Chapter 90
How Experience and Expertise Affect the Use of a Complex Technology

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ABSTRACT

As end-users work with increasingly complex technologies, it is important that these technologies be used to the fullest extent possible. Time is needed to learn how to use these new technologies and fit them to user tasks, but the fact that a user has gained experience does not mean that expertise has also been gained. Using survey data collected from 187 data warehouse end-users, we found that experience and expertise have a significant positive correlation (r = 0.35, p < 0.001), but expertise has a significantly greater effect on ease-of-use perceptions (t=10.2, p < 0.0001) and the use of a technology (t=21.08, p < 0.0001) than experience. Therefore, it is critical that researchers properly delineate which construct – end-user expertise or experience – is being assessed, when measuring the effect that individual differences have on the perceptions and use of technology.

INTRODUCTION

Over the past three decades, end users have been working with increasingly sophisticated and complex technologies (Kanter, 2000; Sykes, Venkatesh, & Gosain, 2009). These tools provide end-users with a range of features, flexibility, and functionality that can help them perform tasks more efficiently, and

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help them accomplish new, more sophisticated tasks. For example, current spreadsheet software (e.g. Microsoft Excel) allows data to be imported quite easily, which improves efficiency. End-users can also use the software to explore data for trends and patterns via the Data Analysis tool, which is a more sophisticated use of the software (Evans, 2013). It can take the end-user a substantial amount of time to learn the technology, fit the technology to his/her current tasks (and vice versa), and then decide if the tool can be applied to new, more sophisticated tasks. There is an understandable concern among managers that tools with such lengthy learning curves need to be used as effectively as possible. Researchers have therefore been focusing on better predicting and explaining the use of technology, not just the initial decision to adopt (Ortiz de Guinea & Markus, 2009).

Several research models explaining the initial adoption of technology have been adapted for examinations of technology use (Barki, Titah, & Boffo, 2007; Kim & Malhotra, 2005; Po-An Hsieh & Wang, 2007; Venkatesh, Thong, & Xu, 2012). In addition, individual differences among end-users may have an important role in explaining the variance of long-term technology use. Differences among Individual end-users affect perceptions and behaviors, and many adoption models incorporate such differences. For example, differences in gender, age, and experience moderate the behavioral intention to use a technology (Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh et al., 2012), and differences in self-efficacy (Compeau & Higgins, 1995) have direct effects on computer use. One individual difference that has received substantial research attention is experience (Lee, Kozar, & Larsen, 2003; Legris, Ingham, & Collerette, 2003), with the assertion being that more experience with a technology leads to more positive attributions regarding that technology, and therefore greater use (Gefen, Karahanna, & Straub, 2003). Although this assertion seems intuitive, research results have been inconsistent. Some studies have found that experience has a positive effect on perceptions and behavior, others have found a negative experience effect, and still others have found no effect (Gefen et al., 2003).

To help clarify the effects of experience on technology perceptions and use, we assimilated research from organizational behavior and personnel psychology that has proven effective at predicting job performance. In addition, our *post hoc* analyses further demonstrate the strength of our findings, and lend support to current sentiments regarding the importance of prior use in explaining the continued use of technology.

BACKGROUND AND LITERATURE REVIEW

Adoption and Use of Technology

The research and literature regarding technology adoption is one of the oldest and richest of any in the IS field. Research models such as the Task-Technology Fit Model (TTF) (Goodhue & Thompson, 1995), the Technology Acceptance Model (TAM) (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989) and its successors (TAM2 (Venkatesh & Davis, 2000), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and UTAUT2 (Venkatesh et al., 2012)) have been helpful at predicting and explaining technology adoption. TAM-based models in particular have a substantial research record (Lee et al., 2003), and meta-analyses have shown that these models and their various additions explain up to 60% of a user's intent to use a technology (Lee et al., 2003), and up to 40% of the user's use of the technology (Legris et al., 2003). The explanatory power and wide applicability of TAM-based models have made them especially useful when analyzing technology adoption (Lee et al., 2003).

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