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Simulating user learning in authoritative technology adoption: An agent based model for council-led smart meter deployment planning in the UK

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ABSTRACT

How do technology users effectively transit from having zero knowledge about a technology to making the best use of it after an authoritative technology adoption? This post-adoption user learning has received little research attention in technology management literature. In this paper we investigate user learning in authoritative technology adoption by developing an agent-based model using the case of council-led smart meter deployment in the UK City of Leeds. Energy consumers gain experience of using smart meters based on the learning curve in behavioural learning. With the agent-based model we carry out experiments to validate the model and test different energy interventions that local authorities can use to facilitate energy consumers' learning and maintain their continuous use of the technology. Our results show that the easier energy consumers become experienced, the more energy-efficient they are and the more energy saving they can achieve; encouraging energy consumers' contacts via various informational means can facilitate their learning; and developing and maintaining their positive attitude toward smart metering can enable them to use the technology continuously. Contributions and energy policy/intervention implications are discussed in this paper.

1. Introduction

Technology adoption (or Innovation diffusion) theories focus on understanding how, why and at what rate innovative ideas and technologies spread in a social system (Rogers, 1962). In technology adoption processes the decisions of whether to adopt an innovative technology can either be made by the actual users freely and implemented voluntarily, or be made by a few authoritative individuals and implemented enforcedly.

In the former type of technology adoption, it is usually assumed that before an actual user makes the adoption decision of a particular technology, he/she has learned some knowledge or even gained some experience about it (e.g., the information search stage in the five-step consumer decision model (Engel et al., 1995)).

In the latter type of technology adoption, once the adoption decision has been made the actual users would be "forced" to use a technology with very limited prior knowledge/experience about it. This type of technology adoption usually takes place at the level of a massive system or infrastructure upgrade. An example for such a case is a university-wide systematic upgrade of the office and lab computer operating system from Windows XP to Windows 7. In this case, the decision is made by the management of the university, and the actual users (e.g. faculty staff and students) are forced to use the innovation with limited or even no knowledge about it beforehand and no influence on the choice.[1]

Whilst free adoption decisions and voluntary use in innovation diffusion received intensive studies (e.g., Griliches, 1957; Mansfield, 1961; Rosenberg, 1972; Geroski, 2000; Hall and Khan, 2003), authoritative adoption decisions and forced use in innovation diffusion seems to be an area in its infancy stage. An innovation cannot benefit the society unless its actual users use it effectively. Thus when an authoritative adoption happens, it is significantly important to understand how actual users start to learn about the innovative technology, use the

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[1] We acknowledge that in technology adoption (or innovation diffusion) studies there is a concept "induced diffusion", which has been defined as "any intervention that aims to alter the speed and/or total level of adoption of an innovation by directly or indirectly internalising positive and/or negative externalities" (Davies and Diaz-Rainey, 2011; p. 1229). Induced diffusion research primarily investigates how the diffusion of new technologies can be altered by policy interventions, e.g. economic incentives, information provision or regulations (Diaz-Rainey, 2009). The preponderance of induced diffusion studies use economic modelling approaches based on firm-level data to examine the macro-level patterns of technology diffusion (Diaz-Rainey, 2009). These studies do not look at the adoption decision-making and post-adoption learning behaviour of individual adopters. As noted by Diaz-Rainey (2009, p.20), "there is clearly a need to understand whether inducing diffusion among individuals is substantially different to doing so among multinational corporations". The term "authoritative adoption" in our paper is defined as "a technology adoption where the adoption decision is made by a few authoritative individuals and implemented enforcedly, and the actually users are forced to use the technology", which is different from "induced diffusion". Thus the positioning of the paper is "post-adoption user learning in authoritative technology adoption".

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technology, and finally make the best use of it and perhaps motivate other users to use it or to improve their knowledge quickly. Users' transition from having zero knowledge about a technology to making the best use of it is a consumer learning process. In technology deployment planning, understanding this learning process would help decision-makers design strategies to accelerate users' transition, maintain users' interest in the technology and maximise the benefits that the technology can bring to the society.

Traditionally, there are some theories aiming to understanding how users (or consumers) learn and adopt a technology, for example, the Technology Adoption Model (TAM) (Davis, 1989) in information systems research and consumer learning models (Solomon et al., 1999) in consumer research. Many of these theories/models are qualitative, static, and only apply to adoption decisions that are made on voluntary basis. In other words, users/consumers seek information and learn knowledge about the product/innovation on their own, and then make purchase decisions voluntarily.

Currently no studies extend their application to authoritative technology adoptions. In this paper, we bridge this academic gap: we draw on the ideas from consumer learning theories/models, and extend the application of them to authoritative technology adoptions by developing a computational model using Agent-Based Simulation (ABS).

The agent-based model we have developed is based on a case of smart meter deployment in the UK City of Leeds. This case provides a good example of an authoritative technology adoption: the city council uses smart metering energy intervention to systematically upgrade the energy infrastructure in the city, and some energy users (i.e. those who live in council-owned properties) will have smart meters installed at their homes and are forced to use them. With the simulation model we would like to visualise the dynamic process of user learning and understand effects of the learning process on making the best use of the technology (i.e., when users make the best use of smart metering technology, they are on effective electricity demand side management, which we can use electricity consumption data to monitor). Similar studies in *Technological Forecasting & Social Change* (e.g. Gordon, 2003; Schwarz and Ernst, 2009; Rixen and Weigand, 2014) have proved that agent-based simulation is an effective approach for studying various areas of technology adoption.

This paper serves two purposes. Academically we want to advance the academic knowledge in technology management by studying for the first time the field of authoritative technology adoption by extending the application of consumer learning theories in conjunction with empirical data to that field via a computational simulation method. Practically we aim to develop a smart meter development planning tool (i.e. a software decision support platform) to provide hands on advice to city council decision-makers with policy implications on how effectively to facilitate user learning and maximise the benefits of smart meters for the city.

The paper is structured as follows. In the second section we review relevant theories about consumer learning. In the third section we describe the case study and the simulation model and its individual components in detail. In the fourth section we carry out four simulation experiments, present the experiment results and their related implications. The fifth section discusses the study, and the sixth section concludes the study.

2. Theoretical background

Amongst the researchers studying learning processes there is no consensus about how learning happens. Thus the definition of learning is diverse. In psychology, researchers view learning as a relatively permanent change in behaviour as a result of increasing experience (Solomon et al., 1999). In marketing, consumer learning is defined as "a process by which individuals acquire the purchase and consumption knowledge and experience they apply to future related behaviour (Schiffman et al., 2008, p. 185). In the real world, individuals learn both directly and indirectly. For example, they can learn from the events that directly influence them; or they can learn from other people's experiences indirectly; sometimes they even learn unconsciously.

Learning covers activities ranging from consumers' responses to external stimuli to a complex set of cognitive processes. There are many learning theories which generally fall into two categories: behavioural learning and cognitive learning.

2.1. Behavioural learning

The behavioural learning approach makes the assumption that learning happens as a result of responses to external stimuli (Solomon et al., 1999). Thus sometimes behavioural learning theories are also known as stimulus-organism-response (SOR) theories, as these theories primarily focus on the inputs and outputs in the learning process. The behavioural approach takes the view that a learner's mind is a "black" box, and emphasizes the observable perspectives of behaviour, as shown in Fig. 1.

In behavioural learning theories learners are mindless passive objects, i.e. they do not make decisions; they can only be taught certain behaviour through repetition or conditioning (Schiffman et al., 2008).

A quantitative expression of the behavioural approach was developed in early marketing literature, e.g. Estes (1950), cited in Bennett and Mandell (1969)), Estes and Burke (1953), cited Bennett and Mandell (1969)), and Bush and Mosteller (1955), cited in Bennett and Mandell (1969)). In all cases learning is treated as a stochastic process and thus response tendencies are treated in probabilistic terms. Howard (1963), cited in Bennett and Mandell (1969)) proposes the following consumer's brand choice learning function:

$$P_A = M\left(1-e^{-kt}\right) \tag{1}$$

where $\boldsymbol{P_A}$ is the probability of response (i.e. purchasing Brand A); $\boldsymbol{M}$ is the maximum attainable loyalty to Brand A; $\boldsymbol{k}$ is the constant that expresses the learning rate; $\boldsymbol{t}$ is the number of reinforced trials.

This quantitative model (see Fig. 2) was empirically validated in Bennett and Mandell (1969) by using the case of new automobile purchase.

2.2. Cognitive learning

The cognitive learning approach assumes that learning is a set of mental processes. In contrast to the behavioural learning approach described earlier the cognitive learning approach takes the view that learners are problem-solvers rather than "black boxes". In other words, learners make purchase/adoption decisions on their own rather than passively repeat trial behaviour. They actively seek information about a product/innovation, process the information and gain motivation or intention to buy/adopt the product/innovation. A typical cognitive learning theory is observational learning theory, which believes that "individuals observe the actions of others and note the reinforcement they receive for their behaviours" (Solomon et al., 1999, p.70). The entire process of observational learning is presented in Fig. 3.

2.3. Our choice

Through a review of the two learning approaches we can see that, whilst both approaches are useful and have been empirically validated, a main distinction between the two is whether users/consumers are passive recipients or active decision-makers. Since the study in this paper focuses on forced authoritative technology adoption in which users passively receive the technology and are taught to use, we draw on the ideas of behavioural learning approach to develop the simulation model.