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What makes products trendy: introducing an innovation adoption model

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Abstract

Here we propose and study a new model of innovation adoption, IA. Our hypothesis is that individuals' decisions regarding the purchase of a new product, are driven by the perceived type of adoption trend. Our assumptions split adopters into four groups, Innovators, Early Adopters, Majority, and Laggards, based on their innovativeness, and assign particular preferences for various adoption trends based on their psychological profile. We have built several mathematical models to test our hypothesis and generated forecasts for retail sales of products sold in a supermarket chain in Poland. The performance in sales forecasting of our IA model, points to evidence of customers' behavior as described by our hypotheses, and the usefulness in quantifying psychological behavior in a general social context of innovation.

Introduction. - Companies that want to survive and flourish in today's fast-changing market need to constantly innovate and adapt to the changing conditions, customers' sentiment, and emerging trends. Innovation is key to a company's survival and development [1, 2, 3, 4]. Companies find it very important to introduce innovations to the market, even though it is often risky [5]. But a novel product in itself is not a guarantee of success. The customers' reaction and opinion have to be considered. The statistics show that between 40% and 90% of new products fail. For example, in the United States, in the packaged goods industry, 70% - 90% of new products are retracted from the stores within 12 months, despite nearly 30000 new products introduced every year [6]. However, it is too simple to assume that all of those products were just bad ideas certain to fail. If all of those products were so obviously bad, then why were they released in the first place, and why was it not obvious before the release? Why do some great innovative products fail and are never adopted? Even when they are superior to existing alternatives? We have to understand that the key component of the product adoption process is consumer psychology. The scale of the innovation failures requires an explanation that we think lies in consumer behavior. Behavioral change that comes with switching to a new product entails both financial and, most importantly, psychological costs [6].

Various theories exist that try to understand why certain people are not likely to accept novelties. However, our approach to the problem of innovation adoption is slightly different. In this work, we offer a new, psychological interpretation of probably the most popular, existing adoption model used widely in marketing. The key part of our interpretation is that different adopter groups are looking for particular properties of adoption trends to inform their decision regarding purchase. Those properties can be formulated mathematically, which provides us with testable predictions and an alternative quantitative description of the innovation diffusion process. Our approach is similar to the one used in the Dynamical Social Psychology [7] or applied by Bass [8]. The goal of this work is to propose and investigate a model with a new interpretation and description of innovation adoption. Our idea is grounded in psychology but can be integrated into various mathematical models. Therefore, it allows for both qualitative and quantitative

predictions.

Models of adoption of innovation. - In the following, we will distinguish the words *Adoption* and *Diffusion*. Adoption takes place at the individual level and means accepting something that has never been used before. By diffusion, we mean spreading of innovation across a group [9]. One of the first, the most influential and the most popular models of innovation adoption, was proposed by Everett Rogers in his book *diffusion of innovations* in 1962 [10]. Rogers (2010) assumed a normal distribution of innovativeness (mean time of adoption of an innovation). His main idea was to introduce the following categories by using standard deviations, SD , from the mean. The categories of people based on their innovation were: 1) *innovators*, less than $-2SD$ from the mean, meaning the 2.5% of people to adopt the innovation first. 2) *early adopters*, between $-2SD$ and $-1SD$ from the mean, the next 13.5% of adopters. 3) *early majority*, between $-1SD$ and the mean, the next 34% of adopters. 4) *late majority*, between the mean and $1SD$, that is, the next 34% of individuals to adopt an innovation. 5) *laggards*, more than $1SD$ from the mean, are the last 16% of people to adopt. It should be noted that Rogers' categorization [10], is exhaustive. The people who never adopt an innovation are not included in those categories. Moreover, it should be emphasized that even though the adopter categories are discrete, the innovativeness itself is continuous and the transition between the categories is also continuous.

Since the innovativeness is understood as a mean time of adoption and the distribution is normal, then the cumulative distribution function is S-shaped. In practice a logistic function is used to represent the innovation diffusion. The reason is that using the logistic distribution simplifies the analysis and is very similar in shape to the normal distribution [11]. The fundamental model of innovation diffusion is in the form of the following differential equation [12]:

$$\frac{dN(t)}{dt} = rN(t) \cdot (1 - N(t)/N_{max}) \quad (1)$$

The logistic function is the solution of this simple first-order non-linear ordinary differential equation 1. This model draws heavily from ecology and is frequently used in

population growth modeling [13]. The logistic curve is often a result of processes such as an unchecked infectious epidemic. If the innovation is spread across the population in a word-of-mouth fashion, then the S-shaped curve of diffusion is expected [10]. The solution to equation 1 (the logistic function) can be written as:

$$N(t) = \frac{N_{max}}{1 + \left(\frac{N_{max}-N_0}{N_0}\right)e^{-rt}} \quad (2)$$

Here, N_0 is the initial size of the population, $N(t)$ is the population size (or the number of adopters in our case), N_{max} is the maximum size of the population (maximum number of adopters), t represents time, and a constant r is the growth rate. In case of innovation diffusion, r is the coefficient (rate) of diffusion and can be some function of time $r(t)$ [12]. The logistic function is S-shaped, and its growth has a shape similar to the normal distribution. Those characteristics meet the assumptions made by Rogers. The example shapes of the population growth and population size curves as functions of time are shown in Figure 1.

Various approaches have been used to model the innovation or idea of adoption dynamic. The examples include the differential equations models such as the Bass model [8, 14] and similar [15], dynamic population models [16], complex network models [17, 18], agent-based models [19] and many others [9]. The Bass model is perhaps the most popular and fundamental model in innovation diffusion, often used in product sales forecasting [10, 20]. The Bass model can be written as in Eq. 3. It has the following interpretation. The probability of a new adoption by a person is proportional to the number of people who have already adopted it.

$$\frac{f(t)}{1 - F(t)} = p + \frac{q}{M}A(t) \quad (3)$$

In the above equation, M is the size of the potential market, p is the parameter of innovation, q is the parameter of imitation, $f(t)$ is the fraction of the potential market that adopts the product at time t . $F(t)$ is the fraction of the potential market that has adopted the product up to and including time t , $A(t)$ is a cumulative number of adopters

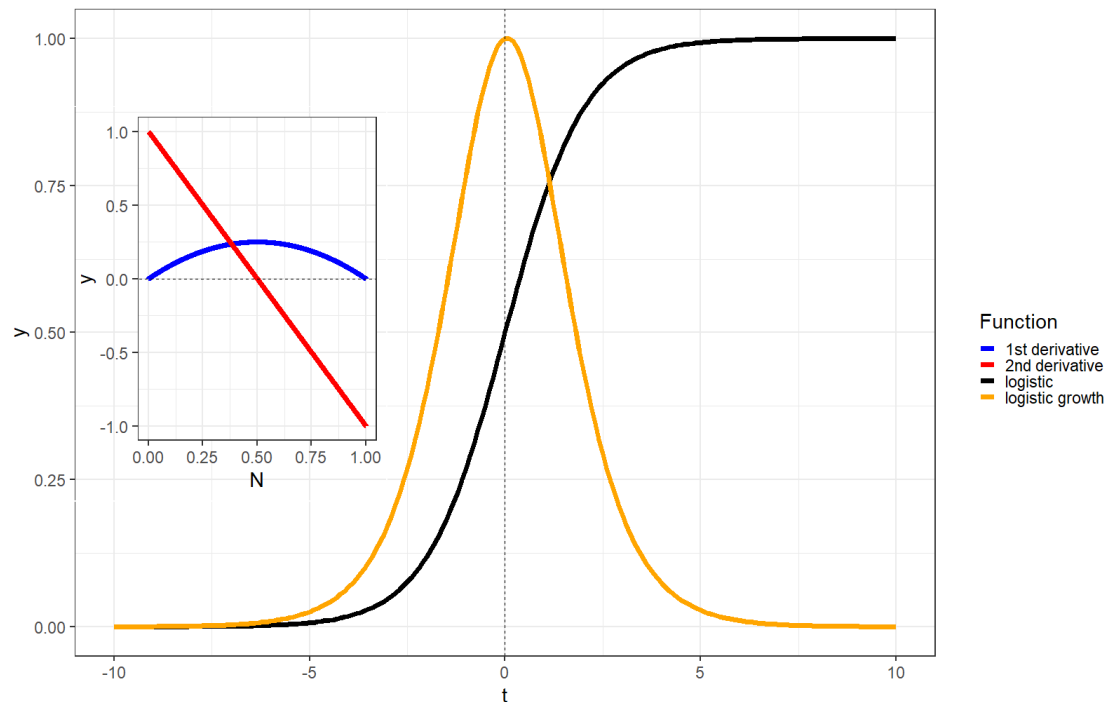


Figure 1: Example of logistic function, as defined in equation 2. In black is the population size $N(t)$. In orange, the population growth (one-step differences of $N(t)$). Both are scaled to 0-1 range. The blue and red curves in the inset show respectively the first and second derivatives of the logistic function with respect to N . The parameters used were: $N_{max} = 1$, $N_0 = 0.5$, $r = 1$

so:

$$A(t) = MF(t) \quad (4)$$

. Also, since $F(t)$ is a cumulative of $f(t)$ we have that

$$f(t) = \frac{dF(t)}{dt} \quad (5)$$

Looking at Eq. 3, we see that q controls how much new adopters are influenced by the previous adoptions. With high q more adoptions come from people following other adopters. The parameter p allows for adoption independent of others, thus it was called a parameter of innovation. Using Eq. 4, Eq. 3 can be rewritten as:

$$f(t) = p + (q - p)F(t) - qF^2(t) \quad (6)$$

Remembering Eq. 5, Eq. 6 becomes a differential equation which has a solution showed

in Eq. 7.

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}} \quad (7)$$

Usually Eq. 7 is recommended for fitting and forecasting [21]. It should be noted that taking $p = 0$ in Eq.3 the Bass model reduces to the logistic Eq. 1, so the logistic function Eq.2 is a special case of solution to the Bass model.

A new IA approach. - We suggest a new approach to understand the origin of the dynamics of innovation adoption. Our approach is based on the adoption curve proposed by Rogers [10] and could possibly be used and integrated into many existing models. We start with the most fundamental model of innovation diffusion [12] presented in Eq. 1. Consider the first and second derivative of the logistic function solution (Eq. 2), as a function of number of adopters N , see the inset to figure 1.

From Rogers' theory, we know that people with the highest innovativeness are the most likely to adopt a new idea first, but that is usually tied to their personality traits (e.g. outward focus, communication needs, opinion leadership, novelty and others), behavior and a person's resources [22]. In some cases people can be classified into their Adopter group using surveys [23, 24].

The second derivative is the highest in the beginning, when not many people have adopted the idea yet. We could expect that an innovative group, such as the Early Adopters, is responsible for most sales at this time, as they are more likely to exert influence on others [25]. Based on this expectation we think that this group is attracted to ideas or products with growth characterized by a high second derivative. It means they see products with accelerating trends as an opportunity. For Early Adopters who are actively looking for next big successful product or fashion, the second derivative is an indicator that they are dealing with a product that will be successful in the future. If the value of the second derivative decreases, so is the attractiveness of the product for this group.

In the inset of Fig. 1 we see that when the second derivative is decreasing (but still positive), the first derivative is increasing. The first derivative reflects the pace at which the popularity of the product grows. We think that the Majority (both Early and Late) is

mostly interested in products which quickly gain popularity. They will see it as a reason to believe that this product is probably good, useful, and worth the money. The buying signal for them is the high first derivative, which characterizes quickly growing trends. After the first derivative reaches its peak, it starts decreasing. After a certain amount of people has adopted the innovation, the Majority's interest decreases. However, contrary to the second derivative, the first is never negative in the logistic function. Hence, when a high percentage of people have the product, the Majority are still interested in buying it. Nevertheless, after a certain point, it might seem too mainstream, and perhaps not special and interesting anymore. After the peak, their interest in the product is decreasing as more people adopt it.

The last group to react is the Laggards, who are more likely to buy when the number of current adopters is high. They do not pay much attention to the trend or its growth. They protect themselves from a possibly costly mistake of buying something faulty. They might adopt mainly for economic reasons as shown in a study on photovoltaics adoption[26]. As time progresses, the Laggards continue adopting until the market is saturated, and the S-curve reaches its plateau.

The last group that we use in our model is the Innovators, which are the first group to react to new products. They serve as an ignition for the whole process because they are the only group that does not require anyone else to have the product already. Their absence may throttle the entire adoption process [27]. The Innovators do not look at others to make a decision, but others look at what they do. They are ready to adopt an idea not a single person has adopted yet, which often requires courage and perhaps a better socioeconomic status or technological skills. Their behavior is highly nonconformist. We expect their behavior to be independent of N .

To sum up, based on Rogers' theory, we divided the adopters into four categories. Innovators look for new products and try them out first, regardless of what anyone else is doing. Early Adopters, who look for new future successful products, try to get them early. They react to the value of the second derivative of cumulative sales when making decisions. The Majority are interested in products quickly gaining popularity and are

more likely to buy when the first derivative of cumulative sales is high. The Laggards see only the total number of adopters (cumulative sales) as a convincing reason to buy.

Summarizing our reflections above, we suggest the following IA model based on the differential equation for the cumulative sales, C_t^i , of product i at a given time (day) t :

$$C_t^i = a_0 + a_1 C_{t-1}^i + a_2 \frac{dC_{t-1}^i}{dt} + a_3 \frac{d^2 C_{t-1}^i}{dt^2} \quad (8)$$

Here, (a_0, a_1, a_2, a_3) is a vector of regression coefficients corresponding to Innovators, Laggards, Majority and Early Adopters respectively. The solution to Eq.8 is given by

$$C_t^i = \frac{-a_0}{a_1 - 1} + c_1 e^{1/2(-\frac{a_2}{a_3} - \frac{\sqrt{a_2^2 + 4a_3 - 4a_1 a_3}}{a_3})t} + c_2 e^{1/2(-\frac{a_2}{a_3} + \frac{\sqrt{a_2^2 + 4a_3 - 4a_1 a_3}}{a_3})t} \quad (9)$$

with c_1 and c_2 to be determined from initial conditions.

Testing our IA model on empirical data and comparing with other models. - In order to test our IA model we used daily sales data of 200 different products sold in a big supermarket chain in Poland. The company's name is not disclosed due to their request for anonymity. The sales data are of different lengths for different products. They come from dates taken in the period between 2015-01-02 and 2019-03-26. Many of those products' time-series include their whole lifetime in the supermarkets. Other products' lifetime has not ended yet, and continues after our last available data point. We first cleaned the data. Four data points had sales equal to -2, and 88 observations were equal to -1. To avoid modeling product refunds, we set those sales to zero. One of the products had zero sales on the first day, and we removed that point.

To compare how well our various models (see further below) explain the empirical data, we employed the following procedure. First, the time series of every product is separated into two sets. The training set is the first 80% of the days available for a product. The out-of-sample set is the last 20%. We always fit our models using only the data from the training set. Next, we project the sales for the rest of the days and compare the projections with the empirical data in the test set. To assess how well our models predict the sales

at the last 20% of the time series, we used the MAPE metric defined in Equation 10, where A_t represents the actual values and F_t the forecasts. MAPE is the mean absolute percentage error, and a high value means that a model's predictions were not accurate.

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right| \quad (10)$$

In order to have benchmarks, we compared our model with the performance of other models often used to describe economic behavior, like e.g. the Auto-Regressive Integrated Moving Average (ARIMA) model. The ARIMA model is a popular tool in general time-series analysis. It makes no assumptions about the customers who made purchases, and thus serves as a benchmark against the other models which all have specific assumptions of customer behavior at their core. The ARIMA model is defined via the ARMA model:

$$C_t = \sum_{i=1}^p \phi_i B^i C_t + \left(1 + \sum_{i=1}^q \theta_i B^i \right) \varepsilon_t \quad (11)$$

B is the backshift operator:

$$B^k x_t = x_{t-k} \quad (12)$$

The ARMA model uses lagged values of the dependent variable and errors from previous steps to build its predictions. The ARIMA(p, q, d) model is an extension of ARMA model in which differentiation is used. Differentiation is simply a subtraction of a previous value from a current value. The time-series is differenced d times until it is stationary. Parameter p refers to the number of lags of the dependent variable used. Parameter q is the number of lagged forecast errors. For more specifications on the various fitting procedures of the various models we refer to [28].

Population Dynamics, PD, models are another class of popular methods used in many sciences. They have been successfully applied in fields such as ecology (Brauer et al., 2012), epidemiology (Anderson, Anderson, & May, 1992), and most interestingly in the quantitative description of spreading of ideas (Bettencourt et al., 2006). The method is very versatile and can also be used for studying online social networks, viral marketing, or financial network contagion (Rodrigues, 2016). One of the most basic assumptions made

in dynamic population models, is what groups the population should be divided into, in order to describe its dynamic. The PD model that we build directly incorporates our hypotheses of four groups with different dynamics. The model itself takes the form of a system of differential equations that describe the number of people in each group. However, it should be noted that since each groups interest in the product was quantified by a separate parameter, the simulations were quite cumbersome with in total nine parameters. The main reason to introduce a PD model was to try to get a better qualitative description of the dynamics of the different groups. For detailed description of the model and the simulation of the model we refer to [28].

Results. - In Fig. 2 we show the density distribution of MAPE values calculated on the out-of-sample sets for every product and every model. Low MAPE value means a model created a more accurate forecast. The higher density in Fig. 2 means a model produced a specific MAPE value more often. Looking at the density plot, it is seen that the ARIMA model gave accurate forecasts the most often.

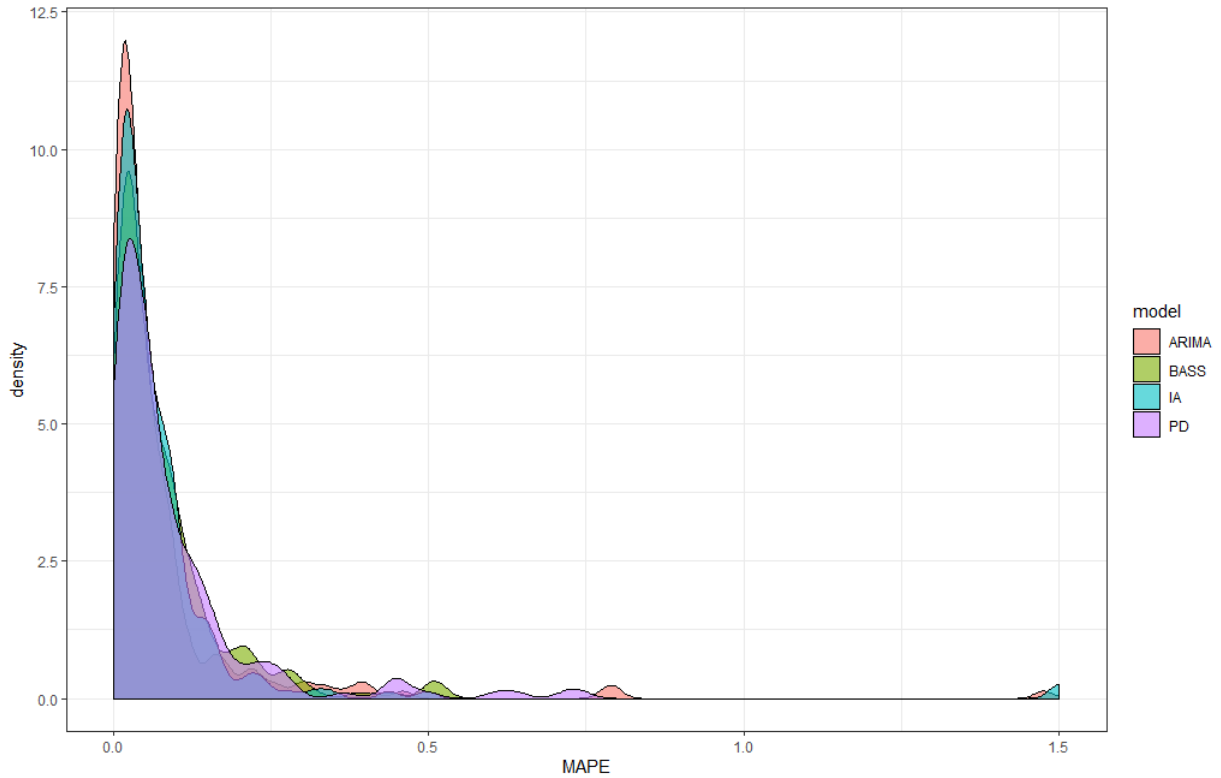


Figure 2: Plot showing the density distributions (smoothed histograms) of fitting results for tested models. Models were fitted on the first 80% of data for every product. MAPE values were calculated on the last 20% of every cumulative sales time series. A lower value of MAPE means a model performed better in forecasting future cumulative sales. Some MAPE values (bigger than 1.5) of the IA model were not plotted to improve the readability of the plot.

None of the distributions seen in Fig. 2 were normal, as confirmed by Shapiro-Wilk tests with $W = 0.65, p < .001$, $W = 0.72, p < .001$, $W = 0.081, p < .001$, $W = 0.45, p < .001$ for the PD, BASS, IA, ARIMA models respectively. We wanted to compare the accuracy of the forecasts on the test sets. A Kruskal Wallis rank-sum test told us that there is a difference between the accuracy of the models ($T(3) = 11.18, p = 0.012$). We then performed the Pairwise Wilcoxon Rank Sum Test with a Bonferroni correction to compare the MAPE values of models (Table 1). We used the paired version of the test because we compare the same set of products between all of the models.

Model	ARIMA	BASS	IA
BASS	0.019	-	-
IA	1.00	0.021	-
PD	0.022	1.00	< .001

Table 1: Paired Pairwise Wilcoxon Rank Sum Test adjusted p values (calculated with a Bonferroni correction) for tested models. The Table compares the accuracy of the models on the test set measured with MAPE.

Based on Tables 1, 2 we see that the ARIMA test performed better than Bass and PD models, but not significantly better than IA. The IA model also had a greater accuracy than PD and Bass, but did not differ significantly from ARIMA model. There was no significant difference in MAPE between Bass and PD, so there is no evidence to say that the PD model performed better or worse than the Bass model.

model	count	mean	sd	median
ARIMA	200	0.0766	0.147	0.036
BASS	200	0.0791	0.0917	0.0455
IA	200	0.0777	0.16	0.0422
PD	200	0.092	0.123	0.0531

Table 2: This Table presents the summary statistics for MAPE values of the models. MAPE values were calculated on the out-of-sample test sets, which were the last 20% of time-series for every product.

Based on Fig. 2, Table 1 and Table 2, we can say that in terms of forecast accuracy (out-of-sample) for various products, that the IA and ARIMA models seem to give qualitatively better forecasts than the BASS and PD models. It was in particular surprising to us that the ARIMA model seemed to give quite reliable forecasts, outperforming the BASS and PD models, and matching or even slightly outperforming our IA model. However, it should be noted that the number of parameter used in fits used by the ARIMA models were larger than the number of parameters in our IA. In average the ARIMA used 4.625 parameters (with a standard deviation of 3.041), compared to the 4 parameters of the IA model. Most importantly we note that our IA model outperform both behavioral models,

(BASS, PD), in particular it's notable that it outperform the BASS model which has become the standard model in business innovation forecasts.

In order to understand worst case performance of the various models, something which could be important to understand in business forecasting, we show the top 5 worst forecasts for each model in Table 3. As seen some of the outliers could possibly lead to a significant risk when trying to predict the sales. We see that the PD and Bass models tend to be more conservative than IA and ARIMA models. Their worst errors are not as extreme as in IA and ARIMA.

Table 3: The Table shows the worst five predictions made by the models. The forecast errors were measured with MAPE metric.

ARIMA		
#	Product	MAPE
1	Color Laboratory toy	1.48
2	Whiskey 1L	0.80
3	BLUE JUICE 100% without sugar 1000ML	0.78
4	City bike 28	0.46
5	Album GREAT PAINTERS	0.40
IA		
#	Product	MAPE
1	SMOOTH HEART plush	28.05
2	Color Laboratory toy	11.55
3	Album GREAT PAINTERS	0.50
4	City bike 28	0.44
5	Big bear with heart PLUSH	0.34
PD		
#	Product	MAPE
1	Jacket type9	0.74
2	USB 2.0 64GB	0.72
3	Jacket type 11	0.64
4	Jacket type 8	0.61
5	Children's carnival costumes	0.50
BASS		
#	Product	MAPE
1	Album GREAT PAINTERS	0.51
2	Color Laboratory toy	0.51
3	Jacket type 10	0.50
4	City bike 28	0.44
5	Jacket type7	0.39

1 Conclusions

We have introduced a new model to study innovation adoption. Our hypotheses were that: the most innovative people are making purchasing decisions independently of others, highly innovative people are more likely to adopt when the adoption trend has an increasing rate of growth (accelerating trend), moderately innovative people are more likely to adopt when the adoption trend has a positive rate of growth (increasing trend), and the least innovative people pay attention only to the total number of adoptions when making the purchasing decision.

We applied our IA model to predict sales data of 200 products of a supermarket chain in a period of four years. We compared the performance in predicting sales of our IA model, to two other innovation diffusion models and one financial time series model. Our IA model outperformed both innovation diffusion models, in particular the standard model for business innovation, and had similar performance as the financial time series model, but fewer parameters. The performance in sales forecasting of our IA model, points to evidence of customers' behavior as described by our hypotheses, but more importantly, it illustrates the usefulness in quantifying psychological behavior in a general social context in particular with respect to innovation.

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