

NAVIGATING DIGITAL TRANSFORMATION

The Dynamics of Educational Technology Adoption

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First published 2026

ISBN: 978-1-032-94407-4 (hbk)

ISBN: 978-1-032-94406-7 (pbk)

ISBN: 978-1-003-57056-1 (ebk)

Chapter 2

EXPLORING THE DYNAMICS OF TEACHERS' TECHNOLOGY ADOPTION THROUGH A LONGITUDINAL LENS

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DOI: 10.4324/9781003570561-2



Routledge
Taylor & Francis Group
LONDON AND NEW YORK

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EXPLORING THE DYNAMICS OF TEACHERS' TECHNOLOGY ADOPTION THROUGH A LONGITUDINAL LENS

Technology adoption in educational settings is a multifaceted process that unfolds over time, rather than a singular, static event. The integration of new technologies enables teachers to grow as they gradually grasp novel methods and become proficient in their application. However, much of the existing research in this domain has predominantly focused on the attributes of innovations and cross-sectional adoption patterns, often overlooking the intricate and dynamic behavioral processes involved in technology usage. To fully comprehend the dynamics of technology adoption in education, it is essential to shift the research lens toward the emerging patterns in the process of teachers' tech adoption longitudinally.

The distinction between process-oriented and variance-based research frameworks is particularly relevant in studying innovation adoption. While variance-based research emphasizes the relationship between specific attributes and innovativeness without considering the temporal sequence of events, process-oriented research investigates how various factors influence the progression of events over time. Despite the prominence of variance-based models, such as the widely utilized Technology Acceptance Model (TAM) in e-learning adoption studies, these approaches often fall short in capturing the dynamic and temporal complexities of the adoption process. This limitation calls for methodologies that can effectively model the progression of adoption behaviors and account for the influence of significant events and interventions over time.

In response to these challenges, this chapter explores the dynamic nature of teachers' technology adoption through a longitudinal lens. By leveraging a non-homogeneous hidden Markov model, this work examines how internal and external factors, including individual experiences, external interventions,

and the heterogeneity of teachers' intentions and usage patterns, conjointly shape the adoption process. The findings provide a deeper understanding of the critical role of peer learning, classroom practice, and targeted interventions in facilitating and sustaining the active use of technology. Furthermore, the proposed approach offers researchers a novel framework to assess both the short- and long-term impacts of interventions, ultimately contributing to more effective strategies for supporting teachers' ongoing engagement with educational technologies.

2.1 Modeling Dynamics of Technology Adoption

The adoption of technology is often conceptualized as a staged process, aiming to approximate user behavior at various points in time (Hall & Hord, 2001; Rogers, 2003; Hameed et al., 2012). This staged framework attempts to approximate the dynamic nature of technology adoption, assuming that the process evolves incrementally as users progress through different phases (Rogers, 2003; Besley & Case, 1993). To better understand these dynamics, researchers have advocated for the use of longitudinal methods that capture patterns of technology usage over extended periods (Chin & Marcolin, 2001). While some studies on technology acceptance claim to address temporal dynamics through longitudinal applications of TAM-based models (Karahanna et al., 1999; Venkatesh et al., 2000; Venkatesh & Davis, 2000; Morris & Venkatesh, 2000; Venkatesh et al., 2007), the majority still rely on data collected at a limited number of points in time. While these studies represent incremental improvements over one-time surveys, they often fall short of fully capturing the dynamic nature of adoption behaviors. Cross-sectional analyses can lead to incomplete or biased conclusions, particularly when the adoption process remains unfinished at certain stages of data collection (Besley & Case, 1993; Moser & Barrett, 2006). Moreover, researchers conducting longitudinal studies with TAM-based frameworks have acknowledged the constraints of their variance-oriented approaches. They emphasize the need for future research to delve deeper into the sequence of events and actions that drive adoption over time, rather than merely focusing on static associations between variables (Venkatesh & Davis, 2000). This shift would enable a more comprehensive understanding of how technology adoption unfolds dynamically.

Previous studies tend to explain the adoption trajectory in a discrete-level structure with the measure of dynamics. For example, Bayerl et al. (2016) suggested that the concept of technology-adoption states can be used as a framework to explain the mechanisms behind the dynamics. A state space was introduced by Ryan and Tucker (2012) as the indicator functions for individual adoption status over time. Similarly, a sentiment-level structure was proposed by Liu et al. (2015) and Moser and Barrett (2006), in which the adoption decision was categorized into different levels of adoption, expansion,

and disadoption. As a step further to understand the trajectory of teachers' technology adoption, the present study established a dynamic model of technology adoption by applying a discrete state-space model. Specifically, we followed a non-homogeneous hidden Markov model (NHMM), which was proposed by Netzer et al. (2008) to model the dynamics of a relationship. In the NHMM, covariate time series, such as time trends and seasonal variations, can be incorporated into the model by allowing some of the parameters to depend on covariates to capture their dynamics. Derived models of the NHMM have been applied in economic dynamic studies (Montoya et al., 2010; Zhang et al., 2014; Chang & Zhang, 2016; Ma et al., 2016) and learning dynamics (Singh et al., 2011; Ansari et al., 2012). However, this methodology has not been adopted in studies focusing on the dynamics of the process of teachers' technology adoption. Thus, the current work employs an NHMM to investigate the factors influencing adoption dynamics and examines their impact on the stability and evolution of adoption patterns.

In particular, this study examines factors that influence teachers' use of e-textbooks. These factors include teachers' personal experience and working environment, both of which may influence their intention to use digital textbooks and their actual usage, thereby shaping the evolution of adoption states. The hidden Markov model (HMM) approach defines a set of hidden states to represent the adoption dynamics, distinguished by varying levels of intention to use an e-textbook. At any given time, a teacher occupies one of the unobserved "use intention" states. To measure the adoption level, the states are constrained to be ordered. Specifically, given a set of use intention states $s \in \{1, 2, \dots, k\}$, 1 represents the lowest use intention state and k the highest. A teacher's past experiences and environmental pressures may influence their transition between states. The HMM approach conceptualizes the impacts as the interactions between the teacher and their personal use experience. Both positive and negative effects may arise from the interactions. This implies that a teacher may gain confidence through use experience but may also feel frustrated by the extra effort required. This model further conceptualizes these impacts as the interventions happening to the teacher and in their environment. Such interventions may include teacher seminars, e-textbook demonstration classes, or institutional pressures related to school culture.

The HMM is a stochastic process model that is not directly observable; instead, it is inferred through another set of stochastic processes that generates observations. In a standard HMM with time homogeneity, the transition between states follows a Markov process, which can be limited in practice (Holsclaw et al., 2017). One way to relax the assumption is to allow the transition to depend on covariate time series (Zucchini et al., 2017). A common way is to drop the assumption of time homogeneity and instead assume the transition probabilities as functions of covariates. HMM can also be modified to account for covariates by allowing state-dependent probabilities to vary

with them. This study applies both methods to model teacher technology-adoption dynamics.

In summary, the NHMM includes several key components: (1) a set of states describing teachers' "use intention" levels at any given time, (2) the process governing state transitions over time, and (3) parametric functions linking user intention states to observed actions, which depend on covariates. The next section details each of these components.

2.2 The Components of Model

The proposed NHMM consists of three main components: (1) a transition probability matrix for the use of intention states, $Q_{i,t-1 \rightarrow t}$; (2) the initial state distribution π_i ; and (3) a probability distribution describing the teacher's actual usage, conditional on their use intention state, $\Pr(y_{it}|s)$.

2.2.1 The Transition Matrix

Ryan and Tucker (2012) conceptualize technology adoption decisions as an optimal waiting problem, where each user adopts a technology when its expected benefits exceed the opportunity cost of non-adoption. Following this framework, we model state transitions as a Markov chain, because each teacher's adoption decision is based on cumulative tendency flows from past experiences. In our model, a teacher's propensity to transition between states is influenced by three factors: teaching experience, school normative pressure, and personal attitude toward technology.

Each state is an indicator function representing a distinct level of technology adoption. To avoid the model parsimony being affected by a random walk of a Markov process, we follow Netzer et al. (2008) and Singh et al. (2011) by restricting transitions to adjacent states only. It means that during any time t , a teacher has three options: (1) decrease adoption by moving down one state, (2) maintain the current adoption level by staying in the same state, (3) increase adoption by moving up one state.

State transitions are governed by threshold mechanisms, where changes in "usage intention" occur when the transition propensity exceeds specific threshold levels that represent adoption costs. For instance, when past experiences are highly negative (e.g., excessive effort with minimal benefits) and there is no facilitator support, the transition propensity may fall below the lower threshold, triggering a transition to a lower state. Conversely, when experiences are highly positive (e.g., receiving significant positive student feedback) and sufficient support is provided, the propensity may exceed the upper threshold, leading to a transition to a higher state. If the previous period's factors have minimal impact, the teacher likely maintains their current usage intention state.

Specifically, the transition probabilities $q_{i,s_{t-1} \rightarrow s_t}$ in matrix $Q_{i,s_{t-1} \rightarrow s_t}$ could be expressed as:

$$\begin{aligned} q_{i,s \rightarrow s-1} &= \Phi(\mu_{sl} - \beta_s R_{it} - \xi_i), \\ q_{i,s \rightarrow s} &= \Phi(\mu_{sb} - \beta_s R_{it} - \xi_i) - \Phi(\mu_{sl} - \beta_s R_{it} - \xi_i), \\ q_{i,s \rightarrow s+1} &= 1 - \Phi(\mu_{sb} - \beta_s R_{it} - \xi_i), \\ \forall s &\in \{1, 2, \dots, K\} \end{aligned}$$

where:

- $\Phi(\cdot)$ denotes the binary logit function.
- μ_{sl} and μ_{sb} are the higher and the lower threshold values for a teacher in a certain state s , respectively.
- To constrain the ordering of the thresholds, the constraint $\mu_{sl} < \mu_{sb}$ is applied to ensure that the higher threshold is larger than the lower threshold. Notice that the lower threshold is set as $\mu_{1l} = -\infty$ in the lowest state, and similarly, the higher threshold is set as $\mu_{Kb} = +\infty$ in the highest state.
- The propensity consists of impacts of factors $\beta_s R_{it}$ and individual-specific propensity ξ_i . Here, R_{it} is a vector of time-varying covariates that represent the experience gained and pressure gained by teacher i in period t . β_s is a vector of parameters capturing the effect of factors impacted on the intention to use e-textbook for the transition from state s to other states.
- The teacher-specific random effects, ξ_i , is used to account for the individual-specific unobserved heterogeneity for using intention transition.

Figure 2.1 illustrates the state transition model in a specific state. The two logit threshold lines (μ_l and μ_b) divide the probability space into three regions, each corresponding to a transition option. As shown, teachers tend to maintain or increase their state when propensity values are larger.

2.2.2 The Initial State Distribution

The probability that teacher i in the state s at the beginning of the observation is denoted by $\pi_{is} = P(s_{i1} = s)$. While homogeneous HMMs typically define the initial state distribution as the stationary distribution of the transition matrix, this approach is not feasible in our study because the transition matrix is a parametric function of time-varying covariates. Instead, we calculate the stationary distribution of a special transition matrix by solving the equation

$$\pi_i = \pi_i \cdot Q_i^0, \text{ under the constraint } \sum_{s=1}^K \pi_{is} = 1, \text{ where } Q_i^0 \text{ represents the transi-}$$

tion matrix where the exogenous covariates set to zero but the threshold parameters and individual random effect parameter of the teacher i are maintained. Specifically, Q_i^0 is modeled as:

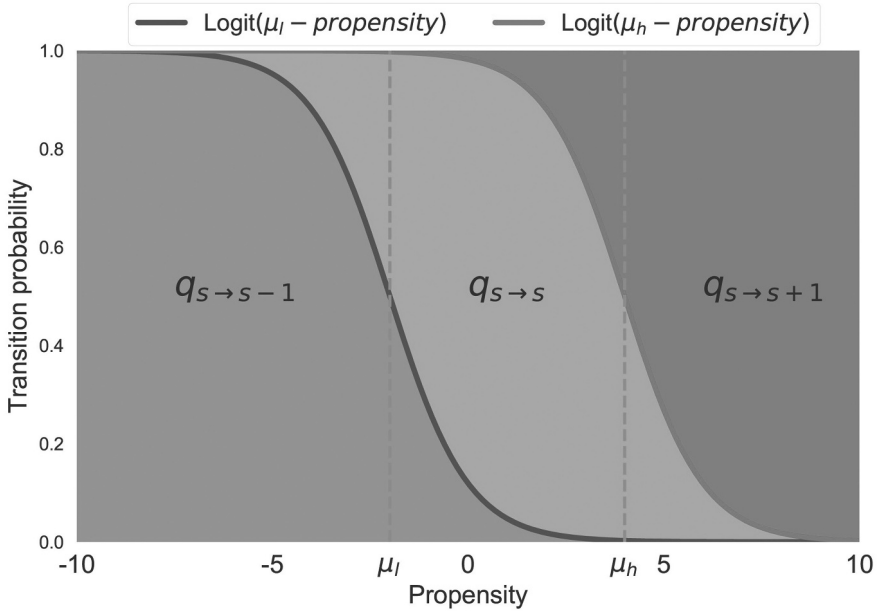


FIGURE 2.1 Using the ordered logit function model transitions in a state.

$$\begin{aligned}
 q_{i,s \rightarrow s-1}^0 &= \Phi(\mu_{sl} - \xi_i), \\
 q_{i,s \rightarrow s}^0 &= \Phi(\mu_{sh} - \xi_i) - \Phi(\mu_{sl} - \xi_i), \\
 q_{i,s \rightarrow s+1}^0 &= 1 - \Phi(\mu_{sh} - \xi_i), \\
 \forall s &\in \{1, 2, \dots, K\}
 \end{aligned}$$

where $\Phi(\cdot)$ denotes the binary logit function. By removing the effects of the time-varying covariates in this transition matrix, we can isolate the impact of individual effect on initial state distribution π_i .

2.2.3 The State-Dependent Usage

The e-textbook usage pattern for teacher i at time t is conditioned on her using intention state and the state-dependent factors. Since teacher makes two inter-related decisions at each time point, we model both the choice to use e-textbooks and the quantity of usage at time t . This creates a bivariate decision process conditioned on the usage intention state, which we model using a bivariate HMM, with bivariate state-dependent emissions.

Following the simultaneity modeling suggested by Netzer et al. (2008), our NHMM model further assumes that these two decisions are contemporaneously independent when conditioned on the user intention state. This

means that any correlation between the decision to use e-textbook and to perform actions in period t is captured in the state.

Based on these assumptions, we employ the zero-inflated Poisson distribution to model the state-dependent usage probabilities. The likelihood function of observing a particular number of actions performed by teacher i at time t is:

$$L_{it|s} = L(\psi_{it|s}, \lambda_{it|s} | y_{it}) = \begin{cases} (1 - \psi_{it|s}) + \psi_{it|s} \exp(-\lambda_{it|s}), & \text{if } y_{it} = 0 \\ \psi_{it|s} \frac{\exp(-\lambda_{it|s}) \lambda_{it|s}^{y_{it}}}{y_{it}!}, & \text{if } y_{it} = 1, 2, 3, \dots \end{cases}$$

where y_{it} is the number of actions performed by teacher i in period t . $\psi_{it|s}$ is the expected proportion of e-textbook adoption conditioned on her using intention state during period t , under the constraint $0 < \psi_{it|s} < 1$. $\lambda_{it|s}$ is the expected number of actions performed by teacher i conditioned on her using intention state during period t , under the constraint $\lambda_{it|s} \geq 0$.

Next, two usage parameters are modelled as follows:

- 1 the probability of the dichotomous e-textbook using choice $\psi_{it|s}$ following the binary logit model:

$$\psi_{it|s} = \Phi(\rho_s X_{it} + \theta_s + \alpha_i)$$

where $\Phi(\cdot)$ is the binary logit function. X_{it} is the vector of factors that directly influence a teacher's choice and ρ_s is a vector of state-specific coefficients for input factors. θ_s is a state-specific intercept parameter for state s . The teacher-specific random effects α_i capture the individual unobserved heterogeneity for using choice.

- 2 the frequency parameter $\lambda_{it|s}$ follows a log-linear model:

$$\lambda_{it|s} = \exp(\zeta_s X_{it} + \delta_s + \eta_i)$$

where ζ_s is a vector of state-specific coefficients for input factors. δ_s is a state-specific intercept parameter for state s . The teacher-specific random effects η_i capture the individual unobserved heterogeneity for action quantity.

To ensure identification of the states, we constrain both $\psi_{it|s}$ and $\lambda_{it|s}$ to be increasing, so that the usage probabilities are non-decreasing in the intention states. As both the intercepts and coefficient parameters are state-specific, we impose this restriction on these parameters $\{\rho_s, \theta_s, \zeta_s, \delta_s\}$ by setting $\rho_1 < \rho_2 \dots < \rho_s \dots < \rho_K$, $\theta_1 < \theta_2 \dots < \theta_s \dots < \theta_K$, $\zeta_1 < \zeta_2 \dots < \zeta_s \dots < \zeta_K$, and $\delta_1 < \delta_2 \dots < \delta_s \dots < \delta_K$.

Note that there is a difference between the vectors of covariates (R_{it}) included in the transition matrix and the vectors of covariates in state-dependent usage (X_{it}). Specifically, R_{it} have long-term or enduring impacts on teachers' e-textbook using intention, while X_{it} have short-term impacts on actual use at time t .

2.2.4 The Likelihood Function

Let $\Upsilon_{it}^T = (y_{i0}, y_{i1}, \dots, y_{iT})$ denote a sequence of T observations for teacher i . Using our notations for the components of the HMM described above, the likelihood function of observing the teacher i 's actual use over T periods can be written in matrix products following Zucchini et al. (2017):

$$L_{iT} = P(\Upsilon_{it}^T) = \pi_i A_{i1} \left(\prod_{t=2}^T Q_{i,s_{t-1} \rightarrow s_t} A_{it} \right) \mathbf{1}'$$

where π_i is the initial state distribution, $Q_{i,s_{t-1} \rightarrow s_t}$ is the transition matrix, A_{it} is a $K \times K$ diagonal matrix containing the elements of $L_{it|s}$ on the diagonal, and $\mathbf{1}'$ is a $K \times 1$ vector of ones.

2.3 Adoption Data Collection and Factor Induction

This study analyzes data from a digital textbook platform used by 110 teachers across different subjects at a primary school in Shanghai. To extract impact factors from log entries, we adopted a mixed-methods approach that combined both quantitative and qualitative techniques. Following the sequential exploratory design phases (Creswell et al., 2003), which included participant observation and qualitative interviews, we collected data from three sources: (1) action records in the platform database; (2) classroom observations to generalize use cases and capture potential impact events; and (3) semi-structured interviews with 15 teachers, including one principal, three subject leaders, six early adopter teachers, and another five teachers representing various usage levels.

The digital textbook platform includes three components: a web-based authoring interface, a teacher-specific iPad application, and a student-specific iPad application. Teachers were given access to customize the digital content for specific teaching objectives. Our classroom observation reveals three primary use scenarios on the platform: (1) pre-class lesson planning (creating course outlines, describing learning activities, uploading media resources from tools like PowerPoint, and preparing quizzes); (2) in-class activities organization through digital resources sharing with students; and (3) post-class assessment (rating performance and providing feedback on homework via the iPad application). The study spans five semesters from October 2014 to January

2017, encompassing a total of 17,071 teachers' actions, 5,698 created lessons, 17,071 uploaded digital resources, and 3,364,533 student responses.

We conducted interviews following Bayerl et al.'s (2016) protocol, to gather insights on adopters' expectations, implementation process, usage experiences, and policy decisions. Features related to technology adoption in real settings, such as, were considered. The semi-structured interviews considered contextual factors such as subjects, grades, and positions, with additional questions exploring emerging topics. The interviews yielded some model-free evidence of adoption dynamics and motivated us to identify key factors affecting teachers' technology adoption in the data. Teachers reported that their prior experience with the tools affected their using intention and they can enhance their skills through both personal exploration and peer learning. A majority of teachers held positive views about the interaction between themselves and students with e-textbooks in class, particularly regarding digital resource distribution, activity implementation, and immediate student performance tracking, which all contribute to achieving their teaching objectives. As noted by one teacher "The greatest advantage is that it can provide us with teaching feedback immediately by tracking the students' answering in class." However, some teachers highlighted increased workload from adopting the e-textbook platform as a challenge: "We used to do it in a paper way. Now, we have to spend more time on searching images, making slides, and uploading them to the platform." Over time, teachers developed conventional practices for common editing tasks, such as applying shared PowerPoint templates for common image designing and adopting consistent file naming conventions (using labels such as "before class," "in class," and "post class") to help others reuse the materials.

Peer learning emerged as a crucial factor in building confidence with technology adoption. Specifically, teachers reported that they acquired specific skills by observing experienced colleagues demonstrate "steps or tricks" in the authoring platform, "utilization of templates" for pre-class resources, and "treatment or timing" of e-textbooks activities in seminars. Typically, a seminar had two sessions. The first session was an open class in which a skilled teacher demonstrated a lesson with e-textbooks while subject team colleagues and occasional external visitors (from other schools or the local educational bureau) observed. The second session was a discussion moderated by the subject leader or the principal where e-textbook pioneers and experienced teachers provide lesson feedback and shared experiences through small tutorials. Moreover, additional professional development occurred on an Open House Day event where observers were encouraged to provide more feedback. Finally, all seminar attendants completed a post-seminar survey with lesson comments.

Our observation revealed two key situations that significantly influenced teachers' e-textbook usage. First, usage frequency increased notably before special events, including visiting activities, open e-textbook seminars, and Open House days, driven by the expectation to showcase the adoption of e-textbooks to visitors. As the principal noted, "the e-textbook has become a

symbol of our school, and it makes our school unique in this district.” Second, more teachers became active after the administrators made the e-textbook usage mandatory during the third semester. This policy shift yielded two changes: (1) incorporating e-textbook teaching performance into teachers’ key performance indicators and (2) requiring teachers to contribute two e-textbook lessons per semester to the digital resource library. Figure 2.2 illustrates the pattern of digital lesson submissions from teachers over the semesters. Notably, the submissions increased significantly in the third semester and maintained high levels in the two subsequent semesters, indicating the policy substantial impact on teacher’s technology adoption.

Furthermore, results showed that the crucial role of the ‘Pioneer’ subgroup in driving the e-textbook adoption, particularly during the first two semesters. This group consisted of three types of teachers: subject leaders who served as opinion leaders in their teams, novice teachers who were recent graduates with strong technology skills, and early adopters who were comfortable with innovation. In contrast, the ‘Follower’ subgroup might be skeptical initially but gradually embraced the technology after observing its effectiveness or responding to external pressures.

The pattern of technology usage varied by subjects but not by grade level. According to the submission entries, English and Chinese teachers predominantly used pictures or images for dialogue-based tasks as using illustration is a common practice. In contrast, math teachers preferred the quiz modules of e-textbooks for performance assessment. The absence of significant

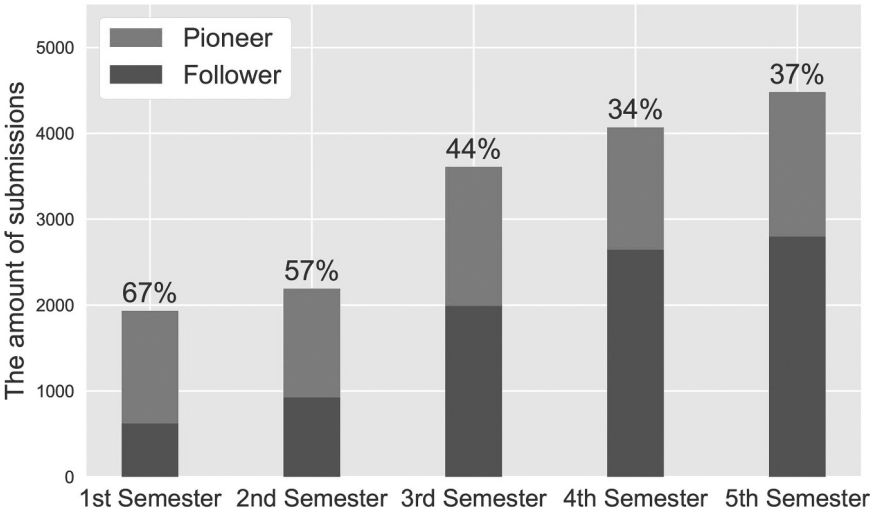


FIGURE 2.2 Amount of digital resource contributions over semesters.

grade-level differences is likely due to the specific teaching arrangement in the school, as most teachers worked for multiple grades in the five semesters, some advancing with their students while others teaching multiple grades simultaneously.

2.3.1 Independent Variables

Authoring digital resource experience: In our study, we define “individual usage experience” as the amount of technology usage a teacher gains through personal practice over time. According to the observations and interviews, we examined two aspects of teacher experience. Following Singh et al.’s (2011) time-discounted cumulative experience function from a learning curve model, we define the authoring e-textbook experience for teacher i as the accumulated number of digital resources submitted up to the previous period $t - 1$. This condition assumes that more recent authoring activities have a stronger impact on use intention than earlier ones. Specifically, this experience model can be expressed as follows:

$$\text{Experience}_{it}^a = \sum_{m=1}^{t-1} d_a^{(t-m-1)} \cdot \log(N_{im}^a + 1)$$

where d_a is a decay factor and is positive but less than or equal to 1. A d_a closer to 1 indicates a lower decay in the impact of the experience. We consider d_a as a hyperparameter that will be assigned by selecting from a series of candidate values. N_{im}^a is the number of digital resources submitted by teacher i over period m . Here, we apply a log-transformation to N_{im}^a to capture potentially diminishing effects given that N_{im}^a is relatively high.

Organizing e-textbook activity experience: the second experience variable captures teachers’ history of using the e-textbook with students. This experience model can be written/defined as follows:

$$\text{Experience}_{it}^o = \sum_{m=1}^{t-1} d_o^{(t-m-1)} \cdot \log(N_{im}^o + 1)$$

where d_o is the decay factor for in-class experience and N_{im}^o is the number of e-textbook activities organized by teacher i over period m . We obtain this variable by aggregating the number of students’ responses. To ensure validity, activities are counted only when they receive at least over 20 responses from different students. Similar to the authoring experience model, we apply a log-transformation to N_{im}^o .

Seminar experience: The seminar is one of the most important channels for peer learning. We consider the time-discounted cumulative number of

seminars attended by teacher i until period t . This experience is defined as follows:

$$\text{Experience}_{it}^s = \sum_{m=1}^t d_s^{(t-m)} \cdot N_{im}^s$$

where d_s is the decay factor of seminar experience, and N_{im}^s is the number of seminars attended by teacher i in period m . Notably, unlike other experiences, seminar attendance in period t can immediately influence the use intention in this period as teachers may want to apply their newly acquired skills.

Pressure from a special event: We found that the occurrence of special events, including the school's open house days, demonstration classes, and visiting activities, significantly influences a teacher's usage of e-textbooks. To capture this effect, we consider the stress from these events as both a short-term influence (during the event week and the preceding week due to preparation requirements) and a long-term impact on subsequent usage behaviors.

Pressure from policy: The extant literature in teacher's technology adoption suggests that, at the school level, leadership appears to play a crucial role in the use of technology by teachers (Miranda & Russell, 2011). Consistent with previous research, our evidence shows a significant shift in collective usage from the third semester following administrative policy changes in the third semester. We control for this effect by incorporating another pressure variable into the model. Similar to the pressure from a special event, both effects of short-term and long-term policy pressure will be tested.

Pioneers: Following Rogers' (2003) theory of innovation diffusion, we identify "pioneers" in our study as teachers who have extra intrinsic motivation for technology adoption, including subject leaders and young teachers who serve as opinion leaders and facilitators. We control for such leadership through the variable "pioneers."

Subject: Usage pattern vary significantly across subject areas. It is also affected by the applicability of certain e-textbook features to the subject. To account for this heterogeneity, we incorporate a subject-specific dummy variable in our model.

2.3.2 State-Dependent Usage

Transformed amount of actions: This is the dependent variable in our data. All teaching-related actions in this platform are captured in this variable, including authoring e-textbooks, organizing in-class activities, managing students, commenting on the student behaviors, and evaluating homework. We assume that a teacher's number of actions represents their e-textbook usage, conditional on their intention to use the platform.

2.4 Estimates

We estimated the model using MCMC Bayes estimation with the Python library PyMC3 (Salvatier et al., 2016). Before estimating the parameters, discount factors and the optimal number of states were identified through model selection. Through this process, a three-state model was determined as the best-fitting model for our data.

2.4.1 Model Selection

The first stage of model estimation focuses on identifying the values of discounted factors. Using the complete dataset for calibration, we estimated the model with discounted factors all ranging from 0.0 to 1.0 and states ranging from 1 to 4. To identify the optimal value of discounted factors for a particular number of states, we compared the log-likelihoods of models for different value combinations and choosing the values that maximized joint likelihood. We ran the MCMC algorithm for 5,000 iterations for each combination of values. Table 2.1 represents the optimal values of three factors for states ranging from 1 to 4.

The second stage in model estimation is selecting the optimal number of states that best represents the data. In this stage, we used the first four semesters of data for calibration and the last semester for validation. We ran the MCMC algorithm for 10,000 iterations, with the first 5,000 iterations served as a burn-in period, and the remaining 5,000 iterations used for posterior parameter estimation. We assessed the convergence of MCMC by comparing the variance for each parameter across multiple parallel chains, following Gelman and Rubin's (1992) method. Specifically, to search to the best number of states, we estimated the model for varying number of states. According to

TABLE 2.1 Selecting the number of states and discounted factors

<i>States</i>	<i>Discounted factor</i>			<i>Log-likelihood</i>
	d_a	d_o	d_s	
1	—	—	—	-33932.50
2	0.4	0.5	0.3	-20057.69
	0.4	0.6	0.3	-20059.85
	0.4	0.4	0.3	-2061.27
3	0.4	0.4	0.3	-19533.75
	0.4	0.4	0.2	-19535.63
	0.4	0.3	0.3	-19537.28
4	0.3	0.2	0.3	-19279.02
	0.2	0.2	0.3	-19280.82
	0.4	0.1	0.3	-19282.01

TABLE 2.2 Selecting the number of states

<i>States</i>	<i>Parameter estimated</i>	<i>DIC</i>	<i>WAIC</i>	<i>Validation log-likelihood</i>
1	234	—	71,906	-6,102
2	260	38,488	54,475	-4,391
3	286	37,279	52,531	-3,942
4	312	41,210	55,380	-4,153

Table 2.2, based on the deviance information criterion (DIC), widely available information criterion (WAIC), and the log-likelihood for the validation data criteria, we selected the three-state model as the best-fitting model.

2.4.2 Model Comparison

We compared this model with two alternative models of this model with no heterogeneity and another restricted one with no dynamics. The first alternative was a restricted version of this model but without the parameters of the individual-specific random effect. This model's key limitation is its inability to distinguish between heterogeneity and dynamics which might lead to overestimating the dynamics. The second alternative is a zero-inflated Poisson regression model which is similar to our one-state model, but along with all dependent variables and individual random effects in every single equation for the decision and quantity parameters respectively that predict the actual use. This model's primary limitation is its inability to capture the dynamics over time. As the results shown in Table 2.3, the comparison of these three models regarding DIC, WAIC, and the validation log-likelihood demonstrates a superior performance of our model, indicating the importance of incorporating both heterogeneity and dynamics in analyzing our data.

TABLE 2.3 Model comparison

<i>Model</i>	<i>DIC</i>	<i>WAIC</i>	<i>Validation log-likelihood</i>
NHMM	37,279	52,531	-3,942
NHMM without heterogeneity	39,002	53,407	-4,156
Zero-inflated Poisson regression	43,724	69,012	-4,342

2.5 Results

2.5.1 Interpreting the States

From the model estimation, we sample the hidden states using the MCMC algorithm to determine the most likely hidden state for each week. The interpretation of three states is primarily based on the aggregated usage, grouped by state membership. The result in Table 2.4 shows that, on average, teachers are unlikely to use e-textbooks (8.9%), with their action close to zero (0.12) in the first state. Accordingly, we label this as the “limited” intention state. In the second state, teachers are more likely to use e-textbooks (73.6%) and perform more actions per week (6.26). Thus, we label this as the “moderate” intention state. In the third state, teachers are certain to use e-textbooks and perform many related actions. Thus, we label this state as the “intensive” intention state. Overall, about 48% of the observations belong to the limited intention state. The moderate intention state accounts for roughly 33% of the observations, and approximately 19% of the observations make up the intensive intention state. This distribution indicates that teachers generally have a low level of intention to use e-textbooks. To further interpret the intention states, we focus on the dynamics of state-dependent usage and intention transition between states.

2.5.2 Parameter Estimates for Actual Use

Tables 2.5 and 2.6 show the estimated state-dependent parameters and transition matrix parameters, respectively. Note that posterior means are calculated across MCMC draws, with significant effects indicated. The variation in coefficients across states for state-dependent usage indicates that a change in intention state leads to a change in a teacher’s actual use behavior. The intercept parameters corresponding to the state-specific tendency to use e-textbooks indicate that a teacher in a lower state is less willing to use technology than a teacher in a higher state. A teacher’s usage tendency and productivity increase as they move from state 1 to 2 to 3.

TABLE 2.4 Description of the states

	<i>State 1</i> <i>Limited</i>	<i>State 2</i> <i>Moderate</i>	<i>State 3</i> <i>Intensive</i>
Use decision probability (%)	8.9	73.6	100.0
Average quantity of actions	0.12	6.26	43.48
Average non-zero quantity of actions	1.3	8.5	43.48
Number of states	3002	2050	1191
Ratio of state (%)	48.1	32.8	19.1

TABLE 2.5 Parameter estimates for use decision and action quantity

<i>Parameters</i>		<i>Intention states</i>		
<i>Variable type</i>	<i>Variable</i>	<i>State 1</i>	<i>State 2</i>	<i>State 3</i>
Use decision state-specific intercept (θ)		-2.022***	-1.281***	0.719***
Use decision parameters (ρ)	<i>Pressure from special event</i>	-0.036	0.289***	0.518***
	<i>Pressure from policy</i>	-0.006	0.309***	0.664***
	<i>Early adopter</i>	-0.246***	0.051	0.434***
	<i>Subject Chinese</i>	-0.199***	-0.140	0.307***
	<i>Subject math</i>	-0.172***	0.007	0.322***
	<i>Subject English</i>	-0.283***	-0.018	0.230**
	<i>Subject society & science</i>	-0.154	0.018	0.285***
Action quantity state-specific intercept (δ)		-2.749***	0.199***	1.782***
Action quantity parameters (ζ)	<i>Pressure from special event</i>	0.087***	0.302***	0.308***
	<i>Pressure from policy</i>	0.288***	0.482***	0.496***
	<i>Pioneer</i>	-1.020***	0.397***	0.518***
	<i>Subject Chinese</i>	-0.051***	0.248***	0.336***
	<i>Subject math</i>	-0.030***	0.246***	0.333***
	<i>Subject English</i>	-0.010	0.245***	0.316***
	<i>Subject society & science</i>	0.096***	0.115***	0.293***

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

TABLE 2.6 Parameter estimates for intention transition

<i>Parameters</i>		<i>Intention states</i>		
<i>Variable type</i>	<i>Variable</i>	<i>State 1</i>	<i>State 2</i>	<i>State 3</i>
Intention transition thresholds (μ)	<i>Upper threshold</i>	2.250***	2.549***	—
	<i>Lower threshold</i>	—	-0.192	1.697***
Intention transition parameters (ρ)	<i>Authoring experience</i>	0.639**	-0.101*	0.122***
	<i>In-class experience</i>	0.251***	0.104***	0.164***
	<i>Seminar experience</i>	0.284***	0.915***	0.493***
	<i>Pressure from special event</i>	0.042	0.024	-0.029
	<i>Pressure from policy</i>	0.428***	0.022	0.088
	<i>Pioneer</i>	0.520***	0.380***	0.489**
	<i>Study week</i>	-1.543***	-0.768***	-1.073***

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

The results show that the impacts of two pressure variables are similar in terms of both decisions made and actions performed. Positive and significant coefficients for use decision probability in the moderate and intensive intention states indicate these two external pressures effectively promote the persistence of teachers who intend to use e-textbooks, whereas teachers with no

intention are less likely to improve their tendency. The positive and significant coefficients for action quantity in each state also indicate that teachers are more active in periods of pressure than in typical periods. Furthermore, the impacts of these two pressures for action quantity become more similar between neighboring states as teachers move to higher states. This indicates that the productivity of active teachers is more sensitive than that of inactive teachers.

The use of decision parameter for “pioneers” indicates that teachers are more likely to use e-textbooks in the intensive intention state but not in the moderate intention state. Early adopters also tend to use e-textbooks much more frequently per week in the moderate and intensive intention states. This finding suggests that pioneers are more productive than non-pioneers. However, in the limited intention state, both the decision and quantity parameters are negative and significant, implying that pioneers tend to decrease their use persistence and intensity when they have no intention. To investigate this issue, we checked action records and found that only a very small fraction of pioneers' observations are labeled as a limited intention state (4%) and all of them are zero. These two reasons may explain the sensitivity of these two parameters in state 1, compared with the others, where observed average actions are greater than zero.

The parameters for the rest of the four variables represent behavior heterogeneity across subjects. The results show no significant difference in usage between subjects. As expected, math teachers tend to be slightly more likely to use e-textbooks than teachers of the two other major subjects.

2.5.3 *Parameter Estimates for Intention Transition*

The threshold for transitioning from the limited intention state to the moderate intention state is 2.250, indicating that the exogenous impact must exceed this positive threshold to facilitate a teacher's movement to a higher intention state. The threshold for dropping from the moderate intention state to the limited intention state is -0.192 , while the threshold for moving from the moderate intention state to the intensive intention state is 2.549. These findings indicate that moving to a higher intention requires a more positive impact as a teacher becomes active, whereas a negative impact is more likely to cause a shift to a lower state. However, the threshold for transitioning from the intensive intention state to the moderate intention state is 1.697, indicating that teachers need considerable positive impacts to avoid moving to a lower state once they reach the intensive intention state. This result implies that teachers may struggle to maintain the highest level of intention.

The parameters corresponding to personal experience variables are all positive and significant, except for the parameter for impact from authoring experience in the moderate intention state. The accumulation of recent lesson

planning exhibits a non-monotonic effect as it benefits the teachers in the limited intention state the most, followed by those in the intensive intention state, and imposes a negative effect on teachers in the moderate intention state. This finding reveals that having lesson planned digitally before class can significantly boost the intention of teachers in the limited intention, but it may create a burden for those who need to exert more effort in additional work. It supports a few negative responses to authoring e-textbook mentioned in interviews.

The parameters corresponding teachers' in-class experience also presents a non-monotonic effect because it benefits the teachers in the limited intention state the most, followed by those in the intensive and moderate intention states. A similar pattern can be observed in both individual experience variables, which indicates that recent user experience may help teachers reuse e-textbooks. Furthermore, the positive parameters in each state indicate that receiving feedback from students can help teachers build the confidence to adopt technology.

Similar to the individual experience variables, the parameters for seminar experience reveal a non-monotonic effect, but the decreasing order is reversed compared to their individual usage experience. We can see that one's individual usage experience benefits the teachers in the moderate intention state the least, followed by those in the intensive and limited intention states. However, seminar experience benefits teachers in the moderate intention state the most, followed by those in the intensive and limited intention states. This result suggests that seminars can help teachers stay in the active state effectively. A teacher with moderate intention may not gain much more from her/his individual usage experience, but participating in seminars allows them to learn from peers and improve their e-textbook skills. The parameters for "pressure from a special event" in each state are insignificant, indicating that teachers are less likely to change their intentions to use e-textbooks after special events, although they may alter their usage temporarily during these events. The parameters for "pressure from policy" are positive and significant for teachers in the limited intention state but insignificant for those in the moderate and intensive intention states. This suggests that teachers in the limited intention state may rely upon facilitators or administrators for external motivation, but become less responsive to this pressure once they begin using e-textbooks.

The positive and significant parameters for "pioneers" in each state indicate that early adopters are more likely to sustain their intention to use e-textbooks compared to followers. Furthermore, the pioneers tend to gain more motivation in the limited and intensive intention states than in the moderate intention state.

During non-studying weeks, teachers tend to have a low intention to use e-textbooks. This finding confirms our hypothesis that teachers, across all intention states, are less likely to use e-textbooks at the beginning or end of the semester than during this period due to the lack of textbook-using situations.

2.5.4 Accounting for Heterogeneity

Unobserved heterogeneity can manifest at two levels including state-specific and teacher-specific. In a dynamic model, it is crucial to account for zero-order heterogeneity distinguish it from time dynamics as ignoring it might lead to overestimating the dynamics (Netzer et al., 2008; Heckman, 1981). To address this issue, we define teacher-specific random effect parameters, ξ_i , α_i , and η_i in the transition matrix, decision usage model, and quantity usage model, respectively. We incorporate heterogeneity by allowing these parameters to vary across individuals. As a result, unobserved heterogeneity at the individual level could affect both intention change and actual use behavior. For instance, a teacher with high motivation to embrace e-textbooks might have a relatively high ξ_i . Conversely, a teacher who tends to use e-textbooks sporadically but intensively each time may have a relatively low α_i but a relatively high η_i . It is noteworthy that we do not allow the parameters for thresholds and covariates to vary across individuals, as suggested by some NHMM studies (Netzer et al., 2008; Montoya et al., 2010; Zhang et al., 2014; Chang & Zhang, 2016). This decision is based on our finding that parameter estimates for some teachers in active states were unreasonable as these teachers never reached a certain active state.

Table 2.7 reports posterior means and posterior standard deviations for the three parameters, calculated across the MCMC samples. It also presents the posterior 95% range and posterior median values. The distribution of each of the three teacher-specific parameters is left-skewed (i.e., the mean is to the left of the peak), indicating a long tail in the negative direction on the heterogeneity line. The posterior means are interpreted as the collective intrinsic propensities of the teachers and will be incorporated into the transition matrix and short- or long-term effects discussed below.

2.5.5 Adoption Dynamics Impacted by a Teacher's Individual Usage Experience

In our study, we define "individual usage experience" as the amount of technology usage a teacher gains through personal practice over time. This differs from the definition proposed by Smith et al. (1999), which refers to "the

TABLE 2.7 Parameter estimates for heterogeneity

<i>Heterogeneity parameter</i>	<i>Mean</i>	<i>Std.</i>	<i>Quantile 2.5%</i>	<i>Quantile 50%</i>	<i>Quantile 97.5%</i>
Intention to use (ξ)	0.751	0.638	0.319	0.761	1.901
Decision to use (α)	1.890	0.871	0.374	2.069	3.168
Quantity of actions (η)	0.846	0.511	-0.198	0.915	1.739

amount and type of computer skills a person acquires over time.” Our focus is on the accumulated experience gained during the process of adoption, rather than prior technology skills. In technology acceptance studies, user-reported experience through questionnaires is often regarded as a common external factor (Abdullah & Ward, 2016), and previous studies have shown that self-reported experiences can influence teachers’ perceived ease of use, actual use, and usefulness of technology (De Smet et al., 2012). Herein, we employ the probabilistic nature of the transition in our model to compare the effect of two types of individual usage experience: authoring and activity-organizing experience. We assess both the duration and magnitude of these impacts over time. Specifically, we simulate the effect of individual usage experience over 20 weeks for a teacher with an average initial state distribution at week 0 ($\bar{\pi}_0 = (0.56, 0.37, 0.07)$) and introduce authoring or activity organizing experience at a mean level in week 1.

Figure 2.3 illustrates the residual impacts after 19 weeks, which can be interpreted as long-term effects following a particular action. Both experience covariates have a lasting impact on the propensity to use e-textbooks. In the first week, the immediate effect of in-class experience is stronger than that of authoring experience. Specifically, the additional actions produced by activity organization are 0.093 while those produced by authoring are 0.038. Furthermore, due to the high probability of an inactive state in the initial state distribution, the effect of authoring experience is slightly stronger in magnitude and longer in duration relative to the effect of activity organization. In particular, the additional actions from authoring experience reach a maximum value of 0.072 in the second week, whereas the effect of activity organization drops to 0.063. This implies that teachers are more likely to persist in using the technology when they are in earlier states than in later ones.

The enduring effect could differ if we simulate the effect of individual usage experience over a longer period. Figure 2.3 (right) shows the increase in actions under a consistent impact over 20 weeks, where activity organizing experience has a stronger enduring impact than authoring experience. This result supports the belief that in-class use of digital resources may cost teachers less effort but provide more senses of achievement than planning instructions and authoring a digital teaching material before class. This finding is consistent with Hughes (2005), who argued that teachers are more likely to develop technology-supported pedagogy by interpreting the new technology’s value for supporting instruction and learning at the classroom. Specifically, teachers’ own beliefs and attitudes about the technology’s value in supporting students’ learning are perceived as having a stronger impact on their success (Ertmer et al., 2012), which encourages them to adopt the technology. Therefore, to sustain teachers’ intention to use e-textbooks, policymakers should encourage teachers to use the technology in class rather than before class.

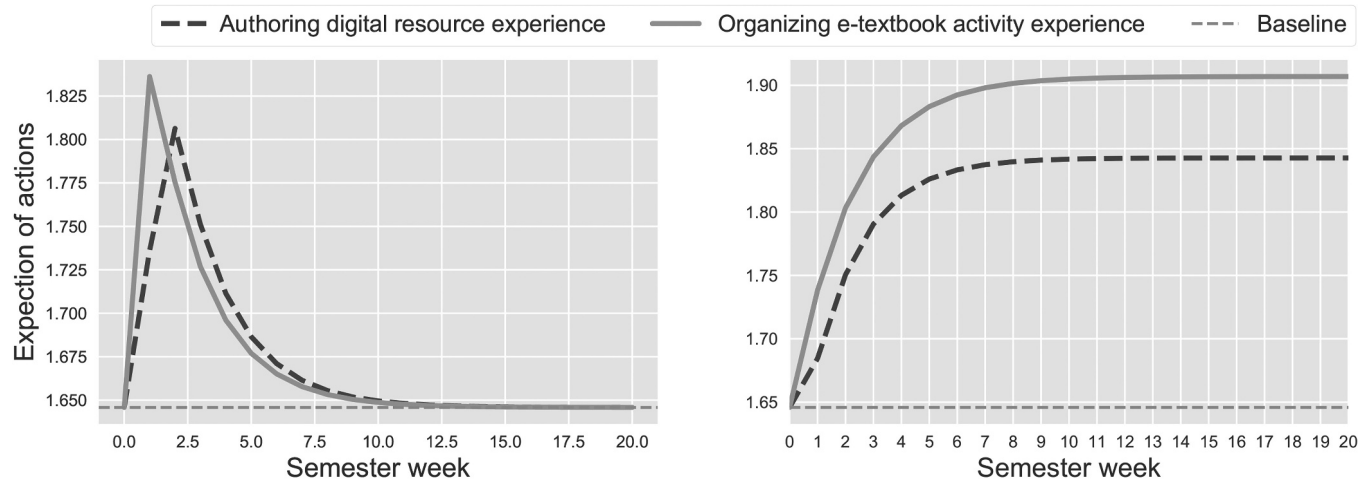


FIGURE 2.3 The long-term effects of the experience covariates.

2.5.6 Intervention for Change in Technology Adoption

In this study, we adopt the term “intervention” to refer to the external influence exerted by administrators or policymakers. An intervention could be any action or event that influences individual teachers involved in or expected to participate in the change process (Hall & Hord, 2001). Three key interventions identified in this study include subject seminars, pressure from special events, and pressure from policy.

To examine how these interventions impact changes in technology adoption over time, we calculate both the immediate and enduring effects of each intervention based on our data. The total effect of interventions was divided into short-term and long-term effects. Specifically, the impact of intervention variables on state transitions, as well as observed usage, is calculated for a one-week period to determine short-term effects and then for a 19-week period after the first week to determine long-term effects. We also calculate the long-term effect of attending seminars in the first week, noting that seminars have no immediate short-term effect because they primarily enhance attendees’ learning experience rather than their actual usage of technology. Figure 2.4 illustrates the changes in action under each intervention over the simulated weeks.

The results show that seminars yield the strongest long-term effect, indicating that teachers benefit the most from them. A possible explanation is that teachers are more receptive to assimilating knowledge shared by their peers. The results also reveal that pressure from school administrators has an

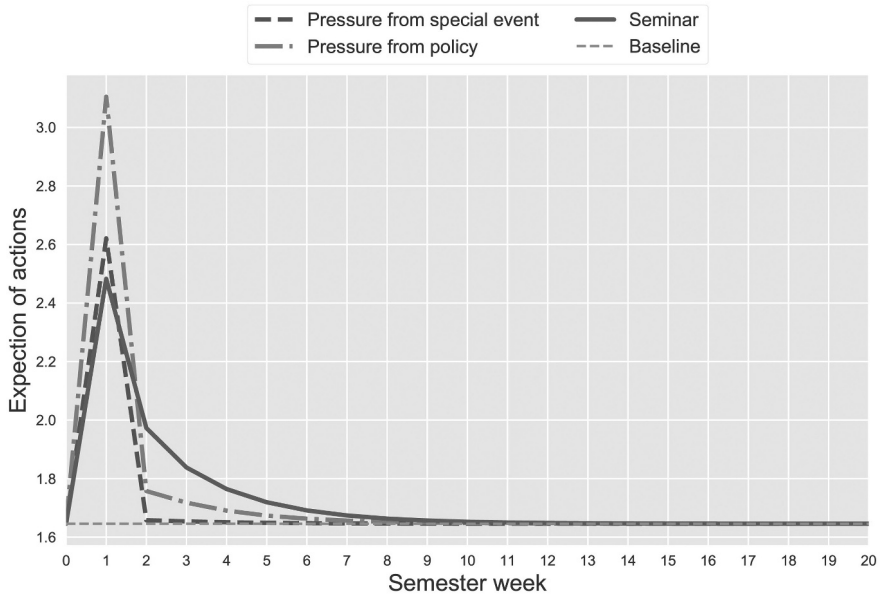


FIGURE 2.4 The long-term effects of the intervention covariates.

immediate effect on teachers' adoption of technology. This supports previous research highlighting the influence of social networks on educational technology adoption, such as subjective norms (Venkatesh et al., 2003; Chen & Tseng, 2012), peer norms (Cheung & Vogel, 2013), and school culture (Ertmer et al., 2012) as "culture pressure." Such culture can motivate teachers to adopt new practices without considering potential risks, especially if experienced teachers or persons in authority within the culture, such as the principal and leaders of discipline teams, endorse the technology (Ertmer & Ottenbreit-Leftwich, 2010; Hall & Hord, 2001). Note that the seminars in this study were led by discipline team leaders who are experienced teachers and central figures in their own subject cultures. This finding is consistent with the suggestion that promoting a change in school culture is essential for facilitating teacher technology change.

2.6 Implications

This chapter highlights the dynamic nature of teachers' technology adoption, emphasizing the importance of understanding how adoption patterns evolve over time. By developing a dynamic model that identifies three malleable states of adoption, we offer a framework for examining how internal and external factors—including prior experience and interventions—influence teachers' intentions and usage behaviors. Our findings underscore non-monotonic effects across different adoption levels, a complexity that traditional variance-based models struggle to capture. For instance, while past experiences benefit teachers during inactive states, active states may still present challenges, such as increased effort demands. Additionally, sustained classroom practice emerges as a critical factor for long-term adoption success, highlighting the value of continued engagement.

The dynamic modeling approach, particularly using a non-homogeneous hidden Markov model (NHMM), offers practical insights for educational facilitators and administrators by distinguishing between short- and long-term intervention effects. This distinction proves valuable for developing sustainable technology adoption strategies. Our findings indicate that peer-led demonstrations and experience-sharing sessions, which help build a collaborative school culture, have yielded more enduring impacts than compulsory measures that typically produce only short-term increases in usage. These findings align with the view that adoption should be approached as a dynamic and ongoing process, requiring continuous facilitation rather than one-time implementation efforts.

By conceptualizing technology adoption as a dynamic process rather than a static outcome, this chapter underscores the need for developing sustained, context-sensitive strategies that foster long-term engagement while supporting teachers as they navigate the evolving demands of technology integration in education.

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