RIETI Discussion Paper Series 26-E-022

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The Research Institute of Economy, Trade and Industry
https://www.rieti.go.jp/en/

RIETI Discussion Paper Series 26-E-022
March 2026

Exiting Unawareness of Kohsetsushi among SMEs in Japan[1]

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Abstract

Public technology support can raise SME productivity, yet many firms may not use it because they remain unaware of it as a viable option. This study reframes low uptake as a discovery problem and examines transitions from unawareness to awareness of Kohsetsushi, public technology transfer organizations in Japan. Using annual online surveys from 2021 to 2024, this study classifies firms as (0) unaware, (1) aware but not using, or (2) using, and tests whether firms that are unaware in one year become aware in the next year. Because identifying adjacent-year transitions requires consecutive observation and panel retention is nonrandom, stabilized inverse-probability weights based on next-wave response likelihood are used to mitigate attrition bias. The results suggest that discovery depends more on information-processing capacity and institutional touchpoints than on firm size: managers' STEM background, prior digital investment, and previous receipt of innovation-related subsidies are positively associated with exiting unawareness, whereas firm size and firm age are not robust predictors. Travel time to the nearest Kohsetsushi facility is not a robust predictor, suggesting that cognitive and informational frictions may matter more than physical proximity at the awareness stage. These findings indicate that policy should be assessed not only by user outcomes but also by whether potential users can discover and interpret available support. Effective outreach therefore requires clear entry points, problem-based messaging, repeatable low-cost contact, and low-burden information design.

Keywords: Technology extension services; awareness formation; inverse probability weight; Kohsetsushi, SMEs

JEL classification: O33, O38, L26, C25, R58

[1] This study is part of the project "Assessment of Innovation Capability of Japanese Industry from an International Perspective (Part 2)" undertaken at the Research Institute of Economy, Trade and Industry (RIETI). Earlier versions of this paper were presented at the RIETI project seminar on 2025-11-04 and at the Innovation Economics Workshop on 2025-11-22, and a subsequent draft was presented at the RIETI Discussion Paper seminar on 2026-01-22. The author is grateful to participants in these events for valuable comments and suggestions. This research was supported by the Japan Society for the Promotion of Science (JSPS) Grants-in-Aid for Scientific Research (KAKENHI), Grant Number JP24K04828.

1. Introduction

Small and medium-sized enterprises (SMEs) are central to productivity, employment, and regional resilience, yet many struggle to access the external knowledge required to upgrade capabilities. Public technology extension has long been positioned as a policy instrument to diffuse practical know-how to smaller firms and to complement in-house R&D constraints, and prior reviews emphasize its role as an intermediary layer between public knowledge infrastructure and firm-level problem solving (e.g., Shapira et al., 2011; Fukugawa, 2024; Howells, 2006). Despite the long-standing presence of technology extension services (TES) providers, utilization remains modest. Surveys and internal evaluations repeatedly suggest that only a minority of potential users engage with TES even in manufacturing sectors where service menus appear well matched to production problems (Fukugawa, 2025). This raises a basic innovation-policy question: why do many firms not even reach the stage of considering an apparently useful public support system?

Most TES research examines firms that already engage with TES. Typical questions concern who uses services, how intensively they do so, and what performance effects follow, conditional on observed engagement (Fukugawa, 2025). This work has clarified complementarities between public support and private R&D, the role of extension centers in regional innovation systems, and pathways through which technical advice can improve productivity. However, the empirical lens is concentrated on the "use" margin. Evidence from firm-support programs suggests that awareness and use can be shaped by distinct mechanisms, implying that low participation may partly reflect a pre-use bottleneck rather than informed non-use (Torres et al., 2016). Firms that never appear as clients because they do not know TES exists are often treated as a residual category. As a result, unawareness is recognized in policy discussions but remains underexplored in TES scholarship. This study therefore shifts attention upstream, centering on the transition from unawareness to awareness as a prerequisite for evaluable take-up.

Unlike welfare benefits that presume a broadly defined and relatively homogeneous eligible population, Kohsetsushi operates under capacity constraints and selective outreach. As a result, awareness hinges on referral pathways and on whether firms become reachable when a concrete problem triggers search. Accordingly, the welfare-policy and administrative burden literatures are used here only for upstream mechanisms—exposure, attention, comprehension, and interface frictions—rather than for any eligibility-based homogeneity assumption. Kohsetsushi is often discovered through uneven local networks (such as suppliers, customers, trade associations, financial institutions, and municipal or prefectural business support offices). Because problem pressure is episodic, non-awareness can reflect channel- and timing-dependent reachability rather than deliberate non-use. This study therefore treats unawareness as a first-order bottleneck in discovery and navigation that can generate persistent participation gaps even when the underlying service menu is valuable for some firms.

Building on this mechanisms-only borrowing, a useful way to sharpen this gap is to distinguish between non-use that reflects an informed decision and non-use that occurs because firms never acquire sufficient information to evaluate TES as an option. The welfare-policy literature on non-take-up makes this distinction explicit. Van Oorschot (1991) separates non-claiming due to lack of awareness from non-claiming as a deliberate choice. Currie (2006) documents how informational barriers and program complexity discourage participation, emphasizing that low take-up can arise even when underlying benefits are meaningful for eligible users. This line of work has been formalized in the administrative burden framework, which conceptualizes citizen–state interactions as involving learning, psychological, and compliance costs that can reduce take-up (Moynihan et al., 2015; Herd and Moynihan, 2018). Attention and learning frictions can also operate prior to substantive evaluation, so that actors do not respond not because expected benefits are low but because information does not arrive in a usable form at the moment it matters (Bhargava and Manoli, 2015).

Firm-side evidence is consistent with this logic: randomized or quasi-experimental studies show that low-cost information and guidance can increase firms' take-up of government support, indicating that informational frictions are consequential prior to evaluation (Custódio et al., 2024; Honda et al., 2024). Recent syntheses further suggest that outreach and behavioral interventions—through framing, intensity, and targeting—can materially increase take-up, reinforcing the importance of informational frictions as an upstream constraint (Daigneault et al., 2025; Linos et al., 2025). Related field-experimental evidence likewise indicates that participation can be shaped by behavioral and informational frictions embedded in program interfaces (Domurat et al., 2021). Cross-country firm surveys during COVID-era support similarly report lack of awareness as a major stated barrier to receiving assistance (Cirera et al., 2021).

This pre-use bottleneck is consistent with work on entrepreneurial alertness, which emphasizes heterogeneity in actors' propensity to notice and interpret weak signals and thereby activate search even before formal evaluation begins (Araújo et al., 2023; Lanivich et al., 2024). In the TES context, this implies that discovery depends on both firms' attention and their ability to translate signals into an actionable option. This complements the information-frictions view by highlighting why otherwise similar firms may differ in whether TES cues are noticed and acted upon.

Applying this perspective to TES reframes the core problem as one of discovery and navigation. Potential users must first encounter TES information, recognize it as relevant, and learn enough to treat TES as a feasible problem-solving option. Both firm-side characteristics and policy interfaces can shape these processes by affecting how quickly decision-relevant information becomes available and usable. While this study cannot directly observe outreach design or institutional "front-door" features, it treats them as part of the broader information environment that can shift awareness over time.

This study therefore centers on the transition from unawareness to awareness. Diffusion frameworks can represent downstream dynamics such as deliberation, adoption, repeated use, and peer reinforcement. However, those mechanisms operate only after firms cross an initial attention gate. Focusing on this first gate aligns the research question with policy levers that operate upstream of observed usage. Accordingly, the empirical focus is whether firms know enough about TES to consider it a viable option, not whether they ultimately use the service.

To structure the analysis, the next section introduces a micro-founded, staged conception of awareness compatible with agent-based reasoning. Awareness is treated as a pragmatic proxy for reaching an "evaluable" state in which managers can assess TES as a feasible option, although the survey measure cannot fully distinguish recognition from depth of understanding. This framing motivates hypotheses on interest triggers, information-processing capacity, and access frictions. Section 3 describes the data, variables, and empirical strategy, including the retention model and stabilized inverse-probability weights (IPW). Section 4 reports the main results and diagnostic checks. Section 5 discusses policy implications for outreach design. Section 6 concludes.

2. Theoretical framework and hypotheses

2-1. The agent-based diffusion model

Sadou et al. (2022) model diffusion as a staged process in which actors move from being uninformed to informed before adoption can be meaningfully evaluated. This staged structure fits the present study because the empirical outcome is discovery (unawareness to awareness), an early pre-adoption stage rather than adoption itself. The model is agent-based because macro diffusion patterns emerge from many individual decision-makers whose information updating and social interactions operate through micro-level rules rather than a single population-level equation. A central modeling choice is a threshold definition of being "informed": an actor is informed only after accumulating a minimally sufficient stock of decision-relevant information. In the model, information is represented as a set of arguments that can support or oppose adoption, and evaluation depends on both the arguments received and the ability to retain and mobilize them.

The model implies a simple causal sequence. First, an interest gate determines whether an uninformed actor remains disengaged or enters an information-seeking state. Second, conditional on information seeking, the arrival of decision-relevant arguments depends on the accessibility of information sources and channels, so high navigation costs can prevent search from translating into being informed. Third, because cognitive capacity is bounded, limited retention can slow or block progression even when arguments are received.

In this study, the transition from unawareness to awareness is treated as crossing this evaluable-state proxy. That is, firms become "aware" once they have enough usable information to treat TES as a plausible option. Because the survey does not observe argument stocks directly, the empirical analysis tests the model's implications using observable correlates of (i) entry into information seeking (exposure and triggers), (ii) successful accumulation and retention of usable information (information-processing capacity), and (iii) navigation frictions that impede information arrival.

2-2. Applying the agent model to Kohsetsushi awareness

This study examines transitions from unawareness of Kohsetsushi to awareness, operationalized as moving from status 0 at time t−1 to status 1 or 2 at time t. The focus is on this upstream step because downstream behaviors such as deliberation and take-up are only possible after Kohsetsushi enters the feasible choice set as a credible option. In the empirical setting, the "threshold" is conceptual rather than directly observed: managers must have enough practical understanding of service scope and access conditions to evaluate whether initiating contact is worthwhile. Accordingly, the observed awareness transition is interpreted as a pragmatic proxy for threshold crossing rather than a direct measure of being fully informed in the simulation sense.

Consistent with the innovation intermediation view, Kohsetsushi can be interpreted as brokers that translate heterogeneous firm problems into workable routes and reduce ambiguity about how support can be used (Howells, 2006; Klerkx & Leeuwis, 2009). In terms of the agent model, this brokerage role can lower navigation costs and increase the usability of information that firms receive, thereby raising the likelihood of crossing the evaluable information threshold.

This framing emphasizes discovery as an upstream determinant of program effectiveness. Nonparticipation may reflect not rejection after evaluation but failure to reach an evaluable state. Accordingly, the unawareness-to-awareness transition captures a first-order source of policy loss: if Kohsetsushi does not become cognitively available as an option, later stages such as deliberation, initial contact, and repeated use are not reachable.

2-3. Mechanisms and hypotheses

Within this staged framework, three mechanisms generate testable predictions about exits from unawareness. First, interest functions as a gatekeeper. When managers face stronger operational or innovation-related problems, the perceived relevance of external support rises, making information seeking more likely. In the Kohsetsushi context, problem pressure can reflect production, quality, prototyping, compliance, or design and process translation challenges that trigger attention and initiate active search.

Second, information-processing capacity determines whether exposure and search translate into awareness. Because awareness requires accumulating and retaining a usable stock of decision-relevant knowledge, managers with greater technical and organizational capacity should be better able to acquire, interpret, and remember information about what Kohsetsushi can deliver and how access works. This mechanism implies that discovery costs depend on capabilities, not only on the external information environment.

Third, navigation costs shape whether information seeking yields sufficient knowledge to cross the awareness threshold. Navigation costs include geographic barriers (travel time) and broader access frictions that affect how quickly managers can reach reliable sources and convert contacts into actionable understanding. In the present empirical setting, travel time proxies geographic frictions, while local accessibility proxies the density or ease of reaching relevant channels.

Based on this framework, this study proposes the following hypotheses.
H1 (Interest trigger). Firms facing stronger operational or innovation-related problems are more likely to transition from unawareness of Kohsetsushi to awareness (status 0→1 or 2), because problem pressure raises managerial interest and initiates active search.

H2 (Information-processing capacity). Firms with higher information-processing and technical capacity are more likely to transition from unawareness to awareness, because they can more effectively acquire, interpret, and retain decision-relevant knowledge about Kohsetsushi.

H3 (Navigation costs). Higher navigation costs reduce the likelihood that a firm transitions from unawareness of Kohsetsushi to awareness, net of problem pressure and information-processing capacity.

3. Method

3-1. Data

This study examines discovery of Kohsetsushi by modeling transitions from unawareness to awareness. TES status is measured in the firm survey and classified into three mutually exclusive states: status = 0 if the firm does not know that Kohsetsushi exist, status = 1 if the firm knows Kohsetsushi but does not use them, and status = 2 if the firm uses Kohsetsushi. The main outcome is a one-year transition out of unawareness.

Table 1

Table 1 summarizes one-year transitions in TES status across consecutive reference years. The matrix shows strong persistence, especially among firms that are initially unaware: 97.49 percent of unaware firms remain unaware in the next year, while only 2.29 percent move to aware non-use and 0.22 percent transition directly to use. Persistence is also high among aware non-users (84.93 percent remain aware non-users), although a nontrivial share transitions into use (15.07 percent). Among prior users, continued use is common (72.73 percent), but 27.27 percent move back to aware non-use. Overall, the dominant pattern is the very low one-year exit rate from unawareness, which motivates modeling transitions out of unawareness as the central empirical object in the analysis.

The analysis uses an unbalanced firm panel drawn from four annual online questionnaire surveys fielded from 2021 to 2024. Each wave asked about the preceding year. Accordingly, time is indexed by the reference year: the 2021 wave corresponds to reference year t = 2020, the 2022 wave to t = 2021, the 2023 wave to t = 2022, and the 2024 wave to t = 2023. The unit of analysis is an adjacent-year pair (t to t+1). The pooled transition sample includes all eligible adjacent-year pairs for which TES status is observed at both t and t+1, so a firm can contribute multiple pairs when observed consecutively.

Reliance on an online questionnaire survey raises potential concerns about sampling, nonresponse, response behavior, and survivorship. Because participation requires online access and willingness to respond, the sample may overrepresent digitally capable managers and firms with stronger administrative capacity or institutional engagement, and budget constraints precluded mixed survey modes (e.g., mail or telephone) that might have broadened coverage. To gauge representativeness on observables, this study compares respondents' regional and industry distributions with national statistics; chi-square tests do not detect statistically significant differences, suggesting broad alignment in sectoral and geographic composition. To assess whether within-wave nonresponse appears pronounced in the primary outcome, this study compares early and late respondents in TES use following Armstrong and Overton (1977) and finds no statistically significant difference, although this diagnostic is not definitive because it relies on the assumption that late respondents approximate nonrespondents. Survivorship remains a limitation because firms that exited during the COVID-19 period are not observed and because nonresponse does not necessarily imply closure; the panel may therefore tilt toward firms with greater organizational slack. Overall, these issues primarily affect external validity, so the results are interpreted with caution regarding generalizability, while the empirical strategy further addresses selection into consecutive observation through the inverse-probability weighting approach described below.

3-2. Inverse-probability weights for consecutive observation

A key identification concern is that inclusion in the transition sample requires consecutive observation. The relevant selection issue therefore extends beyond entry into the panel to whether firms remain observable in adjacent waves. In annual online panels, follow-up response is unlikely to be random and may correlate with stable capacity for survey compliance, administrative engagement, and prior exposure to policy or market interfaces. If retention is selective, complete-case transition estimates implicitly place greater weight on firms that are systematically more likely to remain observable, which can distort inference about transitions in the target population (Si, Little, & Mo, 2024).

This study therefore uses stabilized inverse-probability weights (IPW) constructed from a retention model to mitigate selection into consecutive observation. The logic follows the longitudinal nonresponse and attrition-adjustment literature: when attrition is conditionally explainable by observed, predetermined covariates, weighting observed transitions by the inverse of their estimated probability of being observed aims to reconstruct a pseudo-population in which consecutive observation is less selectively related to those covariates (Si, Little, & Mo, 2024; Kalton & Flores-Cervantes, 2003). This approach is widely used and has been evaluated against alternative methods for handling attrition, with its performance depending on the plausibility of the response model and the stability of the implied weights (Cai et al., 2023).

Formally, let $R_{i,t+1}$ be an indicator that equals one if firm *i* observed in reference year *t* is also observed in *t*+1 (and zero otherwise). Let $X_{i,t}$ denote a set of predetermined covariates measured in or before *t*. The retention model estimates

$$p_{i,t} = \Pr\,(R_{i,t+1} = 1|X_{i,t})$$

and constructs stabilized weights as

$$w_{i,t} = \overline{p}/p_{i,t}$$

where pbar is the sample mean of the fitted retention probabilities. Stabilization is used to limit dispersion in weights while preserving their rebalancing role, consistent with applied longitudinal weighting practice (Damerow et al., 2025).

The baseline retention specification is designed to be both theoretically grounded and predetermined. It includes lagged managerial STEM background, firm size measured by regular employment, firm age, and lagged indicators of prior exposure or engagement (e.g., experience with innovation-related subsidies), along with year fixed effects and broad region and industry-group indicators. Lagging these covariates helps ensure that predictors represent characteristics determined prior to the retention outcome for the adjacent-year pair, avoiding mechanical links to contemporaneous transitions. Year fixed effects capture wave-specific shifts in response propensity common in online panels, while broad region and industry-group indicators absorb stable composition differences that can shape participation.

Recent attrition research emphasizes that IPW can be effective but is not automatic: if the retention model is weakly specified or if estimated probabilities become very small, IPW may become unstable and amplify variance (Metten et al., 2022; Cai et al., 2023; Seaman & White, 2013). Careful choice of predictors and explicit diagnostics of weight behavior are therefore essential. In line with this guidance and with applied panel weighting strategies (Damerow et al., 2025), this study uses stabilized weights and evaluates their distribution to ensure that the adjustment does not rely on a small number of highly influential observations. IPW addresses attrition into consecutive observation conditional on included covariates; remaining selection is discussed as a limitation.

3-3. Model

This study estimates exits from unawareness using logit models defined on adjacent-year pairs. The estimation sample is restricted to observations with status(t)=0, and the dependent variable is coded as either out0_to_1 = 1 if status(t+1)=1 (aware non-user) and 0 otherwise, or out0_to_12 = 1 if status(t+1)=1 or 2 (aware or user) and 0 otherwise. Regressors are measured in or before reference year t and enter the model lagged one period. All specifications include year fixed effects, broad region indicators, and industry-group indicators, and report robust standard errors clustered by firm id. Specifications that include travel time are estimated on the restricted subsample with non-missing travel time.

3-4. Variables

The transition regressions test three hypotheses about exits from unawareness. First, search triggers and prior exposure are expected to increase discovery. This study proxies these upstream triggers using indicators of engagement with policy or upgrading contexts, including innovation-related subsidy experience and export experience, and controls for prior R&D and branding activities. Second, information-processing capacity is expected to increase the likelihood that search converts into awareness. This study measures capacity using the manager's STEM background (bachelor's, master's, or Ph.D. degree in science, technology, engineering, and math) and ICT investment experience, which capture technical ability and routines for acquiring, interpreting, and retaining information relevant to public support options. Third, navigation costs are expected to reduce discovery. This study measures navigation costs using travel time from the firm's location to the nearest Kohsetsushi facility. Control variables include firm size (number of regular employees) and firm age. To proxy the regional collaboration environment, the regressions also include the lagged number of university–industry joint research projects in the region (this measure captures broader collaboration activity and does not include Kohsetsushi). As robustness checks, this study reports unweighted estimates, uses the stricter outcome out0_to_1, and tests alternative specifications for travel time and scale controls.

Table 2 shows descriptive statistics.

Table 2

4. Results

4-1. Retention model and inverse-probability weights

Table 3 reports the logit retention model used to construct stabilized inverse-probability weights for consecutive observation. The dependent variable equals one when a firm observed at reference year t is also observed again at t+1, and zero otherwise. The specification includes year fixed effects and broad region and industry-group indicators, with standard errors clustered at the firm level.

Table 3

The retention model displays strong time dependence: follow-up response is substantially more likely in the middle waves than in the first wave, and the last survey wave's year indicator is omitted due to perfect prediction because next-year observation is mechanically unavailable for a subset of records. Retention is also higher among firms with prior innovation-related subsidy experience, prior R&D activity, and prior ICT investment, and firm age is positively associated with retention, while STEM background is not statistically distinguishable from zero. Industry-group differences are pronounced, whereas regional differences are modest.

Based on the fitted retention probabilities, this study constructs stabilized weights and applies these weights in the transition regressions. Table 4 summarizes the resulting distribution (median = 1.101; interquartile range = 0.642 to 2.446; p99 = 3.227; maximum = 3.275), indicating moderate dispersion without extreme weights.

Table 4

4-2. Logit estimates with and without IPW

Table 5 reports logit estimates of one-year transitions out of unawareness, conditional on being unaware at the start of the wave. Models 1 to 4 apply inverse-probability weights, while Models 5 to 8 report unweighted estimates. Specifications that include travel time are estimated on the restricted subsample with non-missing travel time.

Table 5

STEM education is positively associated with becoming aware in the next wave in the baseline specifications without travel time (e.g., 0.856 and 0.811 in Models 1 and 2), consistent with higher information-processing capacity. When travel time is included, the STEM coefficients remain positive but are less precisely estimated. The ICT investment indicator is also positively associated with exiting unawareness in the baseline IPW models (0.688 in Model 1; 0.626 in Model 2), but this association weakens in the travel-time specifications. R&D, branding, human resource investment, and exporting are not robust predictors across models; because export experience is rare (mean = 0.020 in Table 2), its estimates are imprecise and should be interpreted cautiously. Prior innovation-related subsidy experience is consistently and positively associated with becoming aware in the next wave, with statistically significant coefficients in the IPW models and positive coefficients in the unweighted full-sample models. This pattern is consistent with an exposure-channel interpretation in which prior interactions with public programs facilitate discovery through policy information and referral opportunities. Travel time does not exhibit a stable association with discovery, and its inclusion does not materially alter the key coefficients. Year effects are strong and positive, particularly for 2023, indicating that exits from unawareness increased over time in ways not fully captured by observed firm characteristics. Among controls, firm size is not a robust predictor, and firm age is generally small except in the smaller unweighted travel-time sample. University–industry joint research projects show a negative association in the unweighted full-sample specifications, but this pattern is not stable across weighted models and is treated as suggestive.

Across the full sample, IPW and unweighted estimates are similar in sign and magnitude for the key variables, indicating that the main inferences are not driven by weighting.

5. Discussion

H1 posits that problem pressure activates managerial interest and initiates search, thereby increasing the likelihood of moving from unawareness to awareness. The evidence, however, suggests that discovery is most likely when such pressures are routed through institutional touchpoints. The robust positive association of innovation-related subsidy experience is consistent with an exposure-channel mechanism: it is not necessarily operational difficulty per se that generates discovery, but rather the way problems become visible and actionable through interactions with policy programs, administrative processes, consultation windows, and support menus that bring firms into the relevant institutional space.

Theoretically, interest can initiate search without ensuring arrival. Even when managers become interested, search may not translate into awareness if navigation is costly—because firms do not know what to look for, cannot formulate effective search terms, or face an overload of competing channels. H1 is therefore best interpreted as conditional: problem pressure increases discovery when it is coupled with pathways that connect firms to concrete information sources and referral mechanisms.

This implies a role for entry-point design. Simply expanding information provision may be insufficient for the unaware population. More effective approaches embed referral and diagnosis into existing touchpoints—for example, standardizing a “problem diagnosis to Kohsetsushi referral” step within subsidy consultation and application processes, or integrating Kohsetsushi guidance into broader public support interfaces that firms already use.

H2 argues that higher information-processing and technical capacity increases discovery because firms can acquire, interpret, and retain decision-relevant information about Kohsetsushi. The patterns in Table 5—particularly the tendency for STEM education and ICT capability to be positively associated with exiting unawareness—suggest that discovery is not merely accidental exposure; awareness formation depends on the recipient’s ability to translate incoming signals into usable knowledge. This is plausible given that service menus are diverse and often presented in administrative language, so information may be received but not consolidated as awareness without the capability to map it onto concrete firm problems.

Theoretically, this aligns with a threshold view of early diffusion: awareness emerges only after a minimum stock of decision-relevant knowledge accumulates, and the accumulation rate depends on recipient capacity, including filtering (recognizing relevance), interpretation (linking services to firm needs), and retention (making knowledge durable through reuse and internal sharing).

Policy implications follow in two directions. First, outreach should reduce interpretive burden for lower-capability firms by translating services into problem-based entry points, checklists, short diagnostic tools, and concrete cases. Second, if higher-capability firms discover Kohsetsushi more readily, uniform communication risks widening discovery gaps, making targeted information design central to both equity and productivity objectives.

H3 predicts that higher navigation costs reduce transitions from unawareness to awareness. Table 5 does not show a robust, precisely estimated effect of the travel time proxy, suggesting that discovery-stage navigation costs are not well captured by distance alone.

Theoretically, the transition from unawareness to awareness is an information-arrival stage rather than a service-use stage. When awareness is mediated by online information, business associations, suppliers, municipal support centers, and subsidy windows, physical access barriers are likely to be secondary. More salient constraints are institutional interface and search frictions, such as discoverability, clarity of service categorization, one-stop access, psychological barriers to inquiry, and the time required to reach the appropriate person. This motivates treating H3 as a navigation-cost hypothesis centered on institutional interface frictions rather than a narrow distance-based hypothesis.

If physical proximity is not the dominant constraint at the awareness stage, expanding office networks may do little to increase discovery among firms that are currently unaware. A more promising strategy is to strengthen digital pathways and referral integration—for example, problem-based portals, rapid appointment systems, and interfaces that allow firms to reach Kohsetsushi even without knowing the term "Kohsetsushi." More systematic linking of Kohsetsushi with other public programs and intermediaries can further reduce navigation burdens and shorten the path from initial search to the right contact.

Taken together, the results indicate that exiting unawareness depends on institutional touchpoints that route firms into relevant channels and on recipient capacity that converts signals into retained, decision-relevant knowledge. The strong year effects further suggest that the information environment and policy communication can shift discovery probabilities, implying that awareness is partly a policy-design variable rather than a fixed firm trait.

6. Conclusion

This study reframes the persistently modest use of Kohsetsushi not as a simple lack of demand but as a failure of discovery, and it makes the transition from unawareness to awareness an explicit empirical object. Focusing on this upstream diffusion stage, the analysis links awareness formation to a process-based framework in which interest initiates search, decision-relevant knowledge accumulates, and firms enter the institutional space as a feasible option. The results suggest that discovery does not automatically follow from problem pressure alone. Instead, it is shaped by institutional touchpoints—such as prior interactions with other public support programs—that provide practical entry routes, and by recipient-side information-processing capacity that helps firms interpret and retain relevant information. These findings highlight entry-point design and the reduction of interpretive burden for lower-capability firms as policy levers, implying that awareness can be improved through the architecture of public support interfaces rather than through information volume alone.

This study also has limitations that motivate future research. First, awareness transitions are self-reported, and the data do not distinguish the content of awareness (e.g., name recognition versus functional understanding) or directly observe discovery channels. Second, navigation costs are proxied by travel time, which may miss key discovery-stage frictions such as searchability and one-stop access. Third, reliance on an online survey panel leaves scope for unobserved preferences and information environments to affect both discovery and continued participation across waves. Future research should measure awareness as a multi-stage construct, include items that identify discovery channels, and link survey data with external sources such as web search metrics, consultation records, and referral networks to make entry pathways observable. It would also be valuable to develop indicators of institutional interface friction beyond distance and evaluate their effects using quasi-experimental designs or assessments of concrete interventions, such as outreach webpage redesigns or standardized referral protocols embedded in related public programs.

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Table 1. One-year transition matrix of TES status (reference year t to t+1)

Status at *t* / Status at *t+1*	Unaware (0)	Aware non-user (1)	User (2)	Row total
Unaware (0)	97.49 (893)	2.29 (21)	0.22 (2)	100.00 (916)
Aware non-user (1)	0.00 (0)	84.93 (62)	15.07 (11)	100.00 (73)
User (2)	0.00 (0)	27.27 (12)	72.73 (32)	100.00 (44)
Column total	86.45 (893)	9.20 (95)	4.36 (45)	100.00 (1,033)

Notes

Cell entries are row transition probabilities (percent).

Counts are in parentheses.

t and t+1 refer to consecutive reference years.

Table 2. Descriptive Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
out0_to_1	1,012	0.105	0.306	0.000	1.000
out0_to_12	1,012	0.118	0.322	0.000	1.000
STEM background	4,555	0.280	0.449	0.000	1.000
Firm age	4,555	47.322	41.929	0.000	527.000
Log of regular employees	4,555	1.591	1.647	0.000	5.707
Innovation-related subsidy experience	4,555	0.078	0.268	0.000	1.000
ICT investment experience	4,555	0.131	0.338	0.000	1.000
Human resource investment experience	4,555	0.092	0.289	0.000	1.000
Export experience	4,555	0.020	0.140	0.000	1.000
R&D experience	4,555	0.085	0.279	0.000	1.000
Design investment experience	4,555	0.053	0.224	0.000	1.000
Branding investment experience	4,555	0.069	0.253	0.000	1.000
UI joint research projects in the region	4,200	6.804	1.210	4.344	8.928
Travel time	1,744	3.890	0.711	0.000	6.043
Low-tech	4,555	0.511	0.500	0.000	1.000
Mid-tech	4,555	0.394	0.489	0.000	1.000
High-tech	4,555	0.095	0.293	0.000	1.000
North	4,555	0.062	0.241	0.000	1.000
Kanto	4,555	0.319	0.466	0.000	1.000
Mid	4,555	0.269	0.444	0.000	1.000
West	4,555	0.288	0.453	0.000	1.000
Southwest	4,555	0.062	0.241	0.000	1.000

Notes

out0_to_1: 1 if status 0 at t and status 1 at t+1; 0 otherwise.

out0_to_12: 1 if status 0 at t and status 1 or 2 at t+1; 0 otherwise.

lowtech, midtech, hightech are mutually exclusive industry-group indicators (1 if the firm's industry is in the listed categories; 0 otherwise).

Low-tech: 2 Food; 3 Beverage, tobacco, and feed; 4 Textiles; 5 Wood products (except furniture); 6 Furniture and fixtures; 7 Pulp, paper, and paper products; 8 Printing and related; 12 Rubber products; 13 Leather products and fur; 25 Other manufacturing.

Mid-tech: 9 Chemicals; 10 Petroleum and coal products; 11 Plastics products; 14 Ceramics, stone, and clay products; 15 Iron and steel; 16 Nonferrous metals; 17 Fabricated metal products; 18 General purpose machinery; 19 Production machinery;

20 Business-oriented machinery; 24 Transport equipment.
High-tech: 21 Electronic parts, devices, and circuits; 22 Electrical machinery; 23 Information and communications machinery.
North, Kanto, Mid, West, and Southwest are broad location indicators (1 if the firm's prefecture is in the listed group; 0 otherwise).
North: 1 Hokkaido; 2 Aomori; 3 Iwate; 4 Miyagi; 5 Akita; 6 Yamagata; 7 Fukushima.
Kanto: 8 Ibaraki; 9 Tochigi; 10 Gunma; 11 Saitama; 12 Chiba; 13 Tokyo; 14 Kanagawa.
Mid: 15 Niigata; 16 Toyama; 17 Ishikawa; 18 Fukui; 19 Yamanashi; 20 Nagano; 21 Gifu; 22 Shizuoka; 23 Aichi; 24 Mie.
West: 25 Shiga; 26 Kyoto; 27 Osaka; 28 Hyogo; 29 Nara; 30 Wakayama; 31 Tottori; 32 Shimane; 33 Okayama; 34 Hiroshima; 35 Yamaguchi; 36 Tokushima; 37 Kagawa; 38 Ehime; 39 Kochi.
Southwest: 40 Fukuoka; 41 Saga; 42 Nagasaki; 43 Kumamoto; 44 Oita; 45 Miyazaki; 46 Kagoshima; 47 Okinawa.

Table 3. Logit model of consecutive-wave retention

Variable	Coef.	SE	p-value
STEM background	0.140	0.105	0.182
Regular employees	0.031	0.023	0.169
Firm age	0.003	0.001	0.012
Innovation-related subsidy experience	0.796	0.211	0.000
R&D investment experience	1.086	0.222	0.000
ICT investment experience	0.826	0.163	0.000
Year = 2022	1.215	0.114	0.000
Year = 2023	2.141	0.155	0.000
Kanto	-0.040	0.191	0.835
Mid	0.478	0.198	0.016
West	0.199	0.197	0.313
Southwest	0.218	0.245	0.373
High-tech	1.061	0.179	0.000
Low-tech	1.233	0.097	0.000
Constant	-1.797	0.185	0.000

Notes

Dependent variable is responded_next (1 if a firm observed at reference year t is also observed at t+1; 0 otherwise).

Standard errors are robust and clustered by firm id.

The 2024 year indicator is omitted due to perfect prediction because the panel ends after the 2024 wave.

Coefficients are log-odds from a logit model.

Table 4. Distribution of stabilized inverse probability weights (w_ipw)

Statistic	Observations	Minimum	p25	Median (p50)	p75	p99	Maximum
Value	3,121	0.458	0.642	1.101	2.446	3.227	3.275

Notes

Stabilized weights are constructed as w_ipw = mean(p_resp) divided by p_resp, where p_resp is the fitted probability of being observed in two consecutive waves (retention). Summary statistics are computed over the estimation sample used in the transition regressions.

Table 5. Logit estimates of exits from unawareness, with and without IPW

Dependent variable	0→1 (aware non-user) IPW	0→1 or 2 (aware or user) IPW	0→1 (aware non-user) IPW	0→1 or 2 (aware or user) IPW	0→1 (aware non-user) Unweighted	0→1 or 2 (aware or user) Unweighted	0→1 (aware non-user) Unweighted	0→1 or 2 (aware or user) Unweighted
STEM background	0.856***	0.811***	0.544	0.523	0.787***	0.777***	0.448	0.510
	(0.302)	(0.288)	(0.357)	(0.361)	(0.272)	(0.259)	(0.324)	(0.323)
Innovation-related subsidy experience	0.653*	0.643*	0.816*	0.835*	0.677**	0.646**	0.676	0.649
	(0.363)	(0.339)	(0.494)	(0.487)	(0.317)	(0.307)	(0.415)	(0.419)
R&D investment experience	0.333	0.152	0.121	-0.024	0.631	0.415	0.358	0.146
	(0.441)	(0.417)	(0.399)	(0.392)	(0.388)	(0.385)	(0.374)	(0.382)
Branding investment experience	0.529	0.737*	-0.168	-0.010	0.262	0.614	-0.435	-0.116
	(0.470)	(0.417)	(0.443)	(0.387)	(0.421)	(0.394)	(0.412)	(0.370)
ICT investment experience	0.688**	0.626*	0.489	0.448	0.448	0.390	0.354	0.291
	(0.344)	(0.327)	(0.398)	(0.402)	(0.279)	(0.272)	(0.347)	(0.355)
Human resource investment experience	0.170	0.080	-0.347	-0.474	0.043	-0.064	-0.387	-0.486
	(0.428)	(0.411)	(0.539)	(0.541)	(0.330)	(0.327)	(0.399)	(0.404)
Export experience	-0.568	-0.642	-0.409	-0.812	-0.546	-0.654	-0.398	-0.892
	(0.690)	(0.657)	(1.009)	(0.948)	(0.663)	(0.634)	(0.966)	(0.909)
Regular employees	-0.045	0.007	-0.093	-0.010	0.009	0.070	-0.056	0.056
	(0.071)	(0.064)	(0.089)	(0.082)	(0.066)	(0.058)	(0.085)	(0.078)
Firm age	-0.001	-0.001	-0.005	-0.005	-0.005	-0.004	-0.012**	-0.011**
	(0.003)	(0.003)	(0.006)	(0.006)	(0.003)	(0.003)	(0.005)	(0.005)
University-industry joint research projects	-0.200	-0.194	-0.040	-0.054	-0.240**	-0.239**	-0.079	-0.102
	(0.124)	(0.121)	(0.171)	(0.172)	(0.111)	(0.107)	(0.152)	(0.156)

Dependent variable	0→1 (aware non-user)	0→1 or 2 (aware or user)	0→1 (aware non-user)	0→1 or 2 (aware or user)	0→1 (aware non-user)	0→1 or 2 (aware or user)	0→1 (aware non-user)	0→1 or 2 (aware or user)
year=2022	0.701**	0.789***	0.549	0.654*	0.533**	0.664***	0.478	0.615*
	(0.296)	(0.288)	(0.366)	(0.360)	(0.261)	(0.257)	(0.329)	(0.328)
year=2023	0.810***	0.973***	0.900**	1.247***	0.714***	0.900***	0.948**	1.309***
	(0.285)	(0.276)	(0.405)	(0.406)	(0.251)	(0.247)	(0.369)	(0.379)
High-tech	-0.241	-0.256	-0.074	0.004	-0.218	-0.215	0.054	0.159
	(0.435)	(0.418)	(0.594)	(0.584)	(0.397)	(0.393)	(0.521)	(0.552)
Low-tech	0.135	0.058	0.467	0.294	0.109	0.040	0.532*	0.388
	(0.297)	(0.280)	(0.337)	(0.349)	(0.254)	(0.241)	(0.307)	(0.313)
Kanto	-0.481	-0.460	-0.313	-0.334	-0.350	-0.316	-0.149	-0.057
	(0.574)	(0.577)	(0.755)	(0.783)	(0.460)	(0.462)	(0.625)	(0.638)
Mid	-0.635	-0.452	-0.605	-0.429	-0.262	-0.030	-0.164	0.196
	(0.573)	(0.570)	(0.646)	(0.681)	(0.445)	(0.442)	(0.511)	(0.530)
West	-0.757	-0.513	-0.837	-0.550	-0.491	-0.292	-0.321	-0.011
	(0.591)	(0.588)	(0.661)	(0.695)	(0.466)	(0.463)	(0.523)	(0.538)
Southwest	-0.956	-0.811	-1.049	-0.832	-0.587	-0.441	-0.437	-0.207
	(0.683)	(0.673)	(0.764)	(0.778)	(0.581)	(0.564)	(0.617)	(0.602)
Travel time			0.010	-0.166			-0.176	-0.302
			(0.228)	(0.245)			(0.208)	(0.217)
Constant	-1.288	-1.419	-0.165	0.534	-0.972	-1.183	0.828	1.137
	(1.019)	(0.990)	(1.480)	(1.501)	(0.862)	(0.839)	(1.387)	(1.404)
N	1012	1012	251	251	1012	1012	251	251
Pseudo R2	0.085	0.088	0.076	0.077	0.080	0.092	0.077	0.089

Notes

Full sample” for columns 1,2,5,6 and “Travel-time subsample” for 3,4,7,8.

Columns 1–4 are weighted by stabilized inverse probability weights from the retention model; Columns 5–8 are unweighted.

Dependent variable: exit from unawareness of Kohsetsushi (1 = aware in the next wave, conditional on unawareness in the start wave; 0 otherwise).

Coefficients are logit estimates with robust standard errors clustered by firm id in parentheses.

All specifications include year fixed effects, broad region indicators, and industry-group indicators.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

All regressors are lagged one period.