Education Tech Research Dev (2012) 60:585–600
DOI 10.1007/s11423-012-9249-2

SPECIAL ISSUE ON PERSONALIZED LEARNING

Modelling diffusion of a personalized learning framework

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Published online: 27 April 2012

Abstract A new modelling approach for diffusion of personalized learning as an educational process innovation in social group comprising adopter-teachers is proposed. An empirical analysis regarding the perception of 261 adopter-teachers from 18 schools in India about a particular personalized learning framework has been made. Based on this analysis, teacher training (TT) has been identified as one of the dominant factor which can significantly influence decision by teachers to adopt the educational innovation. Different situations corresponding to fixed and time dependent dynamic carrying capacity of potential adopter-teachers at any time have been developed. New generalized models capturing the growth dynamics of the innovation diffusion process in conjunction with the evolutionary carrying capacity of potential adopters are investigated. The coupled dynamics allows forecasting the likelihood of success or failure of new educational innovation in a given context. Different scenarios for TT are considered based on—constant growth rate model; proportional growth rate model; stratified growth rate model. The proposed modelling framework would be of great interest to education policy makers as it has the potential to predict the likelihood of success or failure of new educational innovation.

Keywords Teacher training · Personalized learning · Carrying capacity · Innovation diffusion · Dynamic model · Educational innovation

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Introduction

Personalised learning is a process innovation for education system. An innovation is not something necessarily new to the system as a whole. Rogers (1995) describes personalised learning as an innovation if it is "perceived as new by an individual or other unit of adoption. If the idea seems new to the individual, it is an innovation". Each element of an innovation is defined by the context within which it is practiced. Rogers has discussed the issue of diffusion of innovation where the major concerns centers around the relationship between the temporal growth curve depicting the number of adopter-teachers of an educational innovation and channels of communication.

According to Horizon Report (2011), "Personalized Learning is not simply a technology but an approach or process that is individualized by design and thus different from person to person". Accordingly to meet the future educational needs one may be required to look for new alternatives that enhance learning capabilities among individual learners (Bentley and Miller 2004). Teachers are key to personalised learning. In order to adopt educational innovations, teachers require extensive learning and training opportunities. As noted by Brandsford et al. (2000) there exists research evidence indicating that the most successful activities for teachers are those that are spread over time.

One of the short comings of the mandatory nature of the educational innovation is that it leads to top–down policy which poses serious challenge in its implementation. This is due to the fact innovation like personalized learning is not based on a product, technology, or system that can easily be installed or configured. Such type of innovation entails changing the relationship between teachers, students and parents and this necessitates empowering and training teachers who are responsible for implementing such a systemic change. The grounding required for the adoption of the innovation varies among the teachers. Grounding means ability to teach which is contingent upon various factors like language skills for effective communication, expertise in ICT and motivation.

It is important to note larger support will be needed if an educational innovation requires a major change in teaching practice than an innovation which demands little change from the teacher's current practice. Since teachers play a pivotal role in implementing innovations, their perception of the innovation will strongly influence this process. In other words, for the innovation to be successful, the personal willingness of teachers to adopt and integrate innovation into their classroom practice is crucial (Gess-Newsome et al. 2003). Watson (1998) strongly advocates integration of innovation with the classroom teacher and the idea that "the teacher is an empty vessel into which this externally defined innovation must be poured". Training programs and didactic practices teachers make use of in their classrooms are greatly influenced by their attitudes and beliefs (Clark and Peterson 1986; Fang 1996; Pajares 1992). Research findings reveal that many educational innovations have failed because they did not influence the beliefs or the practices of the teachers (Cohen and Ball 1990).

In an extensive survey carried out by Bennett (2001), about teacher's attitudes to new teaching methods, including those involving educational technology, it is reported that peer influence, larger classes, university pressure and student expectations are the major factors for adoption. However limited resources, insufficient time and lack of training turn to be major factors to dis-adoption. Teachers are likely to encounter transitional problems when implementing educational innovation that are parallel to those of learners as they move from conventional to new, open, and less-structured learning environments. Personalized learning environments require complex instructional design. Teachers will need to reconsider communication and collaboration skills. They will have to develop new pedagogical reflective thinking in mentoring learning, mediating values and social skills, as well as systematically evaluating students' and teacher's own activities.

It would be pertinent to point out personalised learning framework requires innovative methods of assessment for e.g. integrating both formative and summative assessment, scholastic and co-scholastic skills. Such a holistic assessment will be able to highlight the intellectual capabilities that otherwise may not have been apparent through normal assessment. According to Cranach and Snow (1977) personalization is generally defined as an "adaptation of the learning process and its content adapted to the personal characteristics and preferences of the learner, as much as possible". However, in the context of the personalising learning, it is important to be realistic in terms of the learner's ability to evolve as a competent, adaptive, goal-oriented and motivated learner.

It would be appropriate to mention that the concept of personalized learning is a process of change. This aspect is also addressed in the Concerns-Based Adoption Model (CBAM) (Hall et al. 1973; Hall and Hord 1987) which studies the process of implementing educational change by teachers. The main idea dealing with CBAM is to understand the process from the point-of-view of potential adopters; however it focuses on bottom-up strategies. As observed by Anderson (1997) CBAM theory "posits the change process as occurring to individuals who are part of organizations". It needs to be emphasized that CBAM model deals with the process of tuning teachers to new teaching–learning in terms of stages of development. The primary focus of CBAM as noted above is to address concerns of teachers. Thus CBAM examines the stages through which an individual adopter undergoes transformation before he becomes receptive to an innovation and accordingly CBAM puts emphasis on pre-service training programs.

Another issue which is of major significance in educational setting is diffusion of such innovation. It would be appropriate to identify the causes which can throw insight into success of educational innovation to diffuse. There are several studies which point to teacher training (TT) as a dominant success factor. This is also highlighted in the McKinsey Report on Education (2007). Our survey studies also confirm TT as a dominant success factor for the adoption of educational innovation.

The focus of this paper is to study the diffusion of personalized learning framework in an educational setting. This focus is at variance with CBAM which does not address the problem of temporal growth pattern of adopter-teachers in the target population. Since the adoption of an educational innovation is a matter of individual preferences and motivation we are not getting into the dynamics of conversion of a non-adopter into a potential adopter-teacher. We are interested primarily in the evolutionary dynamics of how the total of population of teachers as potential adopters as defined in terms of carrying capacity. The carrying capacity connotes teachers who have necessary grounding as a pre-requisite to be able to adopt the innovation. The CBAM factors in our model as a motivational phenomenon influencing the dynamics of the carrying capacity but we proceed further and examine how the diffusion of the innovation will ultimately shape up.

Diffusion of educational innovation

Helsel (1972) observes that school principals are pivotal in introducing innovations as they have the authority to adopt change or to maintain the status quo. For implementation of such innovations, principals have to rely on the classroom teacher, which means an unintended source of power for the teacher role who can determine the fate of an innovation. Whenever educational innovations are introduced several issues dealing with training of teachers, increased workload of teachers and corresponding loss of time to teach, adapting curriculum and books to the change, parents misgivings, and finally perceptions of students come up. Bigger question is to identify what kind of new TT contents, models and approaches and conducive environment are required for successful implementation of the educational innovation.

The success of any innovation can be gauged by the fact that what proportion of potential adopters have successfully adopted. While examining how innovations diffuse in an organization, researchers have empirically found that, when viewed over time, the rate of diffusion forms an S-shaped curve which represents a cumulative distribution of adopters. The shape of the curve rises slowly at first, because there are few adopters initially and accelerates to a maximum value till the point of inflection is reached. Thereafter the curve's rate of increase slows down until the remaining individuals have adopted.

One of the pioneers of diffusion theory of innovation is Rogers (1995) who defines innovation, as an idea, practice or object that is perceived as new by an individual or other unit of adoption. In the context of innovation diffusion process, there are four elements viz. (a) innovation, (b) communication channels, (c) the social system, and (d) time. Accordingly, it focuses on the idea of the new learning objects, new ways of teaching, and creation of new learning environments. When an innovation is introduced into a society, not everyone adopts this innovation at the same time. In fact, some never adopt the innovation. It may be highlighted at this stage that the notion of critical mass is very crucial in successful dissemination of educational innovation. Rogers introduced the notion of critical mass and defines it as "the point in time when enough individuals have adopted an interactive innovation where the perceived cost benefit of adopting the innovation changes from negative to positive for individuals in the system, so that a certain minimum number of individuals in the system adopt and the rate of adoption becomes self-sustaining".

Rogers and Jain (1968) describe the importance of adaptive units in an organization that has been positively correlated with more efficient diffusion of innovation. They conclude that larger organizations are more innovative. Further Rogers and Jain observe that "while planning for implementation of the innovation, educators must consider teacher innovativeness and attitudes toward the innovation, since patterns among teachers' personality, communication behaviour, and attitudes affect diffusion". If "precise goals of the new innovation being suggested—that is, have not planned adequately", the status quo will reassert itself. Finally, teacher characteristics like morale are important factors in educational diffusion (Carlson 1968; Emrick and Peterson 1977)

Employing Roger's framework, Bass (1969) proposed mathematical model as a nonlinear differential equation for diffusion of an innovation in a social group through two mechanisms viz. external influence like mass media and internal influence like word of mouth. The solution of the differential equation yields the well known S-shaped curve which is commonly observed in innovation diffusion studies. It is assumed in the Bass model there exists a fixed level of potential adopters in the form of fixed carrying capacity. It is to be underlined that the carrying capacity in general can be time dependent. This aspect raises the issue of the ceiling of potential adopters at any point of time who are familiar with the innovation. In most of the diffusion studies this is assumed to be a constant. An important area is to investigate the dependence of personalized learning framework on carrying capacity.

Case study: factors affecting diffusion of personalized learning framework

Recently Central Board of Secondary Education (CBSE), India has introduced a unique personalized learning framework called *continuous and comprehensive evaluation* (CCE) for its 11,500 K12 schools. The term Continuous means evaluation of learner's growth and development is an ongoing process rather than a discrete event. It includes both assessment of learning in the beginning and end of instruction (summative) and assessment for learning during the instructional process (formative) and is spread over the entire academic session. Regularity of assessment, frequency of unit testing, diagnosis of learning gaps, use of corrective measures, retesting, etc. comprises its key components.

In contrast to continuous evaluation, term comprehensive covers both the scholastic and the co-scholastic (Table 1) aspects of learner's growth and development. In both evaluation schemes, teachers are required to evaluate personal learning styles of learners.

In CCE personalized learning frame work both the teacher and the learner are required to participate actively and continuously. Personalized continuous feed back on learner's performance from the teacher and peer learner is an essential feature of CCE. Due to the comprehensive nature of the evaluation personalized profile for each learner has to be maintained continuously. In summary CCE framework is a new evaluation paradigm which is not only diagnostic in nature but also provides personalized feedback to each learner for his/her all round growth and development.

In order to study the diffusion of CCE personalized learning framework among the potential adopter-teachers community, we have identified the following innovation factors which dynamically affects the carrying capacity in the Bass model viz. (i) TT; (ii) teacher incentives (TI); (iii) teacher workload (TW); (iv) peer influence (PE); (v) school support (SS); (vi) perceived usefulness (PU); (vii) perceived ease of use (PE); (viii) compatibility (C)

In order to study the diffusion pattern of the CCE personalized learning framework we need to identify which of the above eight factors are significant. We have carried out a study (Appendix) of adopter-teachers ($N = 295$) from 18 senior secondary schools from three states of India. The states and schools were selected on the basis of their adoption level of CCE as recommended by CBSE. Total of 261 questionnaires were returned (88.4 % response rate). With inputs from education officers from CBSE who were involved in drafting the CCE framework, teacher survey was prepared. The teacher survey was divided into eight factors with multiple items under each factor: (1) TT (2) TI (3) TW (4) PE (5) SS (6) PU(7) PE (8) C.

Table 1 Evaluation tools for scholastic and co-scholastic skills (adapted from source: CBSE, 2009)

Sample scholastic evaluation tools	Sample co-scholastic evaluation tools
Conversational skills	Social and communication skills
Assignments	Interpersonal skills
Oral questions	Self awareness, values
Projects	Environment awareness
Quizzes	Thinking skills, life skills
Group research work	Creative thinking, decision making
	Critical thinking, problem solving
	Attitudes towards teachers, peers, school property, etc.

Respondents were asked to comment on the CCE factors, items used to measure each factor, language, survey length, format and comprehensibility. Following pilot online surveys with nine teachers from two schools changes were made to the teacher survey. Finally from each state six secondary schools were identified by simple random sampling from the list of CBSE schools. By working with the academic cell of the selected schools, high school teachers who had at least 1 year of experience implementing CCE were identified and presented with online teacher surveys. Most respondents were aged 27–38 years old with the sample having 81 % females and 19 % males. Furthermore, most respondents (81 %) had basic computer skills.

CCE innovation factors were measured on a five point likert scale ranging from 'strongly disagree' to 'strongly agree'. CCE factor scores were obtained by averaging the numeric values of the responses for the related items on the factor. A score near 5 was considered a very high positive attitude or strong agreement, between 3 and 4 a high positive attitude, and a score between 1 and 2 was regarded as the low attitude or a strong disagreement. The detailed description of various factors and teacher responses are given in "Appendix" section.

While several interesting aspects emerged from the teacher survey, most useful aspect of the survey results was that the TT emerged as the single most significant factor (factor score = 4.8) for the successful adoption of CCE personalized learning framework (Table 2).

Modelling of diffusion of personalized learning: constant carrying capacity

In this paper we would like to focus on the spread and speed of diffusion of the educational innovation. The rate at which teacher adopts the personalized learning framework will also determine the likelihood of the success of the personalized learning framework. The well known Bass (1969) model provides a generic framework to deal with this situation. In the context of Bass model we are concerned with innovation diffusion in a social group of size M where adoption of innovation is on account of two processes viz. mass media process and interactive process i.e. word-of-mouth (Karmeshu and Pathria 1980).

The first order differential equation giving the diffusion is described as

$$\frac{dN(t)}{dt} = (\alpha + \beta N(t))(M - N(t)), \quad N(t=0) = N_0 \tag{1}$$

where N(t) is the cumulative number of adopter-teachers who have already adopted by time t, M is carrying capacity (total number of adopter-teachers who will eventually use the

Table 2 CCE factor scores

CCE factors	Factor scores
TT	4.8
TW	3.9
TI	3.3
SS	3.2
C	3.0
PU	2.9
PE	2.8
PE	2.3

innovation), α is the coefficient of innovation or coefficient of external influence (mass media), and β is the coefficient of imitation or coefficient of internal influence (interactive). The diffusion pattern in this category of potential teachers will also follow the typical S-shaped curve even though the entire group of teachers may be technically competent (in terms of grounding in skills), individual variability regarding motivation; risk bearing may not induce everyone to adopt the new innovation simultaneously. It may be noted that the mass media process (α) represents linear mechanism whereas the interactive process (β) represents non-linear mechanism.

In terms of the fraction F(t) of potential adopter-teacher

$$F(t) = N(t)/M \tag{2}$$

the Bass model can be rewritten as

$$\frac{dN(t)}{dt} = (\alpha + \gamma F(t))(1 - F(t)), \quad \mathrm{F}(t = 0) = \mathrm{F}_0 \tag{3}$$

where $\gamma = M\beta$

Equation (3) yields the S-shaped diffusion curve. It is assumed that the carrying capacity M of the adopter-teachers remains constant.

If $N(t = 0) = 0$, the solution of Eq. (1) gives the evolution of adopter-teachers as

$$N(t) = M\left(\frac{1 - e^{-(\alpha+\gamma)t}}{1 + \frac{q}{p}e^{-(\alpha+\gamma)t}}\right) \tag{4}$$

Equation (4) yields the temporal S-shaped growth pattern of adopter-teachers which eventually reaches the carrying capacity M.

Generalized model of diffusion of personalized learning: Time-dependent carrying capacity

The crucial factor is realistic assessment of the potential adopter-teachers. The adoption of the innovation is contingent upon the base requirement of TT as the necessary condition for adoption of personalized learning framework. As the number of adopter-teachers increases, the carrying capacity of potential adopter also increases with time. The notion of the target group is therefore to be understood in the context of the base requirement. It is therefore important to underline the policy initiative which will target the entire population of the potential adopter with respect all factors of motivation. Based on our survey these factors relate to TT, TW, and TI, etc. Accordingly the carrying capacity becomes time dependent and will tend to evolve from m(t) to M with the passage of time. It is pertinent to point out that the crucial factor is the dynamics of m(t) which depends on the policy framework and its implementation.

Accordingly, the diffusion of personalized learning framework is governed by generalized diffusion model given by

$$\begin{aligned} \frac{dN}{dt} &= (\alpha + \gamma N(t))\,(m(t) - N(t)), \\ \frac{dm}{dt} &= f(m), \quad N(t = 0) = N_0,\; m(t = 0) = m_0 \end{aligned} \tag{5}$$

The choice of functional form of f(m) depends upon the approach to bridge the gap (M − m(t)), representing short-fall. Here m(t) denotes the time varying carrying capacity of potential adopter-teachers. It should be emphasized that there are several underlying features which govern the dynamics of the evolutionary path of m(t). The carrying capacity m(t) will be determined by in service TT, TW, peer influence, SS, PU, etc.

Modelling of evolution of carrying capacity

A key issue in modelling the growth dynamics of number of potential adopters is dependent on TT strategies. For example one of the aims could be to reach some proportion of carrying capacity within specified time duration. It would be interesting to see how the diffusion of personalized learning framework unfolds over time. This would also provide insight into success or failure of diffusion of educational innovation amongst teachers.

There are several strategies to bridge the short fall. Each one of these strategies will unfold a different diffusion pattern. For the purpose of illustration we are examining several possibilities regarding the functional form and this choice will allow us to study the emerging diffusion patterns.

Bridging the short fall: constant growth rate model

This approach corresponds to bridging the gap by training adopter-teachers at a constant rate. In this case the training of all potential adopter-teachers can be completed in a finite amount of time and is referred to as finite time strategy. By increasing the rate, the shortfall can be met in smaller time in relation to lower rate. The model can be described as follows

$$\begin{aligned} \frac{dN}{dt} &= (\alpha + \gamma N)\,(m(t) - N(t)) \\ \frac{dm}{dt} &= c, \quad m(t=0) = m_0, \quad N(t=0) = N_0, \quad m_0 > N_0 \end{aligned} \tag{6}$$

where c is the constant growth rate.

Figure 1 shows two sets of growth curves: adopter-TT and the corresponding adoption level during a finite time horizon. Points A_1, A_2 represent preset target training level for the potential adopter-teachers and the Points B_1, B_2 represent the actual adoption level of adopter-teachers. It is interesting to observe that at constant rates $c = 0.1$ and $c = 0.2$ the time it takes to attain the adoption levels are T_1 and T_2 respectively. One finds that the adoption level up to T_1 is fairly low whereas it increases with the decrease in growth rate though at the cost of substantial increase in time to reach the target training level. This suggests that the appropriate growth rate can be identified based on several factors like availability of resources, training programs to ensure the successful diffusion of educational innovation like personalized learning.

One of the main objectives of this study is to choose strategies which can result in increased adoption level. Such an objective can be realized by introduction of things like TI, ICT enablement of the innovation to reduce TW (Raman and Nedungadi 2011). This aspect can be captured by increasing the co-efficient of innovation or mass mediated parameter α.

Figure 2 exhibits the effect of change of increased adoption level when α is increased from 0.1 to 0.3

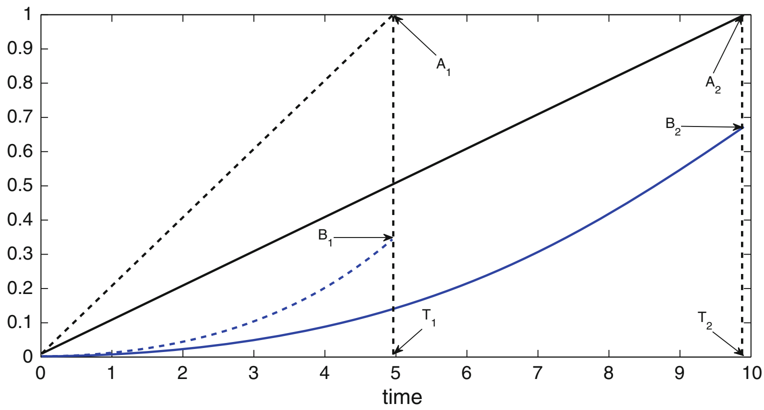

Fig. 1 Evolution of adopter-teachers and their adoption level

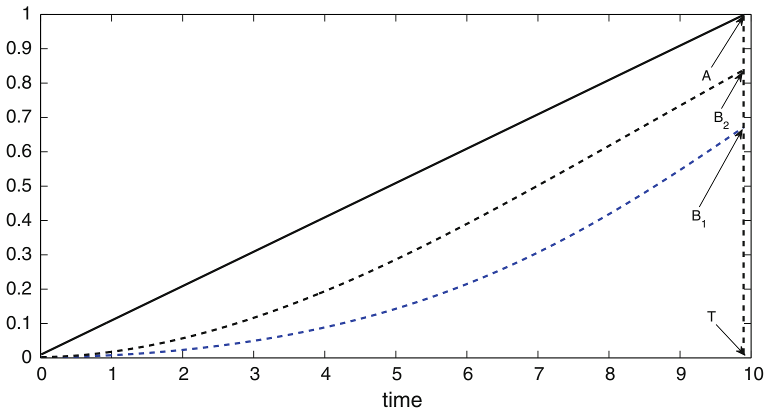

Fig. 2 Increase in adoption level as α (co-efficient of innovation) increases

Bridging the short fall: proportional growth rate model

One of the approaches to bridge the shortfall is to reduce it at a rate proportional to the gap. Accordingly, the rate of growth of potential adopter-teachers starts reducing as this number reaches the carrying capacity M. The dynamic system for innovation diffusion described by

$$\begin{aligned} \frac{dN}{dt} &= (\alpha + \gamma N)\,(m(t) - N(t)) \\ \frac{dm}{dt} &= \lambda(M - m(t)), \quad m(t=0) = m_0, \quad N(t=0) = N_0, \quad m_0 > N_0 \end{aligned} \tag{7}$$

where λ is growth rate for bridging the shortfall.

Solution of Eq. (7) gives

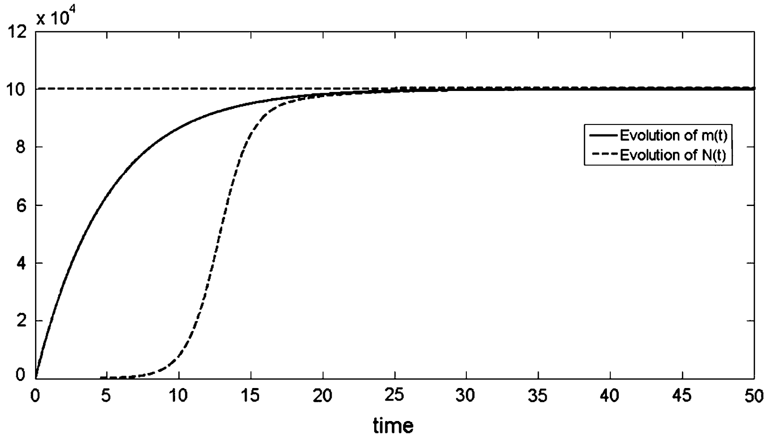

Fig. 3 Proportional growth rate model: evolutionary paths of potential adopter-teachers and their adoption level ($M = 10^5$)

$$\frac{dN}{dt} = (\alpha + \gamma N)\left[M\left(1 - e^{-\lambda t}\right) + m_0 e^{-\lambda t} - N(t)\right], \quad \mathrm{N}(t = 0) = N_0 < m_0 \tag{8}$$

Both the temporal dynamics training level of adopter-teacher and their adoption level are shown in Fig. 3. It can be seen that evolution of adoption level follows a typical S-shaped curve.

From this S-shaped curve one can also gain insight into the process adoption life cycle.

For a particular set of parameter used in Fig. 3, the process adoption life cycle is depicted in Fig. 4. It is easy to note that the maximum rate of adoption corresponds to the modal value at time $t = T^*$.

Bridging the short fall: stratified growth rate model

Population of adopter-teachers will be segmented according to the effort required to train teachers. One can move from segment requiring least effort to segment which requires the maximum effort. The segmentation can be organized on the basis of various factors e.g. logistics, efficiency, prior related knowledge etc.

Based on the segmentation criteria, we partition the total population of potential adopter-teachers into k groups such that

$$\mathrm{M}_1 + \mathrm{M}_2 + \cdots + \mathrm{M}_k = \mathrm{M} \tag{9}$$

The dynamic system of innovation diffusion into groups can be described as

$$\begin{aligned} \frac{dN_1}{dt} &= (\alpha_1 + \beta_1 N_1)\,(M_1 - N_1) \\ &\vdots \\ \frac{dN_k}{dt} &= (\alpha_k + \beta_k N_k)\,(M_k - N_k), \quad N_i(t = 0) = n_i(0), \quad i = 1, 2, \ldots, k \end{aligned} \tag{10}$$

There are several mechanisms for administering the training of adopter-teachers. We for example may consider a mechanism based on a layered approach. Starting from the first

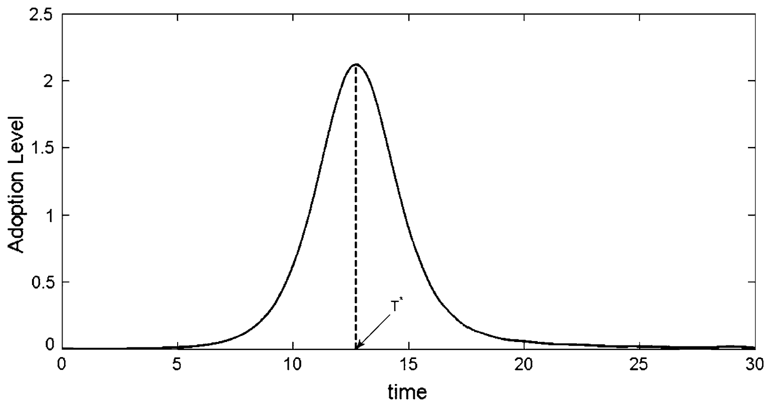

Fig. 4 Process adoption life cycle

segment and proceeding sequentially training members of each segment and simultaneously allow diffusion process to unfold from one segment to another so on. Following the approach suggested in "Bridging the short fall: constant growth rate model" and "Bridging the short fall: proportional growth rate model", the number of differential equation then will become 2k. The explicit analytical solution may not be available. The best we can do is to simulate the entire system.

For the sake of illustration we consider a simplified version of the layered model where training component is absent. This approach is useful in situation where potential adopter-teachers are fairly well acquainted with the educational innovation. We have considered the layered model for diffusion and have used simulation procedure to analyze the system. For the purposes of simulation we move from segment to next when 90 % of the potential adopter-teachers adopt the innovation. The resulting growth curve of the diffusion depicts a stair case pattern as shown in the Fig. 5.

It needs to be emphasized that the innovation diffusion parameters can be large in situations where the segment population is assumed to be fairly conversant with the educational innovation. The advantage of this approach is that with the given resources the

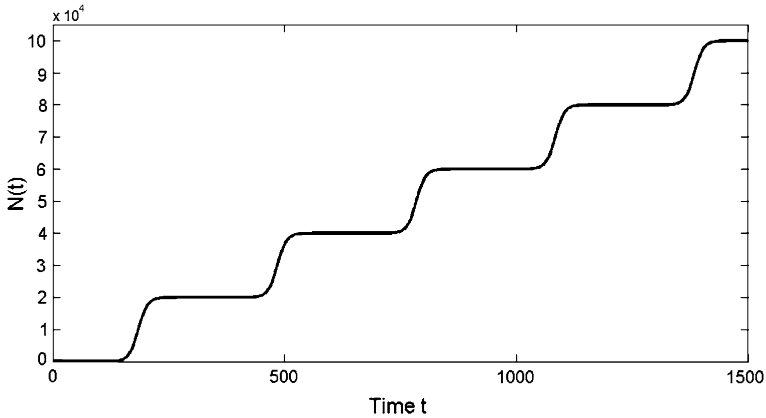

Fig. 5 Stratified growth rate model: stair case growth curve of the diffusion

process of innovation can be accelerated because quick results can be obtained with least effort and resources.

Conclusions

We have proposed a modelling framework for the study of diffusion of educational innovation among the population of potential adopter-teachers. In this context we have modelled the evolution of the potential adopters as a dynamic system by incorporating the teacher's training program which emerged as the dominant factor influencing innovation adoption from the empirical study carried out. The modelling approach has the richness to forecast the efficacy of the teachers training program as exhibited by the desired level of adoption. Our framework has been developed in deterministic setting. Entire framework can be extended to deal with stochasticity at individual adopter-teacher's level. Karmeshu and Goswami (2001) have examined the role of population heterogeneity in diffusion modelling. This may give rise to bimodality of process life cycle curve. Further analysis of this model can yield results in the transient bimodality phenomenon (Karmeshu and Goswami 2008). This aspect of bimodal process life cycle behaviour has also been examined by Vander Bulte and Joshi (2007) by introduction of two segments comprising influentials and imitators. It would be of interest to broaden the proposed modelling framework to incorporate the role of heterogeneity in the context of diffusion of educational innovation.

From the analysis of the model, we conclude that the crucial factor in the success of the adoption of personalized learning paradigm is the in service TT program for the existing teachers. Various training programs equipping the teacher with new pedagogical methods and technology supported teaching skills are offered in schools motivating the teacher to adopt new innovation. Since the teacher's training program is multidimensional, a carefully designed strategy which would speed up the process of training would ensure the successful adoption of this educational innovation. The generalized innovation diffusion model has the ability to capture the multidimensional character of the training program. This would give us various scenarios clearly identifying growth trajectories from which we can choose the optimal solution given the objective function and the resources available to complete the task. While this paper focused on the perspective of teachers, future research utilising similar methodology could consider adoption of educational innovation from the perspective of students.

Acknowledgements The authors would like to thank reviewers whose comments have led to considerable improvement of the quality of the paper, Mr. V. P. Jain for extensive discussions and suggestions about the modelling framework, Mr. Sudheer Sharma for his help with numerical simulations and Dr. V. B. Lal for his thoughtful comments and observations.

Appendix

Factors affecting teacher adoption of CCE personalized learning framework

- TT
  - TT refers to the extent to which individuals consider the amount and type of training they received to be useful in using the CCE.

- TI
    - TI refer to the degree to which individuals perceive school management as providing incentives to encourage CCE implementation. If teachers expect to be rewarded extrinsically, for example, by receiving a bonus or being commended for their achievements, then they will have greater willingness to adopt CCE.
- TW
    - TW represents the perception of the time and effort required to integrate CCE in classroom teaching.
- PE
    - Interpersonal influence appears to be extremely important in influencing potential adopters, as is demonstrated by the fact that the opinions of peers significantly affect the way in which an individual feels pressures associated with adoption of the innovation. On the otherhand, while some teachers oppose the adoption of CCE, other teachers may be influenced by them.
- PU
    - Is defined as “the degree to which a person believes that using a particular system would enhance his or her job performance”. Therefore, teachers will be more willing to adopt CCE if adoption can help them achieve better teaching outcomes.
- PE
    - PE is defined as “the degree to which a person believes that using a new innovation would be free of effort”. When users find an innovation is hard to use, the acceptance and usage rate would be influenced in a negative way. Therefore, if CCE is easy-to-use, teacher adoption intention is enhanced
- C
    - C is defined as the degree to which an innovation is perceived as consistent with the existing values, needs and past experiences of potential adopters. If CCE makes a teacher feel they are using something they are somewhat familiar with and which meets their needs and habits, they adopt CCE in their teaching.

Survey questionnaire with item mean scores

Survey options: strongly disagree (1); disagree (2); neither agrees nor disagree (3); agree (4); strongly agree (5)

TT	Item mean scores
Training sessions provided were very useful	4.9
Training materials provided were very informative	4.8
Training materials provided are effective in expressing the objectives of CCE	4.9
Website for CCE provides information in a variety of ways (text, graphic, animation, audio, video, etc.)	4.8

Appendix continued

TT	Item mean scores
My school does not provide convenient time for getting trained on CCE	4.5
Average factor score	4.8
TI	
My willingness to adopt CCE would be influenced by the rewards the school provides	3.6
My willingness to adopt CCE would be influenced if the school considers using CCE as an item in the teacher performance evaluation	3.3
The school would timely reward the teachers who have adopted CCE	3.1
Average factor score	3.3
TW	
I don't have the time to enter data CCE data	4.1
The effort is high for me to enter CCE data	4.2
I am worried that if give feedback to students, I will have to spend additional time answering follow up questions	3.4
Average factor score	3.9
PI	
My teacher colleagues think that using CCE is valuable for teaching	2.8
My teacher colleagues' opinions are important to me	2.8
If most of my colleagues have started to use CCE to support their teaching, this fact would press me to do the same	3.2
I will learn how to use CCE after seeing my teacher colleagues use it	2.4
Average factor score	2.8
SS	
The school is committed to implementing CCE	4.2
The school is committed to supporting my efforts in using CCE for teaching	3.1
The school strongly encourages the use of CCE by teachers	3.6
The school will recognize my efforts in using CCE for teaching	3.1
The use of CCE for teaching is important to the school	3.3
I have pressures from my organization to use CCE	2.1
Average factor score	3.2
PU	
Using CCE enables me to accomplish my teaching tasks more quickly	2.8
Using CCE improves the quality of my teaching	3.2
Using CCE makes teaching easier	2.7
Using CCE enhances my teaching effectiveness.	3.1
Using CCE gives me greater control over my teaching	3.4
CCE supports student learning in different ways	3.6
Using CCE would improve my performance in teaching (save time and effort)	2.1
Using CCE would improve by productivity	2.4
Average factor score	2.9
PE	
Using CCE to support my teaching is clear and understandable	2.6
When using CCE to support my teaching, it is easy to get the software tools to support CCE	2.1
Overall, I believe that it is easy to use CCE to support my teaching	2.2

Appendix continued

TT	Item mean scores
Average factor score	2.3
C	
Using CCE will fit well with the way I teach and assess students	2.8
Using CCE will fit into my style of teaching	2.4
I feel already over-burdened without adding CCE into my instructional process	3.8
Average factor score	3.0

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