Diffusion Model of Various Modifications of an Innovative Product

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Abstract. Digitalization entails the application of digital technologies to a wide range of existing tasks and enables solution of new tasks. This article is based on data sets on current sales volumes of innovative products to forecast their future sales. The first stage is applying the innovation diffusion in the F. Bass model to calculate the diffusion coefficients of different modifications of Sony's PlayStation. To estimate factors which influence innovation and related results within firms, the company IMPRINTA producing 3D printers was surveyed. It is shown that taking into account technical parameters, a cascade diffusion model of product innovation is the best for describing the process of product realization. The information obtained from the diffusion analysis of two 3D printer models can be used to improve the efficiency of key business processes, including production, procurement, marketing and advertising. The use of the diffusion model made it possible to generate three different scenarios for the release and promotion of a new modification of one of the 3D printer models depending on the selected niche, the time of market launch and the intensity of the marketing and advertising campaign. Each scenario enables adjusting the cost and technical parameters of the future modification.

1 Introduction

One of the key areas of digitalization is the creation and development of digital models for the operation of markets and the diffusion of innovation. This approach will help meet the challenges of planning, managing and optimising the launch of new products.

Today, all companies, regardless of the specific nature of their business, admit that the only way to ensure a continuous competitive advantage is to implement and bring innovative products to market and to do it relentlessly. However, when implementing innovative processes, companies face numerous problems in forecasting and strategic planning, as markets for innovative products are characterized by various kinds of uncertainties and risks caused by both external and internal factors, many of which are uncontrollable. Therefore, a relevant issue in innovation management is the quality management of strategic innovation planning processes at the different levels of production realisation. The introduction of digital technologies and platform solutions in the areas of public administration and public services, including those aimed at providing social benefits and supporting small and medium-sized businesses, makes it easier to achieve this goal. First and foremost, this translates into the

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need to consider the potential size of the market, the speed at which innovations spread on the market, consumer characteristics of innovations, as well as the mutual impact of portfolio innovations on their commercialization. At the macroeconomic level, the digitalisation of the innovation market will enable better management of the commercialisation process and framing of innovation policy, including support measures and instruments.

Most models for predicting innovation diffusion on the market, or estimating sales of new products, differ in the number and types of variables related to consumer behaviour, in the type of data and level of aggregation, and ultimately, in the approaches to mathematical modelling. The most widespread are models based on the product life-cycle concept and implying that product acceptance by different categories of consumers follows an exponential law (the so-called S-curves). Evidence for such a generalised pattern of new product acceptance has been found in a number of studies devoted to diffusion of innovation [1, 2, 3, 4].

In view of the above, this article aims to build an adequate mathematical model of innovation diffusion, with regard to product quality parameters and the possible presence of modifying improvements.

2 Materials and Methods

This article uses mathematical modelling and analysis of the sales volume of three generations of PlayStation game consoles by Sony from 2010 to 2019, and the sales volume of two models of 3D printers with several modifications produced by a small innovative company IMPRINTA from 2014 to 2020.

When building a digital model of the innovation diffusion process, it is more appropriate to take advantage of an information-diagnostic type of model that allows for monitoring; gradation; adaptation; analysis of deviations, failures and abnormal behaviour of the process, i.e. the need to create a digital shadow for predictive analytics [5]. In this work, the authors applied the methods of systems approach and optimisation modelling to study the processes of diffusion of innovations and to create their mathematical model. The diffusion model of innovation cascade [6] and the Bass model served as the framework of the developed model.

2.1 The main concepts of innovation diffusion modelling

Modern research in the field of innovation diffusion dates back to the theory of Evert Rogers, who as early as in 1962 proposed the differentiation of consumers of innovative products into five basic groups: innovators, early adopters, early majority, late majority and laggards (more details can be found in the modern presentment [7]). Rogers points to interpersonal communication between those who have already purchased the product and those who have not yet done so as the main driving force behind the diffusion of innovation [1].

This theory later provided the basis of the mathematical model of diffusion proposed by Frank Bass in 1969. In contrast to Rogers, he offered to distinguish only two categories of consumers according to the principle of attitude towards new products – innovators and imitators. Bass considered not only interpersonal communication, but also advertising, to be the factors determining the speed of the diffusion process. In his work [2] he showed that the developed model is universal, that means that regardless of the specifics of the innovative products, and hence the parameters of the model, the curve of the dependence of sales on time will always be bell-shaped, similar to the graph of the normal distribution.

Further development of this theory is underpinned in [3] by Geoffrey Moore, who first introduced the notion of a gap, or chasm, in the adoption and diffusion of innovation, particularly characteristic of the transition from early adopters to the early majority category; later he formulated a series of tips for bridging these gaps.

Significant work in this area, which draws on some of the premises of Moore's work, is the study [4] by Jacob Goldenberg, Barak Libaya and Eitan Muller. Based on their analysis of a number of empirical data on the sales of innovative products, mainly related to the electronics category, the authors found that in almost half of all cases there is a point of volume decline on the sales curve up to 20% of the initial peak, and later the sales recover to previous volumes in the short term and even exceed them. This phenomenon is referred to as the 'saddle'. This study confirms the existence of two major consumer markets: innovators and followers, the gap between them causing a drop in sales volumes.

Thus, there can be distinguished several fundamental approaches to understanding the process of diffusion, as well as the main factors contributing to its speed. The approaches discussed in this publication are interconnected, which allows their underlying principles to be used to build specific models of innovation diffusion.

Currently, a reasonable number of works are focused on the development of mathematical models of diffusion. Many of them aim to specify and extend Bass mathematical model by introducing new variables into it. The consequence is the possibility to study the influence on diffusion of various marketing factors, such as advertising policy of the company, pricing policy, as well as parameters determining the behavioural characteristics of consumers.

For example, in [8], a modified mathematical Bass model was used to reflect the diffusion of innovation in the regions of Russia on the example of cellular communication diffusion. The resulting model made it possible to conclude that the innovation diffusion is dependent on the way the information about new products is disseminated and the maximum market capacity. However, as the authors themselves point out, the model gives good approximation results in the analysis of disruptive innovations, but it is impossible to use this model to estimate the change in the diffusion rate as a result of market entry of improving innovations. The model specified by the authors allows us to classify Russian regions according to the ratio of innovators and followers, and can be applied in the development strategy of territories, but its application for strategic planning of the product portfolio is not viable.

Modern modelling tools enable building simulation models of innovation diffusion that are best suited to real-world conditions. For instance, [9] describes building a simulation model based on the Bass model in the AnyLogicTM software environment. The main parameters determining the rate of diffusion are the effectiveness of advertising, and the power of persuasion of the buyer, who has already used the product, when communicating with a potential buyer. These parameters are set as constants, and are supervised by expert judgment. This model facilitates investigating the relationship between advertising costs and the rate of diffusion in order to further optimize it. Nevertheless, this model also does not take into account the impact of market entry of innovation modifications. Therefore, only at the early stages of the product life cycle is the model useful for making managerial decisions concerning the size of advertising budget, with the optimization criterion being the expected profit from sales.

A similar problem is solved in [10], where the main purpose of the study is to obtain a mathematical model for calculating the expected discounted cash flow from the implementation of innovations over the entire life cycle period. At the same time, the authors evaluate mutual influence of the basic and improving innovations, which helps explaining the processes of withdrawal of goods from the market as a result of a new modification release. The adequacy of the model was assessed using real data on the distribution of landline telephones. But, as the authors themselves recognize, the model has a rather generalized form, and does not include important parameters quantifying the factors stimulating innovation processes.

Another approach is proposed in [11], where the simulation model is based on econo-physical analogies, namely, on the analogy between the processes of diffusion of innovations and diffusion of diffusing matter in physics, which is described by Fick's laws. Based on this

analogy, a mathematical model of innovation diffusion is derived, in which the determining factor is the diffusion coefficient (reminiscent of the diffusion coefficient in physics). This parameter is complex, and its value depends on the state of the innovation diffusion environment and the specifics of the product itself. The diffusion coefficient was calculated based on empirical data on iPod sales from 2004 to 2014. This model takes into account the mutual influence of basic and enhancing innovations when bringing them to market or planning when to launch them, which justifies using this model in the strategic management of the company's project portfolio.

Nonetheless, issues concerning the determination of the diffusion coefficient itself have not been duly considered. So far the task of assessing the influence of various parameters (primarily, the consumer properties of the innovation itself) on the diffusion rate (the measure of which is the diffusion coefficient) remains relevant and prevents the use of existing models to form the digital shadow of the commercialisation process.

Accordingly, this article attempts to pay heed to the identified shortcomings in order to design a model that not only describes the life cycle of an innovation and the amount of expected profit from its implementation, but also addresses the mutual influence of different innovation modifications on their market position depending on technical and consumer characteristics to be taken into account.

2.2 Peculiarities of innovation diffusion taking into account modifications

Skolkovo experts [12] carried out an analysis of consumer technology diffusion over 110 years, which is presented in Figure 1.

As can be seen from Figure 1, each technology has an inflection point of a 'saddle' shape, which is characterized by a fall in demand for the technology and products made using this technology. Experts [12] attribute the resumption of diffusion speed and the slope of the curve to several factors:
- increase in the speed of information dissemination due to the IT development;
- cost reduction;
- increase in the degree of production automation.
In addition to the above factors, some studies [13] often cite other circumstances, which include:
- company size;
- level of competition in the industry;
- growth rate of the company;
- inter-firm partnerships and collaborations;
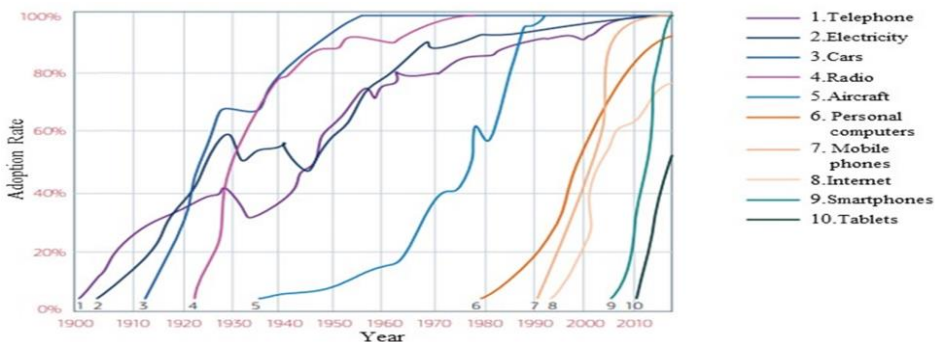- cost of using technology;
- human capital.

Fig. 1. Speed at which consumer technology has spread over the last 110 years [12].

Let us look at the innovation diffusion using the example of one the major companies – Sony and their PlayStation games console from 2000 to 2019 (2, 3 and 4 generations). The data is presented in Table 1.

Table 1. Input data for modelling.

Year	Number of game consoles sold, million pcs.			
	PlayStation 2	**PlayStation 3**	**PlayStation 4**	**Total**
2000	6.4	0	0	6.4
2001	18.5	0	0	18.5
2002	24.69	0	0	24.69
2003	19.91	0	0	19.91
2004	11.8	0	0	11.8
2005	20	0	0	20
2006	2.4	0	0	2.4
2007	14.1	0	0	14.1
2008	13.8	10.46	0	24.26
2009	7.9	13.26	0	21.16
2010	7.3	13.83	0	21.13
2011	6.4	14.42	0	20.82
2012	3,4	11.97	0	15.37
2013	1.41	8.26	7.5	17.17
2014	0	3.56	14.8	18.36
2015	0	1.34	17.7	19.04
2016	0	0.52	20	20.52
2017	0	0	19	19
2018	0	0	17.8	17.8
2019	0	0	12.1	12.1
TOTAL	158.01	77.62	108.9	344.53

The actual data show that there was a drop in demand for the current model when reliable information about the next generation model became available, namely in 2006 when the PlayStation 2 release date was announced and in 2012 when there appeared information about the PlayStation 3 devkits being handed over to game developers. Considering the useful life, which is 5 years, the cumulative number of users of the PlayStation 3 model would look as follows (Figure 2).
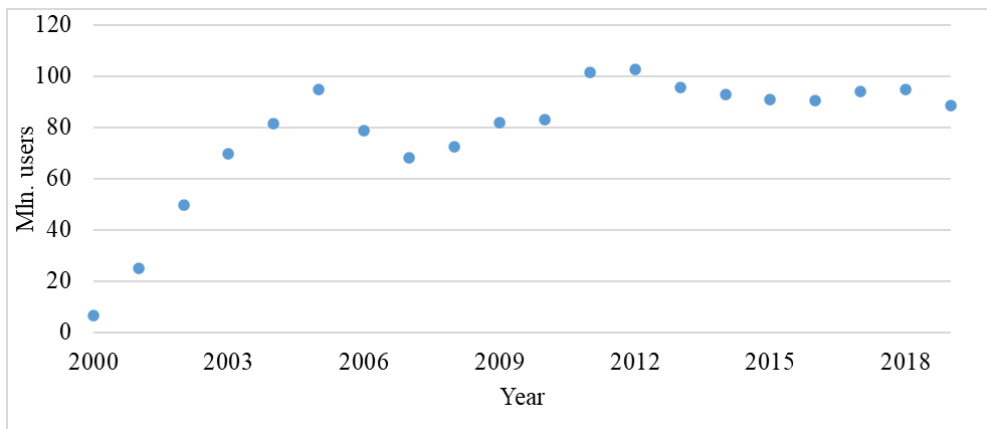

Fig. 2. Total number of PlayStation users.

Two saddles can be observed in Figure 2, the emergence of which is due to the time lag between the announcement of a new game console model and the immediate launch of sales.

2.3 Modelling the innovation diffusion

The innovation cascade diffusion model [5] was used as the basis for constructing a mathematical model of innovation diffusion. Following the analysis of the volumes of game consoles, it was found out that when a new model which improves consumer characteristics of products is released, this generates different effects ranging from the influence of changing characteristics on the growth in total sales rate of this model and the effect of a new model on the sales volume of the previous modification.

To assess this impact, we propose to use the method of expert evaluation. We have to determine the weighting coefficient of each technical parameter of the product.

The proposed model of cascade diffusion of innovative product modifications with regard to technical parameters can be presented in the following form (1):

$$Y(t) = \sum_{i=1}^{n} \left\{ V_i * (1 + e^{(k_i - r_i*(t - p_{i+1} - 1))})^{-1} * \begin{cases} h_i, & S \leq p_{i+1} - t \leq 0 \\ 1, & p_{i+1} - t < S \\ 1, & 0 > p_{i+1} - t \\ 0, & (p_i - t) > 0 \end{cases}, (p_i - t) \leq 0 \right. \tag{1}$$

where Y(t) – the cumulative sales volume of all product modifications at a certain point in time t (day, month, quarter, year),

Vi – available share, taking into account the commercial model and competition of the i-th product model (SOM model), mln roubles or in kind,

pi – time period for the start of sales of the i-th model of the product (day, month, quarter, year),

ri – diffusion coefficient of the i-th model (derived from empirical data, in particular from the optimization model built in AnyLogic based on retrospective data). This indicator is a combination of the impact of advertising on product consumers and their interpersonal communication,

t – time period (day, month, quarter, year),

ki – constant characterising the curvature of the propagation velocity of the i-th model (day, month, quarter, year),

hi – coefficient describing the planned lag of the current product model compared to the next product model in terms of technical parameters and price. This indicator affects the decline in sales when the next model is announced,

S – date when the next product model will be announced with regard to the planned date (days, months, quarters, years),

R – period of increased demand for the product according to the price-performance ratio (days, months, quarters, years). Determined on the basis of market characteristics and the niche of the product in question.

To determine **h**$_i$, the authors suggest assessing the price-quality ratio of the current modification relative to the previous modifications taking into account the interval between the releases of the modifications according to the following formula (2):

$$h_i = \left(\frac{\sum_{j=1}^{m} \left(\frac{E_{j,i+1}}{E_{j,i}} - 1 \right) * g_j}{\left(\frac{C_{i+1}}{C_i} - 1 \right)} - 1 \right) * \frac{1}{(p_{i+1} - p_i)} * 100\%, \tag{2}$$

where Ci is the market price of the i-th product modification, rubles;

$E_{j,i}$ – value of the j-th parameter of the i-th product modification. Each parameter is expressed in its own units of measurement. If there is a parameter that characterizes improvement when the value decreases, the inverse ratio should be used, i.e. $E_{(j,i)}/E_{(j,i+1)}$;

m – the number of parameters used to characterise the product;

g_i – weighting coefficient for the j-th parameter of the product. It is recommended to use the results of market analysis (trends, customer requirements) or the Delphi method to calculate it.

Verification of the model. This mathematical model has been tested on the sales of three models of PlayStation game consoles.

The parameters shown in Table 2 were used to build models of cumulative sales of game consoles.

Table 2. Values of model's parameters.

Parameter	Value
V_1, mln pcs	158
V_2, mln pcs	77.62
V_3, mln pcs	108.9
p_1, year	1
p_2, year	9
p_3, year	14
p_4, year	24
r_1	0.47
r_2	0.8
r_3	0.84
k_1	0.2
k_2	0.9
k_3	0.89
h_1, %	19
h_2, %	22.2
h_3, %	10
S, years	3
R, years	3

In order to evaluate the technical advantage of each modification, the technical parameters were analysed using the Delphi expert method, then four parameters were selected to characterise the main properties of the product. These parameters are presented in Table 3 together with weighting coefficients.

Table 3. Technical parameters of the product.

Parameter	Weighting coefficient	Playstation 2	Playstation 2	Playstation 2
Technological process used in the processor, nm	0.3	180	65	32
Video card frequency, MHz	0.35	147	550	2750
Playback resolution, number of pixels per vertical	0.2	1080	1080	2160
Number of channels with full frequency range	0.15	32	256	8000
Cost, $		178	287	546

The final cumulative sales patterns for 2000-2019 are shown in Figures 3-6.
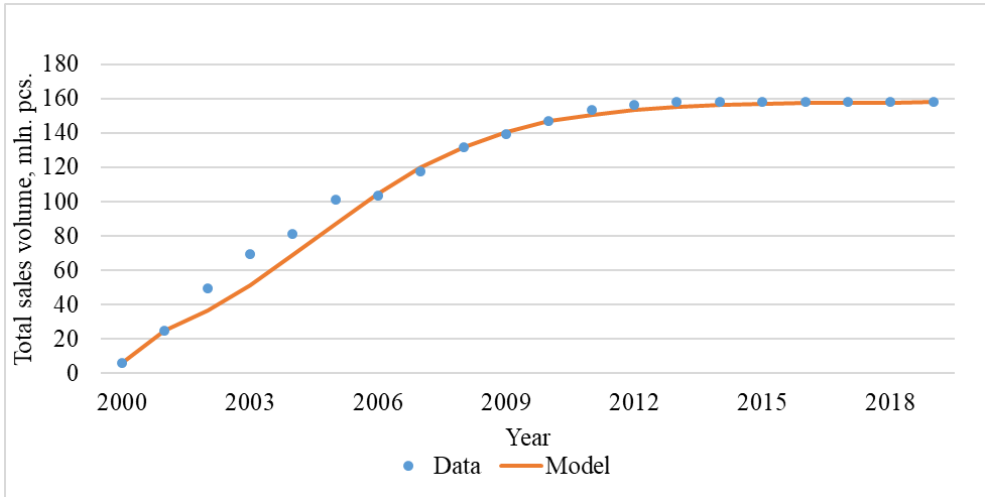
Fig. 3. Results of PlayStation 2 sales volumes modeling.
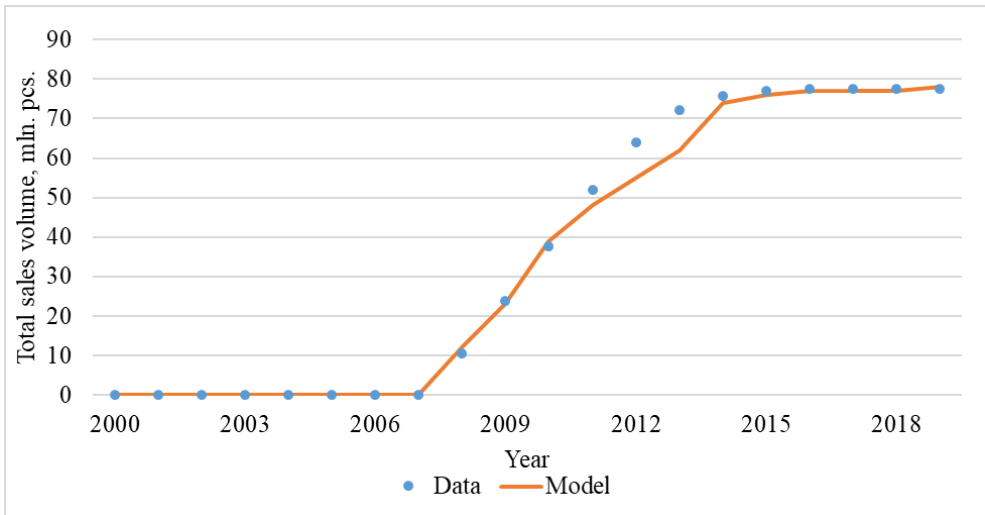

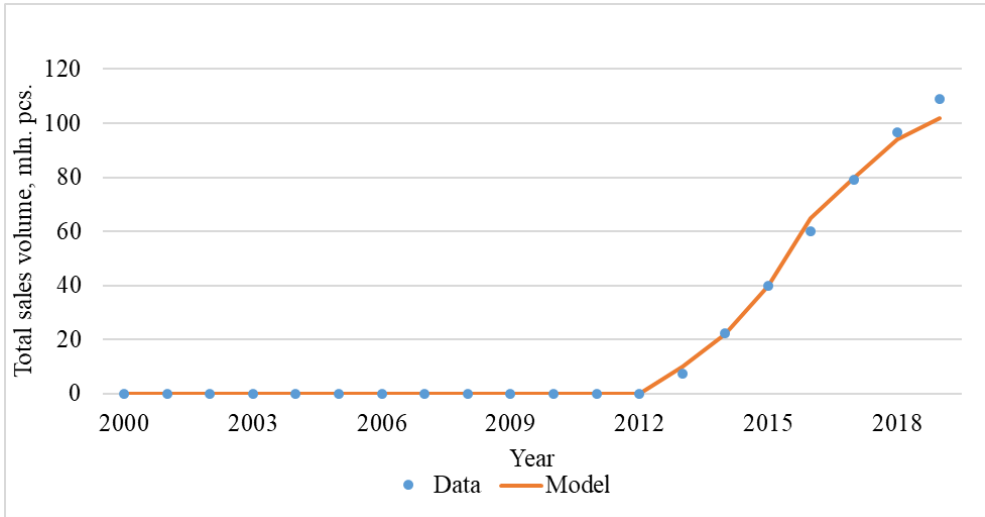**Fig. 4.** Results of PlayStation 3 sales volumes modelling.

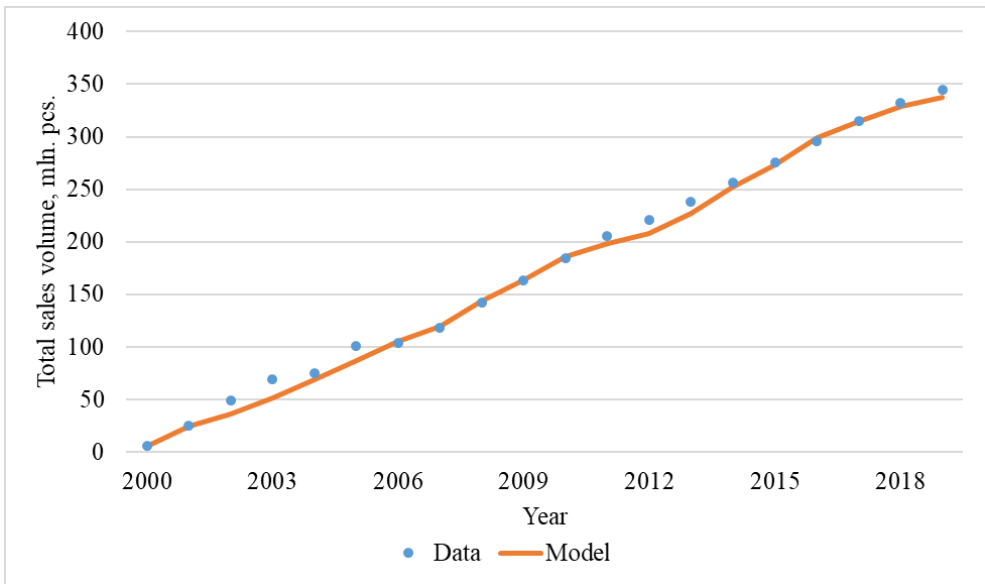**Fig. 5.** Results of PlayStation 4 sales volumes modelling.

Fig. 6. Results of PlayStation cumulative sales modelling.

The overall approximation error was 5.31%, which suggests that the model can be used to forecast sales of new product models.

The bends seen in Figure 6 are related to the effect of increased demand for product modifications in 3-year period after release, as well as a decline in demand for previous modifications after the announcement of the next model. The magnitude of these increase and decrease depends on the value of the modification to the buyer, including its technical and cost characteristics.

However, the resulting 'saddle' on a graph in Figure 2 is not so prominent for two reasons:
- lack of interest in PlayStation products by some users, as can be seen in the decline in sales growth since 2005 in Figure 6;
- buying of the new model by some of the users, which has not led to an increase in the total number of users.

To predict sales volume of a new product modification, let us consider a small company, *IMPRINTA*, which designs and sells 3D printers. This company has been on the market since 2014 and boasts considerable experience in developing more than 9 models of 3D printers, including both self-manufacturing and contract manufacturing.

For the purposes of the study, we used the sales volumes of two 3D printers having been produced since 2015. The first printer has four modifications with the characteristics shown in Table 4. To determine the h-coefficient characterizing the technical lag of the current product model compared to the next one, we used the Delphi method and asked leading designers of *IMPRINTA* and specialists from other companies in the additive manufacturing segment for evaluation. As a result, the most significant technical parameter turned out to be the minimum thickness of the layer the 3D printer can produce. The next most important parameters were the volume of the working space and reliability of printing, which is evaluated with a relative score from 1 to 5 points, where point 1 stands for possible failures at any time of printing without the possibility of resumption, and point 5 means uninterrupted printing during more than 100 hours with the ability to pause and protect against skips in the G-code.

Table 4. Characteristics of printer model No. 1 modifications.

Technical parameter	Modification 1	Modification 2	Modification 3	Modification 4
Camera volume, l	5.832	8	8,4	8,4
Printing speed, sm³/hour	40	50	50	100
Minimum layer thickness, μm	50	50	20	10
Printing temperature, °C	260	260	260	410
Printing reliability, (1-5), see description above	2	3	5	5
Cost, $	820	874	1 421	2 991

As a result of optimising the mathematical model in the AnyLogic software environment, diffusion coefficient values were calculated for modifications of the first 3D printer model. The model parameters are shown in Table 5.

Table 5. Values for modelling the sales volume of printer No. 1.

Printer's modifications	Parameters						
	V_i, pcs	P_i, quarter	r_i	k_i	h_i, %	R, quarter	S, quarter
Modification 1 (i=1)	46	1	1	0.95	0.198	3	3
Modification 2 (i=2)	550	7	0.74	0.44	0.308		
Modification 3 (i=3)	900	13	0.72	0.85	0.075		
Modification 4 (i=4)	1500	22	0.79	0.9	0.25		

The diffusion coefficient for modification 1 is equal to one because of the short sales period (more than 90% of total sales by Q3) of this variant compared to the other modifications and the fact that sales started at the point marking the half of total sales.

The results obtained are shown in Figure 7 separately for each of 3 modifications of model 1Figure 8 shows the cumulative results for model 1, taking into account the sales volume forecast for the modification 4.

The curve in Figure 8 demonstrates 2 intervals of decline in sales growth: from Q10 to Q13 and from Q19 to Q22. These changes in the sales volume growth rate are caused by the release of new modifications, influencing sales of previous models in line with their technological lag and the appearance of a new modifications. After the release of a modification, the rate of increase in sales volume returns to normal with a simultaneous increase in sales volume of the new modification. This leads to a sharp increase in sales (Q7, 13, 22). The duration of these events depends on the type of products and their consumer properties.

The approximation error of the proposed mathematical model was 8.07%, which indicates that it is highly accurate and can be used for forecasting.
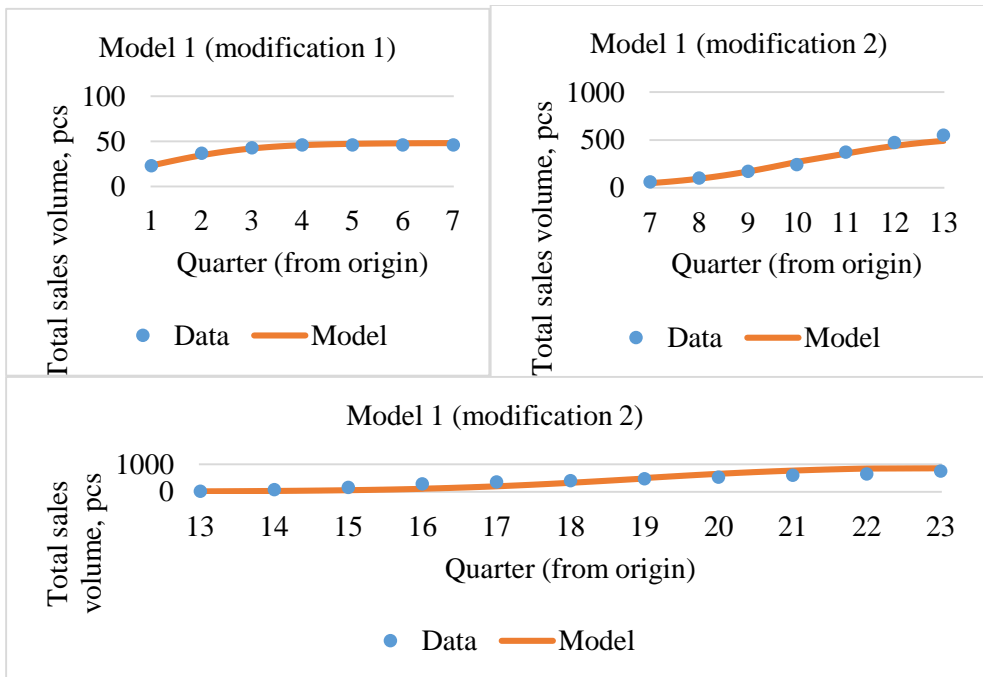

Fig. 7. Modelling results for sales volumes of modifications to printer model No. 1.
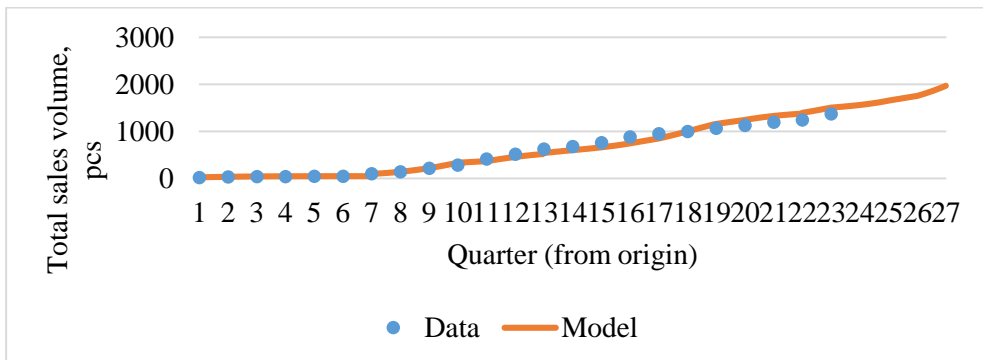

Fig. 8. Cumulative sales modelling results for printer No.1.

The second printer model has 3 modifications with the characteristics shown in Table 6. The Delphi expert method, involving IMPRINTA staff, was also used for the analysis. Printing reliability was identified as the most significant technical parameter. It is followed by the volume of the working space and the minimum thickness of the layer. The changes with respect to model 1 are conditioned by the fact that the second model is aimed at industrial applications.

Table 6. Characteristics of printer model No. 1 modifications.

Technical parameter	Modification 1	Modification 2	Modification 3
Camera volume, m3	32.19	36	36
Printing speed, sm3/hour	50	50	50
Minimum layer thickness, μm	50	20	20
Printing temperature	250	260	280
Printing reliability, (1-5)	2	3	4
Cost, $	2 305	2 459	2 937

As a result of modelling in the AnyLogic software environment, diffusion coefficient values were calculated for different modifications of the 3D printer model No.2. The rest of the model parameters are shown in Table 7.

Table 7. Values for modelling the sales volume of printer No. 2.

Printer's modifications	Parameters						
	V_i, pcs	P_i, quarter	r_i	k_i	h_i, %	R, quarter	S, quarter
Modification 1 (i=1)	250	1	0.31	0.75	0.7649		
Modification 2 (i=2)	384	7	0.68	0.97	0.0062	3	3
Modification 3 (i=3)	500	15	0.76	0.48	0.3		

The results obtained are presented in Figure 9 separately for each modifications 2 and 3 of model No. 2, taking into account the cumulative sales forecast for the next 2 quarters. Due to the limited amount of experimental data on the first modification it is not possible to carry out a detailed analysis of this very modification. Figure 10 shows the cumulative results for model 2.

The curve in Figure 9 displays the change in the growth rate at the launch of each new modification (Q1, Q7 and Q15), with an S-shaped curve characterising patterns similar to those in model No. 1.

The approximation error of the mathematical model was 9.83% for model No. 2.

Forecasting results for the 3D printer model No. 2 signal a decrease in the growth rate of sales, which may require adjustments to the production plan. The decrease is primarily conditioned by the reduced impact of the technological advantage of the third modification.

Thus, a model of innovation diffusion is built. It incorporates, in comparison with known models, not only the influence of innovation modifications on each other in terms of the time of their occurrence and planned market share, but also the impact of technical advantages of each of the modifications. In order to achieve the necessary volume of product sales, the proposed model forecasts and determines the necessary (or sufficient) technical parameters of the planned (next) product modification.
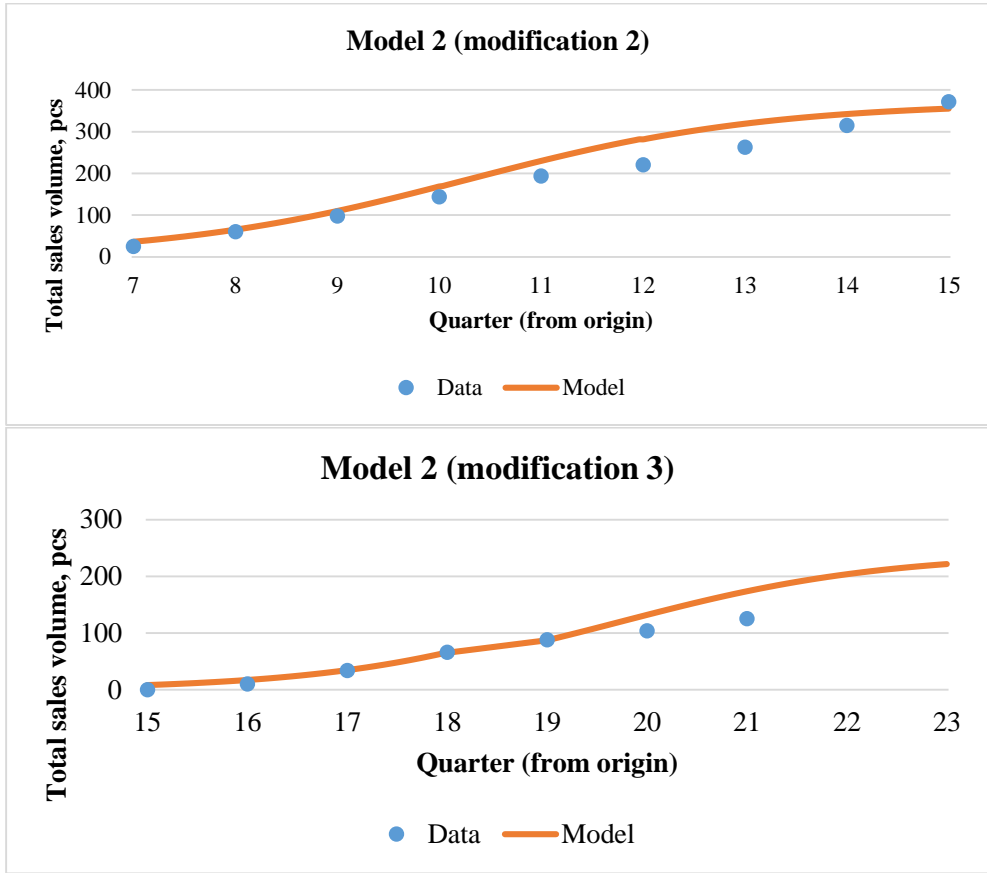
Fig. 9. Modelling results for sales volumes of modifications to printer model No. 2.
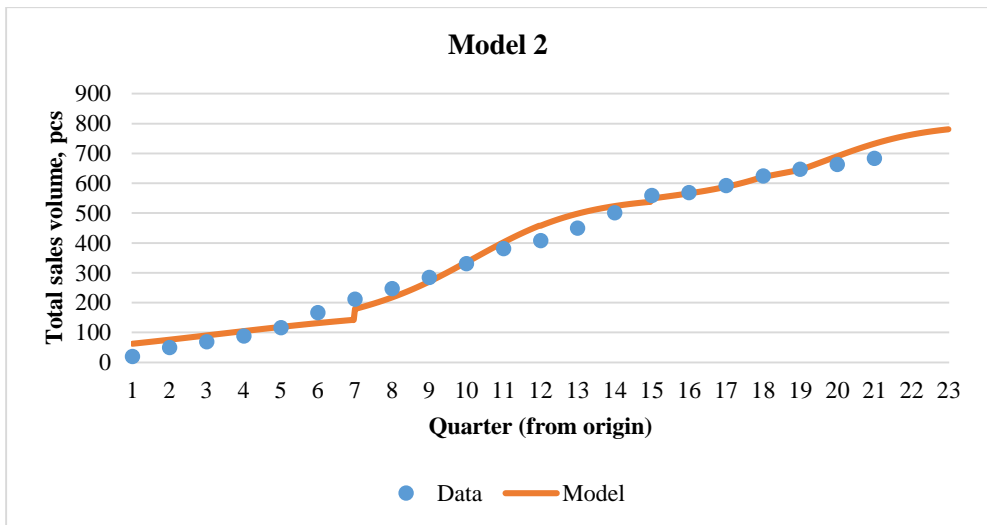

Fig. 10. Modelling results for total printer sales (model No. 2)

The data obtained on the diffusion of the current modifications of the two 3D printer models makes it possible to adjust the required production volume and the procurement

plan for materials and components, as well as to use the information on sales volume for building the marketing and advertising plan (as values for key performance indicators).

Based on the sales volume modelling, there can be elicited the following strategic requirements for the promotion of the 3D printer model No.1 (modification 5):

1.rapid release of the modification (release to market by Q28) with a modest increase in volume for a new niche (15%), planned market share of 50% and growth in total sales by 100%;

2.rapid release of the modification (release to market by Q28) with moderate increase in volume for a new niche (100%), planned market share of 70% and cumulative sales growth by 120%;

3.release of new modification by Q30 with a sizable increase in volume for a new niche (100%), planned market share of 50% and total sales growth by 70%.

3 Conclusion

According to the data got, the company can significantly reduce the requirements for a further product modification by adjusting the sales plan and expanding the niche in which the new modification will be sold, or it can boost sales by increasing the customer value of the product (bringing the price down or improving the technical parameters).

The presented model allows one to establish sufficient quality requirements for the planned product modifications, as well as to define the acceptable timeframe for their release to create a cascade diffusion effect. In this case, it is possible to use the model together with the calculation of the R&D cost to reach the required technical parameters and choose the optimal product upgrade strategies. In addition, the results can be used to build a comprehensive digital model of the markets of high-tech industries.

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