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Mathematical Model of the Impact of Social Media on Technological Innovation Diffusion

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Abstract: -

Online reviews provide consumers with rich information that may reduce their uncertainty regarding purchases. As such, these reviews have a significant influence on product sales. In this paper we discuss a mathematical model which represents the process of diffusing technological innovations, laying much emphasis on social media as one of the major variables in the process of diffusion. The model is developed from a differential equation involving three most important parameters: the coefficient of innovation, the coefficient of imitation and another factor describing the impact of social media on prospective adopters. We calibrated this model for historical sales data from Tata Nexon and conducted a sensitivity analysis to determine what effect each parameter had on the adoption curve. This decomposition implies that small changes in coefficients have large consequences for the course of the diffusion of innovation trajectory. The findings suggest that social media are important in raising the speed of the adoption process, through the imitation effect particularly, and amplifying social influence. This study represents an innovation diffusion literature contribution by quantifying the ways to assess the impact of social media on technology adoption. From the findings, it is suggested that a firm can use social media effectively to enhance the diffusion of their innovations.

Keywords: Innovation Diffusion, Bass Diffusion, Sensitive Analysis, Stability Analysis, Social Media, Social Media Driven Growth.

1. Introduction:

Modelling the diffusion of innovation uses a mathematical model to describe and predict the temporal growth of an innovation entering a social system. In this term, innovation covers a board spectrum of phenomena. An innovation may be new products, technologies, services, ideas, or behaviour. For this reason, the study of new product adoption and diffusion behaviour becomes essential in analyzing the growth pattern of a new product. Diffusion of innovation refers to a process to describe, models and replicates the phenomena of sales behavior of the new technology product. Diffusion of innovation is achieved when the potential buyer accepts the technology and uses it for a certain period.

The rapid diffusion of technological innovations has become one of the defining features of modern economy propelled by heightened connectivity among people and widespread social media influence. Understanding the underlying processes driving this process of diffusion is relevant for businesses, policymakers, and researchers alike, since it may provide a role for accelerating the rate of adoption in new technologies. Traditional innovation diffusion models like the Bass model focus on the innovators and imitators primarily, but these models need to expand in this present day and age of digital and social media. This research will develop a mathematical model that can represent the complexity of technological innovation diffusion influenced by social media. The mathematical model is based on the differential equation description of the rate of change in the number of adopters over time. It incorporates three main parameters, namely the coefficient of innovation, p, which is responsible for the rate at which new adopters are impacted by external influences; the imitation coefficient, q, representing the current adopters who influence potential adopters; and an additional factor, r, introduced specially for quantifying the contribution of social media in the process. Social media have emerged lately as the number one driver for consumer behavior, enabling the rapid diffusion of technological innovations. A complex model that is mathematically based, representing a much more detailed level of information and influence flow, is needed for the understanding of this phenomenon. The current study will explore the creation and analysis of the differential equation-based models detailing the role of social media in driving the rate at which technological innovations occur. Key aspects of major exploration include the following:

Estimation of Parameters: Methods will be done to estimate the coefficients of innovation, imitation, and social media influences. Sensitivity Analysis: The study of the changes in these parameters, upon which rests the rate of adoption and the process of diffusion. Comparative Studies: This is the application of the model across a range of technologies and industries with a view to establishing how the impacts of social media vary across sectors. Forecasting: Application of the model in predictions over future trends of adoptions and driving effective marketing and innovations deployment.

Extension of model: Including further factors in the given model, like market competition, heterogeneity among consumers, and economic conditions, will definitely enrich the predictive power of the model.

This work contributes to the general study of innovation diffusion by embedding social media dynamics in conventional models, thereby making the tool to understand and predict technological innovations more accurate and relevant in the digital era. The findings of this study have practical implications for companies that intend to enhance their marketing strategies and for policy makers seeking to promote innovation in their economies.

2. Literature Review:

Diffusion of technological innovation has been one of the major themes of scholarly inquiry in disciplines like economics, sociology, and marketing. Indeed, the literature on innovation diffusion is wide, with some of the earliest models, such as the Bass Model of 1969, acting like roots for many research studies that followed. In this paper, the prime contributions to the topic will be reviewed, with special emphasis on how social media has been integrated within these models and its effects on the diffusion process.Probably the most accepted model in innovation diffusion was the Bass Model, which Frank M. Bass suggested in 1969[1]. This model stated that heterogeneous adoption of new technologies can be represented basically by two forces: innovation and imitation. The Bass Model has been empirically supported across a wide range of product categories and industries. Moreover, the Bass Model is a certain benchmark for many following studies.Various extensions of the Bass Model have introduced other drivers than the two basic ones, such as price, Bass (1980)[2], marketing effort, Mahajan et al. (1990)[3], and competition, Jain and Rao (1990)[4], Srivastava and Gupta (2015)[5] which have provided further insight into how the process of diffusion takes place. These models are mostly focused on conventional aspects of communications and marketing at best and have digital platforms and social media accounted for loosely.For example, Hinz et al. (2011)[6] and Trusov et al. (2009)[7], note that the imitated rate may substantially speed up the process of diffusion via social media. These studies show that the viral aspect of social media spreads information about new products quicker than traditional media to a larger group of people. Also, since social media is an interactive channel, the influence from peers is stronger, which enhances the imitation effect.For instance, Goldenberg et al. (2009)[8] referred to the "network effects," where the more users a product has, the greater value one derives from it. Social media is particularly suited for this since it really maximizes network effects. What they imply here is that social media spreads not only information but also increases the perceived value of adopting an innovation; hence, it allows diffusion to happen faster.Peres et al. (2010)[9] reviewed a number of diffusion models and suggested embedding social networks into the process of diffusion for capturing the impact brought about by social media.Another notable contribution in the recent literature is the model by Katona, Zubcsek, and Sarvary (2011)[10] that embeds social network structures and the role of influencers in accelerating diffusion. Indeed, their results show that social media can be associated with shorter adoption cycles, especially within relatively close-knit groups where peer influence is strong.Godes and Mayzlin (2004)[11] analyzed conversations from online forums and found that online chatter about new products is predictive of adoption. Similarly, in specific product launches, such as those by Leskovec et al. (2007)[12], social media chatter has been shown to be a leading indicator of sales success.Chintagunta et al. (2010)[13] report for the automobile industry that online reviews and social network sites show strong influence on the diffusion of new models. Their findings indicate that positive online sentiment could considerably increase the imitation effect, accelerating adoption.Later, the model was further extended by Yang and Leskovec (2020)[14], who presented another model, considering data from social media sites like Twitter, that was able to capture the dynamics in real-time on how information was able to spread. They showed that most of the classical models view the process of spread as being uniform and tend to overestimate the actual speed of diffusion, while the network-aware models give closer-to-real predictions.Zhang et al. (2018)[15] have also proposed an ABM about the spread of innovation in a social media environment. Their model captures agent behaviors at the individual level, including decision-making processes under peer-pressure and online reviews. Their study has shown that in environments with strong online connections, social media greatly amplifies the diffusion rate.Sun et al. (2021)[16] further developed a model where there were feedback loops between social media activity and adoption rates. As shown, positive feedback, where increased adoption leads to social media buzz that in turn further fuels the adoption, results in rapid diffusion. On the other hand, they mentioned that negative feedback, such as negative reviews, suppresses diffusion rapidly.Li et al. (2022)[17] combined machine learning with traditional diffusion models to predict adoption patterns. They were able to generate radically better forecasts by training their model on historical data regarding social media and sales. This hybrid approach helps bridge the gap between the theoretical model and its practical application and offers many valuable insights to marketers.Stieglitz and Dang-Xuan (2020)[18] proposed a model in which the sentiments are integrated within the process of diffusion. Their results highlighted that on social media, positive sentiments are very likely to accelerate the process of diffusion, while on the other hand, negative sentiments are capable of bringing a complete stop or even reversing the trending cycles of adoption.Toubia and Stephen (2021)[19] extend this further to study the role of viral content in the process of diffusion. They also proposed a model incorporating the probabilities of content going viral and how it influences innovation diffusion. Based on these findings, it would appear that viral content results in spikes of rapid adoptions; the effect also appears to wear off quickly unless sustained by continuous positive sentiment.In this paper, Hinz, Skiera, and Barrot (2021)[20] investigated ways in which companies can use social media to enhance the diffusion of innovations. They provided a strategic framework that puts the insights from diffusion models into practice for planning more effective timing, targeting, and content of social media campaigns.Bapna and Umyarov (2022)[21] discussed two recommendations of best practices: the continuous tracking of sentiment on social media and proactive engagement of key influential voices in the firm. They realized that this early involvement of key influencers significantly improves the diffusion of new technologies, especially within highly competitive markets.The literature in recent times on the mathematical modeling of the impact of social media on the diffusion of technological innovation is presented as a surge in development. Network structures, agent-based modelling, dynamic time-dependent models, and machine learning techniques are all incorporated features that have greatly enriched the understanding of the diffusion process.These studies have shown how social media can hasten the rate of new technology adoption by magnifying imitation effects and strategically leveraging influencers and content. Future research could also extend these models to examine how different social media platforms interact with one another to exert distinct effects at various stages in the diffusion process.It is an evolving work that not only furthers the body of academic knowledge but provides actionable insights whereby businesses will be better positioned to optimize their marketing strategies in an increasingly digital world. Future research based on these beginnings should be able to provide more exact information about the complex dynamics and diffusion of technological innovation in the era of social media.

3. Innovation Diffusion:

It is assumed that adoption of an innovation is essentially the outcome of learning or communication process and that the diffusion regime or social system is the one in which all the individuals have equal opportunity to adopt. The inherent assumption in these models is that the old technology is completely replaced by the new one. Where as in many cases particularly in developing countries more than one completing technology coexist. Cases of multiple substitutions may be seen in many others. Multiple substitutions are the result of frequent innovation in a particular area i.e. economic viability of old technology, energy resources wood-coal, oil, and non conversional energy sources like biogas, solar energy.

Modelling technology diffusion processes was initially derived from theory of growth of a colony of biologically cell in a medium. since the growth of a cell would be limited due to limited space. similarly, technology diffusion models assume that the growth of a technology or an innovation is dependent on the total potential adopters.

We have to identify the variables and parameters of innovation diffusion model. The number of adopters of new innovation, n(t) till time t is variable and the total a number of potential adopter N is parameter. We assume that the innovation spreads by word of mouth that is communication of information about the product from those who have adopted it to those who have not yet adopted. At any time t, n(t) is number of adopters and (N-n(t)) is non-adopters. If the number of successful adopters, who can communicate the new innovation in efficient manner, is large, the greater will be the number who can possibly adopt it and larger will be the rate of increase is represented by the following differential equation referred to as the internal influence diffusion model

$$\frac{dn(t)}{dt} = k_1 n(t)[N - n(t)] \qquad \text{……………………(1)}$$

Where n(t) is the cumulative adoption at time t , N is the total number of potential adopter and k_1 is the coefficient of diffusion .The equation (1) is called Logistic growth curve and is directly used in technological diffusion which assumes that diffusion process is influenced by previous adopters . $n(t)$ increases at increasing rate when $n(t) < \frac{N}{2}$ and it increases but at decreasing rate when $n(t) > \frac{N}{2}$ and there is a point of inflexion when $n(t) = \frac{N}{2}$. This statement can be represented by figure (1).

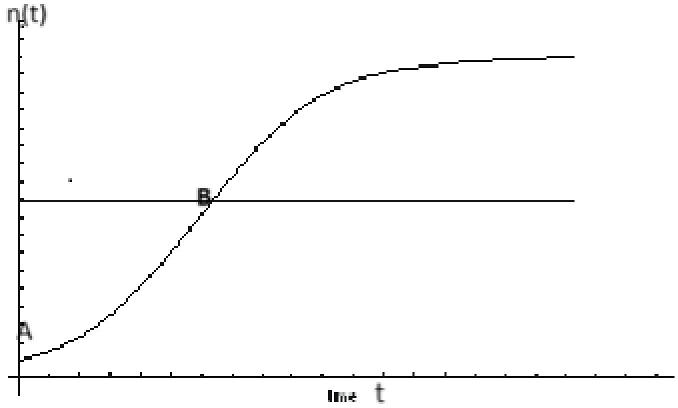

Fig.1

In fig. (1) AB is the convex part, in which number of adopters n(t) rises fast at an increasing rate. B us point of inflexion at which almost half of the potential adopter have adopted the innovation but the number $n(t)$ continues to increases with decreasing rate and this continues till almost all the potential adopters adopt the innovation. For different technology the curve are similar but are not identical.

If the influence on diffusion is external, the equation for the external model is given by

$$\frac{dn(t)}{dt} = k_2 \, [N - n(t)] \quad .... (2)$$

Where n(t) is the cumulative adoption at time t , N is the total number of potential adopter and k_2 is the coefficient of diffusion.

A mixed influence model which combines the equations (1) and (2) was first presented by Bass to represent the first purchase growth of a new product durable in marketing . The Bass model is a mixed influence model with three parameters p, q, N represents the coefficient of innovation, coefficient of imitation of imitation and is the total number of adopters. The Bass diffusion model is given by

$$\frac{dn(t)}{dt} = p\big(N - n(t)\big) + q \, \frac{n(t)}{N}\big(N - n(t)\big)................ (3)$$

where p is external influence and q is internal influence. The function n(t) and $\frac{dn}{dt}$ strongly depends on the coefficients p , q and N.

$$n\,(t,\, p,\, q,\, N) = N\,\frac{1-e^{-(p+q)t}}{1+\frac{q}{p}e^{-(p+q)t}} \;, \quad t \geq 0$$

$$\lim\,(t \to \infty)\,, \quad n\,(t,\, p,\, q,\, N) \;\to\; N$$

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For the inflection points

$$\frac{dn(t)}{dt} = 0$$

$$t = t^* = \left(\frac{1}{(p+q)}\right)\ln\left(\frac{q}{p}\right)$$

$$n(t^*) = N\left(\frac{1}{2} - \frac{1}{2}\frac{p}{q}\right)$$

Figure (1) of function n(t) is an S-shaped curve. If $q > p$, for this curve the point of inflection occurs at $t^* = \frac{1}{p+q}\ln\left(\frac{q}{p}\right)$ with $n(t^*, p, q) = N\left(\frac{1}{2} - \frac{p}{2q}\right)$.

For $q \leq p$, the graph is still S -shaped, but the point of inflection occurs at a negative value of t.

This model is called the Bass model. It is not sufficiently flexible, as it cannot represent situations where the point of inflection occurs after half of the population size is reached. Most research on the diffusion of new products, based on the work of Bass model (3), focuses on parameter estimation (p, q, N), forecasting, qualitative and quantitative models, and the analysis of real cases. In Table 1, we provide a summary of the main results regarding Bass parameters for new propulsion technologies found in the literature. Although there is significant variability among the publications, it can be stated that the determined values generally fit the model applications typically used in the industry.

Diffusion Estimated Parameters of Bass Model				
Authors	**Method**	**Innovation coefficient p**	**Imitation coefficient q**	**Market potential N**
Frank Bass (1969)[1]	consumer durables such as home appliances, electronics, etc.	0.03–0.05	0.3–0.5	Apprximetly 50 million

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Mahajan, Muller, Srivastava (1990)[22]	VCR, Microwave Ovens	0.03	0.05	Approximate 80 million (U.S. market)
Sultan, Farley, LeHorsky (1990)[23]	Various consumer & industrial goods	0.03	0.38	Varies (calculated based on product)
Jiang, Bass, and Bass (2006)[24]	Mobile Phones	0.01–0.03	0.3–0.7	4–5 billion
Van den Bulte and Stremersch (2004)[25]	MRI Machines	0.001	0.49	Thousands
Tellis, Stremersch, Yin (2003)[26]	DVD Players	0.015	0.45	300–500 million Approximate
Peres, Muller, and Mahajan (2010)[27]	Social Networks (e.g., Facebook)	0.005–0.02	0.6–0.8	2 billion Approximate
Goldenberg, Libai, and Muller (2002)[28]	Software	0.015–0.02	0.6–0.8	Millions
Chandrasekaran and Tellis (2007)[29]	Solar Panels	0.005	0.55	Millions
Geroski (2000)[30]	Medical Drugs	0.001	0.45	Thousands to tens of thousands

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Lukas, Spengler, Kupfer, Kieckhafer (2017)[31]	Electric vehicle batteries	0.022	0.413	2,150
Massiani, Gohs (2015)[32]	LPG-vehicles in Germany	0.0779	0.3718	75,566
McManus Senter (2009)[33]	Plug-in hybrid electric vehicle	0.00262	0.70935	1,922.806
Li, Chen, Zhang (2017)[34]	BEVs in China	0.0013	0.0839	5,000
Becker, Sidhu,Tenderich (2009)[35]	BEVs	0.025	0.4	2 scenarios

Table 1

Table 1 above illustrates that the value of p and q would therefore be dependent upon the nature of the product, and in general, the value of p will be lower for high tech and medical innovations and higher for consumer durables. Its value is dominated by the imitation coefficient q in networked or socially influenced markets. The market potential, N, reflects the total adopters for each product from thousands in niche products to billions in globally adopted technologies.

4. Proposed Model:

Most of the literature on the diffusion of new products (or innovations) based on the work by Bass has to do with parameter estimation, forecasting, qualitative and quantitative models, and real case analysis. The social interaction, in general, success of the product does a target consumer's motivation toward a new product will depend on the following mean three factors.

- The factors which are only affected by mass media communication (news paper, advertisement etc) when making purchase decision
- The factor which is potential imitators and whom word -of-mouth communication.
- The factors which are related to the good will of the product such as online review rating.

Given the innovation diffusion model would depend on the above three factors. In order to capture the above three factors' effect in the consumers decision-making process, in our extension of the Boss

Diffusion Model, we accounted for the goodwill of the completing product in the form of online review ratings in our prediction of sales. Assuming,

n(t) is the number of adapters of new innovation till time t

N is the total number of potential adopters

p is the coefficient of innovation

q is the coefficient of imitation

r is the coefficient of online review rating of the product

The differential equation (3) can be modified as follows

$$\frac{dn(t)}{dt} = p\big(N - n(t)\big) + \frac{q}{N}n(t)\big(N - n(t)\big) + r\frac{n(t)}{N}\left[N - \frac{n(t)}{N}\big(N - n(t)\big)\right] \text{..................(4)}$$

$$\lim_{t\to\infty} n(t,p,q,r,N) = N$$

$$n(t^*) = N\,\frac{(p+q+r)^2}{4(q+r)}$$

The first term $p\big(N - n(t)\big)$ represents the direct effect of innovation as more potential adopters remain $\big(N - n(t)\big)$ the rate of new adopter's increases.

The second term $\frac{q}{N}n(t)[N - n(t)]$ represents imitation effects. if models how current adopters $n(t)$ encourage potential adopters $[N - n(t)]$ the coefficient $\frac{q}{N}$ scales this effect according to the total number of potential adopters.

The third term represents a more complex interaction effect involving both adoption and non-adoption, possibly incorporating logistic dynamics $\left(N - \frac{n(t)}{N}\right)$ might represent a fraction of non-adopters interacting will the adopters. $n(t) \to N$ Our model leading to saturation and slowing growth typical of logistic behavior.

Using our model, Equation 4, we can say that after a certain time, the growth of an item is flatter and new items can predict the future progress of the item-whether it increases or decreases-since there are points of inflection where we should be introduced by making sufficient changes in the technology of progress items so that the growth of the industry must be influenced. Model is allowed the time it takes to adopt a new technology that is at its peak of adoption.

5. Sensitivity Analysis:

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This section tries to vary the model parameters p, q, and r, and see the associated alteration in model outcomes given by equation (4). Sensitivity of the model is analyzed with respect to how changes in the parameters p, q, and r influence the rate of adoption, $\frac{dn(t)}{dt}$, and consequently the number of adopters n(t) for large times. The following are obtained for sensitivity analysis

$$\frac{\partial}{\partial p}\left(\frac{dn(t)}{dt}\right) = N - n(t)$$

$$\frac{\partial}{\partial q}\left(\frac{dn(t)}{dt}\right) = n(t)[N - n(t)]$$

$$\frac{\partial}{\partial r}\left(\frac{dn(t)}{dt}\right) = \frac{n(t)}{N}\left[N - \frac{n(t)}{N}\left(N - n(t)\right)\right]$$

That is, in the early stage, when n(t) is small, the innovation effect is stronger but as n(t) approaches N the effect is weaker. This suggests that the imitation effect grows very strong when the number of adopters is at an neither too low nor too high value.

The external influence term has a more complex sensitively profile, depending on the proportion of adopters not the non-adopters. This shows that there is a range of the external factors, so the impacts could be very different depending on the context.

6. Equilibrium Analysis:

Find the equilibrium points of the model (4),

$$\frac{dn(t)}{dt} = 0$$

$$p\big(N - n(t)\big) + \frac{q}{N}n(t)\big(N - n(t)\big) + r\frac{n(t)}{N}\left(N - \frac{n(t)}{N}\right)\big(N - n(t)\big) = 0$$

$$pN - pn(t) + qn(t) - \frac{q}{N}n(t)^2 + rNn(t) - \frac{r}{N}n(t)^2 - rn(t)^2 + \frac{r}{N}n(t)^3 = 0$$

$$\left(\frac{r}{N}\right)n(t)^3 - \left(r + \frac{r}{N} + \frac{q}{N}\right)n(t)^2 + (rN + q - p)n(t) + pN = 0$$

This is a cubic equation in n(t).These cubic equations have two solution one represents trivial equilibrium for n = N and other is non-trivial $n(t)^*$...

7.Stability analysis: To analyze the stability, we linearize the system around the equilibrium points by considering small perturbation around $n(t)^*$.

Let $n(t) = n(t)^* + \varepsilon(t)$, where $\varepsilon(t)$ is a small perturbation

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From equation, we have

$$\frac{d\varepsilon}{dt} = \frac{d}{dt}[n(t)^* + \varepsilon(t)] = \{\frac{dn(t)}{dt}\}_{n(t)=n(t)^*+\varepsilon(t)}$$

$$\frac{d\varepsilon}{dt} = \varepsilon\frac{d}{dt}[p(N - n(t) + \frac{q}{N}(N - n(t)) + r\frac{n(t)}{N}\left(N - \frac{n(t)}{N}\right)(N - n(t))]n(t) = n(t)^*$$

$$\frac{d\varepsilon}{dt} = \varepsilon L$$

$$\text{L}=\varepsilon\frac{d}{dn(t)}[p(N - n(t) + \frac{q}{N}(N - n(t)) + r\frac{n(t)}{N}\left(N - \frac{n(t)}{N}\right)(N - n(t))]n(t) = n(t)^*$$

$$\text{L}=\varepsilon\left\{(-p) + \frac{q}{N}[N - 2n(t)^*] + r\left[\frac{(N-2n(t)^*)(N-n(t)^*)}{N^2}\right]\right\}$$

Which is always negative, hence the equilibrium point $n(t)^*$ is stable.

8.Empirical Analysis:

We will simulate the model with different values of p, q, and r to observe how the adoption behavior changes. Now, let us consider a few specific scenarios by changing the parameters p, q and r to see their effect on the adoption curve. This will enable us to realize the sensitivity of the model to these parameters. These scenarios would give us the overall picture of how different factors are influencing the adoption process. Figure 2: Different combinations of parameters influence the cumulative sales units over time.

Behaviour of the model with Different Values of the Parameters:

	P	q	r	Behaviour of the Model
Low innovation	0.01	0.47	0.22	The adoption starts slower and cumulative adoption grows gradually but reaches saturation later
High innovation	0.05	0.47	0.22	Adoption starts much faster and cumulative adoption reaching saturation sonner
Low imitation	0.02	0.2	0.22	Adoption is slower and cumulative adoption grows but taking longer to reach saturation

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High imitation	0.02	0.7	0.22	Accelerates adoption as moer potential adopters are influenced by others and cumulative adoption rapid growth and earlier market saturation
Low online review influence	0.02	0.47	0.1	Slower adoption and the cumulative adoption is noticeable but not as significant as imitation
High online review influence	0.02	0.47	0.5	Making the adoption is steeper and commulative adoption accelerating market pentration fast to achive earlier market saturation

Table 2

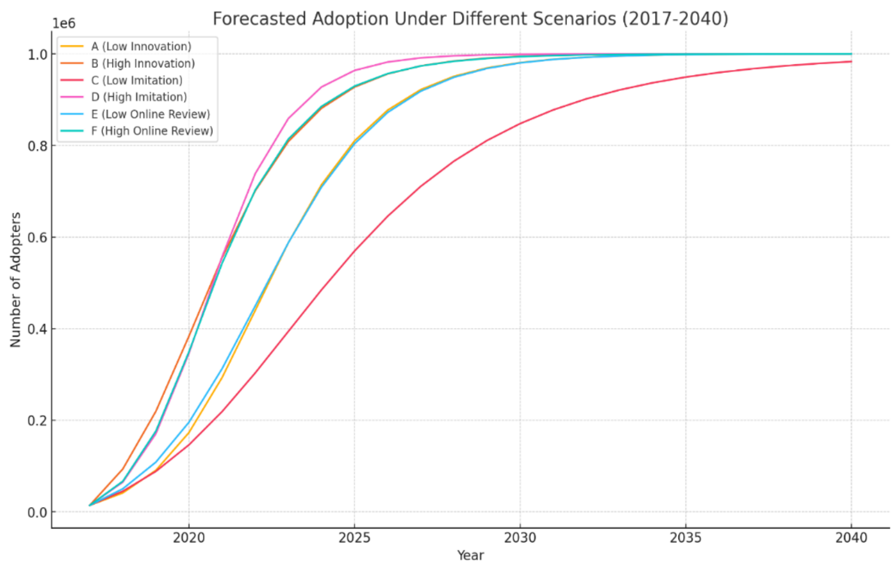

Fig.2

From table (2) and figure (2), it is clear that the model's behavior with different parameter values reveals significant insights into the adoption process. Low innovation results in slower adoption and delayed market saturation, while high innovation accelerates the process, leading to quicker saturation. Low imitation causes a gradual increase in adoption, taking longer to reach saturation, whereas high imitation significantly boosts adoption rates due to the influence of others. Low online review influence also slows down adoption, showing noticeable but limited impact on cumulative growth. In contrast, high online review influence steepens the adoption curve, facilitating rapid market penetration and achieving saturation sooner. Overall, the interplay between innovation, imitation, and online reviews is crucial in determining the pace and success of the adoption process, highlighting the importance of strategic management in these areas for effective market entry and growth. For fast market penetration, a combination of higher innovation, imitation, and strong online reviews is ideal.

9. Case study:

The model for the diffusion of innovation and sales of goods (Tata Nexon cars) focuses on the behavior of product sales and forecasting.

In this section, the proposed model is implemented to describe Tata Nexon Cars growth, where data are cited from Tata Nexon - Wikipedia[36] .

Tata Nexon Cars Sales units

Year	Sales	Comulative sales
2017	14,062	14062
2018	52,519	66581
2019	49,312	115893
2020	49,842	165735
2021	108,577	274312
2022	168,278	442590
2023	170,311	612901

Table 3

To estimate the parameters p, q and r using a questionnaire or survey, we are following a structured approach. This approach involves directly collecting data from consumers and then using statistical techniques to estimate the parameters based on their responses. By designing a focused questionnaire, collecting data, and applying nonlinear regression, we aim to accurately estimate the parameters p, q and r for the modified diffusion model. This will allow us to understand how innovation, imitation, and online reviews influence the adoption of the Tata Nexon, and to adjust marketing strategies

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accordingly. The estimated values of p, q and r are obtained through nonlinear regression applied to the survey data .Below is a table (4) showing the estimated values of the parameters :

p	0.02
q	0.47
r	0.22
N	$1x10^6$

Table 4

In the following table (5) we are forecasting the adopter in unit of Tata Nexon car which can form our model.

Years	Forecasted adopter's units
2017	14062
2018	54637
2019	125949
2020	236804
2021	381889
2022	537709
2023	676988
2024	785131
2025	861750
2026	912563
2027	945432
2028	966191

2029	979145
2030	987170
2031	992120
2032	995165
2033	997035
2034	998183
2035	998886
2036	999317
2037	999582
2038	999744
2039	999843
2040	999904

Table 5

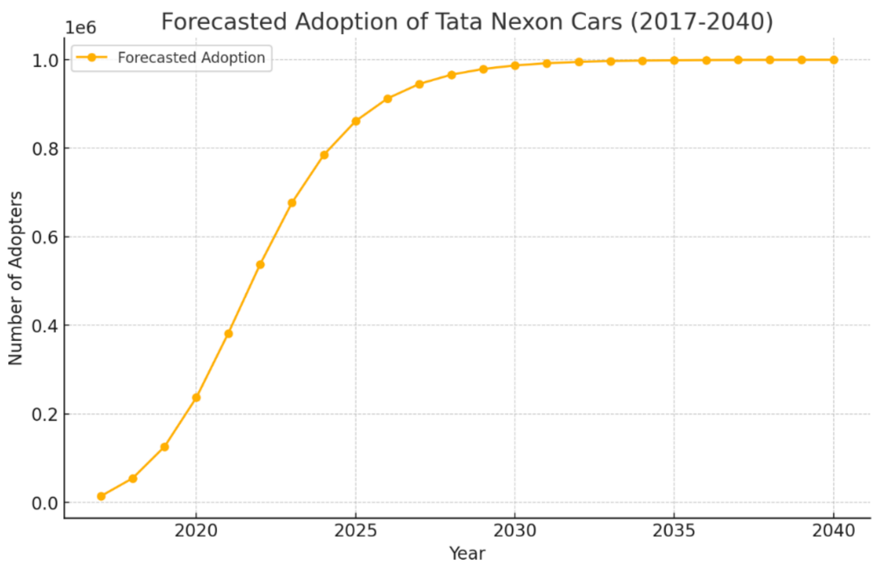

Fig.3

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The model shows that the adoption rate increases rapidly initially and begins to level off as it approaches the saturation level, the adoption is nearly complete, with almost all potential adopters having adopters the Tata Nexon Cars.

10. Conclusion:

In this paper, based on the Bass diffusion model, a more general model is developed. As the proposed model fits within the basic innovation diffusion modeling literature, it introduces a new parameter describing the sales growth of a product depending on its online ratings. From the proposed model, it is known that if the rating of a product is high, then maximum selling time for its product is achievable, and that product is moving towards saturation. Thus, we see any theoretical framework that takes into account the interaction between different dimensions of adoption, i.e., goodwill factors and online ratings, is included. We integrated the time of product persistence in the market and dynamics of ratings to be able to model the diffusion process in a two-dimensional framework.

In the case of many cutting-edge products, online ratings can reduce product uncertainty and effectively play in new product ventures. The proposed model produces reliable and better estimates.

11. Further Research

Whereas the current research has established a good basis upon which the effect of social media on the diffusion of technological innovations can be understood, there are various avenues through which further research may be done. These opportunities could improve the model's applicability, deepen insight into the dynamics of diffusion, and address the limitations that were encountered during analysis.

1. Factors to do with Economics and the Market:

The present model focuses more on social influence and other internal factors leading to adoption. Inclusion of economic variables such as price, income level, and market competition could give a wider perspective of the process of adoption. Besides, examination of the impact of the saturation of markets along with competitive technologies on the diffusion of any particular innovation would be quite useful.

2. Integration of Temporal Dynamics in Social Media Influence:

The effect of social media might not remain homogeneous for all periods of time in the process of diffusion of innovation. In future studies, the way in which the influence of social media changes over time in the adoption process can be modeled. As an example, early adopters could depend more on direct marketing efforts, while for later adopters, peer recommendations may become crucial. Such temporal variations can be modeled in order to obtain better predictions of adoption

3. Network Effects:

The current model assumes homogeneous mixing of the population. Real social networks are actually structured, and a few individuals have a greater influence on their fellow beings. Research could focus on the role of network structure in the process of diffusion, especially how influencers or key opinion leaders can accelerate or slow the process of innovation.

4. Cross-Industry Application:

Generalizability and strength may be imparted to the model by applying it across industries and technologies. Different industries may exhibit different dynamics of diffusion, and such studies across various contexts sharpen the model and bring in industry-specific parameters.

5. Behavioral Economics and Psychological Factors:

In these, future studies may also adopt more perspectives from behavioral economics and psychology in order to investigate how cognitive biases, social norms, and cultural factors drive the adoption process. Knowledge of these mechanism processes may lead to more effective interventions promoting technological innovations.

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