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Analyzing and Visualizing Repeated-Measures Needs Assessment Data Using the Ranked Discrepancy Model

L. K. Narine[1], A. Harder[2]

Abstract

The Ranked Discrepancy Model was introduced in 2021 as an alternative for analyzing Borich-style competency-based needs assessment data which avoided the pitfalls associated with the original methods for analysis. In this article, we sought to expand upon that work by developing and testing a new framework to analyze and visualize repeated-measures needs assessment data using the Ranked Discrepancy Model (RDM). Data for the analyses were taken from statewide community needs assessments conducted in Utah and Florida with paid survey panelists recruited by an online survey vendor. We found it was possible to apply the RDM to repeated-measures data using Microsoft Excel. A comparison of results obtained from analyzing data using paired *t*-tests and the RDM model showed strong positive correlations. Additionally, the transition to a spreadsheet format enabled the expansion of data analysis possibilities to include sorting needs by demographic subgroups. We recommend researchers use Excel for the RDM so they can easily examine subgroup needs and apply data visualization techniques to improve the utility of needs assessments and the decisions made by the individuals who interpret the results.

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1. Lendel Kade Narine, Extension Associate Professor, Utah State University, Old Main Hill Logan, Utah 84322, lendel.narine@usu.edu, https://orcid.org/0000-0001-6962-2770
2. Amy Harder, Associate Dean for Extension, University of Connecticut, 1376 Storrs Road, Unit 4066, Storrs, Connecticut 06269, amy.harder@uconn.edu, https://orcid.org/0000-0002-7042-2028

Introduction and Problem Statement

Needs assessments are plagued with the misapplication of analytical techniques to incompatible variable types. These include the inappropriate selection of inferential statistics rather than nonparametric statistics based on sampling decisions but also mishandling data from individual ordinal items. Both types of error should be of concern for researchers looking to make real-life decisions using the data collected and analyzed during a needs assessment.

In 2021, we proposed the Ranked Discrepancy Model (RDM) to improve upon concerns inherent to the popular Borich (1980) method of analyzing competency assessment data (Narine & Harder, 2021). It has since been applied successfully by Choi and Park (2022) and Seitz et al. (2022). Our experiences with the initial iteration of the RDM led to new questions about if it could be applied to other types of needs assessment data, if it was possible to improve what could be learned from the data analysis, and how to best visualize the results. We explore these topics in the following sections and provide data and examples to demonstrate what is possible using the RDM.

Potential Applications Beyond Borich-Style Data

A paired *t*-test is frequently used to measure the magnitude of difference between paired scores in a repeated-measures design. For example, paired *t*-tests are applied to pre-and-posttest designs to measure changes in knowledge before and after an intervention. Researchers sometimes use similar repeated-measures designs to search for differences between actual and desired states when assessing needs (e.g., Chaudhary & Warner, 2022). Figure 1 illustrates an example of a repeated-measures style set of questions from a needs assessment survey instrument.

Figure 1

Item Structure in the Community Needs Assessment Instrument

	How important is the asset to you?					How satisfied are you with the availability of the asset in your community?				
	Not important	Of little importance	Moderately important	Important	Very important	Very dissatisfied	Dissatisfied	Neither	Satisfied	Very satisfied
High-quality childcare services	○	○	○	○	○	○	○	○	○	○
Reliable public transportation	○	○	○	○	○	○	○	○	○	○
Healthy food options	○	○	○	○	○	○	○	○	○	○
Affordable food options	○	○	○	○	○	○	○	○	○	○
Steady jobs	○	○	○	○	○	○	○	○	○	○
Well-paying jobs	○	○	○	○	○	○	○	○	○	○
Affordable childcare services	○	○	○	○	○	○	○	○	○	○

Given a repeated-measures/paired data structure in a needs assessment instrument as shown in Figure 1, researchers may be tempted to apply a paired *t*-test to examine differences between *importance* and *satisfaction*. However, there are several assumptions of a paired *t*-test that are sometimes overlooked in social science research. Major assumptions of a paired *t*-test are as follows: (a) data must be continuous or scale; (b) no outliers exist; (c) pairs of observations should follow a normal distribution; and (d) sufficient statistical power exists to test the hypothesis (Warner, 2013). Repeated-measures data gathered from an assessment using the item structure in Figure 1 are likely to violate the assumptions of a paired *t*-test (Ghosh et al., 2018). Yet, researchers sometimes apply multivariate techniques and disregard test assumptions in search of significant results, a practice that continues to be a concern in social science research (Hoekstra et al., 2012).

The RDM was presented as an alternative to assessing competency needs using the Borich model to avoid similar concerns about statistical analysis (Narine & Harder, 2021). However, the data structures across competency assessments and community needs assessments can both collect item-level ordinal data in a repeated-measures design. The RDM may provide an appropriate descriptive alternative for analyzing repeated-measures ordinal data in a community needs assessment framework, just as it did for assessing competency-based needs.

Assessing Needs Based on Subgroups

There is little reason to believe that the needs of any population of interest are going to be homogenous, even when the individuals in the population share a common characteristic, such as employment type or community of residence. Demographic variables such as age, gender, race, ethnicity, and education level impact people's perceptions of community needs and assets. For example, Yang et al. (2009) found gender, age, marital status, household size, education, income, and familiarity with extension impacted respondents' concerns about one or more of six community issues factors: helping vulnerable children and youth, chronic diseases, strengthening families, family finances, environmental threats, and agricultural education and sustainability. Ignoring demographics when analyzing needs assessment data can lead to mistakes in interpretation.

Researchers have had cumbersome options for analyzing needs assessment data to yield findings that could be isolated to population subgroups. Analyzing needs by subgroups using the Borich model means the researcher must calculate the Mean Weighted Discrepancy Score (MWDS) for *every* group (or interaction) of interest, a time-consuming process. This replication is also necessary when using paired *t*-tests, or the researcher can build a series of repeated-measures ANOVA model with between-subjects effects. In all the options described, the use of individual ordinal data continues to be problematic and insufficient for handling subgroup data appropriately. An improved option is needed for analyzing needs assessment subgroup data.

Visualizing Needs Assessment Data

Researchers have long used basic data visualization techniques, such as data tables and figures, to aid in communicating their findings. Sadiku et al. (2016) noted common visualization techniques include static graphics such as line graphs, bar charts, scatter plots, and pie charts.

Advancements in data visualization methods, software, and techniques have expanded substantially. By 2010, dynamic graphics were broadly adopted for applications such as social networking, business data, and sports performance management (Beck et al., 2017). Data dashboards have grown in popularity, so much so that in 2019 they were described by Sarikaya et al. as “ubiquitous” (p. 682). Regardless of the type of graphic used, data visualization “is useful for data cleaning, exploring data structure, detecting outliers and unusual groups, identifying trends and clusters, spotting local patterns, evaluating modeling output, and presenting results” (Unwin, 2020, p. 2). Such benefits would improve the utility of needs assessments and should be a consideration when presenting data for decision-making.

Purpose

This methodological study sought to test a framework to analyze and visualize repeated-measures needs assessment data using the Ranked Discrepancy Model (RDM). Objectives were to (a) determine how to analyze repeated-measures data using the RDM, (b) assess the appropriateness of using the RDM compared to a paired *t*-test for analyzing ordinal repeated-measures needs assessment data, and (c) demonstrate the application of RDM to analyze needs by sub-groups in a sample and corresponding options for visualizing results.

Methods

Statewide needs assessments were conducted in Utah and Florida in 2019 and 2020, respectively. Both assessments followed a similar methodology with some minor item-level differences in the survey instrument. The instruments gathered ordinal data on two indicators—importance and satisfaction—for a list of community assets. For example, respondents were first asked to indicate the importance of affordable food options in their community based on a 5-point scale ranging from *not important* to *very important*. Then, they were asked to indicate their satisfaction with the same item on a 5-point scale ranging from *very dissatisfied* to *very satisfied*. The Utah and Florida survey instruments shared 30 asset items that followed this repeated-measures structure. More detailed information about the 2019 and 2020 needs assessments can be found in Narine et al. (2021) and Harder et al. (2023). In both studies, Qualtrics was contracted to gather convenience sample data from their existing research panels.

The results section provides a discussion of how to analyze repeated-measures data using the RDM, a comparison of the results obtained when analyzing data with the RDM and paired *t*-tests, an overview of using the RDM in Microsoft Excel to explore subgroups, and examples of data visualization using the subgroup data. A sample data file (n = 50), a link to which is available in the Appendix, was used to demonstrate applications for the first and third objectives. Data gathered in the 2019 Utah needs assessment (n = 1,043) and 2020 Florida needs assessments (n = 1,500) were used to address the second objective to compare data using the RDM and paired *t*-tests. Due to the nature of our objectives and our desire to demonstrate what steps we have taken, we have provided an in-depth discussion of analytical methods throughout the results section rather than isolating it within the methods section.

Findings

Analyzing Repeated-Measures Data with the RDM

The process for applying the RDM to repeated-measures data differs from our original process (Narine & Harder, 2021), which was intended solely as an alternative for using the Borich model. First, the revised process no longer incorporates SPSS to calculate mean ranks. While not strictly necessary to use SPSS for the 2021 version of the RDM, doing so expedited the process compared to using Microsoft Excel only. Second, using Excel exclusively for RDM analysis expands the options for working with the data, which will be discussed in more depth in the following subsection on data subgroups. However, despite the changes in software, the underlying logic of the RDM is still built upon the comparison of positive ranks, negative ranks, and tied ranks to determine the magnitude of gaps between respondents' perceptions of what exists and what is ideal.

A formula in Excel can be used determine the rank of each observation pair first (e.g., satisfaction and importance). The observation-level rank calculated using the formula, referred to as an Ordered Rank (OR), is categorized as one of three possible values; S < I = -100, S = I = 0, and S > 1 = 100. The OR is analogous to negative, tied, and positive ranks respectively as discussed in Narine and Harder (2021). The Excel formula is provided below and is available in the sample file found in the appendix. Note, cell C3 is the importance rating, and cell H3 is the satisfaction rating.

=IF(OR(ISBLANK(C3),ISBLANK(H3)),"Missing",IF(C3<H3,100,IF(C3>H3,-100,0)))

Using the formula enables individual-level ranking for direct comparisons between subgroups in a sample. Initially, the ranked discrepancy score (RDS) was computed by the item instead of the individual by using frequency distributions. The OR is a precursor to the (Wilcoxon) rank values discussed in Narine and Harder (2021). Note, this step only uses the *ordered ranking* between pairs—it does not rely on the quantitative difference between pairs like a *t*-statistic. For example, if satisfaction is 4 (i.e., satisfied) and importance is 5 (i.e., very important), OR is -100. And, if satisfaction is 2 and importance is 5, the OR is also -100. Hence, the OR is a signal of the *ordering* between individual pairs from repeated-measures data which, in turn, is used to calculate the RDS for each item.

The item-level RDS is consistent with non-parametric procedures (e.g., Wilcoxon rank-sum, Mann-Whitney U) since it uses the *mean ranks* of ordinal items to calculate the statistic (Corder & Foreman, 2014). The RDM's approach to handling ordinal data is also consistent with the literature—*individual* ordinal variables should not be treated as scale measures since the quantitative value assigned in data coding represents an ordering between response options (e.g., low to high, strongly disagree to strongly agree) (Corder & Foreman, 2014). Conceptually, the RDM approach may reduce error since it suppresses response bias because the RDS is based on the ordering between matched pairs, not the quantitative distance between pairs. In perception-type questions, one individual's very satisfied rating may be the same as another's satisfied rating, leading to errors in interpretation (Brinker, 2002).

Figure 2 shows the recommended data structure for applying the RDM in Excel; the formula and files we are presenting as examples can be accessed by using the hyperlinks in the Appendix. The categorial variable, Sex (column B), is coded as text, and the ratings for importance and satisfaction (columns C to L) are numeric. In addition, importance ratings precede satisfaction ratings in paired observations. The Excel formula matches the sample data structure to provide the OR. Note, if one value is missing in a pair, the formula returns "missing" to indicate a pairwise missing case. Pairwise missing values do not affect the RDS calculation and are automatically not factored into the item-level RDS. However, it affects the sample size, which changes the item-level RDS. This treatment of missing values, referred to as available-case analysis, is a default approach in non-parametric and parametric repeated-measures tests (Salgado et al., 2016). However, researchers should examine if data is missing completely at random (MCAR), missing at random (MAR), or missing not at random (MNAR) before handling missing data (Pigott, 2001). Possible alternatives are replacing missing values with a median if data are MCAR, or using multiple imputation if data are MAR or MNAR (Pedersen, et al., 2017).

Figure 2

Data Structure for RDM in Excel

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	ID	Sex	Affordable housing options	Affordable medical clinics	Well-paying jobs	Quality public schools	Affordable internet connection	Affordable housing options	Affordable medical clinics	Well-paying jobs	Quality public schools	Affordable internet connection	*OR - Affordable Housing Options*
2			*Importance*	*Importance*	*Importance*	*Importance*	*Importance*	*Satisfaction*	*Satisfaction*	*Satisfaction*	*Satisfaction*	*Satisfaction*	
3	1	Female	2	5	5	5	5	3	2	2	2	1	=IF(OR(ISBLANK(C3),ISBLANK(H3)),"Missing",IF(C3<H3,100,IF(C3>H3,-100,0)))
4	2	Female	5	4	4	5	4	3	2	4	2	4	
5	3	Female	4	5	4	5	5	2	4	4	3	4	
6	4	Male	2	4	3	4	5	4	4	4	5	5	
7	5	Female	3	3	4	5	3	3	3	4	4	3	
8	6	Male	4	4	4	4	4	4	3	4	3	4	
9	7	Female	5	5	5	5	3	5	5	5	5	3	
10	8	Male	5	5	5	5	5	3	2	4	4	3	
11	9	Female	5	4	5	5	4	4	2	4	4	4	
12	10	Male	3	4	3	5	4	4	4	3	5	4	

When applied to one cell, the formula can be dragged down *and* across for all pairs. As noted, the mean RDS is conceptually aligned to rank-ordering in non-parametric procedures; it is free of any distribution and test assumptions. In the sample data, the largest discrepancy was observed for the asset of affordable medical clinics (RDS = -69). Negative discrepancies indicate a deficit between the current and ideal situation exists, and the magnitude of the deficit should be interpreted as an indicator of the level of priority; interpretation guidelines for the RDM in Excel remain consistent with those we originally outlined in 2021.

RDM vs. Paired *t*-test

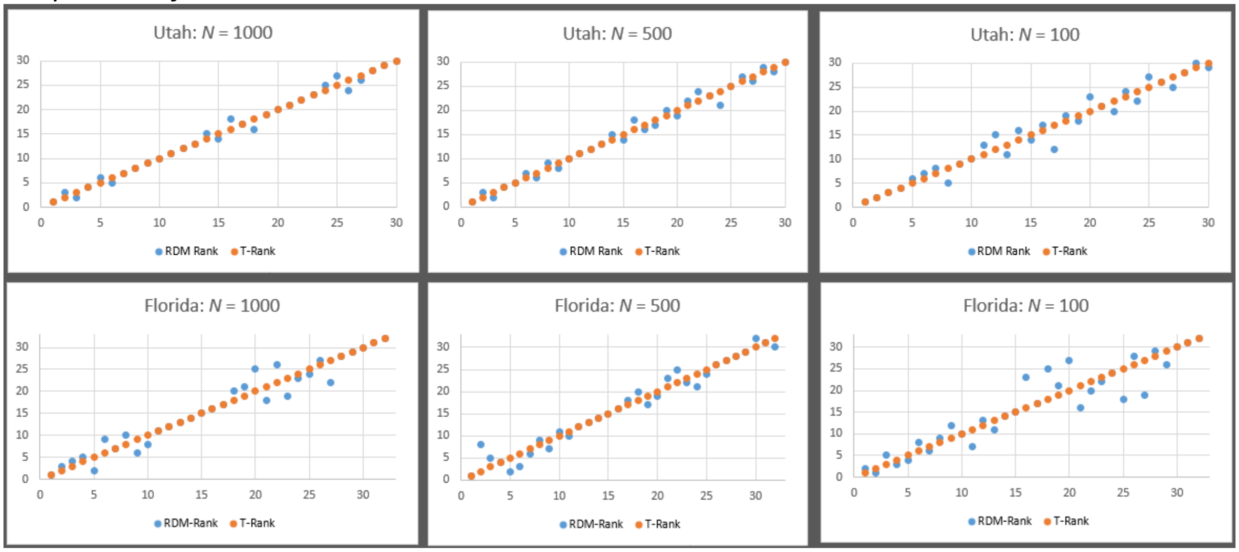
As discussed, the primary goal of a needs assessment is to *rank priority needs* for resource allocation (Altschuld & White, 2010; Kimpston & Stockton, 1979; Witkin, 1994; Witkin & Altschuld, 1995). The RDM and paired *t*-test provide a measure of discrepancy, which can then be used to rank items in need of attention by program planners. The *t*-statistic from a paired *t*-test represents the magnitude of difference between two scores in a repeated-measures design (Warner, 2013). It provides a signal of a discrepancy, gap, or change between two measurements. The *t*-statistic is calculated using the mean difference between pairs and standard error; both terms are based on the measures of dispersion for scale variables (Warner, 2013). While incompatible with item-level ordinal data (Miot, 2020), the *t*-statistic can indicate the difference between two ordinal-level pairs (Kampen & Swyngedouw, 2000). A larger *t*-statistic indicates a wider gap between pairs and vice versa. Therefore, a *t*-statistic can provide *some* insight into the discrepancy between importance and satisfaction (or importance and ability) in a needs assessment framework. For example, if the satisfaction (S) rating is entered first and importance (I) last, a negative *t*-statistic indicates a gap or discrepancy (i.e., S < I). The absolute *t*-statistic also increases as the absolute discrepancy between pairs of observations increases based on mean differences.

While the *t*-statistic may measure discrepancy, Kampen and Swyngedouw (2000) provided a rationale for the incompatibility of the *t*-test (and *F*-test) for measuring differences between ordinal variables, noting “the impossibility of shifting relevant from irrelevant differences disqualifies the analysis of variance as a useful analyzing technique of ordinal variables” (p. 93). Kampen and Swyngedouw’s concern primarily lies in the unbounded nature of the *t*-statistic and its dependence on distribution properties. In contrast, the RDS is always bounded by a lower (-100) and an upper (100) limit regardless of the ordinal range between pairs and distribution properties. The RDS only relies on the ordered relationship (i.e., OR) between pairs through negative, tied, and positive ranks; a foundational feature of nonparametric procedures (Krzywinski & Altman, 2014; Nahm, 2016). The RDS provides a standardized measure of discrepancy based on the proportion of OR across observed pairs with RDS trending toward -100 indicating a larger discrepancy compared to scores trending toward 100.

Three random samples, generated using Excel’s random number feature, were taken from the Utah and Florida dataset each to examine the variation of the rankings by sample size. Figure 3 provides a summary of the 30 ranked needs identified by using a paired *t*-test and the RDM. The rankings shown in Figure 3 are based on the RDS (RDM-Rank, in blue) and *t*-statistic (T-Rank, in orange). Each coordinate (or plot point) represents the location in the ranking indicating the relative need of each of the 30 asset items from the survey. Only orange coordinates are visible when the ranking of a need is the same regardless of which method was applied. Blue coordinates are visible when the RDM-rank is different than the T-Rank. Items with the largest gaps between respondents’ perceptions of the asset’s importance and their satisfaction with it are closest to the origin of the graph.

Figure 3

Comparison of Ranked Needs between the Paired t-test and RDM



From Figure 3, the rankings of 30 items were similar between the paired *t*-test and RDM across all sample sizes. However, greater variation in rankings between the models was observed as the sample size decreased. Notably, the top 10 highest-ranked priority needs remained the same across both models, with only two exceptions in the Florida *N* = 100 sample (i.e., one item was ranked 9th in the RDM and 12th in the paired *t*-test, and another was ranked 11th in the RDM and 7th in the paired *t*-test). A Pearson's correlation coefficient (ρ) was conducted to examine the correlations between rankings across models, the results were as follows: Utah – *N* = 1,000, ρ = 0.993; *N* = 500, ρ = 0.992; *N* = 100, ρ = 0.967; Florida – *N* = 1,000, ρ = 0.992; *N* = 500, ρ = 0.991; *N* = 100, ρ = 0.975. These correlation coefficients confirm the similarities between the paired *t*-test and the RDM when identifying gaps in community assets; a result that complements the comparison between the RDM and Borich model in Narine and Harder's (2021) initial discussion. The comparison between models shows the utility of the RDM in analyzing needs assessment data without the statistical issues tied to using the paired *t*-test.

Sub-Groups and Visualizations

Calculating the observation-level OR using the Excel formula before the item-level RDS enables an assessment of needs by subgroups. Since an OR exists for each observation, the RDS can be computed for a grouping of observations by a known characteristic (e.g., sex, age, income). Text coding of categorical variables is necessary for an analysis of RDS by sub-groups in Excel. Figure 4 shows the data structure necessary for visualizing discrepancies by subgroups using Pivot tables in Excel.

Figure 4

Example Data for Visualizing Discrepancies

	A	B	C	D	E	F	G
1	ID	Sex	RDS: Ordered Ranks (OR)				
2			*Affordable Housing Options*	*Affordable medical clinics*	*Well-paying jobs*	*Quality public schools*	*Affordable internet*
3	1	Female	100	-100	-100	-100	-100
4	2	Female	-100	-100	0	-100	0
5	3	Female	-100	-100	0	-100	-100
6	4	Male	100	0	100	100	0
7	5	Female	0	0	0	-100	0
8	6	Male	0	-100	0	-100	0
9	7	Female	0	0	0	0	0
10	8	Male	-100	-100	-100	-100	-100

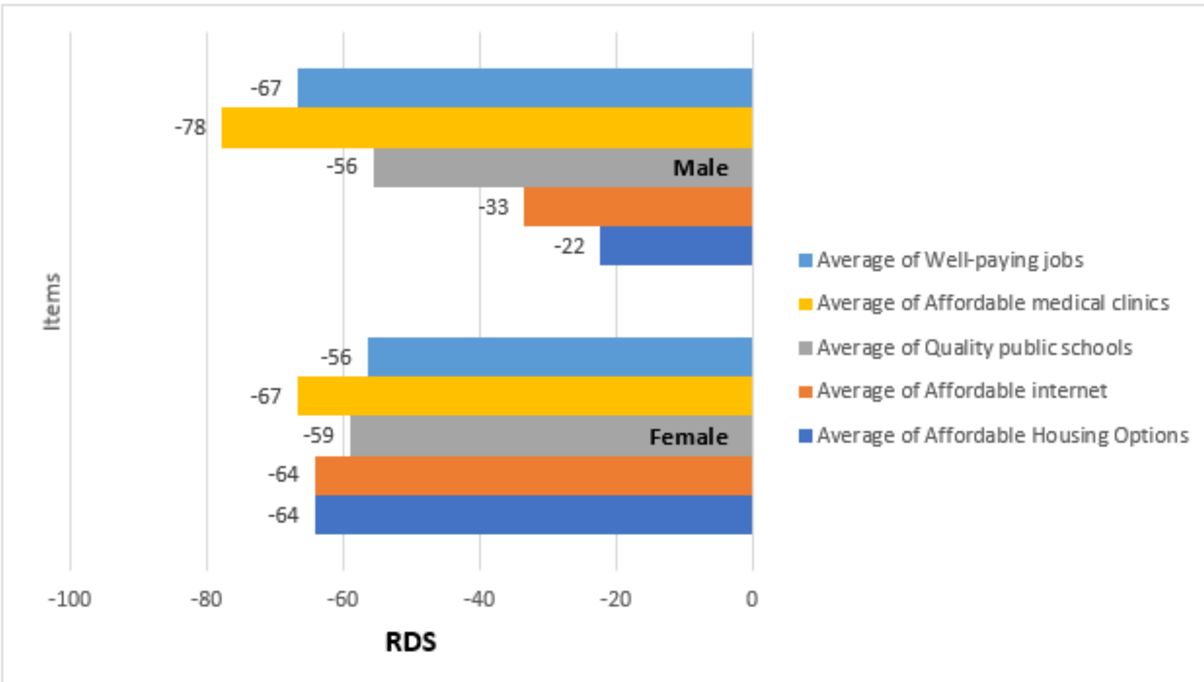
Note. Readers may find a link in the Appendix to Worksheet 3 (Pivot data) which can be used to practice analyzing RDS by subgroups.

Pivot tables provide a vast array of options for data visualizations and interactive dashboards. Pivot tables can be used to layer demographic variables to provide RDS scores for specific subgroups. For example, a pivot table could be used to visualize discrepancies for younger males with lower incomes compared to others when sex, income, and age are applied as demographic variables. Applying the RDM in Excel enables analysis of subgroups and interactions between subgroups, a feat that requires multilevel statistical modeling. Figure 5 displays a basic pivot table showing RDS by Sex, which can be found in Worksheet 4 (Viz) of the sample data in the Appendix links. Note, the values shown in the pivot table are averages of the field, not the default sum value.

Figure 5

Simple Visualization of Needs by Subgroups Using Pivot Tables

	RDS by Sub-group				
Row Labels	**Average of Affordable Housing Options**	**Average of Affordable internet**	**Average of Quality public schools**	**Average of Affordable medical clinics**	**Average of Well-paying jobs**
Female	-64	-64	-59	-67	-56
Male	-22	-33	-56	-78	-67
Grand Total	**-56**	**-58**	**-58**	**-69**	**-58**

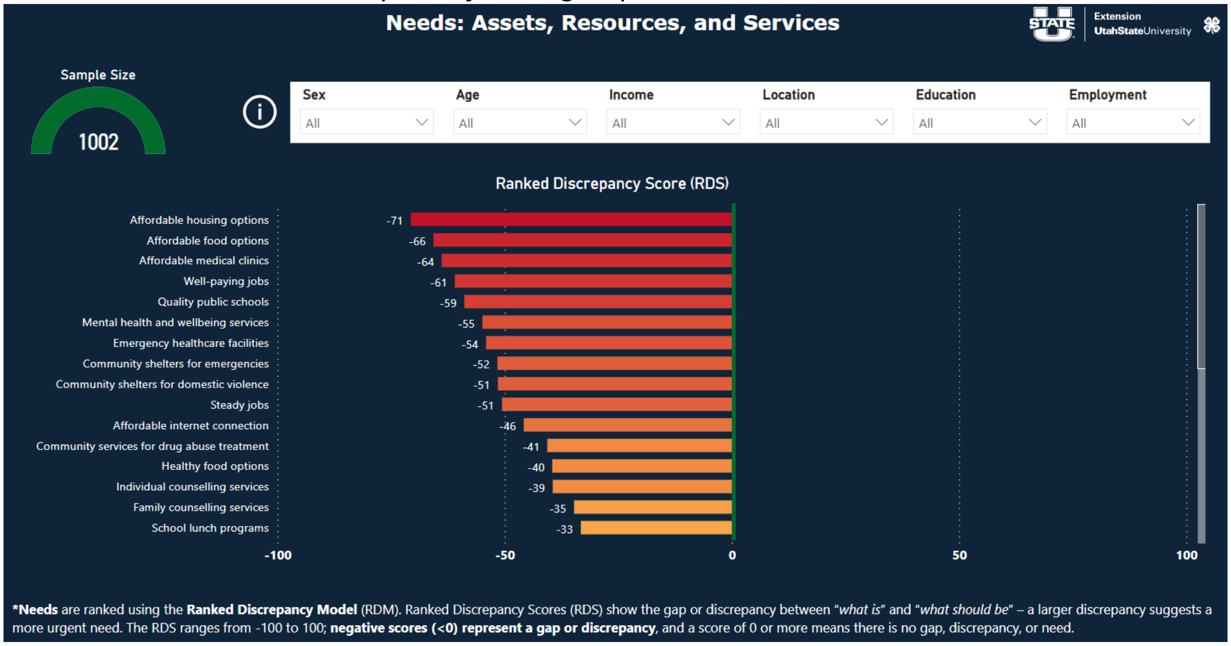


Note. Link to sample data found in the Appendix.

Figure 6 provides a snapshot of the results from the 2023 Statewide Needs Assessment of Utah (Report Page 5 of 9 shown). The OR was calculated in Excel, and Microsoft Power BI was used to enable the visualization of RDS by subgroups. In Power BI, users can view RDS for all items by any subgroups or interactions between subgroups using filter options. The interactive dashboard shows the potential of the RDM for repeated-measures needs assessment data using the procedures described throughout this article.

Figure 6

RDS Visualization with Filter Options for Subgroups



Conclusions, Discussion, and Recommendations

Expanded options now exist for applying the RDM to needs assessment data. Researchers may continue to use the original RDM approach that was intended as an alternative for analyzing competency-based data (Narine & Harder, 2021). However, transitioning to Excel to apply the RDM for competency-based data and other types of repeated-measures needs assessment data creates new and statistically sound options for researchers and improved options for data visualization.

One observation we made after comparing the RDM results with the results from paired *t*-tests is that the new approach is more sensitive to the size of the sample. Variability increased as sample size decreased for the Utah and Florida data but was most evident for Florida. Practically, Utah's population is approximately 3.38 million people while Florida's population is 22.24 million people (U.S. Census Bureau, n.d.). A small sample size, such as n = 100, will be increasingly less likely to be representative of a population as the size of that population increases. Standard error increases as the sample size decreases, resulting in greater variability in sample estimates compared to reliable estimates of population parameters. Therefore, the *t*-statistic from a smaller sample is likely to have a wider confidence interval (and be less precise) compared to a *t*-statistic from a larger sample (Rusticus & Lovato, 2014). Correlations were strong and statistically significant despite the increased variation, but researchers should be aware of this consideration when determining necessary sample sizes if they intend to use the RDM for analysis.

The most significant advantage of the revised approach to applying the RDM is the expanded ability to efficiently and clearly explore differences in results by subgroups. As Unwin (2020) stated, there are many benefits to data visualization which improve researchers' abilities to interpret data and make informed decisions. Pivot tables require relatively little specialized knowledge to use and are readily accessible for many researchers. Software like Power BI illustrates what is possible for researchers who already have a working knowledge of more advanced visualization techniques or who are willing to commit time to learn how to create complex data dashboards with it.

We believe needs assessments will have increased value when data visualizations are used to reveal the underlying patterns, trends, and intersectionality that can be associated with demographic subgroups. Needs assessment methodologies should evolve over time as we seek to improve the application of our science. New technologies create possibilities that were not previously available or readily accessible for previous generations of researchers. Our overarching goal should always be to seek methods leading to improved precision for a more informed distribution of resources to address priorities for action.

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