

การยอมรับนวัตกรรมสู่การใช้บริการซ้ำผ่านการบอกต่อทางอิเล็กทรอนิกส์:

การศึกษาการถดถอยในบริบทสุขภาพดิจิทัล

FROM INNOVATION ADOPTION TO SERVICE RE-INTENTION VIA ELECTRONIC

WORD OF MOUTH: A REGRESSION STUDY IN DIGITAL HEALTH

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บทคัดย่อ

การวิจัยครั้งนี้มุ่งศึกษาบทบาทของการบอกต่อผ่านสื่ออิเล็กทรอนิกส์ในฐานะกลไกเชื่อมโยงระหว่าง การยอมรับนวัตกรรมและความตั้งใจใช้บริการซ้ำในบริบทสุขภาพดิจิทัล โดยเก็บข้อมูลจากผู้ใช้บริการจำนวน 400 คน และวิเคราะห์ด้วยวิธีการถดถอยเชิงโครงสร้างแบบสมการกำลังสองน้อยที่สุดบางส่วน ผลการวิจัย พบว่า การยอมรับนวัตกรรมส่งผลให้เกิดการบอกต่อเชิงบวก และการบอกต่อนี้มีอิทธิพลโดยตรงต่อความตั้งใจที่จะกลับมาใช้บริการซ้ำ นอกจากนี้ยังพบว่าการยอมรับนวัตกรรมมีผลทางอ้อมต่อความตั้งใจดังกล่าว ผ่านบทบาทการใกล้เคียงของการบอกต่อ ผลการศึกษายังชี้ว่าการสร้างคุณภาพบริการที่สามารถส่งต่อได้ การจัดการช่องทางสะดวกสำหรับการให้ข้อเสนอแนะ และการฟื้นฟูบริการอย่างรวดเร็วเพื่อลดผลกระทบเชิงลบ เป็นแนวทางเชิงปฏิบัติสำคัญที่จะช่วยแปลงการยอมรับเบื้องต้นให้กลายเป็นความผูกพันที่ยั่งยืนบนพื้นฐานของความไว้วางใจในการบริการสุขภาพดิจิทัล

คำสำคัญ: การยอมรับนวัตกรรม, การตั้งใจใช้บริการซ้ำ, การบอกต่อแบบปากต่อปากทางอิเล็กทรอนิกส์, สุขภาพดิจิทัล

ABSTRACT

This study examines whether electronic word of mouth (eWOM) serves as the behavioral bridge that links innovation adoption to service re-intention in digital health. Using survey data from 400 users, Partial Least Squares regression was applied to test the proposed model. The findings show strong support for the pathway: innovation adoption encourages positive eWOM, which in turn strengthens intentions to reuse digital health services. Adoption also exerts a substantial indirect effect on re-intention, highlighting the mediating role of eWOM. These results extend continuance models by introducing social proof as a key mechanism between initial adoption and sustained use. From a managerial perspective, the study underscores the need to engineer shareable service quality, facilitate effortless feedback, and ensure rapid recovery to mitigate negative eWOM. Overall, managing eWOM emerges as a pivotal strategy for transforming initial uptake into long-term, trust-based engagement with digital health services.

Keywords: Innovation Adoption, Service Re-Intention, Electronic Word of Mouth, Digital Health

INTRODUCTION

Digital health has become a mainstream channel for accessing and coordinating care, spanning teleconsultation, remote monitoring, and app-based self-management. Despite widespread uptake, many services struggle to convert first use into repeat use, creating a “conversion gap” between adoption and continuance that diminishes clinical and economic value. Classical acceptance models—Diffusion of Innovations and unified technology acceptance frameworks—explain why individuals adopt novel services, while continuance models address post-adoption use (Rogers, 2003; Venkatesh et al., 2003; Bhattacharjee, 2001). Yet these traditions give limited attention to the social information processes that shape subsequent decisions in platformed service environments.

Electronic word of mouth (ratings, reviews, and patient narratives) has emerged as a prominent source of social proof in health contexts characterized by risk and information asymmetry. Prior work links eWOM to credibility formation and choice, but its role as a behavioral bridge between initial adoption and service re-intention remains under-specified, particularly in digital health (Cheung & Thadani, 2012; Hennig-Thurau et al., 2004). We argue that early service experiences following adoption catalyze eWOM; in turn, eWOM updates perceived value and trust, reinforcing one’s own intention to return and influencing peers. This perspective extends continuance logic by inserting a social-proof mechanism between adoption and repeat use.

Positioning eWOM as the intervening process also yields practical leverage. Unlike many attitudinal antecedents, eWOM can be shaped by designable service cues—reliable performance, transparent waiting times, clear follow-up—and by governance features such as reviewer verification and responsive service recovery, alongside privacy and trust assurances that are salient in health services (Zeithaml et al., 2002; Pavlou & Gefen, 2004). Understanding the magnitude of these links can therefore inform interventions that turn initial uptake into durable engagement.

OBJECTIVES

1. To estimate the direct effect of innovation adoption on eWOM in digital health.
2. To estimate the direct effect of eWOM on service re-intention in digital health.
3. To evaluate the mediating role of eWOM in the relationship between innovation adoption and service re-intention in digital health.

LITERATURE REVIEW

Prior work suggests a systematic pairing among innovation adoption, electronic word of mouth (eWOM), and service re-intention in digital health. For the adoption–eWOM relationship, Diffusion of Innovations posits that relative advantage, compatibility, trialability,

and low perceived complexity reduce uncertainty at first use, thereby motivating users to articulate their experiences publicly (Rogers, 2003). Research on online opinion expression further indicates that satisfied users with clear value perceptions are more likely to post and share evaluations, while dissatisfaction can also trigger expressive behavior, often with stronger valence (Hennig-Thurau et al., 2004; Cheung & Thadani, 2012). In health contexts marked by information asymmetry and risk, institution-based trust and privacy assurances increase willingness to transact and to communicate evaluations, implying that early, trustworthy encounters following adoption can catalyze eWOM (Pavlou & Gefen, 2004). Service quality delivered through digital interfaces—efficiency, reliability/uptime, responsiveness, and privacy clarity—provides “shareable” cues that are readily translated into ratings and narratives (Zeithaml et al., 2002).

Adoption and eWOM. Research on innovation diffusion argues that perceived attributes such as relative advantage, compatibility, trialability, and low complexity reduce uncertainty at first use, which increases the likelihood that users will articulate their experiences through ratings and reviews in public spaces (Rogers, 2003). In digital service settings, visible cues of service quality including reliability, responsiveness, and privacy clarity provide concrete material that users can translate into evaluative comments, thereby raising both the propensity and the positivity of electronic word of mouth (Zeithaml, Parasuraman, & Malhotra, 2002). Trust safeguards further lower perceived risk and encourage evaluative communication, suggesting that trustworthy early encounters following adoption can catalyze eWOM in health contexts (Pavlou & Gefen, 2004). Studies of online opinion expression consistently report that value perceptions and satisfaction are antecedents of eWOM creation, while dissatisfaction can also trigger expressive behavior with stronger negative valence (Hennig-Thurau et al., 2004; Cheung & Thadani, 2012).

Hypothesis 1: Innovation adoption has a positive direct effect on electronic word of mouth in digital health service.

eWOM and service re-intention. Electronic word of mouth functions as social proof that shapes beliefs about credibility, value, and expected performance, which are central to decisions to continue using a service. Meta-analytic and empirical evidence links eWOM valence, volume, and perceived helpfulness to downstream attitudes and behavioral intentions, including revisit and repurchase, as public evaluations reduce search costs and perceived risk (Cheung & Thadani, 2012; Godes & Mayzlin, 2004). In postadoption settings, continuance depends on updated beliefs formed after experience; exposure to favorable eWOM reinforces those beliefs, whereas small amounts of negative eWOM can exert disproportionate influence, a pattern consistent with asymmetry effects in the eWOM literature (Hennig-Thurau et al., 2004). This mechanism is especially plausible in digital health, where

services have credence qualities and trust is salient, and aligns with continuance theory that emphasizes confirmation and postuse evaluation (Bhattacharjee, 2001).

Hypothesis 2: Electronic word of mouth has a positive direct effect on service re-intention in digital health service.

Adoption to re-intention via eWOM. Integrating acceptance and continuance perspectives implies a mediated pathway from adoption to re-intention through eWOM. Unified acceptance frameworks explain initial uptake, while expectation–confirmation accounts for postuse persistence; combining them suggests that adoption supplies the experience base from which users generate eWOM, that eWOM then updates both individual and social beliefs, and that these updated beliefs feed into intentions to return (Venkatesh, Morris, Davis, & Davis, 2003; Bhattacharjee, 2001; Rogers, 2003). In digital health, where uptake has grown but sustained engagement remains uneven, positioning eWOM as a behavioral mediator offers a coherent explanation for how early adoption translates into repeat use.

Hypothesis 3: Innovation adoption has a positive indirect effect on service re-intention via electronic word of mouth in digital health service.

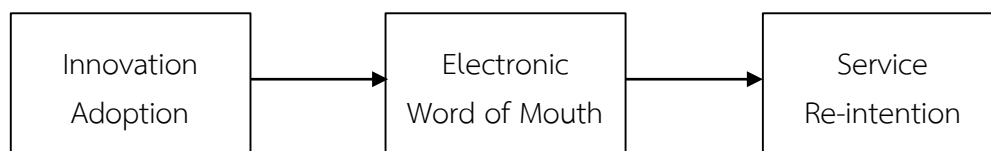


Figure 1 Research framework

RESEARCH METHODS

1. Population and sample

The target population comprised adults in Thailand aged 20 – 59 who had used at least one digital health service (telemedicine, mobile health application). Based on Cochran’s sample size calculation for large/unknown populations, the minimum required sample was approximately 384; allowing for potential nonresponse, we set a target of 400 and obtained N = 400 complete responses. Participants were recruited using purposive sampling restricted to individuals meeting the eligibility criteria.

2. Research Measurement

The instrument comprised four parts: Part A demographics; Part B Innovation Adoption operationalized from DOI attributes (relative advantage, compatibility, complexity, trialability, and observability); Part C Electronic Word of Mouth (intensity, positive/negative valence, and content richness); and Part D Service Re-intention (reuse, loyalty, recommendation intentions). All attitudinal items used a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree), with wording adapted to the digital-health context and reverse-

scored items recoded prior to analysis. Instrument quality will be documented as follows: content validity via expert review (IOC); internal consistency via Cronbach's alpha and composite reliability (reporting whether they meet the $\geq .70$ benchmark); convergent validity via AVE ($\geq .50$) and outer loadings ($> .70$); discriminant validity via Fornell–Larcker and HTMT ($< .85/.90$); collinearity checks via VIF and, where appropriate, Harman's single-factor ($< 50\%$); and model fit for PLS models (e.g., SRMR, NFI, and MICOM for multi-group invariance). Numerical indices for each part will be inserted in the Results section.

3. Data collection

Data were collected during May–July 2025 via a self-administered, cross-sectional questionnaire. Fieldwork took place in the front/lobby areas of three hospital types: a university hospital (Burapha University Hospital), a public hospital (Ramathibodi Hospital), and a private hospital (Phyathai–Paolo Hospital). We used purposive sampling with screening to recruit Thai adults aged 21–60 who had used at least one digital health service during May–July 2025. Participation was voluntary and anonymous, yielding a final analytic sample of $N = 400$. The study received institutional ethics approval and complied with the Declaration of Helsinki and Thailand's PDPA.

4. Data analysis

Only complete and correct questionnaires were selected for data processing by putting codes on the questionnaire, examining the correctness, and then recording into the computer for processing the data. The Statistics program was used for descriptive analysis including frequency, percentage, mean, and standard deviation was used to describe demographic data including gender, age, educational level, employment status, monthly income, and marital status. Moreover, the applied statistical package for PLS-SEM was used for additional statistical analyses. To assess the relationships among the model items, we used multicollinearity analysis, confirmatory factor analysis (CFA), reliability and convergent validity, discriminant validity, path coefficients, hypothesis testing, and Least Squares Structural Equation Modeling (PLS-SEM)

RESEARCH FINDING

The analytic sample ($N = 400$) was predominantly female (62.3%). Most respondents were aged 31–40 (44.3%). Education skewed high in postgraduate (65.0%). Occupations were concentrated among government/state-enterprise employees (40.8%) and business owners/entrepreneurs (40.5%). Monthly income was skewed toward higher brackets: the largest group earned over THB 50,000 (37.3%). Marital status was predominantly single (65.8%). Regarding service use, mobile health applications (mHealth) were most common (74.8%).

The direct effect of innovation adoption on eWOM in digital health.

Innovation adoption positively and strongly predicted eWOM ($\beta = 0.793$, $t = 26.386$, $p < .001$), indicating that higher levels of adoption are associated with greater eWOM intensity, valence, and propensity.

The direct effect of eWOM on service re-intention in digital health.

eWOM exhibited a large, positive effect on service re-intention ($\beta = 0.787$, $t = 27.463$, $p < .001$), showing that more favorable eWOM corresponds to stronger intentions to return.

The mediating role of eWOM in the relationship between innovation adoption and service re-intention in digital health.

Bootstrapped PLS results indicated a significant indirect effect of adoption on service re-intention via eWOM supporting mediation. The total effect of adoption on service re-intention remained sizeable ($\beta = 0.623$, $t = 14.984$, $p < .001$), consistent with a mediated pathway in which innovation adoption influences re-intention primarily through eWOM.

DISCUSSION

The sample profile—predominantly female, concentrated in the 31–40 age group, highly educated, with sizeable representation from government/state-enterprise employees and entrepreneurs and a skew toward higher income—is consistent with a digitally literate, working-age cohort that actively engages with mobile health applications (74.8%). This pattern aligns with evidence that digital health literacy and mHealth uptake vary systematically with sociodemographic factors such as age, education, and income, with younger and more highly educated users exhibiting greater adoption and engagement (Estrela et al., 2023; Shaver, 2022; Zhao et al., 2018; Yang et al., 2025)

The strong, positive path from innovation adoption to eWOM ($\beta = 0.793$, $t = 26.386$, $p < .001$) suggests that once users cross the adoption threshold, their early evaluations translate into expressed advocacy (or critique), aligning with the Diffusion of Innovations view that perceived attributes (e.g., relative advantage, compatibility) drive not only initial uptake but also subsequent sense-making and communication behaviors (Rogers, 2003) and with prior eWOM scholarship on antecedents of online opinion expression (Cheung & Thadani, 2012; Hennig-Thurau et al., 2004).

The large effect of eWOM on service re-intention ($\beta = 0.787$, $t = 27.463$, $p < .001$) indicates that socially visible evaluations function as credibility signals that shape continuance decisions, consistent with research linking eWOM to choice and with continuance models emphasizing post-adoption evaluations (Bhattacharjee, 2001; Cheung & Thadani, 2012). In this sense, users' narratives and ratings appear to consolidate perceived value and trust in ways that reinforce return intentions.

Finally, the significant indirect effect of adoption on re-intention via eWOM—together with a sizable total effect ($\beta = 0.623$, $t = 14.984$, $p < .001$)—positions eWOM as a behavioral bridge that connects individual-level acceptance mechanisms to subsequent reuse, thereby integrating adoption logic (Rogers, 2003; Venkatesh et al., 2003) with continuance theory (Bhattacharjee, 2001). The pattern indicates that, in digital health, much of adoption's influence on repeat use operates through the social information environment created by users' evaluations.

RECOMMENDATIONS

1. Implications of the Study

1.1 Continuance is socially mediated. The results recast continuance as a process shaped by socially visible evaluations; eWOM is not peripheral communication but a behavioral mechanism translating adoption into re-intention.

1.2 Design for “shareable quality.” Early encounters should make reliability, responsiveness, and follow-up observable and easy to articulate, increasing the likelihood and positivity of eWOM that, in turn, sustains reuse.

1.3 Institutionalize feedback capture. Low-friction prompts (post-visit/in-app), timing aligned with service milestones, and seamless review flows convert private satisfaction into public signals that influence continuance.

1.4 Service-recovery as signal management. Rapid acknowledgement and visible resolution markers help contain negativity bias in eWOM, protecting return intentions despite small amounts of negative commentary.

1.5 Platform governance matters. Reviewer verification, clinician replies that add context (without breaching confidentiality), and transparent moderation increase eWOM credibility and impact.

1.6 Target the dominant touchpoint. Given mHealth's prevalence, interventions that enhance app usability, privacy salience, and trust cues are likely to yield the largest returns in eWOM and re-intention.

1.7 Equity and reach. The study's user profile (younger, highly educated, higher income) suggests the need to adapt the same eWOM-aware playbook for lower-literacy or older users to avoid widening digital divides.

2. Recommendations for Future Research

2.1 Collect data in three short waves from the same respondents: Wave 1 measures adoption (week 0), Wave 2 measures eWOM (weeks 2–4), and Wave 3 measures re-intention (weeks 6–12). This simple panel lets you check the time order—whether adoption is followed by eWOM and, in turn, by higher re-intention—without a complex design, and it can be analyzed with the same PLS/OLS framework you already use.

2.2 Link the survey to platform behavior on an opt-in basis. With consent, match each respondent's answers to real actions (e.g., whether they posted a review, average rating, and whether they returned within 90 days). This two-source approach reduces single-method bias and verifies that the observed relationships hold when using behavioral eWOM and actual revisit, not only stated intentions.

2.3 Estimate a practical “negative-review threshold.” Separate eWOM into positive and negative and test at what share of negative reviews (e.g., 5%, 10%) re-intention begins to drop meaningfully. A simple piecewise or cutoff analysis will yield a clear managerial number—how much negative eWOM can be tolerated before return intentions deteriorate—without adding heavy methodological complexity.

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