

Segmenting QRIS Readiness Among Traditional Market Traders Using Technology Readiness Index 2.0 and K-Means Clustering

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ABSTRACT

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Quick Response Code Indonesian Standard (QRIS) is widely available in Indonesian traditional markets, but availability alone does not show whether traders are ready to use it, suggesting that technology readiness may be an important factor beyond physical access to payment infrastructure. This study profiles and segments the technology readiness of 60 smartphone-owning traders at Pasar Beriman Tomohon, North Sulawesi, using the four dimensions of the Technology Readiness Index 2.0 (TRI 2.0): Optimism, Innovativeness, Discomfort, and Insecurity. K-means clustering on standardised dimension scores produced five segments that follow the TRI 2.0 archetypes. The five-cluster solution was chosen on theoretical grounds, because the silhouette check slightly favoured three clusters; the segments are weakly separated and only moderately stable. Internal consistency was assessed using Cronbach's alpha (Innovativeness and Discomfort fell below the 0.60 criterion), and group differences were examined through non-parametric tests. Paranoids formed the largest segment (25.0%) and Pioneers the smallest (11.7%). Insecurity had the higher mean score of the two inhibitor dimensions, exceeding Discomfort. Age showed a stronger demographic association with readiness than merchandise type, and the observed association was concentrated in Innovativeness and Discomfort rather than Insecurity. These findings suggest that segment-differentiated support addressing security and trust concerns may offer a more targeted basis for QRIS adoption programmes among traditional-market traders than uniform market-wide campaigns. Because the sample is small, non-random, and drawn from one market, the results are exploratory.

Keywords: *Technology Readiness Index 2.0, QRIS, ITSM, digital payment, K-means clustering, traditional market, MSMEs*

1. INTRODUCTION

Bank Indonesia's QR Code Indonesian Standard (QRIS) has become the national standard for digital payment interoperability, yet its use among grassroots traders appears uneven. At Pasar Beriman Tomohon, a traditional market in North Sulawesi, QRIS stickers are visible at many stalls, but in the research team's field observation traders still rely heavily on cash. Physical availability of the payment channel therefore does not appear to be the only factor. Traders' readiness, meaning their psychological disposition toward new technology, may also matter.

Resistance to digital payment in traditional markets is not a new observation. [2] conducted qualitative interviews with traditional market traders in Jakarta and found that awareness, trust, and security concerns shape resistance to digital payment adoption. [3] similarly documented resistance among traditional SME traders using innovation resistance theory. [19] interviewed 25 merchants in five Bandung traditional markets and reported that limited technological literacy, a preference for cash, and weak infrastructure were the main barriers to QRIS use, while ease of use, faster transactions, and payment security were the main reasons for acceptance. These studies are qualitative and exploratory by design: they describe why traders resist or accept digital payment, but they do not measure readiness on a comparable scale or show how readiness varies across a trader population.

The Technology Readiness Index 2.0 (TRI 2.0) [1], an updated and shorter form of the original TRI [15], offers such a scale. It has four dimensions: Optimism and Innovativeness, which drive adoption, and Discomfort and Insecurity, which inhibit it. TRI has been applied to QRIS before: [4] measured QRIS readiness among 98 UMKM in Denpasar City using the same four dimensions, but reported descriptive scores only. TRI scores have also been used to segment respondents by cluster analysis. [5] applied K-means clustering to TRI-based scores of 171 SMEs in the Bandung metropolitan area and found three clusters (high, moderate, and low readiness) for general technology readiness. [16] used clusters defined by technology readiness to study mobile payment usage among Italian consumers, and [17] grouped MSMEs in a border region using

TRI and hierarchical clustering. In a traditional-market setting, [18] treated technology readiness as a moderating variable among traders in Bali. TRI-based segmentation is therefore an established approach, and this study does not claim it as a methodological novelty.

The gap this study addresses is contextual rather than methodological. Although TRI-based clustering has been applied to consumers and SMEs [5], [16], [17], limited evidence exists on how TRI 2.0 readiness dimensions are distributed among traditional-market traders in the context of QRIS. These traders work under different transaction conditions, levels of technological exposure, trust concerns, and infrastructure constraints from formal urban SMEs [19], so it is unclear whether the readiness patterns reported for formal MSME samples [4] also describe traditional-market QRIS users. Three gaps follow: a population gap (traditional-market traders rather than formal MSMEs); a segmentation gap (QRIS readiness studies often report aggregate scores, as in [4]); and an intervention gap (studies identify adoption factors without translating readiness profiles into differentiated support). The closest methodological precedent is the Bandung study [5], which used TRI and K-means for general technology readiness among SMEs. The present study differs from it in its population (traders in a traditional market), its context (QRIS), its use of the five TRI 2.0 archetypes as a theory-guided frame, and its translation of segment profiles into intervention recommendations.

This study therefore applies TRI 2.0 to 60 smartphone-owning traders at Pasar Beriman Tomohon and uses K-means clustering to describe five theory-guided readiness segments: Explorers, Pioneers, Skeptics, Paranoids, and Laggards [1]. The study aims to (1) describe the distribution of traders across these five segments, (2) identify which TRI inhibitor dimension has the highest observed score in this population, and (3) translate the segment profiles into evidence-informed recommendations for the agencies and banks promoting QRIS at the grassroots level. The contribution is contextual and practical: K-means itself is used as a standard tool and is not presented as the novelty.

2. METHODS

2.1 Research Design and Setting

This study used a quantitative descriptive design to profile and segment traders at Pasar Beriman Tomohon, North Sulawesi, Indonesia. Three concepts are kept distinct. Technology readiness is a person's general psychological predisposition toward new technology, measured here with the TRI 2.0 framework [1] across four dimensions: two drivers (Optimism, Innovativeness) and two inhibitors (Discomfort, Insecurity). QRIS usage is the behavioural indicator collected in the questionnaire, namely whether a trader had ever used QRIS. QRIS adoption in the sense of sustained, regular use (for example frequency, recency, or share of transactions) was not measured. The study therefore segments readiness; it does not model or predict QRIS adoption.

2.2 Population and Sampling

The target population was smartphone-owning traders at Pasar Beriman Tomohon, because a smartphone is needed to use QRIS. The sampled population is therefore smartphone-owning traders who were encountered during fieldwork and agreed to take part. Traders without a smartphone were excluded, which introduces selection bias (Section 3.9). Because the exact number of traders was not documented by market management, a non-probability accidental sampling technique was used, which limits representativeness and generalisability. A target of 60 respondents was set in line with Roscoe's rule of thumb that sample sizes between 30 and 500 are suitable for much exploratory research [6], and was achieved ($n = 60$). This rule is a practical guide, not a statistical power calculation. The sample size was chosen for exploratory profiling and does not give adequate power for multivariable prediction or for confirming cluster structure.

2.3 Instrument

Data were collected using a structured questionnaire adapted from the 16-item TRI 2.0 scale (4 items $\times$ 4 dimensions) [1], rated on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Because traders in this market mainly speak Manado Malay, the items were

translated and adapted into Manado-dialect Indonesian by the first author. Each Manado item was adapted one by one from the corresponding English TRI 2.0 item, so that the meaning of the original item was kept, and was tied to QRIS, mobile phones, and market situations (for example, customers queuing while the application fails). The items are therefore contextual adaptations and not word-for-word translations. Cross-cultural adaptation guidelines recommend forward translation, back-translation, and expert committee review [25] (for an Indonesian-language example, see [7]). This study followed only part of that procedure: no back-translation, expert review, or semantic-equivalence check against the original English items was done. Face validity was assessed through a pilot readability test with five traders before data collection; the pilot-note column was empty on all five forms, so no wording changes were recorded. The instrument is therefore treated as an adapted, not fully validated, version (Section 3.2).

2.4 Data Collection

Data were collected between 30 June and 4 July 2026 through structured in-person interviews conducted by two trained student research assistants, recorded via Google Forms in the field.

2.5 Data Cleaning

Three preparation steps were resolved and documented in the analysis code prior to statistical testing: (1) Likert-text responses were converted to numeric values 1–5; (2) duplicate respondent identifiers, caused by two field assistants independently numbering their own sheets starting at 1, were reassigned sequentially (R-01 to R-60) by interview timestamp; and (3) one respondent's (R-02) smartphone-ownership response was corrected. The initial answer of "No" was logically inconsistent with the respondent's completed answers to all 16 phone- and app-related TRI items and with the respondent's recorded previous use of QRIS, which indicates an interviewer misclick rather than genuine non-ownership. The research team confirmed that it was a misclick, and the correction was made in the cleaning script before any statistical analysis. The correction is documented in the analysis code, and the raw survey export was

preserved unmodified. Because this correction rests on logical inference, a sensitivity analysis was run in which this respondent was excluded (Section 3.4).

2.6 Validity and Reliability

Item validity was assessed using corrected item-total Pearson correlation. Internal consistency per dimension was assessed using Cronbach's alpha, with $\alpha \geq 0.60$ considered acceptable for exploratory research [8]. Because alpha tends to be low for scales with few items [26], alpha was read together with the mean inter-item correlation. For dimensions below the threshold, pairwise inter-item correlations and the eigenvalues of the inter-item correlation matrix were inspected as descriptive checks for a possible two-component pattern. Items INO4 and DIS4 did not meet the item-total criterion, but they were retained in all dimension scores used for clustering, so that each dimension keeps its full TRI 2.0 content. The effect of this decision was tested by re-clustering without these two items (Section 2.7). KMO, Bartlett's test, and factor analysis were not carried out, because four items per dimension and $n = 60$ are too few for a stable factor solution.

2.7 Segmentation

A composite score per TRI dimension was computed as the mean of its four items (all 16 items retained). Respondents were segmented using K-means clustering [20] on the four dimension scores after z-score standardisation (mean 0 and SD 1 for each dimension, using the scikit-learn StandardScaler). All four dimensions use the same 1–5 scale, but their standard deviations differ (0.49 to 0.72), and standardisation stops the dimension with the largest spread (Insecurity) from dominating the distances. It did not change the result materially: clustering the raw scores gave a solution that agreed closely with the standardised one (adjusted Rand index, $ARI = 0.88$). Clustering and silhouette values use the z-scores, whereas the bar charts and scatter plots show the original 1–5 scores. The algorithm used k-means++ initialisation with 10 random starts ($n_{init} = 10$) and a fixed random seed of 42, and the final run converged in 6 iterations. The choice of $k = 5$ was theory-driven: it was fixed in advance to

match the five TRI 2.0 archetypes [1] and was not selected from the data. To show how well the data support this choice, the average silhouette width [21] and the within-cluster sum of squares (WCSS) were calculated for $k = 2$ to 7, and silhouette values were read with the conventional guide in [22].

Cluster labels were assigned from the cluster centroids and were not assumed from $k = 5$. For each cluster, the driver score (mean of Optimism and Innovativeness) and the inhibitor score (mean of Discomfort and Insecurity) were compared with the sample medians (3.25 and 3.375). A high driver and low inhibitor score was labelled Explorers; high driver and high inhibitor, Pioneers; low driver and low inhibitor, Skeptics; and low driver and high inhibitor, Paranoids. The cluster with the lowest net readiness (driver minus inhibitor score) was labelled Laggards. If two clusters received the same label, the one whose net readiness was closest to zero was given the label that was still unused. The outcome of this rule is reported in Section 3.4. The stability of the five-cluster solution was checked with the ARI [23] across (a) 100 random seeds, (b) leave-one-out re-clustering, (c) 200 bootstrap resamples, in which all traders were assigned to the nearest centroid of the resampled solution [24], and (d) two sensitivity runs, one without INO4 and DIS4 and one without respondent R-02.

2.8 Inferential Analysis

Because the dimension scores are averages of 5-point Likert items and the sample is small, non-parametric methods were used for group comparisons: the Mann-Whitney U test (age, split at the median age of 38.5 years) and the Kruskal-Wallis test (merchandise type, five groups) for each of the four dimensions, with the rank-biserial correlation (r_{rb}) and epsilon-squared (ϵ^2) as effect sizes. A formal normality test was not run, as it adds little for ordinal data and has low power at this sample size. Relationships between dimensions were examined with Spearman's rank correlation (ρ), which suits ordinal data; Pearson's r is reported alongside for comparison. The difference between Insecurity and Discomfort was tested with the Wilcoxon signed-rank test on paired scores. A binary logistic regression (QRIS usage ~ four TRI dimensions) was run only as an exploratory check. With seven non-users, its

events-per-variable ratio (1.75) is far below the usual guideline of about 10 [27], so it is not used to support any conclusion (Section 3.6).

2.9 Tools

Analysis was conducted in Python 3 (Spyder 6), using pandas, scikit-learn, statsmodels, and scipy.

3. RESULTS AND DISCUSSION

3.1 Sample Profile

Data were collected from 60 traders at Pasar Beriman Tomohon, aged 19–67 (mean 39.3, median 38.5). Merchandise distribution is shown in Table 1.

Table 1. Trader distribution by merchandise type

Merchandise Type	N	%
Vegetables/Spices	16	26.7%
Meat/Fish	16	26.7%
Clothing	12	20.0%
Groceries (Sembako)	12	20.0%
Other (furniture, electronics, toys/cosmetics/accessories)	4	6.7%
Total	60	100%

Fifty-three traders (88%) had used QRIS at least once; seven (12%) had never tried it. This finding is relevant to framing the problem: in this sample most traders have already encountered the technology, so the data cannot show a low-adoption problem in the sense of non-use. What the data can describe is how ready traders are, psychologically, to use QRIS. Whether a first trial turns into regular and confident use was not measured, because no data on frequency, recency, or share of transactions were collected. The readiness profiles below are therefore read as indications of where support may be needed, and not as predictors of adoption.

3.2 Instrument Validity and Reliability

Fourteen of sixteen items passed the corrected item-total correlation test (Table 2); INO4 ($r = 0.142$, $p = 0.278$) and DIS4 ($r = 0.208$, $p = 0.111$) did not. Both items were kept in the dimension scores (Section 2.6), and the effect of this choice is tested in Section 3.4. Dimension-level reliability is shown in Table 3.

Table 2. Corrected item-total correlation of the 16 TRI 2.0 items.

Item	Corrected item-total r	Decision
OPT1	0.626	Valid
OPT2	0.562	Valid

Item	Corrected item-total r	Decision
OPT3	0.482	Valid
OPT4	0.461	Valid
INO1	0.320	Valid
INO2	0.464	Valid
INO3	0.333	Valid
INO4	0.142	Not valid
DIS1	0.380	Valid
DIS2	0.308	Valid
DIS3	0.296	Valid
DIS4	0.208	Not valid
INS1	0.565	Valid
INS2	0.750	Valid
INS3	0.296	Valid
INS4	0.584	Valid

Table 3. Cronbach's alpha by TRI 2.0 dimension

Dimension	Cronbach's α	Status
Optimism	0.738	Reliable
Innovativeness	0.515	Below threshold
Discomfort	0.502	Below threshold
Insecurity	0.743	Reliable

Innovativeness and Discomfort fell below the $\alpha \geq 0.60$ threshold [8], while Optimism and Insecurity met it, so the dimension behind the main finding (Insecurity) is the better-measured one. Because alpha is sensitive to the number of items [26], the inter-item correlation matrix of each weak dimension and its eigenvalues were inspected to see whether the low values came from one weak item or from a more mixed structure. The mean inter-item correlation was low (Innovativeness 0.218; Discomfort 0.204) and two eigenvalues exceeded 1.0 in both dimensions, which suggests a possible two-component pattern that warrants further psychometric investigation. Within Innovativeness, items INO1 and INO2 were correlated ($r = 0.61$) and INO3 and INO4 less strongly ($r = 0.27$); within Discomfort, DIS1 and DIS4 ($r = 0.52$) and DIS2 and DIS3 ($r = 0.40$) formed two pairs with little correlation across them. INO4 and DIS4, the two items that failed the item-total test, each belong to only one of these pairs. With four items per dimension and $n = 60$, this evidence is descriptive only, and no two-factor structure is claimed. The low values may be partly related to the adaptation into Manado dialect, but this study cannot separate such an effect from true differences among traders or from the small number of items. A full psychometric examination is left to future work.

Because Innovativeness and Discomfort are two of the four clustering variables, their low reliability matters for the segmentation. Noisy dimension scores blur the boundaries between segments, which is consistent with the

weak separation and moderate stability reported in Section 3.4. Re-clustering without INO4 and DIS4 changed the segment of 6 of the 60 traders (ARI = 0.77; average silhouette width 0.25). The decision to keep all 16 items therefore has a limited but visible effect, and the segment results should be read as exploratory profiles from an adapted instrument, not as precise measurements of Innovativeness and Discomfort.

3.3 Readiness Profile Across TRI 2.0 Dimensions

Table 4. Descriptive statistics by TRI 2.0 dimension

Dimension	Mean	SD	Role
Optimism	3.68	0.489	Driver
Innovativeness	2.75	0.570	Driver (low)
Discomfort	3.19	0.585	Inhibitor
Insecurity	3.56	0.721	Inhibitor (higher)

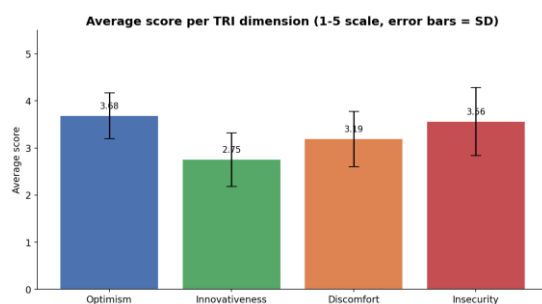


Figure 1. Average score per TRI 2.0 dimension (1–5 scale; error bars = SD).

Insecurity had the higher mean of the two inhibitor dimensions (3.56 vs. 3.19; Figure 1). A paired Wilcoxon signed-rank test showed that traders scored higher on Insecurity than on Discomfort ($W = 202.0$, $p < 0.0001$; matched-pairs rank-biserial $r = 0.67$), with 37 traders scoring higher on Insecurity, 12 higher on Discomfort, and 11 tied. Insecurity is therefore the inhibitor dimension with the highest observed score in this sample: traders report more concern about security and trust than about the complexity of the technology. This is a difference in level only. It does not show that Insecurity explains or causes lower QRIS use, because QRIS adoption was not modelled. The result differs from [4], where Denpasar UMKM scored high on both Optimism and Discomfort in roughly equal measure, although the samples, instruments, and settings differ, so the comparison is only indicative. It is consistent

with the qualitative findings of [2], whose interviewed traders repeatedly raised fraud and safety concerns ahead of usability complaints. This agreement between our quantitative result and their qualitative trust and security theme makes Insecurity a reasonable focus for further investigation and for intervention design.

3.4 Trader Segmentation

Table 5 shows the average silhouette width and WCSS for $k = 2$ to 7. The silhouette width was highest for $k = 3$ (0.311) and lower for $k = 5$ (0.261), a difference of 0.05. All values lie between 0.24 and 0.31, which is conventionally read as weak cluster structure [22], and WCSS fell steadily with k with no clear elbow. The data therefore do not strongly favour any number of clusters, and the choice of $k = 5$ rests on theory (Section 2.7) and not on the silhouette criterion. A three-cluster solution would be statistically defensible: it gives a more ready group ($n = 28$), a less ready group ($n = 24$), and a small group high on both drivers and inhibitors ($n = 8$). However, it would merge distinctions that the TRI 2.0 framework treats as meaningful, and it cannot give the five archetype profiles needed for segment-specific recommendations. Table 6 shows the size and centroid (mean dimension scores) of each five-cluster segment and the net readiness on which the labels were based (Figures 2 and 3).

Table 5. Average silhouette width and within-cluster sum of squares (WCSS) by number of clusters (k)

k	Avg. silhouette	WCSS
2	0.306	150.7
3	0.311	117.0
4	0.277	90.9
5	0.261	78.6
6	0.242	70.1
7	0.246	63.2

Table 6. TRI 2.0 segments: size and centroid (mean scores, 1–5 scale). Opt = Optimism, Inn = Innovativeness, Dis = Discomfort, Ins = Insecurity; Net = driver score minus inhibitor score

Segment	n	%	Opt	Inn	Dis	Ins	Net
Paranoids	15	25.0	3.75	3.00	2.83	3.82	+0.05
Explorers	13	21.7	4.06	3.29	2.73	2.46	+1.08
Laggards	13	21.7	3.02	2.15	3.63	4.00	–1.23
Skeptics	12	20.0	3.71	2.33	3.12	3.44	–0.26
Pioneers	7	11.7	4.04	3.07	4.11	4.43	–0.71
All	60	100	3.68	2.75	3.19	3.56	—

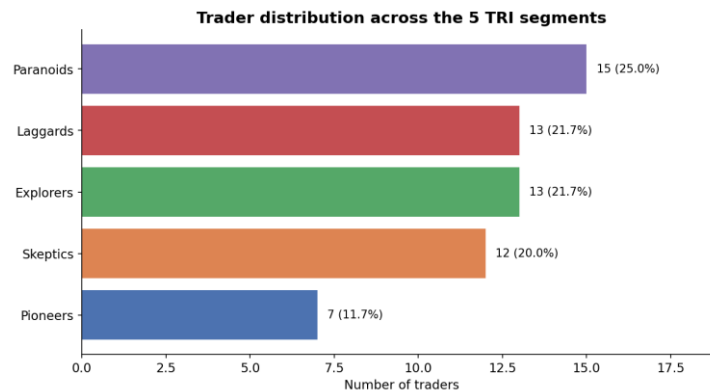


Figure 2. Trader distribution across the five TRI 2.0 segments.

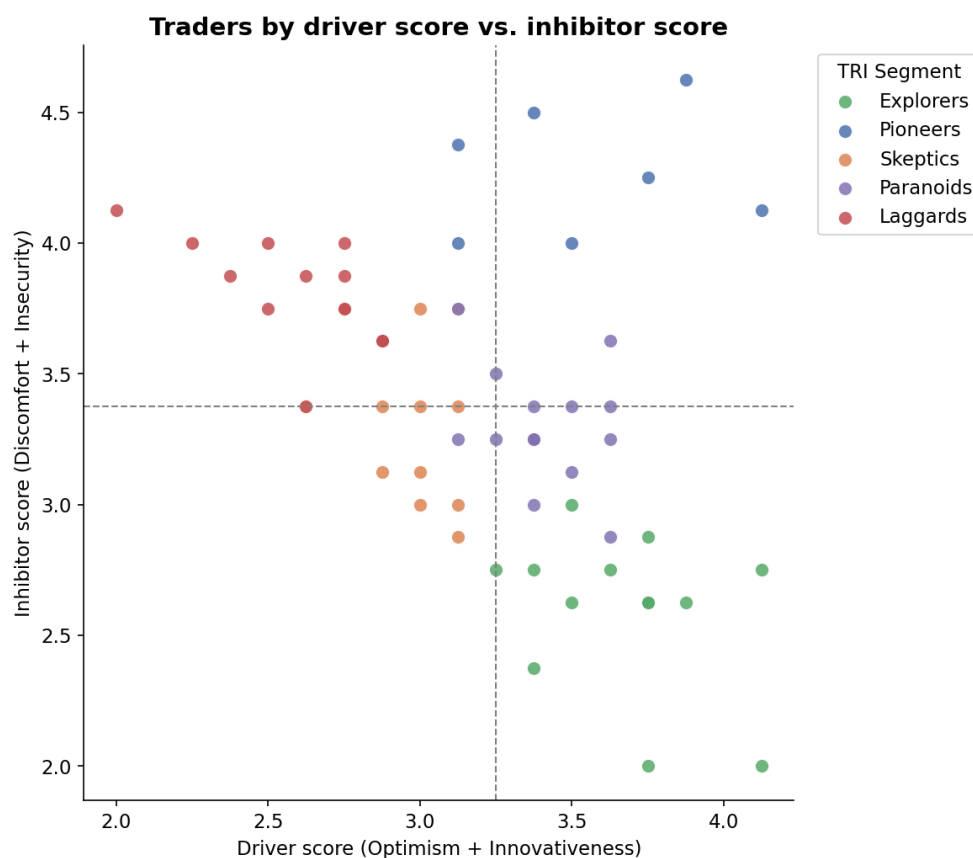


Figure 3. Traders by driver score (mean of Optimism and Innovativeness) versus inhibitor score (mean of Discomfort and Insecurity), coloured by segment.

The labelling rule in Section 2.7 gave the following profiles (Table 6). Explorers have the highest driver scores and the lowest inhibitor scores (net readiness +1.08) and are the most ready segment. Pioneers combine high drivers with the highest inhibitor scores (Discomfort 4.11, Insecurity 4.43; net -0.71): they are enthusiastic but also the most uneasy, so they are not the most adoption-ready group. Laggards have the lowest drivers and high inhibitors (net -1.23) and are the least ready.

Skeptics have Optimism close to the sample mean (3.71) but low Innovativeness (2.33) and moderate inhibitors (net -0.26). The Paranoid label was assigned by elimination: the centroid of this cluster first fell in the Explorer quadrant (driver 3.38, inhibitor 3.32) and was relabelled because its net readiness (+0.05) is the closest to zero. The distinctive feature of this segment is not high inhibition overall but the gap between the two inhibitors: Insecurity is high (3.82, above the sample mean of 3.56) while

Discomfort is low (2.83, below the sample mean of 3.19), a gap of 0.99 against -0.27 to 0.37 in the other segments. The Paranoids are therefore best described as traders with moderate drivers whose main concern is security and trust. They form the largest segment (25.0%), consistent with the higher mean of Insecurity in Table 4, and Pioneers are the smallest (11.7%; Figure 3).

The segmentation should be read with caution for three reasons. First, the separation is weak: the average silhouette width for $k = 5$ is 0.261, 47% of traders have an individual silhouette value below 0.25, and 14% of Pioneers and 8% of Laggards have negative values. The quadrant plot (Figure 3) agrees, showing segments that overlap around the sample median and not in distinct corners. Second, the clusters are only moderately stable. Across 100 random seeds the mean ARI against the reported solution was 0.80 (minimum 0.47). The reported solution has the lowest WCSS (78.6) found in 300 random starts, but only 14% of 10-start runs with other seeds reached it. In leave-one-out re-clustering the mean ARI was 0.81, and a median of 2 (mean 6.7, maximum 19) of the remaining 59 traders changed segment. In bootstrap resamples the mean ARI was 0.57 (5th–95th percentile 0.37–0.86), and a three-cluster solution was not clearly more stable (mean ARI 0.55). Third, the result depends on analysis decisions: removing INO4 and DIS4 changed the segment of 6 traders (ARI = 0.77), and excluding respondent R-02, whose smartphone response was corrected (Section 2.5), changed the segment of 16 of the remaining 59 traders (ARI = 0.62).

The five labels are therefore a theory-guided scaffold for describing a readiness gradient, from the more ready Explorers to the less ready Laggards, and not sharply separated natural groups. The recommendations in Section 3.8 build on this gradient and on the contrast between Insecurity and Discomfort, and should be treated as hypotheses for local

programmes, not as firm segment-specific rules.

3.5 Demographic Patterns Across Segments

Age showed the strongest demographic association with readiness (Figures 4 and 5). Younger traders (below the median age of 38.5 years, $n = 30$) scored higher on Innovativeness than older traders (2.98 vs. 2.53; Mann-Whitney $U = 216.5$, $p < 0.001$, $|r_{rb}| = 0.52$) and lower on Discomfort (2.96 vs. 3.42; $U = 246.0$, $p = 0.002$, $|r_{rb}| = 0.45$), differences of moderate size. Optimism (3.79 vs. 3.58; $U = 332.5$, $p = 0.076$, $|r_{rb}| = 0.26$) and Insecurity (3.45 vs. 3.67; $U = 398.5$, $p = 0.445$, $|r_{rb}| = 0.11$) did not differ significantly. Merchandise type showed a narrower pattern: only Innovativeness differed across the five merchandise groups (Kruskal-Wallis $H = 9.86$, $p = 0.043$, $\epsilon^2 = 0.11$), while Optimism ($H = 6.89$, $p = 0.142$), Discomfort ($H = 6.28$, $p = 0.179$), and Insecurity ($H = 6.89$, $p = 0.142$) did not ($\epsilon^2 = 0.04$ to 0.05). Because four dimensions were tested for each grouping variable without correction for multiple tests, and the "Other" merchandise group has only four traders, the merchandise result ($p = 0.043$) is fragile. Age therefore showed a stronger association with readiness than merchandise type. The age association was seen for Innovativeness (a driver) and Discomfort (an inhibitor), and not for Insecurity.

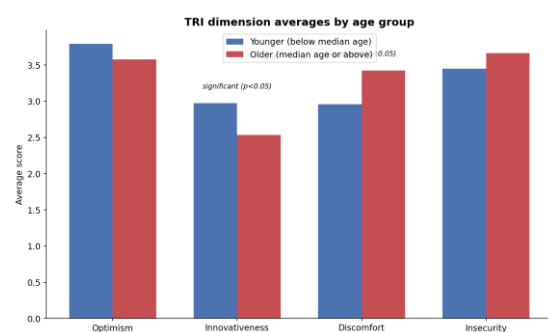


Figure 4. TRI 2.0 dimension averages by age group (younger versus older than median age).

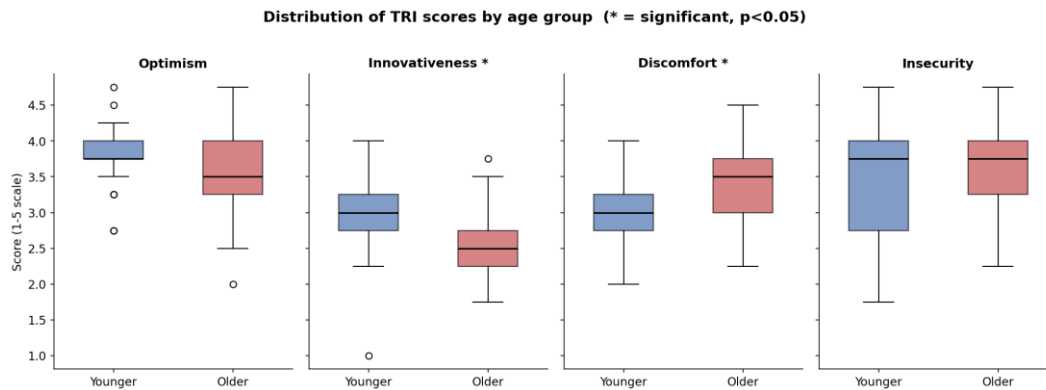


Figure 5. Distribution of TRI 2.0 scores by age group (asterisk = significant difference, $p < 0.05$)

3.6 Relationships Among Dimensions and an Exploratory Check on QRIS Use

Drivers and inhibitors moved in opposite directions, as the TRI 2.0 framework would lead us to expect [1] (Figure 6 shows Pearson correlations; Spearman values are given here and lead to the same conclusions). The two driver dimensions correlated positively (Optimism–Innovativeness $\rho = 0.66$, $r = 0.58$), and so did the two inhibitor dimensions (Discomfort–Insecurity $\rho = 0.54$, $r = 0.56$). All four driver–inhibitor pairs were negative (ρ from -0.28 to -0.41), for example Optimism–Insecurity $\rho = -0.41$ ($r = -0.43$) and Innovativeness–Insecurity $\rho = -0.33$ ($r = -0.39$). The Optimism–Discomfort link was the

weakest and, as a Pearson correlation, not significant ($r = -0.22$, $p = 0.095$; $\rho = -0.28$, $p = 0.031$). These correlations provide preliminary correlational evidence consistent with the expected four-dimension structure, even though two dimensions had low reliability. Correlations alone cannot establish construct validity, which is left to future psychometric work. A binary logistic regression (QRIS usage ~ four TRI dimensions) was run only as an exploratory check. With seven non-users the events-per-variable ratio is 1.75, far below the guideline of about 10 [27], and no predictor was significant. The model is not used as evidence for or against any dimension being related to QRIS use.

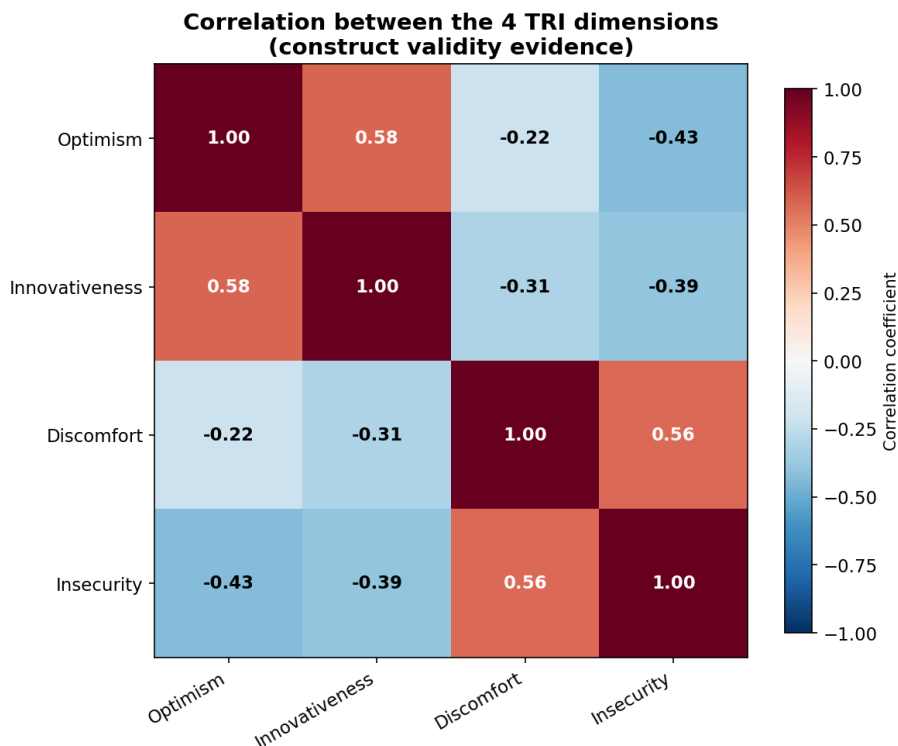


Figure 6. Correlation between the four TRI 2.0 dimensions (construct validity evidence).

3.7 Implications

Read together, the results address the study's three aims. First, readiness at Pasar Beriman Tomohon is spread across five theory-guided segments, with Paranoids (25.0%) the largest and Pioneers (11.7%) the smallest (Sections 3.3 and 3.4). Second, Insecurity has the highest observed score among the inhibitors (Section 3.3). Optimism is also high (3.68), so traders generally perceive QRIS as useful, while their concern about security and trust is higher than their discomfort with the technology. Third, age showed a stronger association with readiness than merchandise type (Section 3.5). A practical reading is that, in this sample, security and trust concerns are more prominent than doubts about usefulness. Because the design is cross-sectional and adoption over time was not measured, this is a pattern to investigate and address, not proof that fear limits adoption. TRI readiness, perceived risk, trust, and adoption intention are related but different constructs: TRI scores describe a general disposition, whereas the studies discussed below measure trust, risk, and intention toward QRIS specifically.

The emphasis on trust and security is consistent with recent evidence on QRIS adoption in Indonesia. Perceived safety and trust have been shown to shape MSME confidence in, and intention to use, QRIS [12], and trust raises continued QRIS use while perceived risk lowers it, with the prevalence of payment fraud weakening the positive effect of trust [13]. The importance of security is not uniform, however: in another MSME sample perceived risk did not significantly predict continued-use intention [14], and studies of formal and urban MSMEs often point to usefulness and ease of use as the leading influences [14]. In the present sample, where Optimism is already high, usefulness seems less likely to be what separates more ready from less ready traders, while the security and trust items stand out. Adoption models built on formal, urban MSMEs may therefore under-weight the security barrier in traditional markets. This is a hypothesis for future comparative research, because the studies cited measure different constructs from TRI readiness [11]–[14].

Reports of QRIS fraud, such as the physical swapping of a merchant's static QR sticker for a fraudulent one or the use of falsified payment screenshots, are a plausible

concern in the fast-moving, lightly supervised conditions of a traditional market at peak hours, although this study did not measure fraud exposure. For a trader with a high Insecurity score, such an incident, or a neighbouring trader's account of one, could reinforce existing concerns and potentially discourage sustained QRIS use. This is a hypothesis: the study did not record fraud incidents or later behaviour. Reducing exposure to this risk is therefore a reasonable focus for intervention in this market.

The demographic findings help to target intervention, but they also carry a caution. Age was significantly associated with Innovativeness and Discomfort, the two dimensions with low reliability (Section 3.2), but not with Insecurity, the inhibitor with the highest observed score. An age-based intervention, such as digital-literacy training for older traders, might therefore address unfamiliarity and discomfort while leaving security-related concerns largely untouched. Segment membership, which uses all four dimensions including Insecurity, may be a more informative targeting criterion than age alone, although the weak separation of the segments (Section 3.4) means that this too is a hypothesis.

3.8 Recommendations for Stakeholders

Because readiness differs between segments, a single market-wide campaign may be less targeted than segment-specific support. The recommendations below are evidence-informed suggestions and have not been validated experimentally. They are addressed to the two stakeholder groups driving QRIS adoption at the grassroots level: government agencies, including Bank Indonesia and local government, and the banks or payment service providers that onboard merchants. They could be delivered within existing frameworks such as Bank Indonesia's SIAP QRIS di Pasar programme [9], whose effectiveness in comparable traditional-market settings has been tied to how well support matches traders' specific concerns [10], [11].

Possible priorities by segment follow. Explorers (21.7%), high on drivers and low on inhibitors, appear ready and could serve as visible peer advocates rather than as training recipients. Pioneers (11.7%), enthusiastic but with the highest inhibitor scores, may represent a promising early target for intervention: they

may need both reassurance on safety and practical help with using the application, after which they could model use for more hesitant neighbours. Paranoids (25.0%), the largest segment, have moderate drivers, high Insecurity, and low Discomfort, so concrete fraud-prevention guidance and visible transaction verification would address their main concern. Skeptics (20.0%) have average-to-high Optimism (3.71) but low Innovativeness (2.33), so simple, low-effort first steps and examples from other traders may suit them better than persuasion about usefulness. Laggards (21.7%), low on drivers and high on inhibitors, are the least ready and may need patient, one-to-one, hands-on assistance. Because the segments overlap (Section 3.4), these are starting points to be tested, not fixed rules.

For government agencies, three priorities follow. First, fraud awareness could be built explicitly into market socialisation: teaching traders to check that their QR sticker is genuine and undisturbed, to wait for the official incoming-payment notification before releasing goods, and to report suspicious codes. Second, because Insecurity did not differ clearly by age, this fraud-and-trust content could reach all segments instead of being folded into age-targeted digital-literacy sessions alone. Third, reliable connectivity and power at the market may matter. Weak infrastructure was a main barrier to QRIS acceptance in the Bandung traditional markets [19], and one Insecurity item (INS3) refers to payment failing when power or signal is lost. That item is a single indicator with a low item-total correlation ($r = 0.296$), and infrastructure was not measured separately, so a link between infrastructure and Insecurity is a contextual hypothesis and not a finding of this study.

For banks and payment service providers, four adjustments could be considered. First, messaging could lead with safety and protection rather than convenience: with Optimism already high, traders may not need persuading that QRIS is useful, but reassuring that it is safe [12]. Second, Pioneers could be recruited early, given priority onboarding and a named contact for problems, and then invited to act as trusted local demonstrators. Third, a fast, human help channel, reachable in Manado dialect for the moment when the application stalls while

customers wait, could address the time-pressure side of Discomfort. Fourth, because Discomfort and Insecurity were positively correlated in this sample ($\rho = 0.54$, Section 3.6), an onboarding that builds skill and shows security features together might reach both inhibitors at once; whether it can replace separate confidence and trust programmes needs to be tested.

These recommendations rest on the study's descriptive findings (the segment distribution, the dimension profile, and the age comparison), which are supported by the reported descriptive and non-parametric analyses, with the caveats in Sections 3.4 and 3.9. They do not rest on the exploratory logistic regression, which could not test any predictor of QRIS use. Stated plainly, the study shows which traders appear more or less ready and on which dimension their scores are highest; it does not show that any dimension causes higher or lower QRIS use.

3.9 Limitations and Future Work

Several limitations qualify these findings. First, the sample is small ($n = 60$) and drawn from a single market using accidental, non-probability sampling, which limits statistical power, representativeness, and generalisability. The sample size was chosen for exploratory profiling and is not adequate for multivariable prediction. Only seven traders had never used QRIS, so the logistic regression was severely underpowered (1.75 events per variable against a guideline of about 10 [27]) and is exploratory only. Second, only smartphone-owning traders were eligible, so traders without a smartphone are not represented. This is a selection bias, and the results describe smartphone-owning traders only. Third, the five-cluster solution is theory-driven and statistically weak: silhouette widths were low for every k and slightly higher for three clusters than for five, and the segments are only moderately stable (Section 3.4), so the segment membership of an individual trader is uncertain. Fourth, the design is cross-sectional and based on self-report. It measures readiness at one point in time and cannot show that any dimension causes adoption. QRIS use was recorded only as ever or never used, so sustained use was not measured. Fifth, Innovativeness and Discomfort showed low internal consistency (Section 3.2) and are

clustering variables, and the adaptation of the instrument did not include back-translation or an expert review (Section 2.3), so the instrument may need re-validation before it is used in other traditional markets. Finally, the correction of one respondent's smartphone answer (Section 2.5) affects the cluster solution when that respondent is excluded.

These limitations set an agenda for future work. A larger, multi-market sample drawn with a probability or quota design would give the regression adequate power; measures of how often, how recently, and for what share of transactions traders use QRIS would allow readiness to be related to sustained use; and a longitudinal design could follow traders from first trial to sustained use or abandonment. A dedicated psychometric study of the adapted instrument, with a documented translation procedure and a larger sample, would show whether the four-dimension model needs adaptation for this setting. Comparing K-means with other segmentation approaches, such as hierarchical or latent class methods, and repeating the analysis in other markets in North Sulawesi would test whether the five-segment structure is stable and transferable.

CONCLUSION

This study aimed to describe the distribution of technology readiness among Pasar Beriman Tomohon traders, identify the inhibitor dimension with the highest observed score, and translate the findings into evidence-informed recommendations for stakeholders promoting QRIS adoption. K-means clustering placed the 60 sampled traders into five theory-guided TRI 2.0 segments, with Paranoids the largest group (25.0%) and Pioneers the smallest (11.7%); the segments are weakly separated and only moderately stable. Insecurity had the higher mean score of the two inhibitor dimensions, exceeding Discomfort, and therefore represents an important area for further investigation and intervention. This differs from prior QRIS-readiness research in urban UMKM settings, where Optimism and Discomfort scored comparably high [4], and is consistent with qualitative accounts of traditional-market resistance that emphasise fraud and security concerns over unfamiliarity [2], [3]. Age showed stronger observed associations with Innovativeness and

Discomfort than merchandise type, but not with Insecurity, so age-based interventions alone would not address the dimension showing the highest observed level of resistance.

The contribution of this study is contextual and practical, not methodological. It extends TRI 2.0-based readiness segmentation to traditional-market traders in the QRIS context and translates the segment profiles into potentially targeted recommendations. Unlike the closest precedent [5], which applied TRI and K-means to SMEs in general, it studies traders in a traditional market and a specific payment technology. The segment-level profile gives a more informative basis than an aggregate readiness score for deciding which traders may need which kind of support, which may be relevant for programmes such as Bank Indonesia's SIAP QRIS di Pasar initiative [9], where undifferentiated, market-wide campaigns may be less targeted than segment-based approaches.

This study has limitations. The sample is small, non-random, drawn from one market, and limited to smartphone owners; Innovativeness and Discomfort did not meet the reliability threshold; the five-segment structure is theory-driven and only moderately stable; and QRIS use was measured only as ever used, so sustained adoption was not studied. The exploratory logistic regression should not be treated as evidence. Future research with a larger and more varied sample, direct measures of sustained use, and a psychometric examination of the adapted TRI 2.0 instrument would show whether the patterns found here hold more widely.

DECLARATIONS

Author Contributions: The first author conceptualised the study, designed the methodology, performed the formal analysis, prepared the visualisations, wrote the original draft, reviewed and edited the manuscript, and acquired the funding. The second author conducted the investigation, curated the data, and reviewed and edited the manuscript. The third author conducted the investigation, validated the results, and reviewed and edited the manuscript. All authors approved the final version of the manuscript.

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Generative Artificial Intelligence Use: Generative AI tools were used to assist with drafting, language editing, and analysis of the data. The authors reviewed and verified all AI-assisted output, including the reported numbers and references, and remain fully responsible for the originality, accuracy, integrity, citations, analysis, interpretation, and conclusions of this work.

Ethics Approval and Informed Consent: This study did not undergo review by an ethics committee. It was an anonymous questionnaire survey of adult traders. No names or other direct identifiers were recorded; respondents were coded R-01 to R-60. Informed consent was obtained from all participants before the interviews.

Data Availability: The anonymised dataset (60 respondents, coded R-01 to R-60) and the analysis scripts are available from the corresponding author upon reasonable request.

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