Diffusion of Innovations: Still a Relevant Theory for Studying Library Technology in the Age of AI?

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Abstract

Purpose: This paper examines the relevance of Rogers' Diffusion of Innovations theory, with a particular focus on the adopter categories concept, for library technology research in light of rapid changes sparked by the emergence of generative artificial intelligence and other emerging technologies at the dawn of the fourth industrial revolution.

Design: The applicability of the Diffusion of Innovation model is critically evaluated, highlighting some discrepancies that exist between the traditional framework and observed behaviors in recent studies. In particular, it appears that many people are more eager adopters of innovations than at any point in the past, perhaps due to the ubiquity of information within the modern media ecosystem.

Findings: The traditional Diffusion of Innovation adopter categories may fail to capture the adoption patterns of specific populations, such as college students and faculty. Revised survey methodologies reveal the potential for more accurate identification of adopter categories by addressing biases in self-reporting and incorporating practical considerations of innovation usefulness.

Originality: This paper proposes refinements to the study of innovation diffusion, particularly in the context of library technology. By adapting the model to better align with modern patterns of technological adoption, it aims to provide a deeper understanding of innovation behaviors in today's rapidly evolving technological environment.

The Diffusion of Innovations (DoI) theory, as proposed by Everett Rogers (1962), has long been a valuable and consistent framework for understanding how people adopt new technologies and ideas. One of the most widely used components of this theory is the adopter categories model, which forms the basis for many analyses of adoption behavior today. This model classifies adopters of innovations into categories that follow a normal distribution. According to the model, 2.5% of people are innovators, who adopt an innovation when it is brand new and lacks proven benefits; 13.5% are early adopters, who adopt once they perceive personal benefits; 34% are early majority, who adopt only after observing widespread adoption and clear productivity benefits; 34% are late majority, who adopt after at least half the population has done so and when ample support for adoption is available; and 16% are laggards, who resist adoption as long as possible.

This normal distribution framework has been successfully applied for over six decades, with some minor hiccups and proposed revisions along the way (MacVaugh and Schiavone, 2010). However, recent studies (e.g., Basileo et al., 2024; Dale et al., 2021) suggest that certain populations cannot be accurately described using the traditional adopter categories model. These studies indicate a right-skewed distribution, with innovators and early adopters representing a much larger share of the population than previously assumed. For instance, research on technology adoption among college students and faculty has shown that the traditional model often fails to capture their adoption patterns. In these populations, the proportions of innovators and early adopters frequently exceed those of the “early majority” and “late majority”—a misalignment that challenges the validity of the model’s categorization.

This discrepancy may stem from the unique characteristics of college students and faculty. These groups tend to have higher educational attainment and greater intellectual curiosity, making them more receptive to new technologies. Additionally, they are more likely to pursue white-collar careers, where emerging technologies often have a different impact compared to blue-collar industries. While college students and faculty are not representative of the broader public, they are accessible and important to study—particularly for academic librarians. However, the limitations of the DoI model in describing these populations pose challenges for the research ecosystem. Addressing these shortcomings is crucial for developing more accurate frameworks for studying technology adoption in specific contexts.

Acknowledging the limitations of the DoI adopter categories as originally constructed, what can be done to address these issues? One potential solution is to reimagine the distribution of adopters. Perhaps, given the conditions of the Information Age, where knowledge about new technologies and how they work is widely available and marketing of these products is rampant, the adoption behavior of consumers is just different than it was six decades ago. In these circumstances, perhaps a normal distribution of adopters is inaccurate. Given the criteria used to determine an adopter category of an individual fifty years ago, perhaps 50%+ of people today would qualify as innovators or early adopters. In this case, the DoI model itself may need to be revised.

We may also need to reconsider how we define and measure each of these categories. The characteristics of an innovator today may differ significantly from those of decades ago. For instance, being an innovator might no longer simply mean adopting a new innovation quickly after its public release (e.g., within a few days). Instead, it might now involve adopting an innovation immediately—even before it gains widespread attention or goes “TikTok viral.” Similarly, the definitions of the late majority and laggards may also need adjustment. In 2005, over ten years after its emergence, only 68% of people in the United States used the internet, a figure that aligns with the late majority stage described by the Diffusion of Innovations model (Perrin & Duggan, 2015). By comparison, smartphones reached the same 68% adoption rate in the United States within just five years of their release. As of 2024, smartphone adoption has surpassed 90% of the population (Gelles-Watnick, 2024). This shift highlights how much faster the adoption of new innovations has become in recent decades. Given these changes in behavior, we may need to revise the classifications of adopters to reflect the evolving pace and patterns of innovation adoption in the modern era.

It is clear that a redefinition and reconceptualization of some concepts and terminology associated with the model would be beneficial. The model is widely favored by researchers for guiding inferential analyses, as it categorizes individuals into five groups that can be used for regression analysis, ANOVA, and other statistical methods. However, when more than 50% of the population falls into a single category, the quality and reliability of the statistical analysis are significantly reduced. For the model to produce meaningful results, it is essential to establish groupings that accurately and meaningfully reflect distinct behavioral patterns.

Survey Questions to Identify Diffusion of Innovation Adopter Category

To see how we may be able to come at some better groupings through redefining how we categorize adopters, let us first look at some questions used in a 2020 study to measure DoI adopter categories, which have been utilized in several other studies in recent years (Lund et al, 2020). Notably, some issues with the phrasing of these questions highlight opportunities to refine survey design, enabling us to better target and identify adopter categories.

1. In general, I am…
    a. The very first person to adopt a new idea or way of thinking
    b. One of the first to adopt a new idea or way of thinking
    c. Not one of the first, ahead of the majority
    d. About middle of the pack
    e. Very late to adopt a new idea or way of thinking
    f. I almost never adopt a new idea or way of thinking
2. In general, I am…
    a. The very first person to use a new technology
    b. One of the first to use a new technology
    c. Not one of the first, but ahead of the majority
    d. About middle of the pack
    e. Very late to adopt a new technology
    f. I almost never use a new technology
3. Rate your knowledge of [innovation] as a concept
    a. Extremely knowledgeable
    b. Very knowledgeable
    c. Fairly Knowledgeable
    d. Somewhat Knowledgeable
    e. Not Very Knowledgeable
    f. Extremely Little Knowledge
    g. No Knowledge of this Technology
4. Rate your knowledge of trends in [innovation]

    a. Extremely knowledgeable
    b. Very knowledgeable
    c. Fairly Knowledgeable
    d. Somewhat Knowledgeable
    e. Not Very Knowledgeable
    f. Extremely Little Knowledge
    g. No Knowledge of Trends
5. Rate your level of optimism about the future of [innovation] for improving library services
    a. Extremely optimistic
    b. Very optimistic
    c. Fairly optimistic
    d. Somewhat optimistic
    e. Not Very optimistic
    f. Extremely Little optimism
    g. No optimism

The responses to these questions would be scored in the following way: Response A is scored as a 6, Response B as a 5, C as a 4, D as a 3, E as a 2, F as a 1, and G as a 0. The average score across the five questions is calculated. A score of 5.00 or above indicates that individual is an "innovator," 4.00-4.99 points as "early adopter," 3.00-3.99 points as "early majority," 2.00-2.99 points as "late majority," and 1.99 and below as "laggard." However, respondents often overestimate their knowledge and interest in innovations, especially when completing surveys on this topic. This can result in a misalignment between their self-reported and actual behaviors.

To address this, the questions can be revised to go beyond self-perceptions of general behavior by referencing the practicality and usefulness of an innovation as factors in decision-making. Additionally, respondents could be asked to compare their behavior to that of the average person in their community or profession. This rephrasing reduces the bias toward selecting "innovator" as the most desirable option (as in the original set of questions) and instead encourages more realistic and comparative self-assessment.

Here is a revised set of questions, based on the first, but geared to get a better distribution of respondents:

1. In general, I am…
    a. Likely to adopt a technology immediately before evaluating its practicality and usefulness.
    b. Likely to adopt a technology quickly, but only after briefly considering its practicality/usefulness in my life.
    c. Likely to adopt a technology once I see several other people around me adopting it, and I see its practicality/usefulness in my life.
    d. Likely to adopt a technology when a majority of the people around me have already adopted it, and I see its practicality/usefulness in my life.
    e. Likely to adopt a technology when nearly everyone around me has already adopted it, and I see its practicality/usefulness in my life.
    f. Likely to never adopt a technology, even if I see some practicality/usefulness in my life.

2. In general, I am…
    a. Likely to adopt a new idea or way of thinking immediately before evaluating its practicality and usefulness.
    b. Likely to adopt a new idea or way of thinking quickly, but only after briefly considering its practicality/usefulness in my life.
    c. Likely to adopt a new idea or way of thinking once I see several other people around me adopting it, and I see its practicality/usefulness in my life.
    d. Likely to adopt a new idea or way of thinking when a majority of the people around me have already adopted it, and I see its practicality/usefulness in my life.
    e. Likely to adopt a new idea or way of thinking when nearly everyone around me has already adopted it, and I see its practicality/usefulness in my life.
    f. Likely to never adopt a new idea or way of thinking, even if I see some practicality/usefulness in my life.
3. Rate your knowledge of [innovation] as a concept, when compared to the average person in your profession
    a. Extremely knowledgeable
    b. Very knowledgeable
    c. Fairly Knowledgeable
    d. Somewhat Knowledgeable
    e. Not Very Knowledgeable
    f. Extremely Little Knowledge
    g. No Knowledge of this Technology
4. Rate your knowledge of trends in [innovation], when compared to the average person in your profession
    a. Extremely knowledgeable
    b. Very knowledgeable
    c. Fairly Knowledgeable
    d. Somewhat Knowledgeable
    e. Not Very Knowledgeable
    f. Extremely Little Knowledge
    g. No Knowledge of Trends
5. Rate your level of optimism about the future of [innovation] for improving library services, when compared to the average person in your profession
    a. Extremely optimistic
    b. Very optimistic
    c. Fairly optimistic
    d. Somewhat optimistic
    e. Not Very optimistic
    f. Extremely Little optimism
    g. No optimism

Note the key differences in these sets of questions. Whereas the first set of questions made option A seem desirable (‘I am the first to adopt’), the second set of questions imposes more of the risks and realities of being an innovator or early adopters – that innovation you adopt may not actually be useful. These questions also introduce greater comparison of the respondent version people in their community or profession. Respondents may view themselves as fairly knowledgeable about a new technology, but also view their peers as fairly knowledge, meaning that they rank themselves lower (and perhaps more accurately) when asked to make a comparison to this population. These small tweaks in the set of questions can produce more meaningful distributions of adopters, supporting further statistical analysis. Additional future research may further validate this set of questions and reconceptualization of the innovation adopter categories.

Alternative Approaches for Sorting into Adopter Categories

An alternative approach to achieving a distribution that aligns with the anticipated proportions of 2.5%-13.5%-34%-34%-16% is to directly impose this structure onto the data. Rather than using fixed score ranges—such as defining scores of 5.00 and above as “innovators,” 4.00–4.99 as “early adopters,” and so on—this method categorizes individuals based on their relative positions within the dataset. For example, the top 2.5% of scores are labeled as “innovators,” the next 13.5% as “early adopters,” and so forth. This ensures that the proportions of each category exactly match the intended distribution.

However, a significant drawback of this a priori classification is that it may misrepresent individuals’ true profiles. For instance, a respondent with a score of 5.28 might be categorized as part of the “early majority” rather than an “innovator” or “early adopter” if their score does not fall within the top 16%. This could occur even if the individual identifies strongly as “one of the first to adopt a new idea or way of thinking,” expresses deep knowledge of and optimism about the technology, and exhibits behavior consistent with early adoption. Thus, this approach risks misclassifying individuals simply because their relative position within the dataset does not align with their self-reported traits or behavior.

Alternatively, some might argue that the limitations of the model in accurately describing adoption behavior today indicate that its usefulness has come to an end. While this view may be too narrow, it is reasonable to question whether new models of adoption behavior are needed and should be “adopted” in place of a model that is now over six decades old. Several alternative frameworks already exist and could be explored by researchers seeking a more up-to-date version of a diffusion model (Wisdom et al., 2014).

Conclusion

DoI is a useful model for understanding user behavior relative to emerging library technologies. However, the effectiveness of this model is threatened by shifts in human behavior, stimulated by the proliferation of information in our world today. Understanding that the users of libraries -especially academic libraries- is more informed and educated than human beings at any other point in history should lead us to reconsider how we define these adopter categories in our innovation adoption studies. In doing so, we can produce more meaningful insights into our users behavior while simultaneously driving forward the evolution of our existing theory base and potentially fostering the development of new theory for our discipline.

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