved model can then be used to simulate different intervention strategies, allowing policymakers and health institutions to evaluate the potential impact of specific interventions [18]. The SIR model provides a valuable framework for understanding epidemic dynamics and planning interventions. However, its results must be interpreted with caution, given the simplifications and assumptions inherent in mathematical modelling approaches [19].

Although it is a deterministic model, which is simpler than stochastic models or simulation models, if it is difficult to collect good quality and detailed data, the SIR model is a preferable alternative [20]. The model is based on a system of nonlinear differential equations that describe the rate of change of each covariate over time. These equations take into account parameters such as transmission rate, recovery rate, and initial population size [21]. The following mathematical representation of the SIR model reflects the individual changes between the covariates.

Change in the number of susceptibles (S):

$$\frac{dS}{dt} = -\beta \bullet I \bullet \mathrm{S}$$

, where "•" represents multiplication.

Change in the number of infected (I):

$$\frac{dI}{dt} = \beta \bullet I \bullet \mathrm{S} - \gamma \bullet I = I \bullet (\beta \bullet \mathrm{S} - \gamma)$$

Change in the number of recoveries (R):

$$\frac{dR}{dt} = \gamma \bullet I$$

Reproduction number R_0:

$$\mathrm{R}_0 = \frac{\beta}{\gamma}$$

Explanations:

R Recovered.

R_0 Reproduction number.

I Infected/infected.

S Contagious (susceptible)

t time (T)

β number of contacts (infectious with infected) per day (average number of people who come into close contact with a given infected individual per day) [T-1]

γ inverse of mean duration of illness [T-1] [20].

In general, it is difficult to estimate β contact rates, which depend on specific diseases and social factors. On the other hand, β can be inferred from changes in individual interventions, such as wearing personal protective equipment, limiting contact, or complete quarantine [22].

An important variable that emerges from the SIR model is contained in the reproduction number R_0. In epidemiology, this is a key parameter that helps to understand disease transmissibility and assess potential outbreaks [23]. In the context of the SIR model, R_0 depends on factors such as virus infectivity, infectivity time, and contact rate β. The reproduction number can serve as an assessment tool over time for the various interventions that have been adopted to contain the infection [24].

The answer to the research question RQ1 is as follows: The reproduction number R_0 derived from the basic SIR model serves as a critical parameter to evaluate different intervention strategies by assessing their impact on disease transmissibility and potential outbreak control. By adapting the model to include factors like infectivity, contact rate, and intervention measures such as quarantine or protective equipment, R_0 helps policymakers and health institutions gauge the effectiveness of their strategies over time.

RQ2. What are the key factors determining the infectivity of viruses, and how do these factors affect the overall dynamics of transmission among human populations?

3.1.1. *Properties of viruses*

Viruses exhibit a remarkable diversity of characteristics, with each viral species presenting unique characteristics that reflect a specific threat to a group of susceptible [25]. One of the most significant features of viruses is their ability to undergo genetic mutations, leading to the emergence of new variants that may exhibit increased virulence and transmissibility [26]. This evolutionary adaptability of viruses contributes to the complexity of viral dynamics and the challenges associated with controlling their spread [27].

The process of viral mutation, driven by errors in genetic recombination and replication, can result in the development of variants with altered biological properties [28]. Thus, new variants may exhibit different virulence [29].

In addition to genetic variability, viruses also exhibit different levels of infectivity, which are defined by their ability to establish infection in host cells and replicate in the host organism [30]. Factors affecting viral infectivity include the efficiency of viral attachment and entry into host cells, the rate of replication, and the host immune response [31]. These characteristics contribute to the varying transmission potential of viruses, with some showing high rates of human-to-human spread while others exhibit more limited transmission dynamics [32]. Understanding the complex interplay between viral properties, mutation dynamics, infectivity levels, and intervention responses is essential in designing strategies leading to the prevention and control of viral infections [33].

The answer to the research question RQ2 is as follows: The key factors determining the infectivity of viruses include their ability to undergo genetic mutations, which leads to new variants with potentially increased virulence and transmissibility, and their efficiency in attaching to and entering host cells. Additionally, the rate of viral replication and the host's immune response significantly influence transmission dynamics among human populations.

RQ3. What are the key factors influencing the dynamics of virus transmission?

3.1.2. *Influence of the environment on the spread of the virus*

A key factor influencing the spread of the virus is the environment, which plays a crucial role in the dynamics of transmission [34]. Different environmental characteristics such as population density, social interactions, health infrastructure, climatic conditions, and hygiene practices can significantly influence the spread of viruses. Population density and mobility patterns can facilitate rapid transmission, especially in crowded and highly connected environments where individuals are in close contact with others [35]. Social interactions such as gatherings, events, and public transportation serve as potential avenues for viral spread, highlighting the importance of physical distance measures in mitigating transmission rates [36,37]. The healthcare infrastructure in the region is also important. Access to health services, diagnostic tests, and medical facilities can affect the detection, containment, and treatment of infected individuals, influencing the overall trajectory of an outbreak [38]. Climatic conditions, including temperature, humidity, and seasonal changes, can affect the survival and transmission of certain viruses. For example, some respiratory viruses show increased stability in cold and dry environments, potentially leading to higher transmission rates during the winter months [39]. Individual levels of immunity play a crucial role in determining susceptibility to viral infections, subsequently influencing the spread of the virus in the population. Immunity can be acquired by previous exposure to the virus (natural immunity) or by vaccination (acquired immunity). Individuals with a robust immune response are less likely to become infected or develop severe disease, reducing their potential to transmit the virus to others [40–42]. Conversely, individuals with weakened immune systems, such as the elderly, immunocompromised individuals, or those with underlying health conditions, are at higher risk of infection and serious disease outcomes. Such vulnerable populations can serve as reservoirs for viral transmission, underscoring the importance of vaccination efforts and targeted public health interventions to protect those at increased risk [43]. In short, the interplay between environmental factors, individual immunity, and viral characteristics shapes the spread of the virus within a community. Understanding these multifaceted dynamics is essential in implementing effective public health strategies to control outbreaks, protect vulnerable populations, and mitigate the impact of infectious diseases.

The answer to the research question RQ3 is as follows: Key factors influencing the dynamics of viral transmission include not only the infectivity of the virus itself but also environmental characteristics such as population density, social interactions, health infrastructure, and climatic conditions, all of which significantly affect the spread of viruses. Additionally, individual immunity—whether acquired through natural exposure or vaccination—plays a crucial role in determining susceptibility to infections, thereby influencing the overall dynamics of transmission within the population. In summary, three fundamental parameters affect the spread of viruses: the characteristics of the virus, the environmental context, and the immunity of susceptible individuals.

RQ4. What are the similarities and differences between the diffusion of innovation and the spread of viruses, and how can this knowledge be used to improve innovation adoption strategies?

3.2. *Diffusion of innovation*

Innovation diffusion is a complex process that defines the spread of new ideas, technologies, or products within companies or organizations. According to Schumpeter's theory, diffusion of innovation is a process of cumulative increase in the number of imitators who implement innovations after the innovator in the expectation of more stable and higher profits [44,45]. Adoption of innovations is influenced by several key factors, such as compatibility, relative advantage or the complexity of the innovation itself. 'Relative advantage' refers to the perceived superiority of innovation over existing alternatives, while 'compatibility' highlights the alignment of existing innovations, needs, and practices [46]. Compatibility is one of the most important variables that is fundamentally influenced by society's trust in specific innovations. Other variables include complexity, which is related to the understanding and implementation of innovations and is linked to the ability to test the innovation before its actual adoption [47,48].

The diffusion of innovation has attracted many scientists to combine theories, concepts, and models from the natural and social sciences. Diffusion of innovation uses mathematical models to describe and predict the temporal increase of an innovation entering a social system [49]. Rogers himself pointed out that research in this area grew out of a series of independent studies linking seemingly separate sciences [50]. Modeling of dynamic processes was explored by Vespignani, who pointed out the similarities in the framework of information diffusion and epidemics. Processes involving the spread of viruses or the growth of organisms are similar to those operating in a social system [51] in other words, this means that information in the form of innovation spreads on a similar basis to the virus itself.

The basic theories that deal with the diffusion of innovation include the Bass model, which addresses the diffusion of innovation from a quantitative perspective, and Rogers' diffusion theory, which uses a qualitative perspective. It is Rogers' theory that has become very widespread and this is mainly due to questions from technologists who wanted to understand why some innovations diffused more widely and more quickly [52].

3.2.1. *Rogers theory*

Rogers recognizes five categories of adopters in society in terms of their ability to adopt particular innovations (Fig. 3). Based on empirical research, he has determined that the first category is the group of innovators, who make up about 2.5 % and are risk-takers. The second group is the early adopters, who comprise 13.5 % and represent the tipping point in the diffusion of innovation. The third group is the early majority, which is made up of 34 % cautious adopters who move the innovation into the mainstream. The fourth group, labeled the late majority, is also represented by 34 % and is made up of adopters who do not like change. The last group includes the late adopters, 16 % who are often resistant to communication channels and adopt innovation as necessary [12].

Rogers perceives the attributes affecting diffusion potential in five basic points. The first is relative advantage, which reflects an innovation with better characteristics than the original state. The second point is compatibility, capturing the degree to which the innovation is accepted based on the current state and experience. The third point is the degree of complexity with which the innovation is understood and used. The fourth point is the extent to which the innovation can be experimented and tested on a limited basis. The fifth point is concerned with observing the extent to which the results of the innovation are visible to others [50].

Based on Rogers' diffusion theory, a critical analysis was conducted to identify specific assumptions and behaviors within the model that may differ from real-world observations in certain contexts. This check led to the identification of various characteristics of

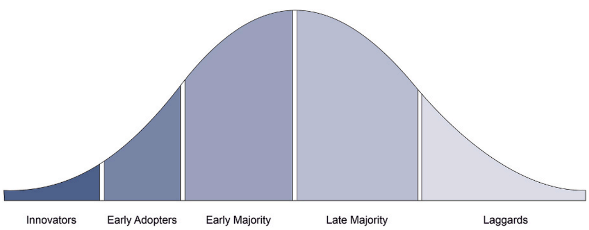

Fig. 3. Rogers innovation adoption curve.

the model that may be considered as shortcomings [53–56].

As with Bass, Rogers overlooks the diversity (heterogeneity) of individual adopters that fundamentally influences the adoption of a given innovation [12,53]. Rogers' theory may not account for the challenges posed by the regulatory environment, as it primarily focuses on how innovations diffuse through social systems as well as the factors that influence the decisions of individuals and organizations. While the theory is dynamic in capturing the adoption process over time, it does not address large-scale changes in the external environment and their direct impact on the diffusion of innovation [54–56].

3.2.2. Bass model

The Bass diffusion model, developed by Frank Bass in the 1960s, is a mathematical model used to predict the adoption and diffusion of new products or innovations in the marketplace [57]. In many ways, it also resembles Rogers' diffusion theory. Bass model is based on the assumption that there are two types of adopters: innovators and imitators [53]. Innovators include subjects who have a higher propensity to take risks and want to try new things. Imitators, on the other hand, are adopters with a tendency to adopt already tested innovations and are most influenced by the experience of others. The Bass model uses differential equations to describe how the number of adopters increases [58]. Within this, the influence of both innovators and imitators is taken into account. The model predicts that adoption follows a cumulative curve that starts slowly and accelerates with a higher number of adopters. Eventually, due to market saturation, the rate of adoption slows down again [53,57,59]. This model is relatively complex and was modified by Eryarsoy and used to predict the spread of the COVID-19 pandemic [60].

The Bass model assumes that the adoption curve follows an S-shape, which is not necessarily the case for all innovations. In fact, adoption patterns can vary significantly based on the nature of a particular innovation [61]. Thus, the Bass model may not capture all aspects of technological adoption, especially in complex or rapidly changing technological environments. External factors negatively affecting the model may include regulatory changes or other unexpected events [62]. Bass model assumes a homogeneous population with uniform adoption behavior and overlooks the diversity of individual characteristics that can influence adoption patterns. There is limited predictive power in the Bass model. This is where the weakness of the generalization approach in predicting the diffusion of innovations occurs [63].

3.3. Using the SIR model for innovation

The use of the SIR model in the field of innovation diffusion is a relatively new issue that has historically received little attention in the literature. Nevertheless, there are several papers that have started to form a theoretical framework for potential use in the field of innovation over the last decade. These few articles highlight the benefits of the SIR model and attempt to find an analogy in the context of innovation diffusion. Table 1 briefly summarizes the contributions of each article linking the SIR model to innovation and viewing it as an applicable tool for diffusion dynamics.

From the above literature search, it is clear that the SIR model can be a useful and relevant tool in the field of dynamic diffusion of innovation. A basic description of how to use the SIR model in the field of innovation was first outlined by Carayannis and Evangelatos in 2014, who specified the different groups and established the model's conditions. The main focus of the research was the diffusion of patent citations reflecting the diffusion of innovation, where (S) is the group of firms that have not yet used the patent, and (I) shows the entities that have cited the patent. By analogy, firms (R) should reflect the group that can no longer be infected by the patent and therefore has disappeared or is no longer in the original industry [64].

Carayannis and Evangelatos are mainly concerned with the abbreviated SI model, where authors do not elaborate in detail on the group (R) or the transfer from the compartment (I) itself. As already mentioned, the authors acknowledge that it is also possible to use the SIR model, where (R) will reflect firms that are no longer in the same group or, for example, have disappeared due to insolvency [69].

The SI model can be used under the following conditions [64].

1. The population remains constant, i.e. the number of firms that disappear equals the number of firms that enter the industry.
2. The population size (N) is large enough to allow the deterministic model to be used and the error due to the approximation to be acceptable in percentage terms.
3. There are two groups (S) and (I), where (S) shows firms that have not yet cited the patent but are inclined to do so and (I) reflects firms that have already cited the patent and are also contagious to others. Once infected, a firm also remains infected forever because it cannot forget the knowledge it has acquired, despite its decision not to use the knowledge.
4. Interactions between individuals are assumed to be random.
5. Stability of interaction rates over time is assumed.
6. (N) denotes the total number of firms evaluated, such as the number of firms in the cluster. $I(t)$ represents the number of firms that cited the patent at time t, and $S(t)$ the number of firms that are citation-sensitive. Thus, the relationship $S + I = N$ holds based on this information.

The combination of Rogers' theory and the SIR model may provide an interesting tool for analysing the diffusion of innovations [67]. In many cases, an innovation may behave similarly to a virus in diffusion. Viruses mutate to adapt to their environment and move more efficiently from host to host. Mutation can help a virus acquire characteristics that allow it to reproduce faster or be more resistant [75]. Similarly, the emergence and spread of one innovation can lead to the emergence and subsequent spread of another innovation [71,76]. In many cases, this is the case when two complementary technologies are combined, which may, moreover, lead to the emergence of a radical innovation [4,76,77].

3.3.1. Factors influencing the diffusion of innovation

One argument for using the SIR model in the field of technological innovation is contained in the similarity of the phenomena affecting the diffusion of innovations and viruses. Just as the spread of viruses is affected by the environment and the characteristics of the virus itself, so too are innovations subject to the environment and their own ability to spread. Based on Rogers' assertion that diffusion depends on the characteristics of each innovation, the authors chose a specific technology.

For the analogical comparison with viruses, an innovation from the field of nanotechnology is chosen, which has specific properties that may resemble a virus in many respects. Nanotechnology holds promise through innovation in many areas [78]. Nanoscale has specific capabilities where high specific surface area and volume is present which modulates the physical, chemical and biological properties [3]. It is due to these properties that nanotechnology is referred to as a radical innovation [4,79] that tend to fuse with available technology and generate disruptive applications.

Nanotechnology has the potential to transform various industries and impact different market segments due to the physical properties of the dimension. It is also one of the so-called horizontal technologies. This means that they tend to "mutate" into different fields ranging from electronics, IT, energy and healthcare. Within nanotechnologies, there is the potential for the emergence of new technologies hitherto unseen [80–82].

How nanotechnology is "mutating" can be illustrated by the example of nanofibre membranes, which are commonly used for filtration applications due to their high specific surface area and low pressure gradient [83]. In the case of transferring the same technology to another entity in the form of a company or research team, the nanofibrous membrane used for filtration becomes a substitute for skin tissue [84]. In other words, a new technology has emerged that is likely to be characterized by a different "infecity" but at the same time subject to the same foundation.

Innovation generally spreads rapidly in an environment with weak regulatory policy. As with viruses, a high concentration of 'susceptibles' in the form of innovative firms and development centres has a positive impact on diffusion [85,86]. Increased rates of innovation diffusion are typical of clusters, for example, which increase the degree of interaction and facilitate the exchange of ideas [87]. The innovation infrastructure comprising individual centres and hubs is intended to stimulate the diffusion of innovations and facilitate faster implementation [88,89]. The success of innovation adoption is positively influenced by the technological maturity of individual firms, with more mature firms being among the more 'likely' to adopt an innovation [90].

Another aspect influencing the diffusion of innovation is technological trends, which are similar to the seasonal changes characteristic of viral spread. New technologies can influence the diffusion of innovations by shaping consumer preferences. Innovations that exploit or are in line with prevailing technological trends are more likely to take off [91]. This is also the case for nanofibres in respirators, which have only been allowed to spread globally by the pandemic [92].

The pandemic crisis COVID-19 was also an example of government policy that did not always support the spread of nanotechnology innovations. The study identified specific interventions that worsened the competitive environment by recognizing non-equivalent standards for imported respirators. Some governments excluded small businesses from tenders for the purchase of protective equipment on the basis of low production, which prevented a large number of nanotechnology companies from competing. At some point, most governments also issued restrictive measures on the export of respirators, which prevented nanotechnology companies from expanding abroad. At the same time, bulk purchases of lower-quality respirators from abroad reduced prices in individual markets and consequently reduced the profitability of higher-quality nanofiber respirators [93].

Within the framework of individual countries' innovation policies, if an increased diffusion of a specific technology is identified, such policies could be adjusted to address this problem. The aim would be to accelerate diffusion in that area and improve the overall innovation environment. For example, including nanotechnology companies in state tenders could increase the profitability of the sector and promote further diffusion of innovations in this field.

The answer to the research question RQ4 is as follows: The similarities between the diffusion of innovation and the spread of viruses lie in their comparable processes and frameworks, as both involve a dynamic increase in adoption among individuals influenced by various factors. Factors affecting the diffusion of innovation include relative advantage, compatibility with existing practices, and complexity, which parallels how viruses spread based on characteristics like infectivity and environmental conditions. Moreover, just as the spread of a virus can lead to new variants, the emergence of one innovation can catalyze the development of additional innovations, particularly when complementary technologies are combined. This understanding can be leveraged to enhance innovation adoption strategies by fostering an environment conducive to interaction and trust, as well as addressing regulatory challenges. Ultimately, recognizing the parallels between these two domains can inform strategies to optimize the spread of innovative ideas and technologies.

4. Discussion

The research comes with a summary of the different characteristics affecting the spread of technological innovations and viruses. Viruses, like innovations, exhibit a remarkable diversity of characteristics, with each viral species presenting unique features that reflect a specific threat to a susceptible group. It is reasonable to point out certain similarities that viruses and innovations share in their propagation. The commonalities make it tempting to view information disseminated by viruses or innovations through a similar lens. By crossing the barrier between viral and innovation, the same tools and models could be applied to both fields. The case for linking epidemiology to innovation diffusion theory is not only made by the current literature on linking the SIR model to innovation but also by the use of the Bass model by Eryarsoy (2021) during the COVID-19 pandemic.

In this context, nanotechnological innovations are a very interesting subject that faces environmental barriers and at the same time has the ability to penetrate into different areas. Based on current models, it is difficult to quantify the impact of the adoption of regulatory frameworks on the diffusion of nanotechnology. However, the SIR model, which was widely used during the pandemic, can incorporate this fact. The results come with a summary of the current literature that points to the SIR model's connection to innovation, while also coming up with its own interpretation of how to use the model. The following table (Table 2) summarizes the characteristics and influences of the environment on the spread of innovations and viruses sorted by similarity features.

Just as viruses are subject to external factors and their characteristics in their propagation, innovation is subject to similar phenomena. Viruses can mutate when replicating in a new organism, creating an error that can affect the properties of the new mutation. Similarly, the adoption of nanotechnology by a new firm can be seen as a new experience that can transform the technology into a different product and introduce it into new markets. An example can be demonstrated with a nanofibre membrane commonly used for filtration purposes. A company manufacturing a softening machine has 'infected' two companies by selling the device. Still, one uses the material for filtration, and the other has transformed it into a material used to replace skin tissue. The same technology has thus generated two different mutations that spread at different rates and are infectious to different susceptible groups.

The viruses' and innovations' spreads are then influenced by the environment, where higher concentrations of susceptibles are positively correlated with the rate and extent of infection. In both cases, this is also conditioned by the level of interaction that facilitates transmission. Government interventions have a negative impact on the spread of viruses. These can be perceived as regulations that either slow down the spread or stop it altogether. This was evident during the COVID-19 pandemic, where widespread adoption of personal protective equipment, including nanotechnology-enhanced materials, was significantly influenced by regulatory guidelines and government mandates. Another aspect that affects the success of adoption is the season, which for viruses is contained in seasonal changes, and for technologies, the season can be seen in trends. The propensity to adopt an innovation is shown by the technological maturity of individual firms, which in the world of viruses analogously reflects demographic distribution or other aspects affecting the likelihood of infection.

4.1. Proposal for the application of the SIR model in the field of innovation

Fig. 4 illustrates the fusion of the SIR model in the field of innovation. The fundamental aspects influencing the transition from the susceptible group to the infected group are derived from three factors identified in the literature. The first is the infectibility of the virus or the selected technology. The second aspect that Rogers also discusses in his diffusion theory is susceptibility. This can be understood within the process of adoption by groups with different propensities to adopt an innovation. The last aspect that influences the spread is the environment, which significantly affects both the diffusion of viruses and the diffusion of innovations.

For the application of the SIR model in the field of innovation, the definition of the individual compartments is important, which is partly based on Carayannis and Evangelatos (2014). In our case, the compartment (S) analogically depicts a group of firms that do not possess a given technology but have all the predispositions for its use. The compartment (I) includes firms that have "contracted" and possess the technology in question. The compartment (R) reflects the group that can no longer be infected with the technology, either due to disappearance or transfer to another sector [64]. Group (R) is one of the most controversial displacements that has not received much attention in the current literature. The group must satisfy the condition of being immune to the virus and, at the same time, not

Table 2
The characteristics and effects of the environment on the spread of innovations and viruses.

Factors affecting the spread of viruses	Factors influencing the diffusion of nanotech innovations
Genetic mutations give rise to new variants that may show increased virulence and transmissibility. This evolutionary adaptability of viruses contributes to the complexity of viral dynamics and the problems associated with controlling their spread [26,27,94].	Nanotechnological innovations belong to the so-called horizontal technologies, which have a high propensity to transform [80]. A basic innovation may change its original principle when implemented in a random firm and thus transform into a new technology with different characteristics but also a different set of susceptible [95].
Viruses exhibit different levels of infectivity, defined by their ability to introduce infection into host cells and multiply in the organism [32,96].	According to Rogers, each innovation spreads at different speeds [12]. In other words, it can be stated that it is infectious in different ways. In the case of innovation, this fact can be demonstrated, for example, by the capital intensity, which greatly influences the diffusion [97].
Within the environment, population density influences the spread of viruses, where higher concentrations increase the likelihood of infection [35,98].	As with viruses, a high concentration of "susceptibles" in the form of innovative companies and development centres has a positive impact on diffusion [85].
Social interactions serve as potential avenues for the spread of viruses and highlight the importance of physical distancing measures [37,99].	An environment that is characterized by a higher level of interaction facilitates the exchange of ideas [87].
The health infrastructure in the region is important in terms of interventions to contain the spread of the virus. With the help of diagnostic tests and medical facilities, it can influence the detection of the virus, which can have an indirect impact on the trajectory of the outbreak [38,100].	Innovation, like viruses in general, spreads rapidly in an environment with weak regulatory policy [86]. At the same time, innovations are facilitated by the infrastructure developed to increase interaction and promote diffusion [89].
Climatic conditions, including seasonal changes, can have a major impact on the transmission of certain viruses. Some respiratory viruses show increased stability in cold and dry environments, which increases the transmission rate [39,101].	Technological trends are another aspect influencing the diffusion of innovation. New technologies can influence the diffusion of innovation by shaping consumer preferences. Innovations that exploit or align with prevailing technological trends are more likely to take off [91].
Individual levels of immunity fundamentally affect susceptibility to viral infections and subsequently influence the spread of the virus in the population [40,102].	The success of innovation adoption is positively influenced by the technological maturity of individual firms, with more advanced firms being among the more "prone" to adopt innovation [90].

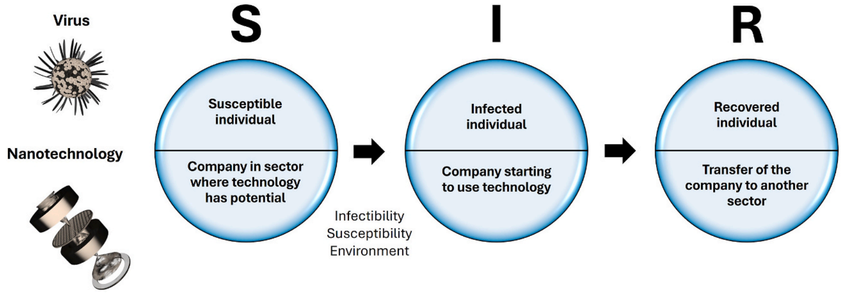

Fig. 4. SIR model diagram in the field of innovation.

infectious to the original susceptible group. Going forward, the SIR model in innovation could be supplemented with a compartment (D) that splits the original compartment (R) into groups of firms (R) that have modified the technology and are in a different industry and a group (D) that contains only firms that have abandoned the technology.

In designing the application of the SIR model to innovation, it is important to base the deductive thematic analysis as much as possible on the process of viral spread. A viral strain reflects a technology that has specific characteristics and moves in a certain environment affecting its diffusion potential. This innovation spreads by means of purchases or self-construction of a specific technology. The diffusion rate depends on the interaction rate β and also on the size of the susceptible group (S) and the size of the infected group (I). This relationship can be captured by a basic formula reflecting the attrition of individuals from the susceptible group.

$$\frac{dS}{dt} = -\beta \bullet I \bullet \mathrm{S}$$

The parameter γ is important to capture the size of the infected group (I) in a situation where firms simultaneously enter a compartment (R) at some point in time. This reflects the number of healing in a given time horizon, which for viruses is represented by the time unit day. For technological innovations, it makes sense to perceive the parameter γ over a much longer time interval. We obtain the number of infected and also infectious subjects by the following equation.

$$\frac{dI}{dt} = \beta \bullet I \bullet \mathrm{S} - \gamma \bullet \mathrm{I}$$

As already mentioned, group (R) contains firms that have been taken out of the original group by technology transformation or complete extinction. Thus, its increment reflects the loss of firms from group (I), whose interaction with group (S) increased the diffusion of innovation. We obtain the change in the number of recoveries using the following equation.

$$\frac{dR}{dt} = \gamma \bullet \mathrm{I}$$

In order to increase the predictive power of the SIR model, it is worth considering adding a complement (D) to the model, which will allow the complement (R) to measure only successful technologies that led, for example, to a patent or a move to a completely different group. The (D) compartment could then report only cases where the implementation of a particular technology was not successful. We obtain the change in the number of unsuccessful implementations using the following equation.

$$\frac{dD}{dt} = \varepsilon \bullet \mathrm{I}$$

$$\frac{dI}{dt} = \beta \bullet I \bullet \mathrm{S} - (\gamma + \varepsilon) \bullet \mathrm{I}$$

In exploring the field of diffusion of innovation theories, both Bass model and Rogers' theory offered important insights into how new ideas and technologies permeate society. However, a closer look reveals inherent limitations within these theories, particularly in their ability to account for the dynamic interactions between adopters and the impact of external interventions. It is in this area that there is a gap that the SIR model could fill, thereby improving our understanding of the diffusion of technological innovation.

A major advantage of the SIR model over Rogers's theory or the Bass model is the ability to measure the impact of environmental changes over time. Based on this capability, it would thus be possible to quantify the impact of the adoption of particular regulations and other interventions in the innovation environment. The SIR model also allows for working with the heterogeneity of the population, which can be divided into multiple homogeneous groups based on similar characteristics.

Based on our findings and information from the existing literature that examines the use of the SIR model in innovation, we can conclude that the SIR model could also measure the post-adoption process of individual firms. However, it would be necessary to split the comparator (R) into two different comparators to satisfy the original condition.

By leveraging the strengths of the SIR model to address specific aspects of innovation diffusion, it is possible to develop a comprehensive theory examining individual interventions and post-adoption behaviour of innovators. Given its ability to model the evolution of innovation adoption rates over time, the SIR model can improve predictive capabilities beyond the curve fitting used in the Bass model or Rogers diffusion theory. Thus, the model has the potential to overcome some of the shortcomings of current theories.

5. Conclusion

This paper conducted an extensive literature review to uncover a list of factors that influence the spread of innovations and viruses. It highlights the shared characteristics between viruses and innovations in their diffusion processes, emphasizing the striking parallels in their propagation dynamics. The paper shows that viruses, like innovations, exhibit a remarkable diversity of characteristics, with each viral species presenting unique features that reflect a specific threat to a susceptible group.

Examining theories of the diffusion of innovation, particularly those formulated by Bass and Rogers, has provided a valuable framework for understanding how innovation diffuses in society. However, as the investigation highlighted, these models reveal inherent limitations when applied to the complex and rapidly evolving innovation environment generating technological progress. This necessitates a shift towards more adaptable and interdisciplinary approaches. From this perspective, the debate has been directed towards a critical analysis of traditional models in the field of innovation diffusion, where the SIR model is proposed as a new alternative in addressing gaps in the current literature.

Based on a conceptual framework that integrates diffusion of innovation theories (such as Rogers diffusion theory) with the epidemiological SIR model, the paper identifies commonalities between the spread of viruses and the spread of technological innovation, with a focus on nanotechnology. This interdisciplinary comparison reinforces the argument for integrating the SIR model into the study of technological innovation diffusion. Due to its interdisciplinarity, nanotechnology can take a leading position in many fields. Therefore, it is important to have a model that can outline the impact of the adoption of regulatory frameworks that affect the application side of nanotechnology and other interventions in the innovation environment.

The research summarizes the strengths of the SIR model, particularly its ability to handle propagation dynamics. The model can capture temporal changes as subjects move between states over time. Its capacity to simulate intervention scenarios and evaluate their effectiveness makes it highly relevant for policymaking and strategic planning. The model can integrate social heterogeneity in population distribution based on common interaction patterns. Advanced modifications of the model allow the integration of network theory and can account for uneven connections and the influence of nodes with a high number of contacts. Overall, the SIR model is a valuable tool for analyzing the diffusion of innovations in the context of a diverse society subject to external influences.

The paper summarizes the main ideas of the current theoretical framework linking the SIR model to innovation and adds an argument for its use. The literature examining the SIR model in the context of innovation diffusion has underlined the importance of social network structures and the properties of individual nodes. The paper contributes to the debate on the potential of the epidemiological model to improve our understanding of innovation diffusion. The paper contributes to the debate on the potential of the epidemiological model to improve our understanding of innovation diffusion. By drawing parallels between the spread of viruses and technological innovation, a further argument is made to eliminate the barriers that stand against interdisciplinary exploitation. The properties of the SIR model can provide a valuable framework for understanding the dynamics of nanotechnological innovation diffusion.

The need for future empirical research to validate the SIR-based model is essential. Potential avenues for empirical validation include detailed case studies of nanotechnology adoption in industries such as healthcare, electronics, or environmental applications, which would help contextualize the model's application. Additionally, surveys targeting key stakeholders, including researchers, industry professionals, and early adopters of nanotechnologies, could gather data on adoption rates, barriers, and influencing factors such as peer effects or perceived benefits. Longitudinal data analysis offers another avenue by tracking the adoption patterns of specific nanotechnologies over time across various regions or sectors. This would enable researchers to validate the model's predictive capabilities using both contemporary and historical data.

In the future, the integration of the SIR model promises a more sensitive understanding of individual interventions in the innovation environment. Its interdisciplinary potential and adaptability position it as a critical tool for advancing the study of innovation diffusion in a rapidly changing technological landscape.

CRediT authorship contribution statement

David Svoboda: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Ondřej Havelka:** Writing – review & editing, Supervision, Methodology, Investigation, Formal analysis. **Julie Holendov:** Writing – review & editing, Methodology. **Jiří Kraft:** Supervision.

Availability of data and materials

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