

Measuring Organizational Readiness for Quantum Technology Adoption: Scale Development and Validation

KAZUYA TAIRA

`taira.kazuya.qiqb@osaka-u.ac.jp`

The University of Osaka <https://orcid.org/0000-0002-1560-5454>

Yusuke Kodaira

The University of Osaka

Emi Kamada

The University of Osaka

Osamu Kamatani

The University of Osaka

Yusuke Kobayashi

The University of Osaka

Miyuki Imada

The University of Osaka

Research Article

Keywords: Quantum technology, technology adoption, organizational readiness, scale development, exploratory factor analysis, innovation management

Posted Date: October 7th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11262393/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: The authors declare no competing interests.

Measuring Organizational Readiness for Quantum Technology Adoption: Scale Development and Validation

Kazuya Taira^{1*}, Yusuke Kodaira¹, Emi Kamada¹,
Osamu Kamatani¹, Yusuke Kobayashi¹, Miyuki Imada¹

^{1*}Center for Quantum Information and Quantum Biology, The
University of Osaka, Osaka, Japan .

*Corresponding author(s). E-mail(s): taira.kazuya.qiqb@osaka-u.ac.jp;

Abstract

As quantum technologies move toward practical application, organizations face the question of whether they are prepared to adopt them, yet, to our knowledge, no validated instrument exists for measuring organizational readiness for quantum technology adoption. This study developed the Quantum Technology Readiness Scale (QTRS) and provides initial psychometric evidence for it. A mail survey of all 3,890 publicly listed firms in Japan yielded 154 responses, and supplementary eligibility analyses suggested that respondents represented roughly 8–11% of the practically relevant target population. Exploratory factor analysis (maximum likelihood, oblimin rotation; $n = 102$) of an initial pool of 15 Likert-type items supported a two-factor structure with 10 retained items: Implementation Capacity (7 items, $\alpha = 0.88$, $\omega = 0.88$) and Perceived Benefits (3 items, $\alpha = 0.78$, $\omega = 0.79$), with a weak inter-factor correlation ($\phi = 0.28$). The two dimensions showed sharply asymmetric validity patterns. Implementation Capacity differed across adoption stages ($p < 0.001$), was strongly associated with advanced adoption (odds ratio = **6.48** per scale point, 95% CI [2.44, 17.23]), and correlated with quantum technology budgets ($\rho = 0.46$); Perceived Benefits was uniformly high and unrelated to any behavioral criterion. Firms thus broadly expect quantum technologies to deliver value ($M = 3.84$ on a 5-point scale) but report low implementation capacity ($M = 2.61$), and it is capacity—not expectation—that distinguishes firms engaged in concrete adoption activities. The QTRS offers a psychometrically grounded alternative to checklist-style quantum readiness assessments; confirmatory validation in larger samples is the immediate next step.

Keywords: Quantum technology, technology adoption, organizational readiness, scale development, exploratory factor analysis, innovation management

JEL Classification: O32 , O33 , L20

1 Introduction

Quantum technologies are moving from scientific promise toward industrial and societal adoption. They encompass quantum computing, sensing, secure communication, and simulation, and have been discussed as potentially relevant to optimization, machine learning, materials science, finance, logistics, pharmaceuticals, healthcare, and other sectors (Gupta, Wood, Engstrom, Pole, & Shrapnel, 2025; Purohit, Kaur, Seskir, Posner, & Venegas-Gomez, 2024). However, organizational adoption should not be understood solely as a function of technological maturity or market expectations. Current application domains remain exploratory, and practical utility often depends on problem selection, hardware constraints, scalability, noise tolerance, and integration with classical systems (Gupta et al., 2025; Teitsma, Ahmed, & van Velzen, 2025). For firms, engaging with quantum technologies therefore requires more than general awareness: it requires the ability to identify relevant use cases, allocate specialized resources, collaborate with external partners, conduct proof-of-concept experiments, and evaluate uncertain outcomes. These organizational conditions are particularly important because many quantum applications depend on interactions between emerging technical capabilities, existing business processes, and broader innovation ecosystems (Purohit et al., 2024; Teitsma et al., 2025).

This study focuses on organizational readiness for quantum technology adoption. Drawing on organizational readiness theory and organizational-level technology adoption perspectives, we define organizational readiness for quantum technology adoption as the extent to which an organization recognizes the potential value of quantum technologies and possesses the managerial, human, technical, and relational capacity to initiate, govern, and learn from quantum-related activities (Baker, 2011; Weiner, 2020). This definition distinguishes between two conceptually related but practically different dimensions: perceived benefits and implementation capacity. Perceived benefits reflect expectations that quantum technologies can improve operations, enhance competitive advantage, or generate outcomes beyond existing technologies. Implementation capacity reflects the organizational ability to translate such expectations into action through resources, leadership support, governance, experimentation environments, and external collaboration.

Several streams of work have begun to address readiness for quantum technologies. At the industry level, IBM’s Quantum Readiness Index represents a prominent attempt to benchmark organizational preparedness for quantum computing using indicators related to strategy, technology, and operations (IBM Institute for Business Value, 2025). In academic literature, recent work has proposed Quantum Organisational Readiness Levels to describe staged progression from awareness and exploration

toward experimentation and implementation (Teitsma et al., 2025). Other ecosystem-oriented approaches have introduced Quantum Technology Readiness Levels and Quantum Commercial Readiness Levels to assess technological maturity, commercial viability, and ecosystem development (Purohit et al., 2024). These efforts are valuable because they make quantum readiness visible as an organizational and ecosystem-level issue rather than merely a technical issue. However, they are primarily proprietary indices, qualitative stage models, or technology/commercial maturity frameworks. To our knowledge, no transparent, reusable, psychometrically examined scale has yet been developed to measure organizational readiness for quantum technology adoption among firms.

This measurement gap matters for both research and practice. Without a reusable scale, firms, policymakers, and ecosystem actors cannot easily distinguish between two different problems: a lack of perceived value and a lack of implementation capacity. Generic technology readiness instruments provide important methodological precedents, but they often focus on individuals' predispositions toward technology rather than the organizational conditions required to adopt a specific emerging technology (Parasuraman, 2000). Similarly, organizational readiness for change research emphasizes the importance of both valuing a change and believing in collective implementation capability, but existing instruments were not designed for quantum-specific adoption contexts (Weiner, 2020). Scale development literature also emphasizes that new measurement instruments should begin with clear construct definitions, domain specification, item generation, content validity, dimensionality assessment, reliability testing, and validity evidence (Boateng, Neilands, Frongillo, Melgar-Quinonez, & Young, 2018; MacKenzie, Podsakoff, & Podsakoff, 2011). Applying these principles to quantum technology adoption can move the field from case-specific checklists and maturity narratives toward cumulative, comparable, and empirically testable evidence.

This measurement gap is important because organizational readiness is not directly observable. In measurement research, scales are commonly used to operationalize latent constructs—such as attitudes, perceptions, capabilities, or readiness—that cannot be assessed directly through a single observable indicator. Scale development therefore requires more than writing survey questions: it involves defining the construct domain, generating items, examining dimensionality, evaluating reliability, and accumulating validity evidence. Such procedures are well established not only in psychology and health research, but also in information systems and innovation research, where validated instruments have been developed to measure perceptions of information technology adoption and other latent constructs. Applying this approach to quantum technology adoption allows readiness to be studied as a measurable organizational construct rather than as an informal checklist or proprietary index.

To address this gap, the present study develops and provides initial psychometric evidence for the Quantum Technology Readiness Scale (QTRS). Using a nationwide corporate survey targeting all listed firms in Japan, we examine whether organizational readiness for quantum technology adoption can be measured as a multidimensional construct and whether its dimensions are associated with firms' adoption stages. This study makes three contributions. First, it conceptualizes quantum technology readiness as a distinction between perceived benefits and implementation capacity. Second,

it develops a parsimonious scale and evaluates its exploratory factor structure, internal consistency, known-groups validity, and criterion-related validity. Third, it shows that, among responding firms, progression toward PoC and pilot stages is more clearly differentiated by implementation capacity than by perceived benefits. These findings suggest that the social and industrial adoption of quantum technologies may require not only awareness-building and use-case promotion, but also targeted capacity-building in resources, governance, experimentation, and external collaboration.

2 Methods

2.1 Participants and Data Collection

This study used a cross-sectional corporate survey design to examine organizational readiness for quantum technology adoption. The survey targeted publicly listed firms in Japan identified through the Corporate Data Bank file provided by Toyo Keizai Inc. using the Kaisha Shikiho database, 2025 Fall Edition (Toyo Keizai Inc., 2025). This database was used as the sampling frame because it provides standardized company-level information for listed firms in Japan, including market segment, industry classification, company size, paid-in capital, and other corporate attributes.

The questionnaire was distributed by mail to firms included in the sampling frame. Because responsibilities related to quantum technologies may be located in different organizational units depending on the firm, responses were requested from a representative in a quantum-related department or, where no such department existed, from a department responsible for corporate planning, research and development, technology strategy, or related innovation activities. The survey period was from December 22, 2025, to January 28, 2026. For firms that had not responded as of January 15, 2026, follow-up reminders were made by telephone to encourage participation.

Survey responses were linked to company-level attributes from the Corporate Data Bank using unique anonymized company identifiers. This linkage enabled the characterization of responding firms and comparison with non-responding firms while preserving company confidentiality. Response patterns, respondent characteristics, and comparisons between responding and non-responding firms are reported in Section 3. Supplementary analyses conducted to contextualize the broad sampling frame and potential eligibility of target firms are reported in Appendix B.

2.2 Scale development rationale and item generation

The purpose of the QTRS was to operationalize organizational readiness for quantum technology adoption as a measurable latent construct. In measurement research, a scale is used when the target concept cannot be directly observed and must instead be inferred from multiple observable indicators. Organizational readiness is such a construct: it cannot be measured directly by a single factual question, but can be assessed through patterns of responses regarding perceived value, managerial support, resources, governance, experimentation capability, and external collaboration (Boateng et al., 2018; MacKenzie et al., 2011).

This approach differs from a checklist or a proprietary composite index. A checklist identifies whether specific conditions are present, and a composite index often aggregates predefined criteria using explicit or implicit weights. In contrast, a psychometric scale is developed to measure underlying latent dimensions reflected in correlated survey items. Scale development therefore requires explicit construct definition, item generation, dimensionality assessment, reliability evaluation, and validity evidence (Boateng et al., 2018; MacKenzie et al., 2011). This approach is well established not only in behavioral, organizational, and health research, but also in information systems research, where validated instruments have been developed to measure constructs such as technology perceptions, innovation adoption, and implementation-related beliefs (Moore & Benbasat, 1991; Straub, 1989).

In this study, organizational readiness for quantum technology adoption was defined as the extent to which an organization recognizes the potential value of quantum technologies and possesses the managerial, human, technical, financial, and relational capacity to initiate, govern, and learn from quantum-related activities. This definition was informed by organizational readiness theory, technology adoption research, and emerging discussions of quantum readiness. Organizational readiness theory distinguishes between valuing a change and perceived capability to implement that change, while technology adoption perspectives emphasize that organizational adoption depends not only on perceived technological value but also on organizational resources and environmental conditions (Baker, 2011; Tornatzky & Fleischer, 1990; Weiner, 2009).

Based on this definition, the initial item pool was designed to capture two theoretically expected domains: Perceived Benefits and Implementation Capacity. Perceived Benefits refers to the extent to which an organization expects quantum technologies to improve operations, strengthen competitive advantage, or generate outcomes that cannot be achieved with existing technologies. Implementation Capacity refers to the extent to which an organization has the internal and external conditions needed to translate interest in quantum technologies into action, including personnel, technical infrastructure, budgetary resources, top management support, strategic alignment, governance mechanisms, experimentation environments, and external collaboration.

The initial item pool consisted of 15 Likert-type items. Items were generated by the research team through a review of prior literature on technology readiness, organizational readiness, innovation adoption, and quantum readiness frameworks (IBM Institute for Business Value, 2025; Moore & Benbasat, 1991; Parasuraman, 2000; Purohit et al., 2024; Teitsma et al., 2025; Weiner, 2009). The items were written to be answerable by corporate respondents in quantum-related, planning, research and development, or technology strategy functions. They were also designed to avoid excessive technical specificity so that the scale could be applied across industries and across different types of quantum technologies, including quantum computing and related quantum-enabled applications.

The item pool was reviewed within the research team for conceptual coverage, clarity, redundancy, and relevance to organizational-level adoption. Because this study represents an initial scale development effort, the empirical analyses focused on

exploratory dimensionality assessment, item refinement, internal consistency reliability, known-groups validity, and criterion-related validity. Formal external expert-panel rating, cognitive interviewing, confirmatory factor analysis, and measurement invariance testing were not conducted in this study and are therefore identified as priorities for future validation research(Boateng et al., 2018; MacKenzie et al., 2011).

We treated the proposed QTRS dimensions as reflective latent constructs in this initial psychometric analysis. That is, the retained items were expected to co-vary because they were designed as observable manifestations of broader organizational readiness dimensions. We acknowledge, however, that some readiness frameworks may alternatively conceptualize organizational capacity indicators as formative components of an index. Future research should compare reflective scale and formative index specifications as empirical evidence accumulates and quantum adoption practices mature(MacKenzie et al., 2011; Petter, Straub, & Rai, 2007).

2.3 Measures

Company characteristics

To describe the characteristics of the respondent company, we linked the survey responses to company-level attributes obtained from the Corporate Data Bank (Kaisha Shikiho) compiled by Toyo Keizai Inc. (2025 Fall Edition). Each company was assigned a unique anonymized identifier, which enabled company-level merging of the survey data with the Kaisha Shikiho dataset while maintaining confidentiality. The company characteristics reported in Table 1 (e.g. market segment, industry sector, company size and capital) were derived from this merged dataset.

Quantum Technology Readiness Scale

Organizational readiness for quantum technology adoption was measured using a set of Likert-type items developed for this study. An initial pool of 15 items (Appendix A) was constructed based on prior research on technology adoption and organizational readiness. The items were designed to capture two conceptual dimensions: implementation capacity for quantum technology and perceived benefits of quantum technology adoption. All items were measured using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). Two of the 15 items (Items 6 and 7) were negatively worded with respect to readiness—referring, respectively, to the difficulty of understanding quantum technologies and to the presence of barriers to their internal use. These two items were reverse-scored prior to all analyses (i.e., recoded so that a response of 1 became 5, 2 became 4, and so on), so that for every item a higher value consistently indicated greater readiness.

Adoption Stage

The stage of quantum technology adoption in the organization was measured using six response options: no interest, interest only, PoC planning, PoC implementation, pilot or limited deployment, and full deployment. For known-groups validity analyses, organizations reporting no interest were excluded because readiness is conceptually

defined among organizations considering adoption. For regression analysis, a binary variable representing advanced adoption was constructed. Organizations conducting PoC, pilot deployment, or full deployment were classified as advanced adopters.

Organizational Quantum Resources

Organizational resources were assessed using two indicators: annual budget allocated to quantum technology activities and number of quantum dedicated personnel. Annual budget allocated to quantum technology activities was measured by six options: no budget, less than 5 million JPY, 5 to 20 million JPY, 20 to 50 million JPY, 50 to 100 million JPY, more than 100 million JPY. Quantum dedicated personnel was measured by five options: none, 1-5 persons, 6-10 persons, 11-20 persons, 21 and more persons. These variables were used to examine criterion-related validity of the readiness scales.

2.4 Exploratory Factor Analysis

Exploratory factor analysis (EFA) was conducted to examine the dimensionality of the initial 15-item QTRS item pool and to refine the scale. EFA was selected because this study represents an initial scale development effort and the empirical dimensionality of organizational readiness for quantum technology adoption had not yet been established. The analysis followed standard scale development procedures in which item dimensionality, factor interpretability, and internal consistency are evaluated before subsequent validity analyses (Boateng et al., 2018; Costello & Osborne, 2005; Fabrigar, Wegener, MacCallum, & Strahan, 1999).

Before conducting EFA, sampling adequacy and factorability were assessed using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett’s test of sphericity. These diagnostics were used to evaluate whether the item correlation matrix was suitable for factor analysis. Because the theoretically expected dimensions of organizational readiness were assumed to be related rather than independent, an oblique rotation was used. Specifically, EFA was conducted using the maximum likelihood method with oblimin rotation.

The number of factors to retain was evaluated based on theoretical interpretability, the pattern of eigenvalues, the scree plot, and the clarity of the rotated factor solution. Items were considered for removal if they showed weak primary factor loadings, substantial cross-loadings, low communalities, or conceptual inconsistency with the emerging factor structure. The prespecified item refinement criteria were: primary factor loading < 0.40 , cross-loading > 0.30 , communality < 0.30 , and lack of conceptual interpretability. Item removal was conducted iteratively, with the factor solution re-estimated after each removal to evaluate the stability and interpretability of the remaining item set.

The final factor solution was selected based on a combination of statistical criteria and conceptual coherence. The retained items were assigned to factors according to their primary loadings and theoretical meaning. Factor labels were determined after reviewing the content of the retained items. The full initial item pool, item retention status, and final factor assignment are reported in Appendix A.

2.5 Reliability and Validity Analysis

After the final factor structure was determined, scale scores were calculated as the mean of the retained items within each factor. Higher scores indicated higher levels of the corresponding readiness dimension. Because the two negatively worded items (Items 6 and 7) were both removed during item selection, the final subscales contained only positively worded items; the reverse-scoring described above therefore affected the factor-analytic item-screening stage rather than the final scale scores. Internal consistency reliability was evaluated using Cronbach’s alpha and McDonald’s omega. Cronbach’s alpha was reported for comparability with prior scale development studies, while McDonald’s omega was included because it is less dependent on the assumption of tau-equivalence and is increasingly recommended as a complementary reliability estimate (Dunn, Baguley, & Brunsden, 2014; Hayes & Coutts, 2020).

Validity evidence was examined in two ways: known-groups validity and criterion-related validity. Known-groups validity was assessed by comparing QTRS scores across quantum technology adoption stages. The theoretical expectation was that organizations at more advanced adoption stages would show higher readiness, particularly in the Implementation Capacity dimension. Because readiness scores were not assumed to be normally distributed and adoption stage was ordinal with uneven group sizes, differences across adoption stages were evaluated using the Kruskal–Wallis test. For the primary known-groups analysis, firms reporting “no interest” were excluded because readiness for adoption was considered conceptually most relevant among firms that had at least begun to consider quantum technologies.

Criterion-related validity was examined using logistic regression analysis. The outcome variable was advanced quantum technology adoption. Firms reporting PoC ongoing, pilot or limited deployment, or full deployment were classified as advanced adopters, whereas firms reporting interest only or PoC planning were classified as not yet advanced adopters. The primary predictors were the two QTRS subscale scores: Implementation Capacity and Perceived Benefits. Odds ratios, 95% confidence intervals, and p-values were reported for each predictor. Overall model fit was evaluated using the likelihood ratio test and pseudo R^2 .

Because the analyses were cross-sectional, the logistic regression results were interpreted as associations between readiness dimensions and current adoption stage rather than as evidence of causal effects. In particular, higher Implementation Capacity may reflect both organizational conditions that enable adoption and capabilities accumulated through engagement with quantum-related activities.

2.6 Non-response and eligibility analyses

Because the survey was distributed broadly to all listed firms rather than only to firms with known quantum-related activities, additional analyses were conducted to characterize the response context and to assess observable differences between responding and non-responding firms. These analyses were intended to inform interpretation of the survey data and not to establish population representativeness.

First, responding and non-responding firms were compared using company-level attributes obtained from the Corporate Data Bank. Continuous variables, including number of employees, paid-in capital, and company age, were summarized using medians and interquartile ranges and compared using nonparametric tests because their distributions were skewed. Categorical variables, including market segment and industry sector, were summarized using counts and percentages and compared using chi-square tests or Fisher’s exact tests where appropriate.

Second, supplementary eligibility analyses were conducted to contextualize the broad sampling frame. Because many listed firms may have had no current involvement or perceived relevance regarding quantum technologies, we explored whether the practically relevant target population was smaller than the full listed-firm sampling frame. Two binary eligibility definitions were constructed among responding firms with non-missing adoption-stage information. The broad eligibility definition classified firms as eligible if they reported any level of interest or engagement with quantum technologies, including interest only, PoC planning, PoC ongoing, pilot or limited deployment, or full deployment. Firms reporting no interest were classified as not eligible under this definition. The narrow eligibility definition classified firms as eligible if they reported PoC planning, PoC ongoing, pilot or limited deployment, or full deployment; firms reporting no interest or interest only were classified as not eligible.

Eligibility status was modeled using observable company characteristics, including market segment, industry sector, number of employees, paid-in capital, and company age. Missing values in continuous predictors were imputed using the sample median, and categorical predictors were represented using indicator variables. Two predictive approaches were compared: logistic regression and a decision tree classifier. Class imbalance adjustments were applied because eligible and non-eligible firms were unevenly distributed, particularly under the narrow definition. Model performance was evaluated using stratified five-fold cross-validation and summarized using accuracy, balanced accuracy, precision, recall, F1 score, area under the receiver operating characteristic curve, and area under the precision–recall curve.

The fitted models were then used to estimate the potential size of the practically relevant target population within the original listed-firm sampling frame. These estimates were treated as supplementary and exploratory. They were used only to contextualize the crude response rate and the broad sampling strategy, not to reweight the primary analyses or to claim that the respondent sample was representative of all listed firms.

All statistical analyses were conducted using Python statistical libraries. Exploratory factor analysis, reliability analyses, nonparametric tests, logistic regression models, and supplementary predictive models were implemented using standard open-source packages. Statistical significance was evaluated using two-sided tests, with $p < 0.05$ considered statistically significant.

2.7 Ethics statement

This study was conducted as an organization-level survey of publicly listed firms. The questionnaire asked designated corporate representatives to report on company-level conditions and activities related to quantum technology adoption. It did not collect

biomedical or health-related information, human specimens, or information of human origin, and it did not involve any intervention with individuals. Accordingly, the study was outside the scope of the Japanese Ethical Guidelines for Medical and Biological Research Involving Human Subjects and was not submitted for review under those guidelines. Participation was voluntary. The survey materials explained the purpose of the study, and return of a completed questionnaire was regarded as consent for the company-level responses to be used in aggregate research analyses. Survey responses were linked to licensed company-level attributes using anonymized company identifiers, and no individual respondent names or identifiable company-level responses are reported.

3 Results

3.1 Response Patterns and Sample Characteristics

Of the 3,890 questionnaires mailed, 154 responses were received, corresponding to a crude response rate of 4.0%. Among the 153 respondents with non-missing adoption-stage information, 50 firms (32.7%) reported no interest in quantum technologies, 73 (47.7%) reported interest only, 13 (8.5%) reported that a proof of concept (PoC) was planned, 13 (8.5%) reported a PoC ongoing, 3 (2.0%) reported pilot or limited deployment, and 1 (0.7%) reported full deployment.

Table 1 compares responding and non-responding firms on company-level attributes from the Corporate Data Bank. Responding firms were significantly larger (median 1,679 vs. 847 employees), had larger paid-in capital (median 6,750 vs. 2,220 million JPY), and were older (median 73 vs. 52 years) than non-responding firms (all $p < 0.001$, Mann–Whitney U tests). Responding firms were also more likely to be listed on the TSE Prime market (55.8% vs. 40.8%, χ^2 test $p < 0.001$), and the industry composition differed significantly ($p = 0.006$), with chemicals/pharmaceuticals and electronics/precision firms overrepresented among respondents. These results indicate that the respondent sample is skewed toward larger, more established firms, and the findings should be interpreted accordingly.

The supplementary eligibility analyses (Appendix B) suggested that the practically relevant target population was considerably smaller than the full listed-firm sampling frame: depending on the eligibility definition and model, an estimated 1,456–1,868 of the 3,890 firms (37.4–48.0%) were potentially eligible, and the 154 respondents corresponded to 8.2–10.6% of these estimated eligible firms. These estimates are exploratory and were used only to contextualize the crude response rate.

3.2 Factorability and Number of Factors

Complete responses to all 15 QTRS items were available for 102 firms, and these complete cases were used for the factor analyses. The item correlation matrix was suitable for factor analysis: the overall Kaiser–Meyer–Olkin measure was 0.79 (item-level KMO values ranged from 0.57 to 0.92), and Bartlett’s test of sphericity was significant, $\chi^2(105) = 628.45$, $p < 0.001$.

Table 1 Comparison of responding and non-responding firms on company-level attributes.

Characteristic	Respondents (<i>n</i> = 154)	Non-respondents (<i>n</i> = 3,736)	<i>p</i>
<i>Continuous attributes, median [IQR]</i>			
Number of employees	1,679 [648–6,784]	847 [302–2,625]	<0.001
Paid-in capital (million JPY)	6,750 [2,183–22,976]	2,220 [672–8,242]	<0.001
Company age (years)	73 [39–86]	52 [24–76]	<0.001
<i>Market segment, <i>n</i> (%)</i>			
TSE Prime	86 (55.8)	1,523 (40.8)	<0.001
TSE Standard	46 (29.9)	1,523 (40.8)	
TSE Growth	16 (10.4)	589 (15.8)	
Other domestic	4 (2.6)	97 (2.6)	
Other/unknown	2 (1.3)	4 (0.1)	
<i>Industry group, <i>n</i> (%)</i>			
Manufacturing	32 (20.8)	652 (17.5)	0.006
Electronics/precision	24 (15.6)	371 (9.9)	
IT/services	22 (14.3)	565 (15.1)	
Chemicals/pharmaceuticals	20 (13.0)	287 (7.7)	
Finance	6 (3.9)	168 (4.5)	
Other	50 (32.5)	1,693 (45.3)	

Note. Continuous attributes were compared using Mann–Whitney *U* tests; categorical attributes were compared using chi-square tests across all categories of each attribute. IQR = interquartile range.

Criteria for the number of factors were not fully consistent: the Kaiser criterion suggested four factors, parallel analysis suggested three factors under the mean criterion and two factors under the 95th-percentile criterion, and the scree plot showed a clear drop after the second to third factor (Figure 1). A three-factor solution was therefore examined first for the purpose of item screening, and the dimensionality of the refined item set was subsequently re-evaluated.

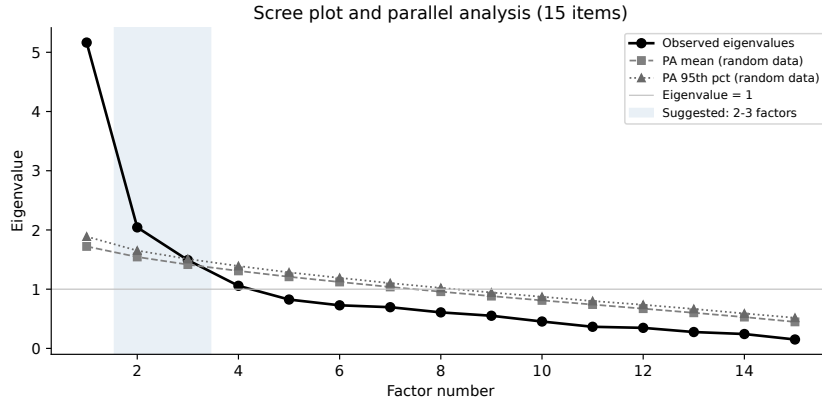


Fig. 1 Scree plot and parallel analysis for the initial 15-item pool. Random-data eigenvalues are based on 1,000 simulated datasets; the shaded region indicates the range of factor numbers suggested by the mean and 95th-percentile criteria.

3.3 Exploratory Factor Analysis of the Initial Item Pool and Item Selection

In the three-factor maximum likelihood solution with oblimin rotation (48.1% of variance explained; $\chi^2(63) = 125.56$, $p < 0.001$; RMSEA = 0.099; SRMR = 0.071), the first factor was defined by seven capacity-related items (Items 5 and 10–15; loadings 0.48–0.86), and the second factor by three benefit-related items (Items 1–3; loadings 0.68–0.86). The third factor was defined almost entirely by a single item (Item 7, loading 0.99), accompanied only by a weak loading of Item 6 (0.37). The varimax solution showed an essentially identical loading pattern, indicating that the structure was not driven by the choice of rotation method.

Application of the prespecified statistical criteria flagged four items: Item 4 (cross-loadings of 0.43 and 0.40 on the first two factors), Item 6 (primary loading 0.37, communality 0.14), Item 8 (maximum loading 0.27, communality 0.14), and Item 9 (maximum loading 0.32, communality 0.15). In the subsequent substantive review, all four flagged items were removed. Item 7 was not flagged statistically but was also removed because it constituted a near-single-item factor that cannot form a reliable subscale and did not align conceptually with either of the two theoretically expected dimensions. Notably, although the two negatively worded items (Items 6 and 7) had been reverse-scored so that all items shared a common direction, they still failed to load on either substantive dimension and instead defined this separate third factor—a pattern frequently observed for negatively worded items and consistent with their removal.

The factor solution was re-estimated after item removal, and the remaining 10 items showed a stable and interpretable structure. The full item pool, statistical flags, and final retention decisions are reported in Appendix A (Table A1).

3.4 Final Factor Structure

For the 10 retained items ($n = 102$ complete cases; KMO = 0.80; Bartlett’s $\chi^2(45) = 462.54$, $p < 0.001$), the Kaiser criterion and both parallel analysis criteria consistently indicated two factors. Table 2 presents the two-factor maximum likelihood solution with oblimin rotation, which explained 53.7% of the total variance. Seven items loaded on the first factor, labeled *Implementation Capacity* (loadings 0.49–0.86), and three items loaded on the second factor, labeled *Perceived Benefits* (loadings 0.64–0.89). No item showed a cross-loading of 0.30 or above, and the varimax solution yielded the same assignment of items to factors. The two factors were weakly correlated ($\phi = 0.28$), supporting their treatment as related but distinct dimensions.

Model fit of the two-factor solution was mixed: the chi-square test of exact fit was rejected, $\chi^2(26) = 56.87$, $p < 0.001$, and the RMSEA (0.108) exceeded conventional cutoffs, whereas the SRMR (0.049) indicated good fit. Given the modest sample size, which inflates RMSEA in models with small degrees of freedom, the overall pattern of results was judged to provide acceptable support for the two-factor structure in this initial development study, while clearly indicating the need for confirmatory replication in larger samples.

Table 2 Factor loadings (pattern matrix) of the final 10-item QTRS: maximum likelihood estimation with oblimin rotation ($n = 102$).

Item	F1: Implementation Capacity	F2: Perceived Benefits	h^2
Item 5	0.49	0.24	0.30
Item 10	0.68	0.04	0.46
Item 11	0.75	-0.01	0.56
Item 12	0.86	0.01	0.74
Item 13	0.73	0.06	0.53
Item 14	0.81	-0.08	0.66
Item 15	0.60	-0.07	0.36
Item 1	-0.03	0.73	0.53
Item 2	0.06	0.89	0.80
Item 3	-0.12	0.64	0.42
SS loadings	3.56	1.81	
Proportion of variance	0.36	0.18	

Note. Primary loadings are shown in bold. h^2 = communality. Inter-factor correlation $\phi = 0.28$. Cumulative variance explained = 53.7%. Fit: $\chi^2(26) = 56.87$, $p < 0.001$; RMSEA = 0.108; SRMR = 0.049.

3.5 Dimensionality of the Implementation Capacity Subscale

Because the Implementation Capacity factor retained seven items, one-factor and two-factor solutions for these items were compared. The one-factor model explained 51.3% of the variance with loadings of 0.56–0.87, but its exact fit was rejected, $\chi^2(14) = 40.20$, $p < 0.001$, RMSEA = 0.136, SRMR = 0.060. The two-factor model showed better global fit, $\chi^2(8) = 11.23$, $p = 0.189$, RMSEA = 0.063, SRMR = 0.034; however, the solution was improper: it produced a Heywood case (the communality of Item 13 exceeded 1), one of the two factors was defined essentially by that single item, and the two factors were strongly correlated ($\phi = 0.63$). Because the two-factor solution was not admissible as a basis for separate subscales, the Implementation Capacity items were retained as a single subscale in the subsequent analyses, and the possibility of finer-grained capacity subdimensions is noted as a question for future research with larger samples.

3.6 Reliability

Internal consistency was satisfactory for both subscales (Table 3): Cronbach’s $\alpha = 0.88$ and McDonald’s $\omega = 0.88$ for Implementation Capacity (7 items), and $\alpha = 0.78$ and $\omega = 0.79$ for Perceived Benefits (3 items). Corrected item-total correlations ranged from 0.51 to 0.80 for Implementation Capacity and from 0.54 to 0.70 for Perceived Benefits. Mean scale scores indicated that perceived benefits were rated substantially higher ($M = 3.84$, $SD = 0.64$) than implementation capacity ($M = 2.61$, $SD = 0.80$), and the two scores were weakly correlated (Pearson $r = 0.23$).

Table 3 Descriptive statistics and reliability of the QTRS subscales.

Subscale	Items	n	M (SD)	Cronbach's α	McDonald's ω	Item-total r
Implementation Capacity	7	102	2.61 (0.80)	0.88	0.88	0.51–0.80
Perceived Benefits	3	103	3.84 (0.64)	0.78	0.79	0.54–0.70

Note. Scale scores are item means (range 1–5). n = complete cases per subscale. Item-total r = range of corrected item-total correlations. Inter-scale correlation: $r = 0.23$.

3.7 Known-Groups Validity

Among the 102 firms that reported at least some interest in quantum technologies and had complete scale scores, Implementation Capacity differed significantly across adoption stages, Kruskal–Wallis $H(3) = 34.80$, $p < 0.001$, whereas Perceived Benefits did not, $H(3) = 1.26$, $p = 0.740$ (Table 4; Figure 2). Median Implementation Capacity scores increased markedly from the interest-only stage (2.36) to the PoC-planned stage and beyond (3.29–3.86), consistent with the theoretical expectation that organizational capacity, rather than perceived benefits alone, distinguishes firms that have moved toward concrete adoption activities. Perceived Benefits scores were uniformly high across stages (medians 3.67–4.67).

Table 4 QTRS subscale scores by quantum technology adoption stage.

Adoption stage	n	Implementation Capacity median [Q1–Q3]	Perceived Benefits median [Q1–Q3]
Interest only	72	2.36 [1.71–2.86]	3.67 [3.33–4.00]
PoC planned	13	3.29 [3.00–3.71]	4.00 [3.67–4.67]
PoC ongoing	13	3.29 [3.14–3.71]	4.00 [3.67–4.33]
Pilot/limited deployment	3	3.29 [2.64–3.43]	4.67 [3.33–4.67]
Full deployment	1	3.86	3.67
Kruskal–Wallis		$H(3) = 34.80$, $p < 0.001$	$H(3) = 1.26$, $p = 0.740$

Note. Firms reporting no interest were excluded. The single firm reporting full deployment is shown descriptively but was excluded from the Kruskal–Wallis tests, which therefore compare four groups ($df = 3$).

3.8 Criterion-Related Validity

In the logistic regression predicting advanced adoption (PoC ongoing, pilot or limited deployment, or full deployment; $n = 17$ of 102 firms), the overall model was significant, likelihood ratio $\chi^2(2) = 20.86$, $p < 0.001$, pseudo $R^2 = 0.23$. Implementation Capacity was strongly associated with advanced adoption (OR = 6.48 per scale point, 95% CI [2.44, 17.23], $p < 0.001$), whereas Perceived Benefits was not (OR = 0.58, 95% CI [0.21, 1.60], $p = 0.294$) (Table 5). Because the data are cross-sectional, this association should be interpreted as consistent with, but not demonstrating, a facilitating role of implementation capacity; higher capacity may also reflect capabilities accumulated through engagement in quantum-related activities.

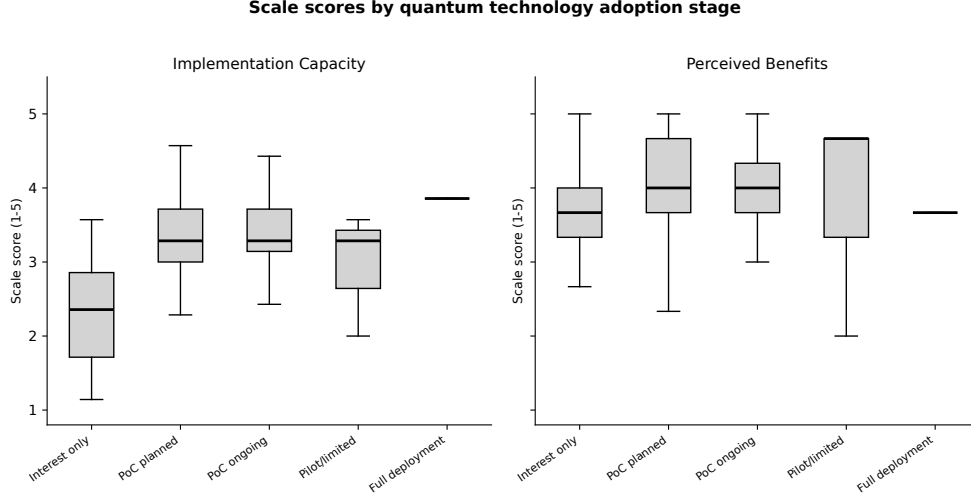


Fig. 2 Distribution of QTRS subscale scores by quantum technology adoption stage (box plots; firms reporting no interest excluded).

Table 5 Logistic regression predicting advanced quantum technology adoption from QTRS subscale scores ($n = 102$).

Predictor	OR	95% CI	p
Implementation Capacity	6.48	[2.44, 17.23]	<0.001
Perceived Benefits	0.58	[0.21, 1.60]	0.294

Note. Outcome: advanced adoption (PoC ongoing, pilot or limited deployment, or full deployment; $n = 17$) vs. interest only or PoC planned ($n = 85$). Intercept OR = 0.007 ($p = 0.014$). Likelihood ratio $\chi^2(2) = 20.86$, $p < 0.001$; pseudo $R^2 = 0.23$.

3.9 Differential Associations with External Criteria

The two subscales showed clearly different patterns of association with the external criteria (Table 6). Implementation Capacity correlated substantially with the quantum technology budget (Spearman $\rho = 0.46$, $p < 0.001$) and with the ordinal adoption stage ($\rho = 0.59$, $p < 0.001$); its correlation with the number of dedicated quantum personnel was positive but did not reach significance ($\rho = 0.20$). In contrast, Perceived Benefits was not significantly correlated with any of the external criteria ($\rho = -0.04$ to 0.12). This divergent pattern, together with the weak inter-scale correlation, supports the discriminant validity of the two dimensions: Implementation Capacity reflects resource

commitment and behavioral engagement, whereas Perceived Benefits captures generalized expectations that are widespread even among firms without concrete quantum activities (Figure 3).

Table 6 Spearman rank correlations between QTRS subscale scores and external criteria.

External criterion	Implementation Capacity	Perceived Benefits
Quantum technology budget (ordinal)	0.46***	0.12
Dedicated quantum personnel (ordinal)	0.20	−0.04
Adoption stage (ordinal)	0.59***	0.10

Note. Pairwise complete observations. *** $p < 0.001$. Adoption stage excludes firms reporting no interest.

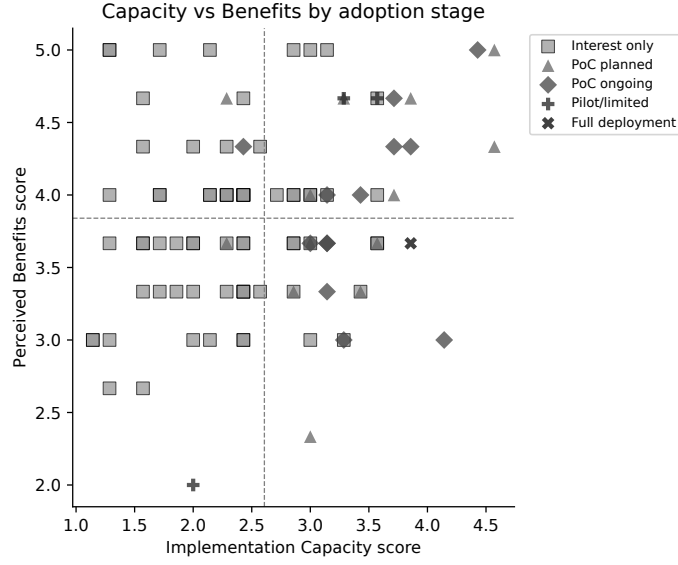


Fig. 3 Implementation Capacity and Perceived Benefits scores by quantum technology adoption stage. Dashed lines indicate sample means.

4 Discussion

This study developed the Quantum Technology Readiness Scale (QTRS) and provided initial psychometric evidence for it using a survey of publicly listed firms in Japan. Three findings stand out. First, organizational readiness for quantum technology adoption was empirically represented by two weakly correlated dimensions—Implementation Capacity and Perceived Benefits—consistent with the theoretically expected structure. Second, the two dimensions showed sharply asymmetric validity patterns: Implementation Capacity differentiated firms across adoption stages, was

strongly associated with advanced adoption, and correlated with resource commitment, whereas Perceived Benefits was uniformly high and unrelated to any external criterion. Third, the absolute levels of the two dimensions diverged substantially, with firms reporting high perceived benefits ($M = 3.84$) but low implementation capacity ($M = 2.61$). Together, these results suggest that at the current stage of quantum technology diffusion, what separates firms that act from firms that merely watch is not conviction about the technology’s value but the organizational capacity to do something with it.

4.1 Theoretical Implications

The two-dimensional structure of the QTRS provides empirical support, in the quantum technology context, for the central distinction in organizational readiness theory between valuing a change and perceived capability to implement it (Weiner, 2009). The weak correlation between the two dimensions ($\phi = 0.28$; inter-scale $r = 0.23$) indicates that these are not interchangeable expressions of a single underlying enthusiasm: a firm can be convinced of the promise of quantum technologies while possessing little of the personnel, budget, governance, or experimentation infrastructure needed to engage with them—and, empirically, this combination appears to be the modal condition among Japanese listed firms. The two-dimensional representation is also consistent with how readiness has been operationalized in organizational change research, where validated instruments likewise separate commitment-related and efficacy-related components (Holt, Armenakis, Feild, & Harris, 2007; Shea, Jacobs, Esserman, Bruce, & Weiner, 2014), and it positions the QTRS as an organizational-level complement to individual-level technology readiness instruments (Parasuraman, 2000; Parasuraman & Colby, 2015).

The asymmetric validity pattern extends this distinction in a way that is specific to early-stage technologies. Perceived Benefits showed a compressed, uniformly high distribution and did not discriminate between firms at different adoption stages. We interpret this as reflecting the diffusion environment of quantum technologies (Rogers, 2003): as the sociology-of-expectations literature emphasizes, shared expectations mobilize attention and resources around an emerging technology well before its value is realized (Borup, Brown, Konrad, & Van Lente, 2006), and commercially realized applications of quantum computing remain largely prospective (Bova, Goldfarb, & Melko, 2021). Expectations of long-term value are therefore widely shared—sustained by extensive promotional and policy attention—and carry little information about what a firm will actually do. Implementation Capacity, by contrast, showed the expected pattern for a readiness construct: it rose monotonically with adoption stage, predicted advanced adoption with a large effect size ($OR = 6.48$ per scale point), and correlated with budget allocation. In terms of the technology–organization–environment framework (Baker, 2011; Tornatzky & Fleischer, 1990), perceived technological value appears to be a near-constant across firms at this stage of diffusion, so that differences in adoption stage were more closely associated with organizational capacity than with perceived technological value. This echoes a long-standing pattern in technology acceptance and implementation research: perceived usefulness is a powerful driver of individual acceptance (Davis, 1989), but implementation outcomes in organizations

depend on implementation climate and capability rather than on favorable attitudes alone (Klein & Sorra, 1996). A similar primacy of resource- and capability-related factors over attitudinal factors has been reported for organizational readiness for artificial intelligence (Jöhnk, Weißert, & Wyrski, 2021), suggesting that the pattern observed here may characterize emerging general-purpose technologies broadly rather than the quantum context specifically. This finding also implies a methodological caution for the growing number of quantum readiness frameworks and indices (IBM Institute for Business Value, 2025; Purohit et al., 2024; Teitsma et al., 2025): instruments that weight attitudinal or awareness components heavily may overstate readiness, because such components do not distinguish adopters from non-adopters.

The negative (though non-significant) coefficient of Perceived Benefits in the logistic regression should not be over-interpreted; given the restricted variance of the subscale and the modest number of advanced adopters, the appropriate conclusion is that perceived benefits provide no incremental information about adoption stage beyond implementation capacity, not that optimism impedes adoption.

4.2 Practical Implications

For individual firms, the QTRS offers a brief diagnostic that separates two questions that are often conflated in internal discussions of emerging technologies: “do we believe in this?” and “could we act on it?” The results suggest that self-assessment efforts should concentrate on the capacity dimension—dedicated personnel, budgetary commitment, top management support, governance, experimentation environments, and external collaboration—because this is where firms differ and where movement toward adoption becomes visible.

For policymakers and industry bodies, the divergence between high perceived benefits and low implementation capacity suggests that awareness-raising alone may be insufficient to advance adoption. The binding constraint identified here is capability: the median respondent saw clear value in quantum technologies but reported capacity levels below the scale midpoint. Interventions that lower the cost of building capacity—talent development programs, shared experimentation infrastructure and testbeds, matchmaking with quantum technology vendors and research institutions, and funding instruments tied to proof-of-concept activity—map directly onto the items of the Implementation Capacity subscale and address the deficit the data actually reveal. In particular, the shortage of quantum-literate personnel is well documented as a sector-wide constraint (Fox, Zwickl, & Lewandowski, 2020; Hughes et al., 2022), so the personnel component of capacity is one that individual firms can rarely build in isolation.

4.3 Limitations and Future Research

Several limitations qualify these conclusions, and most of them define the agenda for subsequent validation work.

First, the analytic sample was modest ($n = 102$ complete cases), yielding a subject-to-item ratio of roughly 7:1 for the initial 15-item pool. The sample was sufficient for the exploratory purpose of this initial development study, and the factorability

diagnostics were satisfactory, but the factor structure reported here must be treated as provisional until it is replicated. Confirmatory factor analysis in an independent sample, followed by tests of measurement invariance across industries and firm-size classes, is the necessary next step (Boateng et al., 2018; MacKenzie et al., 2011).

Second, the global fit of the final two-factor model was mixed: the SRMR (0.049) indicated good fit, but the RMSEA (0.108) exceeded conventional cutoffs. RMSEA is known to be upwardly biased in models estimated on small samples with few degrees of freedom (Kenney, Kaniskan, & McCoach, 2015), and the clean loading pattern and parallel-analysis convergence support the two-factor solution, but fit should be re-evaluated in a larger confirmatory sample before strong structural claims are made.

Third, generalizability is constrained by the response process. The crude response rate was 4.0%, and although the supplementary eligibility analyses suggest that the practically relevant denominator was substantially smaller—placing the effective rate at roughly 8–11%—responding firms were significantly larger, older, and more often listed on the TSE Prime market than non-respondents. The readiness levels reported here therefore describe a sample skewed toward firms with greater absorptive capacity (Cohen & Levinthal, 1990), and capacity levels in the broader population of listed firms are, if anything, likely to be lower than those observed. The eligibility estimates themselves rest on models with only moderate discrimination and should be read as rough context, not as population parameters.

Fourth, the validity evidence for the Perceived Benefits subscale is thinner than for Implementation Capacity. With three items, a high mean, and restricted variance, the subscale demonstrated internal consistency and a theoretically interpretable *lack* of association with behavioral criteria, but no positive predictive evidence. Whether perceived benefits acquire discriminating power as the technology matures—when realistic and inflated expectations begin to diverge—is an open question that longitudinal administration of the scale could answer; expanding the item pool for this dimension would also reduce its vulnerability to ceiling effects.

Fifth, the criterion-related analysis rested on 17 advanced adopters—fewer than the commonly recommended ten events per predictor (Peduzzi, Concato, Kemper, Holford, & Feinstein, 1996)—yielding wide confidence intervals; the point estimate for Implementation Capacity should be interpreted as evidence of a strong positive association rather than as a precise effect size. Relatedly, the cross-sectional design cannot separate capacity as an antecedent of adoption from capacity accumulated through adoption activity itself, as absorptive-capacity research would predict (Cohen & Levinthal, 1990). Both readings are theoretically plausible, and only longitudinal designs that measure readiness before subsequent stage transitions can distinguish them.

Sixth, the subscale-level analysis hinted that Implementation Capacity may contain finer-grained structure: a two-factor solution fit better than a one-factor solution but was statistically improper in this sample. With larger samples, it would be worth examining whether resource-related capacity (personnel, budget, infrastructure) and governance-related capacity (strategy, oversight, external collaboration) form distinguishable facets. In the same spirit, future work should compare the reflective

specification adopted here with a formative index specification, as some readiness frameworks implicitly assume the latter (MacKenzie et al., 2011; Petter et al., 2007).

Finally, all measures were self-reports from a single informant per firm, collected in a single country. Common method variance cannot be ruled out (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003), although the sharply different criterion patterns of the two subscales argue against a pervasive method factor, and the external criteria (budget categories, personnel counts, adoption stage) are comparatively factual in nature. Validation in other institutional contexts, ideally with multiple informants per firm or linkage to objective indicators of quantum activity (e.g., patents, partnerships, job postings), would substantially strengthen the evidence base.

5 Conclusion

This study introduced the Quantum Technology Readiness Scale, a 10-item instrument measuring two dimensions of organizational readiness for quantum technology adoption, and provided initial evidence of its factorial validity, reliability, and construct validity among Japanese listed firms. The substantive picture that emerges is one of widespread conviction and scarce capability: firms broadly expect quantum technologies to matter, but few possess the organizational capacity to act on that expectation, and it is capacity—not expectation—that distinguishes firms that have begun concrete adoption activities. For research, the QTRS offers a psychometrically grounded alternative to checklist-style readiness assessments; for practice and policy, the findings redirect attention from persuasion to capability building. Confirmatory replication in larger and more diverse samples is the immediate priority for establishing the scale’s broader utility.

Supplementary information. Not applicable. Additional eligibility analyses are included in Appendix B of the manuscript.

Acknowledgements. The authors sincerely thank all the companies and their representatives who took the time to respond to the survey.

Statements and Declarations

Funding. This work was supported by the Japan Science and Technology Agency (JST) COI-NEXT program (Grant No. JPMJPF2014).

Conflict of interest. On behalf of all authors, the corresponding author states that there is no conflict of interest.

Ethics approval and consent to participate. This study was conducted as an organization-level survey of publicly listed firms in Japan. The questionnaire asked designated corporate representatives to report on company-level conditions and activities related to quantum technology adoption. It did not collect biomedical or health-related information, human specimens, or information of human origin, and did not involve any intervention with individuals. Accordingly, the study was outside the scope of the Japanese Ethical Guidelines for Medical and Biological Research Involving Human Subjects and was not submitted for review under those guidelines.

Participation was voluntary. The survey materials explained the purpose of the study, and return of a completed questionnaire was regarded as consent for the company-level responses to be used in aggregate research analyses.

Consent for publication. Not applicable.

Data availability. The data analyzed in this study contain confidential company-level information and are therefore not publicly available. Aggregated data supporting the findings of this study may be available from the corresponding author upon reasonable request, subject to applicable confidentiality and data-use restrictions.

Materials availability. The final items of the Quantum Technology Readiness Scale and the corresponding item-selection information are provided in Appendix A of the manuscript.

Code availability. Analysis code may be available from the corresponding author upon reasonable request.

Author contributions. Kazuya Taira contributed to the conception and design of the study, data analysis, interpretation of the results, and preparation of the original manuscript. Yusuke Kodaira, Emi Kamada, Osamu Kamatani, Yusuke Kobayashi, and Miyuki Imada contributed to the study design, data collection, interpretation of the findings, and critical revision of the manuscript. All authors reviewed and approved the final manuscript.

Appendix A Initial Item Pool and Item Selection

Table A1 reports the full initial 15-item pool with the three-factor pattern matrix, communalities, statistical flags from the prespecified screening criteria, and the final retention decision and reason for each item.

Table A1 Three-factor pattern matrix of the initial 15-item pool (maximum likelihood, oblimin rotation; $n = 102$), statistical flags, and retention decisions.

Item	Item wording	F1	F2	F3	h^2	Statistical flag	Decision
Item 1	Quantum technologies have the potential to improve our company's operational efficiency.	-0.01	0.73	-0.08	0.53	—	Retained (Perceived Benefits)
Item 2	Quantum technologies can enhance our company's competitive advantage over competitors.	0.09	0.86	-0.06	0.76	—	Retained (Perceived Benefits)
Item 3	Quantum technologies can generate better outcomes than conventional technologies.	-0.18	0.68	0.24	0.55	—	Retained (Perceived Benefits)
Item 4	Quantum technologies are compatible with our company's existing operations and values.	0.43	0.40	0.02	0.34	Cross-loading ≥ 0.30	Removed
Item 5	Quantum technologies are aligned with our company's internal technology development strategy.	0.48	0.26	0.09	0.31	—	Retained (Implementation Capacity)
Item 6 ^R	The mechanisms underlying quantum technologies are very difficult to understand.	0.03	0.06	0.37	0.14	Loading < 0.40 ; $h^2 < 0.30$	Removed
Item 7 ^R	There are many barriers to making quantum technologies usable within our company.	0.03	-0.01	0.99	0.98	—	Removed (single-item factor)
Item 8	Business partners and customers expect our company to adopt quantum technologies.	0.27	0.26	-0.02	0.14	Loading < 0.40 ; $h^2 < 0.30$	Removed
Item 9	Trends among industry associations and competitors influence our company's adoption decisions.	0.32	0.19	-0.10	0.15	Loading < 0.40 ; $h^2 < 0.30$	Removed
Item 10	Quantum-related personnel and facilities, including cloud-based resources, are available within our company.	0.67	0.02	0.07	0.45	—	Retained (Implementation Capacity)
Item 11	Top management has expressed a clear policy and supportive stance toward the use of quantum technologies.	0.74	0.00	0.09	0.56	—	Retained (Implementation Capacity)
Item 12	Our company has the budget and environment needed to conduct small-scale proof-of-concept experiments with quantum technologies as needed.	0.86	-0.01	-0.05	0.74	—	Retained (Implementation Capacity)
Item 13	Our company can conduct trials in collaboration with external partners, such as universities and firms.	0.73	0.04	-0.04	0.53	—	Retained (Implementation Capacity)
Item 14	Indicators and responsible persons for evaluating the outcomes of quantum technologies have been defined.	0.81	-0.09	0.04	0.66	—	Retained (Implementation Capacity)
Item 15	The outcomes of quantum technologies can be easily visualized and shared both inside and outside the company.	0.60	-0.05	0.02	0.36	—	Retained (Implementation Capacity)

Note. Superscript R denotes a negatively worded item that was reverse-scored prior to analysis (see Measures), so that for every item a higher value indicates greater readiness. Statistical flags follow the prespecified criteria (primary loading < 0.40 , Cross-loading > 0.30 , communality $h^2 < 0.30$). Item 7 was removed on substantive grounds: it defined a factor with no other substantive loading and therefore could not form a reliable subscale. Fit of the three-factor solution: $\chi^2(63) = 125.56$, $p < 0.001$; RMSEA = 0.099; SRMR = 0.071; cumulative variance explained = 48.1%. Inter-factor correlations: $\phi_{12} = 0.21$, $\phi_{13} = 0.09$, $\phi_{23} = 0.28$.

Appendix B Supplementary Eligibility Analyses

Among the 153 responding firms with non-missing adoption-stage information, 103 (67.3%) were classified as eligible under the broad definition (any interest or engagement) and 30 (19.6%) under the narrow definition (PoC planned or beyond). Table B2 reports the cross-validated performance of the logistic regression and decision tree models predicting eligibility from observable company attributes. Discrimination was moderate under the broad definition (ROC-AUC = 0.68–0.73) and weak under the narrow definition (ROC-AUC = 0.61–0.62), indicating that company attributes alone identify potentially quantum-relevant firms only imperfectly; the resulting estimates should therefore be regarded as rough approximations.

Applying the fitted models to the full sampling frame (Table B3) yielded an estimated 1,751–1,868 potentially eligible firms under the broad definition (45.0–48.0% of the 3,890 firms) and 1,456–1,462 under the narrow definition (37.4–37.6%). Relative to these estimated target populations, the 154 obtained responses corresponded to 8.2–8.8% (broad) and 10.5–10.6% (narrow), compared with the crude response rate of 4.0%. These figures are exploratory and were used only to contextualize the broad sampling strategy; they were not used to reweight any of the primary analyses.

Table B2 Cross-validated performance of the eligibility models (stratified five-fold cross-validation; mean across folds).

Definition	Model	Accuracy	Balanced acc.	Precision	Recall	F1	ROC-AUC	PR-AUC
Broad	Logistic regression	0.67	0.67	0.82	0.66	0.73	0.73	0.87
Broad	Decision tree	0.63	0.65	0.80	0.60	0.67	0.68	0.82
Narrow	Logistic regression	0.71	0.62	0.33	0.47	0.39	0.61	0.49
Narrow	Decision tree	0.73	0.62	0.39	0.43	0.41	0.62	0.40

Note. $n = 153$ responding firms with non-missing adoption stage. Predictors: market segment, industry group (indicator variables), number of employees, paid-in capital, and company age (median-imputed). Class imbalance was addressed with balanced class weights. ROC-AUC = area under the receiver operating characteristic curve; PR-AUC = area under the precision–recall curve.

Table B3 Estimated size of the practically relevant target population within the sampling frame ($N = 3,890$).

Definition	Model	Estimated eligible firms	% of frame	Respondents / estimated eligible
Broad	Logistic regression	1,751	45.0	8.8%
Broad	Decision tree	1,868	48.0	8.2%
Narrow	Logistic regression	1,462	37.6	10.5%
Narrow	Decision tree	1,456	37.4	10.6%

Note. Estimated eligible firms = sum of model-predicted eligibility probabilities over all firms in the sampling frame. The last column relates the 154 obtained responses to the estimated eligible population and is reported only to contextualize the crude response rate (4.0%).

References

- Baker, J. (2011). The technology–organization–environment framework. Y.K. Dwivedi, M.R. Wade, & S.L. Schneberger (Eds.), *Information systems theory: Explaining and predicting our digital society, vol. 1* (pp. 231–245). New York, NY: Springer.
- Boateng, G.O., Neilands, T.B., Frongillo, E.A., Melgar-Quinonez, H.R., Young, S.L. (2018). Best practices for developing and validating scales for health, social, and behavioral research: A primer. *Frontiers in Public Health*, 6, 149, <https://doi.org/10.3389/fpubh.2018.00149>
- Borup, M., Brown, N., Konrad, K., Van Lente, H. (2006). The sociology of expectations in science and technology. *Technology Analysis & Strategic Management*, 18(3–4), 285–298, <https://doi.org/10.1080/09537320600777002>
- Bova, F., Goldfarb, A., Melko, R.G. (2021). Commercial applications of quantum computing. *EPJ Quantum Technology*, 8, 2, <https://doi.org/10.1140/epjqt/s40507-021-00091-1>
- Cohen, W.M., & Levinthal, D.A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1), 128–152, <https://doi.org/10.2307/2393553>
- Costello, A.B., & Osborne, J.W. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research & Evaluation*, 10(7), 1–9, <https://doi.org/10.7275/jyj1-4868>
- Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340, <https://doi.org/10.2307/249008>
- Dunn, T.J., Baguley, T., Brunsden, V. (2014). From alpha to omega: A practical solution to the pervasive problem of internal consistency estimation. *British Journal of Psychology*, 105(3), 399–412, <https://doi.org/10.1111/bjop.12046>
- Fabrigar, L.R., Wegener, D.T., MacCallum, R.C., Strahan, E.J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods*, 4(3), 272–299, <https://doi.org/10.1037/1082-989X.4.3.272>

- Fox, M.F.J., Zwickl, B.M., Lewandowski, H.J. (2020). Preparing for the quantum revolution: What is the role of higher education? *Physical Review Physics Education Research*, 16(2), 020131, <https://doi.org/10.1103/PhysRevPhysEducRes.16.020131>
- Gupta, R.S., Wood, C.E., Engstrom, T., Pole, J.D., Shrapnel, S. (2025). A systematic review of quantum machine learning for digital health. *npj Digital Medicine*, 8(1), 237, <https://doi.org/10.1038/s41746-025-01516-2>
- Hayes, A.F., & Coutts, J.J. (2020). Use omega rather than cronbach's alpha for estimating reliability. but... *Communication Methods and Measures*, 14(1), 1–24, <https://doi.org/10.1080/19312458.2020.1718629>
- Holt, D.T., Armenakis, A.A., Feild, H.S., Harris, S.G. (2007). Readiness for organizational change: The systematic development of a scale. *Journal of Applied Behavioral Science*, 43(2), 232–255, <https://doi.org/10.1177/0021886306295295>
- Hughes, C., Finke, D., German, D.-A., Merzbacher, C., Vora, P.M., Lewandowski, H.J. (2022). Assessing the needs of the quantum industry. *IEEE Transactions on Education*, 65(4), 592–601, <https://doi.org/10.1109/TE.2022.3153841>
- IBM Institute for Business Value (2025). *Quantum readiness index 2025* (Report). IBM Corporation.
- Jöhnk, J., Weißert, M., Wyrski, K. (2021). Ready or not, AI comes—an interview study of organizational AI readiness factors. *Business & Information Systems Engineering*, 63(1), 5–20, <https://doi.org/10.1007/s12599-020-00676-7>
- Kenny, D.A., Kaniskan, B., McCoach, D.B. (2015). The performance of RMSEA in models with small degrees of freedom. *Sociological Methods & Research*, 44(3), 486–507, <https://doi.org/10.1177/0049124114543236>
- Klein, K.J., & Sorra, J.S. (1996). The challenge of innovation implementation. *Academy of Management Review*, 21(4), 1055–1080, <https://doi.org/10.5465/amr.1996.9704071863>

- MacKenzie, S.B., Podsakoff, P.M., Podsakoff, N.P. (2011). Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. *MIS Quarterly*, 35(2), 293–334, <https://doi.org/10.2307/23044045>
- Moore, G.C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, 2(3), 192–222, <https://doi.org/10.1287/isre.2.3.192>
- Parasuraman, A. (2000). Technology readiness index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research*, 2(4), 307–320, <https://doi.org/10.1177/109467050024001>
- Parasuraman, A., & Colby, C.L. (2015). An updated and streamlined technology readiness index: TRI 2.0. *Journal of Service Research*, 18(1), 59–74, <https://doi.org/10.1177/1094670514539730>
- Peduzzi, P., Concato, J., Kemper, E., Holford, T.R., Feinstein, A.R. (1996). A simulation study of the number of events per variable in logistic regression analysis. *Journal of Clinical Epidemiology*, 49(12), 1373–1379, [https://doi.org/10.1016/S0895-4356\(96\)00236-3](https://doi.org/10.1016/S0895-4356(96)00236-3)
- Petter, S., Straub, D., Rai, A. (2007). Specifying formative constructs in information systems research. *MIS Quarterly*, 31(4), 623–656, <https://doi.org/10.2307/25148814>
- Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y., Podsakoff, N.P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903, <https://doi.org/10.1037/0021-9010.88.5.879>
- Purohit, A., Kaur, M., Seskir, Z.C., Posner, M.T., Venegas-Gomez, A. (2024). Building a quantum-ready ecosystem. *IET Quantum Communication*, 5(1), 1–18, <https://doi.org/10.1049/qtc2.12072>
- Rogers, E.M. (2003). *Diffusion of innovations* (5th ed.). New York, NY: Free Press.
- Shea, C.M., Jacobs, S.R., Esserman, D.A., Bruce, K., Weiner, B.J. (2014). Organizational readiness for implementing change: A psychometric assessment of a new

- measure. *Implementation Science*, 9, 7, <https://doi.org/10.1186/1748-5908-9-7>
- Straub, D.W. (1989). Validating instruments in MIS research. *MIS Quarterly*, 13(2), 147–169, <https://doi.org/10.2307/248922>
- Teitsma, M., Ahmed, I., van Velzen, J. (2025). Quantum organisational readiness levels. *arXiv preprint arXiv:2502.16489*, , <https://doi.org/10.48550/arXiv.2502.16489>
- Tornatzky, L.G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington, MA: Lexington Books.
- Toyo Keizai Inc. (2025). *Corporate data bank (Kaisha Shikiho database), 2025 fall edition*. (Machine-readable data file. Tokyo: Toyo Keizai Inc.)
- Weiner, B.J. (2009). A theory of organizational readiness for change. *Implementation Science*, 4, 67, <https://doi.org/10.1186/1748-5908-4-67>
- Weiner, B.J. (2020). A theory of organizational readiness for change. P. Nilsen & S.A. Birken (Eds.), *Handbook on implementation science* (pp. 215–232). Cheltenham, UK: Edward Elgar Publishing.