Data Repositories as a Service Supporting Research and Teaching: A Conceptual Framework

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I. Introduction

Some recent studies have explored data curation activities to promote research data sharing and reuse through data repositories.[1] Fewer studies, however, have used theoretical models to explain library faculty users' data repository use behaviors. This study mainly focuses on institutional data repositories (IDR) as a library service supporting research and teaching in academic communities. The purpose of this study is to explore a conceptual framework for IDR as a service facilitating research data engagement in both research and teaching. Through examining the relationship between faculty users' data engagement and their intentions to use IDR, the study explains whether and how IDR can be used to support research and teaching in academic environments.

Employing an integrated theoretical framework combining the theory of planned behavior[2] and the technology acceptance model,[3] this study identifies some subjective beliefs and behavioral control factors related to research data engagement and proposes that these factors directly or indirectly associate with intentions to use IDR for research and teaching. The behavioral factors include data practice in research and teaching, demand for research data management, and use of disciplinary data repositories; while the subjective factors include attitudinal and normative factors related to data engagement.

For many academic communities, especially communities in which there are potential needs for IDR yet not much experience with its operating mechanism, it is essential to make stakeholders aware of the values of data repositories to the communities. From this perspective, the current study proposes an IDR conceptual framework to help stakeholders better understand how IDR can be used to support academic research and teaching. Explaining relationships between intentions to use IDR and related factors, this study will also provide valuable insights for academic libraries to develop customized data curation and data services and add more values to library services.

II. Literature Review

Studies have revealed that researchers are required by more and more funding agencies to submit their data management plans with their grant applications and are encouraged by journal publishers and scholarly communities to provide access to their research data.[4] In this context, research data is not only material supporting research but also becomes one type of publications that can be cited and reused for repurposed new research projects. Around research activities, research data is continually collected, managed, and reused to support different types of research investigations in natural sciences, social sciences, and humanity disciplines.

In addition to research, some undergraduate and graduate courses, such as research methods and statistics in multiple disciplines, commonly utilize data for teaching. To some extent, finding appropriate and quality data is critical to the success of these courses. Research data engagement in academic environments therefore include both the practice of research data management (RDM) and using data for teaching. RDM practice involves research data collection, preservation, and access for data sharing and reuse.[5] Using data for teaching usually involves data finding, data preparation, and data analysis for teaching purposes.

To support researchers' needs for RDM mandated by funding agencies and publishers, more and more disciplinary data repositories have been used to provide trusted infrastructures to secure data management activities, such as data storage, data organization, data documentation, and data dissemination.[6] In addition to offering data management tools (i.e., software, hardware, and infrastructure) and self-deposit functionalities (i.e., storing, publishing, and sharing), more and more academic libraries have developed data curation policies and data curation techniques (i.e., employing effective metadata, indexing, and arrangement to improve data discovery) to facilitate data sharing and reuse.[7]

Data curation is thought as a central element from the lens of data stewardship.[8] In addition to serving the needs for research data management, data repository services, including providing data management tools and data curation services, can bring ancillary values to an academic community. Facilitating research data sharing and reuse, data repository services can help nurture a culture of openness and sharing among community members.[9] Moreover, data consumers, including researchers, instructors, and students, can use research data in IDR for repurposed research, teaching, and learning.[10]

According to the technology acceptance model (TAM), individuals' information system acceptance is related to four factors—perceived usefulness (PU), perceived ease of use (PEOU), behavioral intention, and behavior.[11] It assumes that PU can directly predict behavioral intention and behavior, while PEOU is a significant antecedent of PU and can indirectly affect the acceptance through PU.

Focusing on the behavior over which individuals have incomplete volitional control, the theory of planned behavior (TPB) helps explain human behavior in specific contexts and design effective interventions to produce behavior change.[12] TPB argues that attitudes toward the behavior, subjective norms with respect to the behavior, and perceived control over the behavior are the factors which can predict behavioral intentions. In addition, in the context of predicting behavior from intentions and perceptions of control, beliefs about resources and opportunities are viewed as underlying perceived behavioral control.[13]

For this study, a conceptual framework based on TAM and TPB is developed, and nine factors related to data engagement are identified to help explain intentions to use IDR. These factors include six subjective beliefs and three behavioral controls, which are assumed to be interrelated factors which can directly or indirectly impact intentions to use IDR for research and for teaching. The subjective factors include subjective norm of data sharing (SNDS) and reuse (SNDR), attitude toward data sharing (ADS) and reuse (ADR), attitude toward data curation and data services (ADCDS), and attitude toward using data for teaching (ADT). The behavioral factors include demand for research data management (DRDM), perceived usefulness of disciplinary data repositories (PUDDR), and data engagement (DE).

According to the conceptual model, eight research questions are designed to investigate the relationship between behavioral and subjective factors and intentions to use institutional data repositories for research (IDRR) and for teaching (IDRT).

RQ1: What behavioral and subjective factors are correlated with IDRR?

RQ2: What behavioral and subjective factors are correlated with IDRT?

RQ3: What subjective and behavioral factors regarding DE are correlated with each other?

RQ4: Do subjective factors mediate the effects of behavioral factors on IDRR?

RQ5: Do subjective factors mediate the effects of behavioral factors on IDRT?

RQ6: What subjective and behavioral factors influence each other?

RQ7: What factors directly and singly influence IDRR?

RQ8: What factors directly and singly influence IDRT?

The first two questions investigate what factors are correlated with IDRR and IDRT. Research question 3 investigates the associations between behavioral factors and subjective factors. Research questions 4 and 5 examine if subjective beliefs mediate the effects of behavioral control factors on IDRR and on IDRT, respectively. Research questions 6, 7 and 8 examine what behavioral and subjective factors have direct or indirect effects on IDRR and on IDRT, respectively.

III. Research Method

This study uses an online survey to examine the relationship between faculty users' subjective and behavioral factors and intentions to use IDR for research and for teaching. The investigated relationships include (1) the relationship between the factors and IDRR; (2) the relationship between the factors and IDRT; (3) the mediations between the factors on IDRR; and (4) the mediations between the factors on IDRT.

III.1 Key Concepts and Measurements

According to the conceptual model, a total of eleven main constructs are defined and measured with a survey instrument. Intention to use IDR for research (IDRR) and intention to use IDR for teaching (IDRT) are two dependent variables. IDRR refers to the degree to which faculty users expect to deposit their research data in IDR, share their research data via IDR, and reuse secondary research data in IDR for repurposed research. IDRT refers to the degree to which faculty users expect to use research data in IDR for teaching purposes.

Data engagement (DE), demand for research data management (DRDM), and perceived usefulness of disciplinary data repository (PUDDR) are three behavioral control factors assumed to associate with IDRR and IDRT directly or indirectly. DE refers to how frequently faculty users engage in research data management activities (i.e., data deposit, data sharing, and data reuse for research) and finding and using research data for teaching. DRDM is a loose construct containing participants' awareness of RDM policies and a resultant need for RDM support. PUDDR refers to the degree to which faculty users are aware of the availability of disciplinary data repositories (DDR) for data deposit, data sharing, and data reuse.

Attitude toward data curation and data services (ADCDS) and attitude toward using research data for teaching (ADT) are two attitudinal factors assumed to associate with IDRR, IDRT, and behavioral factors directly or indirectly. ADCDS refers to the degrees to which faculty users consider data curation (i.e., guidance for data deposit and metadata) and data services (i.e., data finding, preparation and visualization; statistical analysis support) is important for their data engagement. ADT refers to the degree to which faculty users believe that using research data is important for teaching.

Meanwhile, attitude toward data sharing (ADS), attitude toward data reuse (ADR), subjective norm of data sharing (SNDS), and subjective norm of data reuse (SNDR) are four attitudinal and normative factors assumed to associate with IDRR, IDRT, and behavioral factors directly or indirectly. ADS refer to the degree to which faculty users think that sharing research data is good, while ADR refers to the degree to which faculty users believe that it is valuable to reuse others' research data. SND refers to the degree to which faculty users consider that data sharing is a common research practice in their research communities, while SNDR refers to the degree to which faculty users think that data reuse is a common research practice in their research communities.

III.2 Survey Administration and Procedure

An online administered survey questionnaire was used as the research instrument of this study. The survey questionnaire was adapted from prior studies[14] and further designed based on the conceptual framework combing the theory of planned behavior (TPB) and the technology acceptance model (TAM).

The online survey was hosted on Qualtrics and distributed to faculty participants in a senior college in the northern United States. The volunteer participants were recruited in the beginnings of fall 2019 and fall 2020. Using an online survey questionnaire, the study asked the participants to rate their attitudinal and normative beliefs and behavioral experience with data engagement and disciplinary data repositories using a 7-point Likert scale. The participants were also asked to provide comments on data services.

III.3 Participants

A total of 127 faculty participants were recruited. Some participants' records were removed because they did not complete the key question about their research publications. After screening the data, the records of 97 participants were retained.

The participants were diverse in gender, age, education, status, and position. Respondents' age ranged from 20s to 60s, and female (66%) were more than male (30.9%). Most respondents were faculty with a PhD or doctoral degree (72.2%) and held a rank of professorship (70.1%). More than half of respondents were tenured or on tenure track (66%).

The participants were also diverse in research and teaching fields and publication experience. More than a third (39.2%) were in social sciences, followed by arts and humanities (25.8%), math and natural sciences (15.5%), and education (14.4%). Most respondents published empirical journal articles in past five years or five years ago (69.1%). Some respondents had non-empirical publications (13.4%), while some did not have research publications (17.5%).

Most participants answered the question asking if they used data for teaching (90.7%). More than 40% respondents answered "yes," while almost the same number of respondents answered "no" (41.2%). Meanwhile, some were not sure or did not answer the question (18.6%).

IV. Data Analysis Results

IV.1 Inter-item Reliabilities

Inter-item reliabilities (Cronbach's α) tests were conducted to examine the inter-item reliabilities of the constructs (Table 1). The results showed that Cronbach's α, ranging from 0.53 (DRDM) to 0.96 (ADR and SNDR), and all the measured items had more than the acceptable value of 0.45.[15] The results supported the construct inter-item reliabilities for further data analysis.

Table 1: Cronbach's α, CR and AVE values

Variables	Cronbach's *α*	*N*
IDRR	.94	57
DRDM	.53	63

Variables	Cronbach's α	N
PUDDR	.95	60
DE	.85	25
ADS	.84	53
ADR	.96	53
SNDS	.89	55
SNDR	.96	55
ADCDS	.87	78
ADT	.83	30

IV.2 Pearson Correlations and Construct Validities

Pearson correlation tests were performed and the square roots of the constructs' AVEs were calculated based on principal component analysis results to examine the construct validities, including convergent and discriminant validities. The results (Table 2) showed that intention to use IDR for research (IDRR) was significantly, moderately, and positively correlated ($.3 < r < .7$) with attitude toward data curation and data services (ADCDS), perceived usefulness of disciplinary data repository (PUDDR), and demand for research data management (DRDM). Intention to use IDR for teaching (IDRT) was significantly, moderately, and positively correlated ($.3 < r < .7$) with PUDDR, attitude toward using data for teaching (ADT), attitude toward data sharing (ADS), and subjective norm of data sharing (SNDS).

Meanwhile, some significant, moderate, and positive correlations ($.3 < r < .7$) were also found (Table 2) between subjective and behavioral factors, such as data engagement (DE) with PUDDR, ADT, ADS, ADR, SNDS and subjective norm of data reuse (SNDR); PUDDR with ADT, SNDR, and SNDS; DRDM with ADCDS. Moreover, ADS, ADR, SNDR and SNDS were significantly, moderately, and positively correlated ($.3 < r < .7$) with each other. The correlation results showed the convergent validities of the key constructs and suggested that mediation effects may exist between attitudinal and behavioral factors on IDRR and IDRT.

In addition, the results showed that the square roots of the constructs' AVEs (bolded in Table 2) were greater than the inter-construct correlations, and this indicated the discriminant validities of different constructs. The square roots of AVEs for the same construct ranged from 0.73 (DE) to 0.96 (ADR and SNDR), which were greater than the correlation coefficients between different constructs (ranging from −0.01 to 0.68). The inter-construct correlations and constructs' AVEs therefore supported reliable convergent and discriminant validities of the constructs.

Table 2. Pearson correlation matrix and square roots of AVEs

	IDRR	IDRT	ADCDS	DRDM	PUDDR	ADT	DE	ADS	ADR	SNDR	SNDS
IDRR	**.94**										
IDRT	.36										
ADCDS	.53***	0.27	**.89**								
DRDM	.47***	0.38	.49***	**.82**							
PUDDR	.30*	.43*	.20	.21	**.95**						
ADT	.27	.53**	.15	.21	.49**	**.79**					
DE	.15	.28	-.05	.25	.49***	.38*	**.73**				
ADS	.08	.43*	-.04	.00	.22	.18	.67***	**.87**			
ADR	.04	.22	.04	.03	.20	.32	.52***	.51***	**.96**		
SNDR	.01	.23	-.04	.02	.43**	.13	.68***	.58***	.61***	**.96**	
SNDS	0.14	.42*	0.09	.28*	.43***	0.31	.58***	.54**	.32*	.61***	**.91**

Note: *p < .05; ** p < .01; *** p < .001. The numbers in bold were square roots of AVEs.

IV.3 Structural Equation Modeling Tests

As the constructs showed acceptable validities, the structural modeling was estimated using R. According to the correlation matrix and considering the variate sample sizes of key constructs—IDRR ($N = 57$) and IDRT ($N = 34$) (Table 1), two structural equation modeling tests, (1) SEM for IDRR, ADCDS and DRDM; (2) SEM for IDRT, ADT and PUDD—were conducted to examine the relationship between the attitudinal and behavioral factors and IDRR and IDRT, respectively.

The first SEM was conducted to examine the relationship between IDRR and DRDM and ADCDS. Considering the limitation of sample size and following the suggestion of the minimum ratio (5 cases per variable) for sufficient analysis when latent variables have multiple indicators,[16] the mean of three observed items for IDRR was computed and hence IDRR was presented as an observed variable in the model. The test output showed a good-fitting model (0.99 < CFI /TLI <1, RMSEA =.029, SRMR = .035). The attitudinal factor ADCDS was found to have a significant positive effect on IDRR ($\beta = 0.55$, $p < 0.05$). The significant effect of behavioral factor DRDM on IDRR ($\beta = .84$, $p < 0.001$) became unsignificant when this relationship was significantly and positively mediated by the effect of DRDM on ADCDS ($\beta = 0.59$, $p < 0.01$). This suggested that ADCDS fully mediated the effect of DRDM on IDRR.

The second SEM was conducted to examine the relationship between IDRT and ADT and PUDDR. IDRT was an observed variable. Considering the limitation of sample size, the mean of four observed variables for ADT was computed and hence ADT was presented as an observed variable in the model. The test output showed a good-fitting model (0.99 < CFI /TLI <1, RMSEA =.034, SRMR = .033). The attitudinal factor ADT significantly and positively influenced IDRT (β = 0.74, p < 0.01). The significant and positive effect of behavioral factor PUDDR on IDRR (β = .34, p < 0.05) became unsignificant when this relationship was significantly and positively mediated by the effect of PUDDR on ADT (β = .25, p < 0.05). This suggested that ADT fully mediated the effect of PUDDR on IDRT.

IV.4 Regression Tests

Next, regression tests were conducted to investigate the relationship between the subjective and behavioral factors, which were correlated with one or two factors in the two SEMs. The single regression test results (Table 3) showed that (1) PUDDR statistically significantly predicted IDRR, SNDS, and SNDR; (2) ADS statistically significantly predicted IDRT; (3) SNDS statistically significantly predicted DRDM; (4) DE statistically significantly predicted ADT and PUDDR, and (5) ADS, ADR, SNDS, and SNDR statistically significantly and respectively predicted DE.

Table 4 summarizes the testing results to answer the eight research questions. A full conceptual model for IDR as a service supporting research and teaching is summarized as Figure 1.

V. Discussion

The conceptual model for institutional data repositories (IDR) based on the data analysis results demonstrates how faculty users' intentions to use IDR for research and for teaching associate with their subjective beliefs and behavioral controls regarding their data engagement (Figure 1).

The model shows that faculty users' subjective beliefs (i.e., ADCDS, ADT, ADS, ADR, SNDS, and SNDR) and behavioral controls (DE, DRDM, and PUDDR) directly or indirectly influence their intentions to use institutional data repositories for research (IDRR) and for teaching (IDRT). It is identified that perceived usefulness of disciplinary data repository (PUDDR) influences attitude toward using data for teaching (ADT), and then ADT in turn influences IDRT. It is noticed that ADT fully mediates the effect of PUDDR on IDRT, which suggests that the effect of PUDDR on IDRT goes through ADT.

Table 3. Summary of single regression reults

Single Regression Predictions	***B***	***SE B***	β	R^2	***F***	$df_{regression}$	$df_{residual}$
PUDDR predicting IDRR	.25	.11	.30*	.09	5.67*	1	57
SNDS predicting DRDM	.25	.12	.28*	.08	4.49*	1	53
DE predicting ADT	.72	.29	.38*	.15	6.43*	1	38
ADS predicting IDRT	.47	.21	.43*	.19	5.06*	1	22
DE predicting PUDDR	.53	.13	.49*	.24	6.43***	1	55
PUDDR predicting SNDS	.42	.12	.43	.19	12.33**	1	53

Single Regression Predictions	*B*	*SE B*	*β*	R^2	*F*	$df_{regression}$	$df_{residual}$
PUDDR predicting SNDR	.45	.13	.43	.19	12.22	1	53
ADS predicting DE	.96	.15	.67	.44	42.23***	1	53
ADR predicting DE	.90	.20	.52	.27	18.82***	1	53
SNDS predicting DE	.62	.12	.58	.34	27.29***	1	53
SNDR predicting DE	.67	.01	.68	.47	46.35***	1	53

Note: *p < .05; ** p < .01; *** p < .001.

Meanwhile, faculty users' demands for research data management (DRDM) influence their attitudes toward data curation and data services (ADSDC), and ADSDC in turn influences IDRR. Similarly, ADSDC fully mediates the effect of DRDM on IDRR, which suggests that the effect of DRDM on IDRR goes through ADSDC. Moreover, subjective norm of data sharing (SNDS) predicts DRDM, but it has no direct effect on IDRR, while faculty users' data engagement (DE) can influence SNDS. This suggests that SNDS could be an intervening factor through which DE can facilitate DRDM and they in turn influence ADCDS, which can facilitate IDRR.

In addition to influencing IDRT through ADT, PUDDR is identified to predict IDRR independently. Meanwhile, ADS is identified to predict IDRT independently. Also, interrelated relationships exist between subjective factors (ADS, ADR, SNDR, and SNDS) and behavioral factors (DE, DRDM, and PUDDR). The findings suggest that ADS might be an intervening factor between DE and IDRT, and DE might influence DRDM through SNDS—and in turn they can influence ADCDS and then facilitate IDRR.

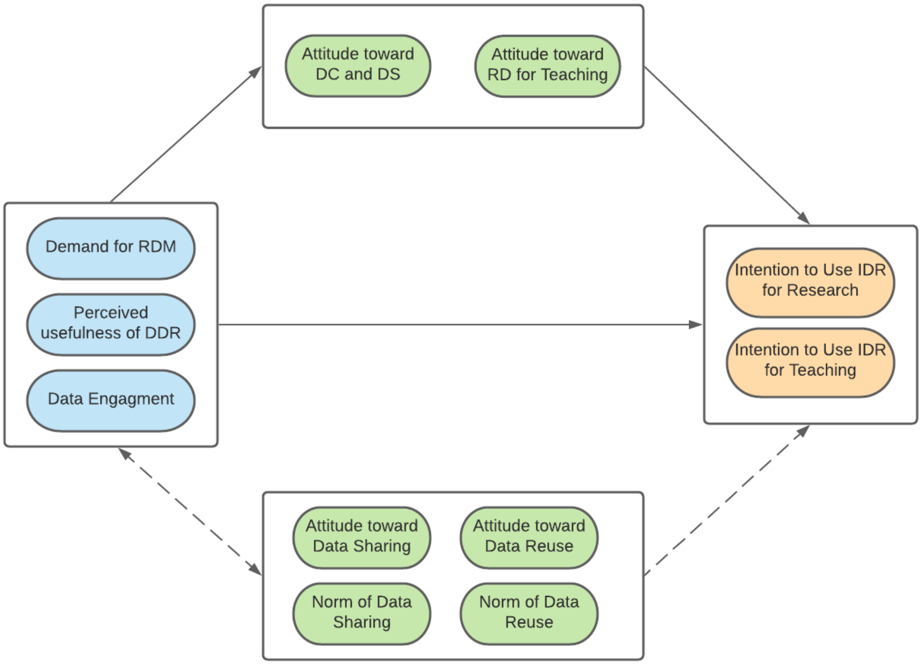
The above findings suggest that the interrelated factors attitude toward using data for teaching (ADT), perceived usefulness of disciplinary data repository (PUDDR), and data engagement (DE) are three main factors influencing intentions to use institutional data repositories for teaching (IDRT). Meanwhile, the interrelated factors attitude toward data curation and data services (ADCDS) and demand for research data management (DRDM), along with PUDDR, are three main factors affecting intentions to use institutional data repositories for research (IDRR). PUDDR therefore is a key factor, which influences intentions to use IDR for research and for teaching.

Table 4. Summary of research questions results

RQs	**Statements**	**Result**	**Analysis Method**
RQ1	What subjective and behavioral factors are correlated with IDRR?	IDRR significantly correlated with ADCDS, DRDM and PUDDR.	Pearson Correlation
RQ2	What subjective and behavioral factors are correlated with IDRT?	IDRT significantly correlated with PUDDR, ADT, ADS and SNDS.	Pearson Correlation

RQs	Statements	Result	Analysis Method
RQ3	What subjective and behavioral factors are correlated with each other?	DRDM significantly correlated with ADCDS. PUDDR significantly correlated with ADT, SNDR and SNDS. DE significantly correlated with PUDDR, ADT, ADS, ADR, SNDS and SNDR. ADS significantly correlated with ADR, SNDR and SNDS. ADR significantly correlated with SNDR and SNDS. SNDR significantly correlated SNDS.	Pearson Correlation
RQ4	Do subjective factors mediate the effects of behavioral factors on IDRR?	ADCDS fully mediated the effect of DRDM on IDRR.	SEM
RQ5	Do subjective factors mediate the effects of behavioral factors on IDRT?	ADT fully mediated the effect of PUDDR on IDRR.	SEM
RQ6	What subjective and behavioral factors influence each other?	PUDDR significantly predicted IDRR, SNDS and SNDR. ADS significantly predicted IDRT and DE. SNDS significantly predicted DRDM and DE. ADR and SNDR respectively significantly predicted DE. DE significantly predicted ADT. DE significantly predicted PUDDR.	Single regression
RQ7	What factors directly and singly influence IDRR?	PUDDR significantly predicted IDRR.	Single regression
RQ8	What factors directly and singly influence IDRT?	ADS significantly predicted IDRT	Single regression

Figure 1. The conceptual model for IDR as a service supporting research and teaching



V.1 Theoretical and Practical Implications

This research has significant theoretical and practical implications. The findings of this study validate the theoretical assumption of TAM and TPB that individuals' behavioral experience influence their attitudinal beliefs and they in turn influence their intentions to use a new system. Through investigating factors related to data engagement and intentions to use IDR, this study expands the application of TAM and TPB and enrich the theories by adding more interrelated factors to an exploratory model.

Practically, this study suggests that it is critical to enhance faculty users' awareness of data curation and data services (DCDS) and develop more customized data services to support faculty users' research data management and data finding and data use for teaching. The faculty users' comments on DCDS indicate that they would benefit from instructions or workshops on data findings, data processing, good sources for datasets, and access and use data tools. Meanwhile, they also need library data services to help them access special software and resources to support their research.

The study implies that broadcasting data curation and data services to faculty users, particularly those who have not used IDR and DCDS yet, would help them understand how DCDS can support their research data management and using data for teaching. It also suggests that customized library data curation and data services may facilitate faculty users' research productivity and help them find and use data for teaching more effectively.

In addition, the study suggests that it is worth nurturing a culture of data sharing and data reuse to facilitate data engagement activities. An encouraging culture may positively influence faculty users' attitudes toward data sharing and reuse and then they may in turn promote data engagement and accordingly facilitate the use of data repositories, which will benefit both research and teaching of an academic community.

V.2 Limitations

This study has some limitations in methodologies. First, the sample size is not big enough to conduct more complicated structural equations modeling tests, and this limited the interpretation of data analysis results. Considering the model fitness, some latent variables were turned into observed variables through computations (i.e., IDRR, ADT and DE) and this results in some vagueness in discussions.

Moreover, some concepts need further explorations so that they can be defined more strictly. For example, the inter-item reliability of DRDM is poor, which might result from its fewer observed items. This calls for more qualitative studies to explore more closely faculty users' motivations for research data management and demands for RDM support.

VI. Conclusion

This study examines how library faculty users' subjective belief and behavioral control factors influence their IDR use behaviors. The findings of this study make an important contribution to the data repository literature by providing a broad explanation of the relationships between the factors and IDR use behaviors. The study suggests that subjective norms of data sharing and reuse, perceived usefulness, attitude toward data curation and data services, attitude toward using data for teaching, and attitude toward data reuse should be considered in any effort to facilitate data engagement and IDR use. Moreover, faculty users' intentions to use IDR for research and for teaching can be facilitated by customized data curation and data services. The study also emphasizes that nurturing a culture of positive norms of data sharing and reuse would make faculty users' research and teaching benefit more from the active data engagement in the whole community.

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Endnotes

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