Journal of Applied Research in Higher Education

Research analytics capabilities (RAC) survey: development, validation and revision using the Rasch model

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Received 13 December 2023
Revised 16 April 2024
11 June 2024
Accepted 25 June 2024

Abstract

Purpose – The research enterprise within higher education is becoming more competitive as funding agencies require more collaborative research projects, higher-level of accountability and competition for limited resources. As a result, research analytics has emerged as a field, like many other areas within higher education to act as a data-informed unit to better understand how research institutions can effectively grow their research strategy. This is a new and emerging field within higher education.

Design/methodology/approach – As businesses and other industries are embracing recent advances in data technologies such as cloud computing and big data analytic tools to inform decision making, research administration in higher education is seeing a potential in incorporating advanced data analytics to improve day-to-day operations and strategic advancement in institutional research. This paper documents the development of a survey measuring research administrators' perspectives on how higher education and other research institutions perceive the use of data and analytics within the research administration functions. The survey development process started with composing a literature review on recent developments in data analytics within the research administration in the higher education domain, from which major components of data analytics in research administration were conceptualized and identified. This was followed by an item matrix mapping the evidence from literature with corresponding, newly drafted survey items. After revising the initial survey based on suggestions from a panel of subject matter experts to review, a pilot study was conducted using the revised survey instrument and validated by employing the Rasch measurement analysis.

Findings – After revising the survey based on suggestions from the subject matter experts, a pilot study was conducted using the revised survey instrument. The resultant survey instrument consists of six dimensions and 36 survey items with an establishment of reasonable item fit, item separation and reliability. This survey protocol is useful for higher educational institutions to gauge research administrators' perceptions of the culture of data analytics use in the workplace. Suggestions for future revisions and potential use of the survey were made.

This project has been advised and developed with support from Shannon Sampson, Associate Professor, Educational Policy Studies and Evaluation; Director, Evaluation Center; University of Kentucky, Lexington, Kentucky.

Funding: This material is based upon work supported by the U.S. National Science Foundation under Grant No. 2215223 (Baron G. Wolf, University of Kentucky, Principal Investigator).

Journal of Applied Research in Higher Education

2050-7003
DOI 10.1108/JARHE-12-2023-0578

Originality/value – Very limited scholarly work has been published on this topic. The use of data-informed and data-driven approaches with in research strategy within higher education is an emerging field of study and practice.

Keywords Data analytics, Research evaluation, Research assessment, Rasch measurement, Research administration, Research analytics

Paper type Research paper

Over the past 2 decades, administrators have made attempts to take advantage of leveraging data and analytics to realize competitive business advantages outside the academic field. Companies that utilize analytics are 5% more productive and 6% more profitable than other companies (McAfee *et al.*, 2012). A McKinsey study (Bughin *et al.*, 2018; cited in Gökalp *et al.*, 2021) predicts that the potential impact of data analytics and artificial intelligence (AI) on the global economy will be around 13 trillion US dollars by 2030. Davenport (2018) reminds us that while technology was stable for several decades in analytics, it is changing rapidly today. With the advent of big data, AI, cloud and open-source options, creating an effective technology strategy for analytics is a critical prerequisite for success (Davenport, 2018).

Data analytics has been attracting great attention from not only industry but also academia by providing valuable insights to support strategic decision making (Gökalp *et al.*, 2019). This trend is in part due to the success in the use of data, statistical analysis and explanatory and predictive models to inform decision making on complex issues across academic and learning domains of higher education (Alyahyan and Düştegör, 2020; Avella *et al.*, 2016; Van Barneveld *et al.*, 2012). Especially with the increasing volume of available data, data analytics continues to gain prominence in transforming day-to-day operations, strategic planning, research productivity and the culture of data use across higher education institutions. Mounting research evidence and insights point to the myriad benefits of higher education research valuing data analytics infrastructure as core assets, and the prospects of expanding the investment and implementation of data analytical tools to improve research productivity and research operations (Campbell *et al.*, 2007; Picciano, 2012; Sinha *et al.*, 2013). Yet many of those investing resources into data collections are still not unlocking the full potential required to turn that data into strategic information that supports and informs decision making (Thompson, 2016, p. 48). Higher education institutions must also become more data driven to capably respond to new demands and to become more effective and flexible in meeting both institutional objectives as well as new regulatory requirements (Grajek, 2016; cited in Campbell, 2018, p. 1).

The research administration profession has over time evolved into an active partner with their corresponding institution in the process of inquiry (Kaplan, 1959; Kulakowski and Chronister, 2006). During the early years of the profession, research administration professionals frequently served "as a source of information" (Kaplan, 1959, p. 29) for several administrative procedures, including "obtaining equipment, for keeping inventory of available equipment, for employing new personnel, for traveling to scientific meetings, and so on" (Kaplan, 1959, p. 28). More recently, the role of research administrators has become significantly diversified and an expanded workforce at research-intensive institutions. According to Allen-Collinson (2009), research administrators are responsible for a myriad of research related activities, including administration of research projects, from seeking out potential funding, through costing projects, submitting bids, monitoring and all stages through to the submission of final reports. Research administrators are also responsible for research degree provisions, or Graduate School/registry type functions, such as student records, quality assurance, monitoring progress, coordinating examinations and servicing research/research degree committees. Both zones of work usually included maintaining complex databases of research-related activity (Allen-Collinson, 2009). This is largely no different than decades of prior analysis that found that research administrators were understood to have "crucial importance for understanding large-scale research organizations" (Kaplan, 1959, p. 21). The increasingly diversified responsibilities and workload of research administration render the use of data more crucial to their success as an institutional partner. For this study, research administrator refers to personnel within the research enterprise at all levels of the research sponsored project lifecycle. It includes both senior leadership roles as described in Kaplan (1959) and administrative staff at various downstream levels who help to manage the research enterprise for active scientific researchers.

Currently, research administrators find themselves transforming the field itself into a strategic position to support research and development in higher education institutions and translate basic research to applied fields (Cole, 2010). In research administration, research evaluation frameworks, such as the widely cited SCOPE research evaluation framework (International Network of Research Management Societies, 2021) have been proposed to measure levels of research activity and effectiveness with the focus on institutional values. These frameworks emphasize robust evaluation designs using responsible research evaluation principles (Himanen *et al*., 2024). Although the emphasis on research and evaluation rigor is commendable, we argue that data analytics should be part of this important initiative as well. Our research proposes that data analytics plays a pivotal role in research and evaluation by leveraging the use of data and metrics to drive continuous improvement cycles and make iterative adjustments to implementation and strategy. In essence, the use of data analytics needs to be elevated more within research administration in the higher education domain.

Provided that a scalable system is available for supporting and managing large volumes of data, a clear institutional strategy on how to approach data and metrics will help drive impact across the entire hierarchy of challenges (Wolf *et al*., 2021). Finally, although a variety of tools – including data analytics surveys and maturity models – have been developed to assess the data analytics practice and use across most industries, we are not aware of any that have been specifically created for the research administration discipline. The field and the role of research administrators are rapidly evolving and diversifying, with an increasing reliance on data analytics to inform decision-making.

Given a host of advantages with introducing data analytics into higher education research administration, the immediate next step is to increase employee buy-in to establishing a culture of data analytics within the research administration functions for both operational efficiency and workload planning, but also institutional strategy building and allocation of resources. It is therefore crucial for research institutions to periodically gauge employees' perception of research analytics capabilities as a way of providing feedback, ideas and increasing employee engagement in this data analytics initiative (Lee and Lee, 2024; Wolf *et al*., 2021). In doing so, research institutions need a well-researched, well-developed, validated measurement tool to obtain employees' perceptions of research analytics capabilities of their institutions and departments with precision. In addition, applications of well-developed survey instruments improve data quality and increase the usability of the data collected (Üstun *et al*., 2005).

Therefore, this study aims to develop, validate and revise a survey measuring research administrators' perceptions of research analytics capabilities within the higher education research administration domain. The survey development process starts with a conceptual framework construction, a review of literature and existing scales, the writing of items and response scales. And a new survey instrument was developed. For validation of the survey, the Rasch rating scale model was applied to perform a range of scale diagnostics analyses to establish psychometric evidence to validate and eventually inform survey revision. Rasch analyses also offer measures and statistics regarding the extent to which the institutional system is enabling analytics culture, the breadth of data use and how those uses derive insights for decision making within the context of organizational processes.

Existing survey instruments measuring data analytics

Data analytics maturity models

Since data analytics have taken shape in businesses and industries, there has been a call for appropriate instruments to be developed to measure how organizations grow in terms of the organizational culture of using data analytics to impact operation and strategy. Maturity models are among several other existing options that address this need. According to Proença and Borbinha (2016), a maturity model is a technique used to a business process or aspects of an organization, with the goal of moving toward a more organized and systematic way of doing business (cited in Webber *et al.*, 2019). Currently, several well-established data analytics maturity models are available to gauge and benchmark companies and organizations' data maturity. For example, Davenport (2018) developed the 5 Stages of Analytics Maturity and their subsequent DELTA Plus (Davenport, 2018) helped organizational leaders measure growth in analytic capabilities. TDWI Analytics Maturity Model is a similar assessment tool created in response to organizations' need to understand how their analytics deployments compare to those of their peers and to provide best-in-class insight and support (Davenport, 2018). For data maturity models with a focus on impacting higher education institutions, Educause (through their Core Data Service, CDS) offers a current maturity analytics maturity index that measures 32 factors contributing to analytics maturity (Dahlstrom, 2016). Data maturity has also been explored in government agencies. The Office of Data Governance from the United States Department of Labor (n.d.), for example, proposed the Data Management Maturity Model to provide an assessment framework that is "useful in evaluating existing data management processes and capabilities, to identify how they meet mission needs, and suggesting opportunities for improvement."

While maturity models have been held in high regard for years as proven templates for continuous improvement, implementation of maturity models alone is not adequate in capturing holistically the data analytics capabilities of organizations. Maturity models are more likely designed for use by senior leaders and upper management personnel. The questions and the rating scale in a maturity model often require respondents to have an organizational-level understanding of the capabilities and culture of the key attributes measured. In addition, maturity models are not without their limitations. O'Reilly (2019) stated that the structure of maturity models is actually their greatest flaw—far too static, a snapshot, a single perspective and a solution path unable to keep up with an ever-changing world.

Data analytics surveys

In 2011, Transforming Data With Intelligence (TDWI) conducted a survey research study with the purpose to "accelerate users' understanding of the many new tools and techniques that have emerged for analytics with big data in recent years" (Russom, 2011, p. 3). In 2020, Gartner published the *Marketing Data and Analytics Survey 2022* Report, aiming at investigating the challenges and failed expectations companies and businesses encounter with marketing analytics, and exploring the potential of continued investments in market analytics in the future (Kune *et al.*, 2020). The closest existing data analytics survey that this study aims to develop is the one by Wolf *et al.* (2020), which investigates the influence of data analytics practices in various levels of higher educational institutions, with a key focus on impacting institutional research. This current survey development study is predicated on the previous survey by Wolf *et al.* (2020) and is informed through a systematic literature review, which identifies the major characteristics that influence the scope of data analytics capabilities in research administration. This current study expands on the work of Wolf *et al.* (2020) by first conducting a systematic literature review to better understand the existing fields, trends and developments within academic literature. In addition, Wolf *et al.* (2020) was a small pilot-type study that included fifty-six respondents. This current study is focused on a full-national survey implementation and study to better understand the emerging field of research evaluation. Additional survey validation, testing and deployment strategies have been used in this current study compared to the work of Wolf *et al.* (2020).

What is research analytics?

Robershaw and Wolf (2023) coined the term "research analytics" to refer to "the science of analyzing data to make data informed decisions for strategic planning, research and development, and business processes around research administration functions" (Robershaw and Wolf, 2023, p. 6). The purpose of research analytics is to identify areas that could be enhanced, troubleshoot current issues discovered by data, and resolve them with evidence-based solutions. Information derived from research analytics can enhance research performance, build capacity and discover and strengthen knowledge within higher education institutions (Robershaw and Wolf, 2023, p. 6)

The research analytics capabilities (RAC)

Based on existing literature on data analytics, Robershaw and Wolf (2023) identified and compiled a six-dimension model with multiple indicators that influence research analytics capabilities in the higher education research administration domain. According to Robershaw and Wolf (2023), the development of research analytics capabilities depends on six major dimensions, namely:

(1) *Data* – the sources and types of data collected and analyzed,

(2) *Analytics* – the analytics staffing, and tradecraft needed to generate insights from data,

(3) *Technology* – the availability of IT infrastructure to support an analytic initiative,

(4) *Governance* – the policies and standards around leveraging data analytics in the institutions,

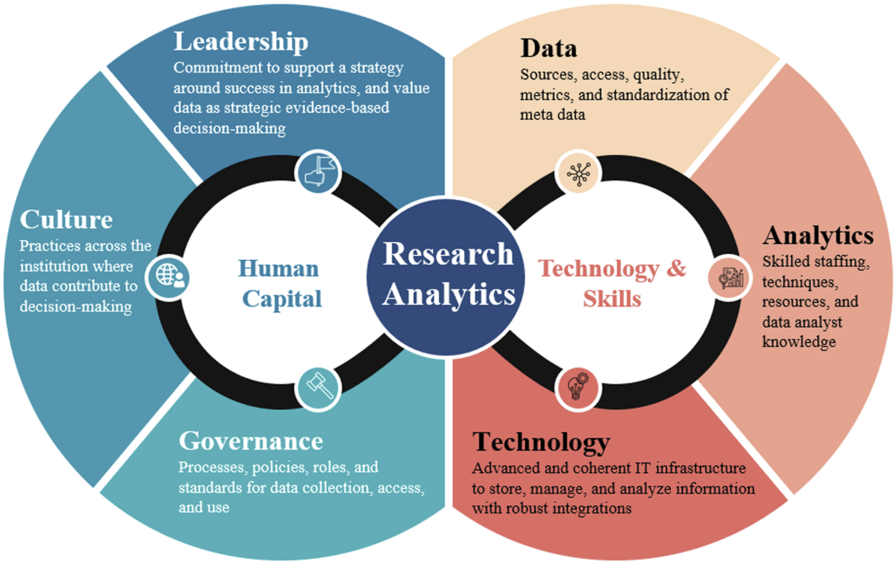
(5) *Culture* – data-informed decision-making culture, and

(6) *Leadership* – senior leadership's commitment to support an organizational strategy around success in analytics.

Figure 1 summarizes the conceptual framework of research analytics capabilities (Robershaw and Wolf, 2023) and the descriptions of each of the six dimensions in the context of research administration in higher education institutions.

(1) Data

Data identifies the sources, access, quality and standardization of data and metrics, and the system of data documentation and metadata management. Specific to the field of research administration, the *Data* dimension of the survey includes questions are designed to measure the relevance and quality of the data collected by the institution that are available and easily accessible to research administration at all levels. Examples of data and metrics that are of interest to research administrators include number of faculty proposals versus awards won, turnaround processing time, indirect cost (IDC) recovery rate averages, and success rates per department for applications submitted to sponsors (Qureshi, 2022). Respondents are also asked about their ease of access to the data they need, the procedures in place to standardize and ensure quality of the data, and proper data and metadata management.



Source(s): Figure created by authors'

Figure 1.
The conceptual framework of Research Analytics Capabilities (RAC)

(2) Analytics

Analytics identifies the development of analytics staffing and hiring process to acquire the analytic tradecraft and techniques needed to generate insights from data. The *Analytics* dimension of the survey includes items that measure respondents' perception of the availability of an analytics person or team to provide insights for driving data driven decision making, profiling and data talent sourcing of analytics staff, and the presence and effectiveness of relevant professional development and training in leveraging data analytics in research administration.

(3) Technology

Technology identifies the availability of an advanced and coherent IT infrastructure to store, manage, analyze data and support an analytic initiative and its integration into existing environment. The *Technology dimension* of this survey includes items that measure respondents' perception of the analytical tools employed for data-driven decision making, the capacity to store, manage and analyze data, information security, and the funding and resources available to invest in an advanced and coherent IT infrastructure that supports analytics for all parts of research administration and potential users.

(4) Governance

Governance identifies the processes, policies, roles and standards around data collection, access and use to allow for effective leverage of analytics without applying too many restrictions. In the field of research administration, the *Governance* dimension of the survey includes items that measure respondents' perceptions of the policies on data collection, access, use and efficiency; the coherence of the data governance strategy in support of the analytics program, and other aspects of data governance such as IT risk management, IT governance, etc.

(5) Culture

Culture, identifies the practices within and between departments in exploring areas where data can contribute to decision making across the organization to improve processes, share insights and inform action planning. Specific to the field of research administration, the *Culture* dimension of this survey includes items that measure respondents' perceived use and cultural acceptance of data analytics in their department or work units, the interactions between IT and institutional research offices, enterprise orientation to managing analytics, exploration and utilization of opportunities where analytics can be leveraged to drive decision making, the extents to which results and insights are used to inform strategic targeting, value creation, and action planning, etc.

(6) Leadership

Leadership identifies the senior leadership's commitment to support an organizational strategy around success in analytics, and valuing data as a strategic asset to support evidence-based decision making. Specific to research administration, the *Leadership* dimension of the survey includes items that measure respondents' perceptions of senior leadership's cultural acceptance of analytics, their commitment to support the growth of data analytics capabilities across all aspects and departments of research administration to establish a data-driven decision-making culture across all levels of employees.

Materials and methods

The instrument

A draft survey protocol was created following the development of a theoretical framework for the RAC. The instrument was reviewed by a panel of subject matter experts for face validity and topic relevancy. The panel's review indicated that all items and the format in which they were presented were clear and easy to understand. The first pilot study of the survey instrument was conducted between March and April 2023 for the purpose of gathering improvement feedback from respondents regarding the content, quality and usability of the survey. The revised survey, after using feedback from respondents from the first pilot, resulted in a total of 42 items, comprising the following:

(1) 36 items on research analytics capabilities in higher education research administration,

(2) five demographic items and

(3) one open-ended question inquiring respondents' input on ways to address current challenges on developing a research analytics program in their research administration office.

Study design

Following the survey revision, the second pilot study of the revised RAC survey was conducted in June 2023 for the purposes of instrumental testing and item calibration. The target population for the pilot study were professionals from the higher education research administration field in the United States. After the IRB modifications of the second pilot study and initial communication with the consulting team to determine response frame, the research team prepared and sent an anonymous online survey link together with survey communication materials to the point of contact of participating research institutions. The survey administration period lasted five weeks. The data collection for the survey used a snowball sampling methodology where the survey link was sent to a group of individuals to complete the pilot survey, but also encouraged them to send on to colleagues who may have an interest in the topic.

Respondent demographics

After the data cleaning process, a total of 211 responses from the second pilot study were included in the analysis. Table 1 summarizes the respondent demographics of the second pilot study.

Rasch analysis

The Rasch model was used as the measurement model for this survey construction because it is the only model that meets the requirement of invariant measurement (Engelhard, 2013, p. 70). The data elicited from the survey were analyzed with the Rasch Rating Scale model using WINSTEPS 5.4.3 (Linacre, 2023), a Rasch software. The formula for the Rasch Rating Scale model is displayed below (Linacre, 1997):

$$\log\left(\frac{P_{nik}}{P_{ni(k-1)}}\right) = B_n - D_i - F_k$$

where P_{nik} is the probability of a person n achieving category k on item i, $P_{ni(k\text{-}1)}$ is the probability of a person n achieving category $k\text{-}1$ on item i, B_n is the ability (B) of person n, D_i is the overall difficulty (D) of item I, and F_k is the step difficulty [threshold] of category k.

The analyses were used to test the capacity of the instrument to measure the hypothesized constructs, including unidimensionality and reliability of the hypothesized model of parents' awareness and perspectives, individual item fit and differential item functioning.

Measurement properties. Employing the Rasch Rating Scale model with data from survey analyses serves several multiple purposes. The Rasch model has the ability to recognize raw

Demographic Variable^	*n*	Percent (%)	Cumulative percentage (%)
Employment Category			
Staff	33	20.75	20.75
Supervisor or mid-level leader	37	23.27	44.02
Unit director	59	37.11	81.13
Senior leadership	22	13.84	94.97
Other	8	5.03	100.00
Department			
Research analytics	29	18.35	18.35
Post-award	45	28.48	46.83
Research development	13	8.23	55.06
ERA*	2	1.27	56.33
Innovation	1	0.63	56.96
Research compliance	6	3.80	60.76
Pre-award	23	14.56	75.32
Other	39	24.68	100.00
Tenure			
0–2 years	19	12.10	12.10
3–5 years	24	15.29	27.39
6–10 years	23	14.65	42.04
11–15 years	27	17.20	59.24
16+ years	64	40.76	100.00

Note(s): ^Results are not computed for variables with no responses
*ERA stands for Electronic Research Administration
Source(s): Table created by authors

Table 1.
Demographic characteristics of RAC survey respondents (valid $N = 211$)

scores collected from surveys as ordinal data, carrying out non-linear transformations of raw scores from survey data, instead of treating raw scores directly as interval data (Bond and Fox, 2007, p. 4). Rasch measurement can also easily correct bias estimation resulted from short tests or small samples (Linacre, 1999; Wright, 1988), which is ideal for pilot survey studies. Another purpose of using Rasch analysis is to interpret the person ability and item difficulty measures, fit statistics, reliability and separation, dimensionality and more. The information obtained is useful for the researcher's evaluating and improving the instrument's validity, reliability and other issues with the existing instrument (Linacre, n.d.a). The threshold for person and item reliability indices are expected to be > 0.5, as a reliability less than 0.5 implies that the differences between measures are mainly due to measurement error (Wright and Masters, 1982, pp. 105–106). For person and item separation indices, the acceptable value is > 2, indicating that the measure can separate respondents or items into more than 2 distinct groups (Kook and Varni, 2008). Guidelines for rating scales and Andrich thresholds are applied to assess the psychometric properties of the RAC survey. Some guidelines are listed below (Linacre, 1997):

(1) Before data collection, it is essential to make sure the scale is oriented with latent variable.

(2) There are at least 10 observations in each category.

(3) Observations should be regularly distributed.

(4) Observed average measures of the persons advance monotonically with category.

(5) Outfit mean-square estimates for the fit statistics must be less than 2.0.

(6) Andrich thresholds advance between response categories should be at least 1.4 logits and no more than 5 logits apart.

Results

Unidimensionality

The survey validation analysis began with an examination of the dimensionality of the RAC scale to make sure the scale was oriented in a single underlying latent variable. The dimensionality of the RAC scale was examined with principal component analysis of the residuals (PCAR) that remained after the linear Rasch measure had been extracted to identify any common variance remaining among the data unexplained by the primary Rasch measure. Table 2 summarizes the PCAR findings on the RAC scale.

Examination of the Rasch PCA of residuals reveals evidence of multidimensionality of the RAC scale. The primary Rasch dimension explained 49.3% of the total raw variance.

		Eigenvalue	Observed (%)		Expected (%)
Total raw variance in observations	=	70.9415	100.0		100.0
Raw variance explained by measures	=	34.9415	49.3		48.7
Raw variance explained by persons	=	21.3684	30.1		29.8
Raw unexplained by items	=	13.5731	19.1		18.9
Raw unexplained variance (total)	=	36.0000	50.7	100.0	51.3
Unexplained variance in 1st contrast	=	4.4522	6.3	12.4	
Unexplained variance in 2nd contrast	=	3.0141	4.2	8.4	
Unexplained variance in 3rd contrast	=	2.3807	3.4	6.6	
Unexplained variance in 4th contrast	=	1.8078	2.5	5.0	

Source(s): Table created by authors

Table 2. Table of standard residual variance in eigenvalue units/item information units (The RAC scale)

The variance explained by the items, 19.1%, is more than three times larger than the variance explained by the largest secondary dimension, "the first contrast in the residuals," which is 6.3%. The eigenvalue of the first contrast is 4.4522 (an equivalent of 4 items), which is larger than 2 (a strength of 2 items), the smallest amount that could be considered a "dimension."

Table 3 provides the standardized residual loadings for the first contrast. Figure 2 provides a plot of the item residual loading for the first contrast. Of the 36 items on the RAC scale, 17 items had positive loadings, and 19 items had negative loadings. An examination of the items with positive loadings revealed that all items in contrast 1 belong in the *Culture* or *Leadership* dimensions. These items measure the data culture of respondents' job functions and beliefs about leveraging data in research administration, such as senior leadership's support of a data culture and respondents' perceptions of the importance of data-informed decision making in research administration. One the other hand, all items with negative loadings belong in the *Data*, *Analytics*, *Technology* and *Governance* dimensions of the RAC scale. The items measure investments in recruiting data analytics talents and technological infrastructure within the research administration offices. Further tests were run to confirm the presence of a second dimension.

In addition to standardized residual loadings for items, PCA of residuals also estimates the correlation coefficients of person measures on item clusters disattenuated of measurement error to further investigate dimensionality of a scale. High disattenuated correlations suggest that the person measures on the item clusters share a majority of variance, probably part of the same dimension. Low disattenuated correlations suggest that the two clusters being compared are measuring something different. Table 4 summarizes the disattenuated correlations between item clusters in the 1st contrast.

The estimates provided in Table 4 indicate that item clusters 1–2 and 2–3 are highly correlated (0.7984 and 0.9149 respectively), clusters 2 and 3 are moderately correlated (0.6418). According to Linacre (n.d.b), disattenuated correlations of 0.57 or higher indicate that person measures on the two item clusters have more than half as much variance in common as they have independently. This suggests that although there may be the presence of a second dimension in the scale, the dimensions are highly correlated. After a closer investigation into the items belonging in clusters 1 and cluster 3, results revealed that respondents score high on items related to cultural attitudes, values and strategic vision around research analytics development (cluster 1), but they score low on the actual investments in staffing data analytics roles and financing the technological input necessary for enhancing research analytics efforts. The multidimensionality of the current RAC Scale warrants further investigation. The examination of other psychometric properties of the RAC Scale will continue in the forthcoming sections.

Reliability and separation indices

For the RAC Scale, the person reliability (0.92) and item reliability (0.98) are above 0.5, indicating a meaningful person and item hierarchy. The person separation (3.37) and item separation (8.07) are both larger than 2, meaning that the measure and the respondent sample are sufficiently diverse to separate persons and items into more than two distinct groups.

Individual item measures and fit

An examination of individual items within the RAC Scale shows that Ability to finance analytics development (Q12) was the most difficult item for survey respondents to endorse (JMLE Measure = 1.35), whereas Perceived importance of data use to the future of research administration (Q22) was the easiest item on the scale (JMLE Measure = -2.75). The infit and outfit mean squares of all items on the scale are less than 2 (Linacre n.d.-a). The fit statistics confirm that all the items on the RAC Scale are productive for measurement. Table 5 presents the individual item difficulty measures and fit statistics of the RAC Scale.

Item		Loading	Contrast cluster group
A	Q30 Senior leadership's belief that data-driven innovation can improve research success	0.68	1
B	Q32 Senior leadership supporting a data-informed culture	0.65	1
C	Q33 Senior leadership's commitment to establishing a data-informed culture	0.65	1
D	Q27 Importance of data-informed decision-making in research administration office	0.49	1
E	Q26 Data analytics' influence on decision making in research strategy and institutional investment	0.48	1
F	Q34 Senior leadership deploying analytical solutions to key strategic priority areas	0.48	1
G	Q28 Belief that data analytics is useful for organizing and visualizing strategic data	0.43	1
H	Q23 The belief that data analytics increases ROI in research administration	0.38	1
I	Q35 Alignment of research administration's analytics efforts with business goals	0.30	1
J	Q22 Perceived importance of data use to the future of research administration	0.28	1
K	Q24 All employees encouraged to use data to perform analysis	0.27	1
L	Q36 Data professionals being seen as a strategic partner	0.23	1
M	Q31 Presence of a data analytics strategy in research administration office	0.17	2
O	Q11 Frequency of reviewing or revising research analytics processes and tools	0.07	2
N	Q25 Collaboration between data and non-data specialists in sharing knowledge of analytics	0.07	2
P	Q29 Presence of a compelling business case to support development of analytics	0.04	2
Q	Q18 Presence of policies/internal controls to limit data permission	0.03	2
a	Q04 Employees having easy access to relevant data	−0.56	3
b	Q05 Employees well-equipped with skills to support research analytics	−0.52	3
c	Q06 Availability of analytical tools to perform analysis	−0.51	3
d	Q02 Research analytics based on high quality data	−0.45	3
e	Q01 Internal data being sourced from a consistent data warehouse	−0.43	3
f	Q03 Research analytics based on data trusted throughout the institution	−0.38	3
g	Q08 Availability of self-service analytic tools to perform analysis	−0.29	3
h	Q15 Current data system's ability to provide customized reporting	−0.24	3
i	Q20 Accuracy and consistency of institutional data	−0.24	3
j	Q09 Availability of full-time staff for reporting or analysis	−0.23	3
k	Q13 Feasibility of developing analytics in research administration units	−0.22	3
l	Q21 Data governance model facilitating individual access to the right data	−0.21	3
m	Q16 Availability of in-database analytics in current database software	−0.18	3
n	Q07 Availability of educational trainings to improve data literacy	−0.16	3
o	Q19 Presence of effective data governance strategy to protect data	−0.11	3
p	Q14 Adequacy of current IT infrastructure to support volume of data	−0.10	3
q	Q10 Availability of the institution to staff data and technical roles	−0.04	3
r	Q17 Tools used for interaction with data only require minimal training	−0.02	3
R	Q12 Ability to finance analytics development	−0.01	3

Source(s): Table created by authors

Table 3. Initial loadings for first contrast and cluster group (The RAC scale)

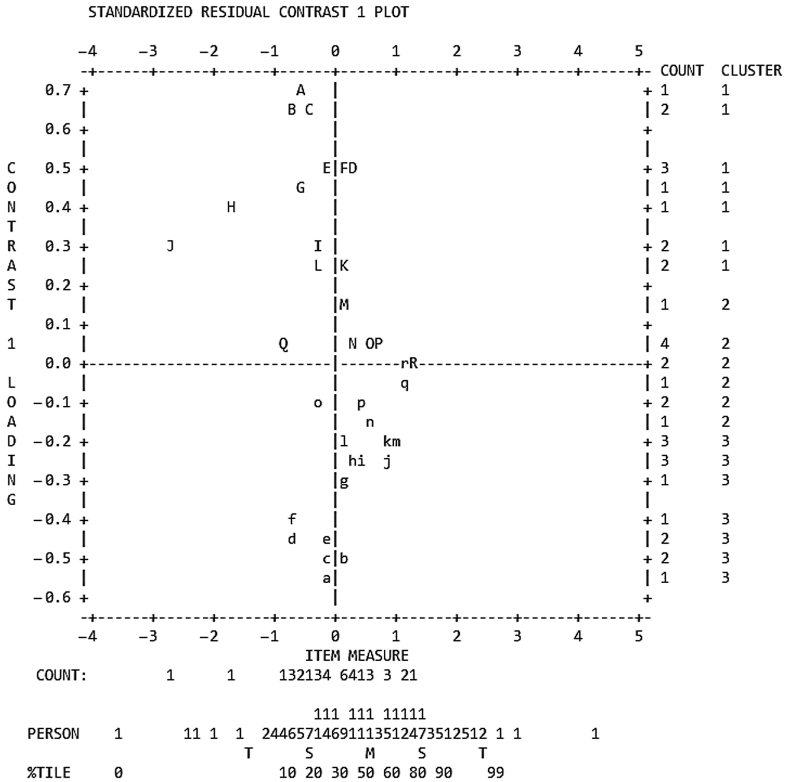


Figure 2. Standardized residual plot of contrast 1 (The RAC scale)

Source(s): Figure created by authors using Winsteps

Table 4. Correlation coefficients of item clusters within contrast 1 (The RAC scale)

PCA contrast	Item clusters	Pearson correlation	Disattenuated correlation
1	1–3	0.5629	0.6418
1	1–2	0.6697	0.7984
1	2–3	0.7720	0.9149

Source(s): Table created by authors

Rating scale diagnostics

The Rasch model provides a set of diagnostics to examine whether the categories within the four-point Likert scale measures are performing as expected. First, respondents used the full range of response scale (1: *Strongly Disagree* – 5: *Strongly Agree*) in all 36 items on the RAC Scale. There are at least 10 observations in each response category in the entire RAC Scale (a requirement for Rasch rating scale models). For the step calibrations, three out of the four Andrich thresholds between the response categories are within the acceptable range of 1.4–5.0 logits. The threshold between categories 2 and 3 is 1.27, slightly below the lower limit of 1.4 as recommended in the Rasch literature. Drawing from this finding, the RAC interval scale was revised and run again by (1) combining original categories 2 and 3, (2) removing original

Item	JMLE measure	Infit MNSQ	Outfit MNSQ
Q12 Ability to finance analytics development	1.35	1.18	1.87
Q23 The belief that data analytics increases ROI in research administration	−1.73	1.88	1.69
Q18 Presence of policies/internal controls to limit data permission	−0.93	1.44	1.55
Q01 Internal data being sourced from a consistent data warehouse	−0.08	1.5	1.53
Q22 Perceived importance of data use to the future of research administration	−2.75	1.35	1.5
Q17 Tools used for interaction with data only require minimal training	1.12	1.32	1.34
Q14 Adequacy of current IT infrastructure to support volume of data	0.4	1.2	1.24
Q09 Availability of full-time staff for reporting or analysis	0.92	1.17	1.22
Q36 Data professionals being seen as a strategic partner	−0.22	1.16	1.22
Q04 Employees having easy access to relevant data	−0.1	1.19	1.16
Q28 Belief that data analytics is useful for organizing and visualizing strategic data	−0.6	1.18	1.15
Q15 Current data system's ability to provide customized reporting	0.35	1.08	1.12
Q16 Availability of in-database analytics in current database software	0.81	1.11	1.12
Q24 All employees encouraged to use data to perform analysis	0.13	1.1	1.11
Q29 Presence of a compelling business case to support development of analytics	0.54	1.02	1.1
Q19 Presence of effective data governance strategy to protect data	−0.32	0.98	1
Q31 Presence of a data analytics strategy in research administration office	0.17	0.87	1
Q11 Frequency of reviewing or revising research analytics processes and tools	0.51	0.96	0.98
Q10 Availability of the institution to staff data and technical roles	1.19	0.91	0.97
Q20 Accuracy and consistency of institutional data	0.31	0.95	0.97
Q30 Senior leadership's belief that data-driven innovation can improve research success	−0.51	0.88	0.89
Q07 Availability of educational trainings to improve data literacy	0.6	0.88	0.88
Q08 Availability of self-service analytic tools to perform analysis	0.21	0.91	0.88
Q05 Employees well-equipped with skills to support research analytics	0.17	0.89	0.87
Q26 Data analytics' influence on decision making in research strategy and institutional investment	0.2	0.87	0.87
Q03 Research analytics based on data trusted throughout the institution	−0.77	0.86	0.86
Q02 Research analytics based on high quality data	−0.66	0.76	0.79
Q06 Availability of analytical tools to perform analysis	−0.13	0.82	0.79
Q27 Importance of data-informed decision-making in research administration office	0.23	0.77	0.77
Q25 Collaboration between data and non-data specialists in sharing knowledge of analytics	0.22	0.79	0.76
Q33 Senior leadership's commitment to establishing a data-informed culture	−0.39	0.78	0.76
Q34 Senior leadership deploying analytical solutions to key strategic priority areas	−0.21	0.77	0.74
Q32 Senior leadership supporting a data-informed culture	−0.66	0.76	0.72
Q13 Feasibility of developing analytics in research administration units	0.83	0.64	0.68
Q35 Alignment of research administration's analytics efforts with business goals	−0.25	0.61	0.65
Q21 Data governance model facilitating individual access to the right data	0.07	0.61	0.62

Source(s): Table created by authors

Table 5. The item difficulty measures and fit statistics of the RAC scale

category 3 and (3) combining original categories 3 and 4. The analyses on the revised scales show that all the Andrich thresholds are within the specified range, meaning all the revisions have improved the Andrich thresholds of the RAC Scale's original response categories. Of the three revisions, revised RAC Scale 2 (removing category 3) achieved the best results. Table 6 summarizes the statistics of response category structure of the RAC Scale. Figure 3 plots the category probability curves for the original and revised RAC interval scale, respectively.

Discussion and conclusion

Dimensionality

The examination of the dimensionality using the Rasch Rating Scale Model (RSM) found that, although the RAC Scale is established as a multidimensional scale, disattenuated correlation results show that the dimensions are highly correlated with one another. It is noteworthy to dive deeper into understanding the moderate disattenuated correlation between items categorized in cluster 1 – cultural and strategic attitudes toward research analytics and cluster 3 – financial commitments in analytics staffing and technology. While cluster 1 items emerge as strengths shared by respondents' institutions, cluster 3 items reflect correlated areas of growth. For institutions in early or developmental stages of data

Table 6.
Category response statistics of the RAC scale

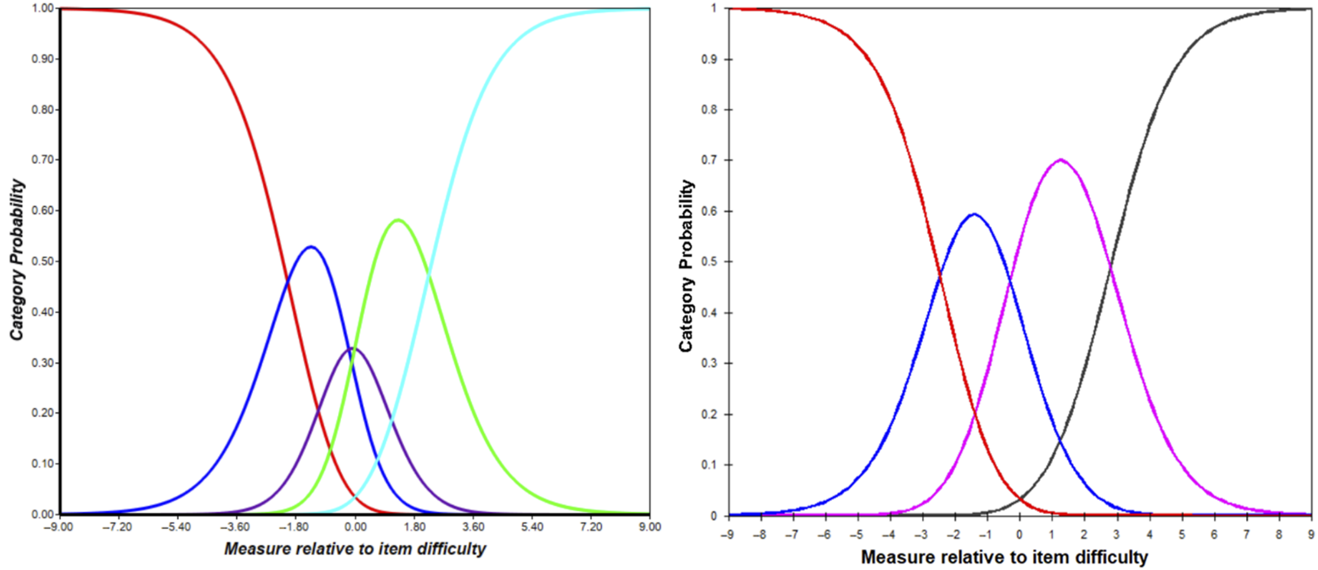
Category Label	Observed count	%	Infit MNSQ	Outfit MNSQ	Andrich threshold	Category measure
Original RAC Scale (5-point Likert)						
1	415	6	1.03	1.11	None	(−3.26)
2	1,434	21	1.01	1.03	−2.05	−1.34
3	1,504	22	0.97	1.09	−0.19	−0.07
4	2,565	37	0.93	1.00	−0.01	1.31
5	1,021	15	1.01	1.03	2.25	(3.43)
Revised RAC Scale 1 (4-point Likert; Combined Categories 2 and 3)*						
1	415	6	1.09	1.06	None	(−4.12)
2	2,938	42	0.95	1.02	−2.99	−1.29
3	2,565	37	0.90	0.96	0.46	1.51
4	1,021	15	1.06	1.09	2.53	(3.72)
Revised RAC Scale 2^ (4-point Likert; Removed Category 3)						
1	415	8	1.18	1.23	None	(−3.65)
2	1,434	26	0.81	0.82	−2.47	−1.41
3	2,565	47	0.85	1.06	−0.31	1.26
4	1,021	19	1.13	1.10	2.79	(3.92)
Revised RAC Scale 3^{+} (4-point Likert; Combined categories 3 and 4)						
1	415	6	1.06	1.14	None	(−3.48)
2	1,434	21	0.91	0.88	−2.23	−1.54
3	4,069	59	0.97	1.12	−0.83	1.15
4	1,021	15	1.03	1.00	3.06	(4.17)

Note(s): * The new category 2 is the combination of categories 2 and 3 in the original RAC Scale. The new category 3 is the original category 4 in the old RAC Scale. The new category 4 is the original category 5 in the old RAC Scale

^ The new category 3 is the original category 4 in the old RAC Scale. The new category 4 is the original category 5 in the old RAC Scale. The original category 3 is removed from the analysis

$^{+}$ The new category 3 is the combination of categories 3 and 4 in the original RAC Scale. The new category 4 is the original category 5 in the old RAC Scale

Source(s): Table created by authors



Source(s): Figure created by authors using Winsteps

Figure 3. Category probability curves of the original (left) and revised (right) versions of the RAC Scale

analytics maturity, it is typical to see leadership and staff highly value and prioritize the development of research analytics. However, the necessary infrastructure, knowledge and skills to advance these initiatives may still be in the process of being established. Given that research analytics remains an under-explored academic discipline and considering that most institutions are at the early stages of research analytics maturity, we propose a continuous investigation of the two elements in question. Instead of concluding them as two separate dimensions, it is crucial to periodically revisit and examine the evolution of these two aspects over time. As higher education institutions become more mature in their data analytics capabilities, the distinction between culture and investment may blur. Mature institutions might integrate their cultural appreciation of data analytics more deeply with their strategic investments in technology and talent. This can result in a more unified approach where cultural attitudes and financial commitments reinforce each other. To measure this possibility, we propose a continual measurement of institution's research analytics capabilities over multiple time points to examine how changes in one dimension correlate with changes in the other over time. This approach could provide insights into whether the two dimensions converge.

Other measurement properties

Overall, respondents confirmed our assumptions and framework. The only changes made to the instrument included updating rating scales and the wording of several items which were not equally interpreted by all respondents. Examinations of other measurement properties also found that the RAC Scale exhibits good item fit, good item reliability, person reliability, item separation and person separation qualities. The fit statistics results confirm that all the items on the RAC Scale are productive for measurement. Rasch analyses detected insufficient distinctions between response categories, especially between categories 2 and 3. After reexamination of the RAC Scale by removing category 3, the Andrich thresholds of all response categories of the revised RAC Scale are performing as expected. This finding points to the recommendation of removing category 3 "Neither Agree nor Disagree" from the RAC Scale. Drawing findings from the validation study of the RAC Scale using Rasch rating scale model, in terms of individual item fit, reliability and separation indexes, the revised RAC Scale, featuring a transition from a 5-point to a 4-point Likert response scale, is proven to be demonstrating strong evidence of validity and reliability. While the multidimensionality of the RAC Scale warrants further investigation, overall, the instrument is well-suited for practical use in the field of higher education research administration.

Limitations and next steps

One of the limitations of the study is a nonprobability sampling method with the survey piloted through posting an online survey link in a research administration community social media page. The sampling method is only limited to research administration professionals who access the community page of the social media platform during the period of survey administration. Suggestions for future development of this study include the adoption of a more robust sampling method, such as stratified or systematic random sampling. In addition, not all research administrators work with or have roles that include the use of research data. As a result, they may either not know how to respond to many of the survey items or not complete the survey at all.

This validated and revised survey instrument will be deployed in a full survey implementation across the United States to collect empirical data to inform the field of research administration. As data from ongoing survey disseminations are used to further refine the survey instrument, it is recommended that future research integrates qualitative research methods, such as interviews or case studies with institutions recognized for their maturity in analytics, could shed light on how these institutions perceive and enact the relationship between culture and investment. Another recommendation in future survey dissemination is to diversify our sample by including responses from institutions at various stages of research analytics capabilities. Insights from these institutions will be instrumental in understanding the interrelationships between the dimensions in the survey instrument. Further investigations on the potential relationships enhance the development of a theoretical model that posits the integration of these dimensions as a characteristic of research analytics capabilities. The modeling of these relationships can then be empirically tested using structural equation modeling to see if the data supports the model. Finally, in future research, it is advisable to consider the impact that any existing structures, enabling and/or disabling conditions may have on research analytics capabilities. External pressures such as regulatory requirements, competitive forces and economic conditions, for instance, may influence how higher education institutions prioritize and integrate their research and analytics culture and investments.

Contributions to the field of research

The primary contribution of this survey validation study is that research administration professionals now have this validated and revised tool, specifically designed for the field of higher education research administration, to measure data analytics capabilities of their functional areas and units. They no longer must rely on existing instruments that measure data analytics capabilities in general or specific to another discipline. Such instruments often require adaptations to align accurately with the unique elements of the research administration profession. This survey instrument, once validated and revised based on the measurement properties, further creates a unique opportunity to collect empirical data related to the use of data-informed decision making, the use of research analytics, benchmarking and challenges research administrators have related to strategic decision making within their institutions. Findings from a fully deployed survey will provide data on the state of the field as it relates to how institutions use data-informed decision-making to drive strategy and grow the research enterprise—both for operational efficiency and growths within research funding.

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