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Psychological Factors in Research Data Management

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Abstract

Data sharing and open science are increasingly emphasized as a means to increase transparency and reproducibility in science. Despite the consensus on the importance of research data management (RDM), the public availability of data sets remains limited, and researchers often fail to share data upon request. This study explores the psychological mechanisms underlying RDM intentions, using the Theory of Planned Behavior (TPB) as a framework. TPB, a prominent theory in psychology, links beliefs about behavior to intentions and actual behavior, taking into account attitudes, subjective norms, and perceived behavioral control. This paper applies the theory to RDM, addressing the ambivalence researchers experience towards data sharing, characterized by simultaneous positive and negative evaluations. Empirical analysis of a reused data set supports the existence of ambivalent attitudes towards data sharing. Furthermore, we provide insights from psychological literature as well as anecdotal evidence from practical RDM-service experience to discuss all three factors (attitudes, subjective norms, and perceived behavioral control). To address these factors in practice, we propose strategies for RDM staff and institutions, that emphasize transparent communication, supportive environments, and practical resources that pave the way for good RDM. However, addressing psychological factors concerning data publication can only overcome a small part of barriers to data sharing, and structural changes are needed first.

1 Introduction

Data sharing and open science have become recurring topics for researchers, funders and universities. Sharing data publicly is supposed to increase trust and transparency in science. However, a *Science* survey shows that most results are not replicable by researchers themselves, let alone by others (Baker, 2016). Although most people seem convinced that proper management and the sharing of research data is an integral part of research and good research practice requires storing data for at least ten years, very few data sets are available for reuse. And although many researchers indicate to provide their data “upon request”, research has shown that this is mostly not the case when they are actually asked to share their data (Tedersoo et al., 2021). This is likely due to data loss, conflicting priorities or time constraints rather than intentional misconduct. This work will examine the psychological mechanisms concerning intentions regarding Research Data Management (RDM) and provides suggestions on how to facilitate subsequent behavior through the Theory of Planned Behavior (Ajzen, 1991).

The Theory of Planned Behavior (TPB) by Isaac Ajzen in 1991 is one of the most influential theories in psychological research. With over 149 000 citations listed on Google Scholar (March 2025) it is updated and extended continuously and has led to a bet-

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ter understanding of why people do what they do. The theory is supported by meta-analyses (e.g., Armitage and Conner (2001)), and has been applied successfully to domains such as health-related behaviors (Rich et al., 2015), smoking (Topa & Moriano, 2010), or consumer behavior (Han & Stoel, 2017). However, it should be noted, that there is an ongoing scientific discussion concerning the components and their interconnections, as might be expected given the inherent oversimplification of such a model. In this work, we aim to apply the Theory of Planned Behavior to research data management in order to come to a better understanding of researchers' application of RDM, psychological barriers, apparent contradictions and future research directions. We will extend these findings with both reports from practical experience and insights from previous research. Specifically, we address social psychological literature on attitudes, particularly attitudinal ambivalence, as well as literature addressing intentions, habits and values. In addition, the part on attitudes and ambivalence will be illustrated with the help of a secondary analysis of an existing data set.

The current work aims to help RDM staff and researchers understand the development of attitudes towards RDM and their interrelationship with RDM compliant intentions and behavior – in short, it aims to help understand why people behave the way they do in terms of managing their research data. We focus on RDM-related behavior generally, covering the research data life cycle from project planning, data collection, organization, analysis, sharing, and archiving, to re-use (Cox & Tam, 2018). Furthermore, we use the publication of research data as a specific example since this is a central outcome of good RDM practice. Additionally, we share our experience of the practical RDM service implementation at TU Dortmund University provided by the central research data service revealing detailed insight as well as suggestions for RDM services that are under development.

However, it should be noted that this article focuses primarily on psychological factors concerning data sharing – of course there are many more relevant environmental factors (e.g., on a structural or technological level) which may have a strong impact on sharing data. A discussion of those factors is provided, for example, by Fetcher and colleagues, 2015.

2 The Theory of Planned Behavior

The Theory of Planned Behavior aims to explain how beliefs are linked to intentions and subsequent behavior (see Figure 1). These beliefs include people's attitudes about a certain behavior, the perceived norms associated with the behavior and the perceived behavioral control over the respective behavior. It is important to note that the facts concerning social norms or the difficulty of a behavior are irrelevant; rather, people's perception of these aspects matter. E.g., beliefs about data sharing (individual attitudes, the perception of norms, and the perceived behavioral control) influence the decision to publish a data set (intention), which may then lead to the publication of a data set (behavior). In the following, we will elaborate on each of these beliefs in the context of research data management.

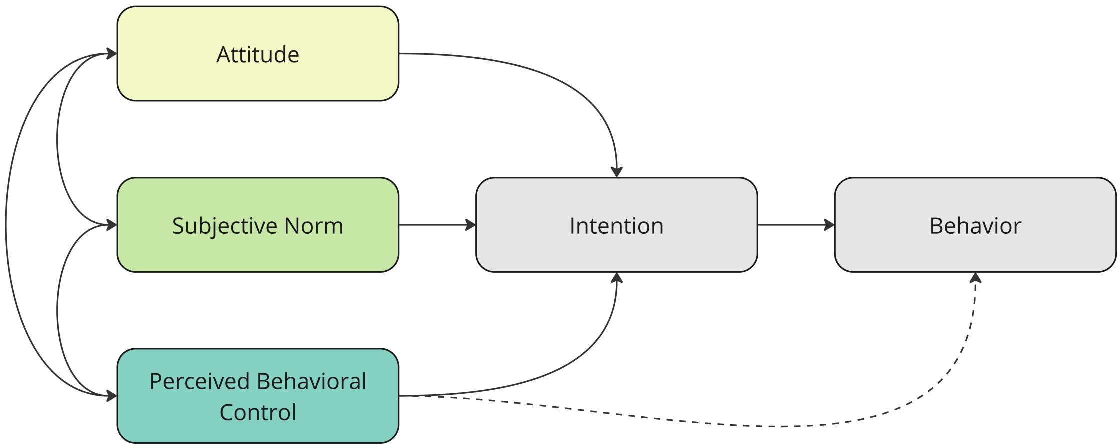

Figure 1: Theory of Planned Behavior (Ajzen, 1991). Attitude, Subjective Norm and Perceived Behavioral Control influence the formation of an intention and subsequent behavior.

2.1 Attitude towards the behaviour

An attitude towards an attitude object consists of all positive and negative evaluations about said attitude object (Priester & Petty, 1996). Concerning RDM, these evaluations may depend on the specific RDM practice (e.g., making data available to others, implementing standard documentation practices), personal preference and institutional policies. However, many evaluations may occur rather universally. Positive evaluations might be simplifying communication between researchers, making research more sustainable, accelerating science, the motivation to engage in good research practice, career advantages, etc. Negative evaluations may be more concrete and personal, such as more work in the short term, sharing research methods or data and potentially losing a head start compared to colleagues, having to invest valuable resources, fear of data misuse, career disadvantages, etc. (Pook-Kolb, 2021; Stieglitz et al., 2020). In a series of semi structures interviews with 62 principle investigators, we previously identified a lack of time, a lack of staff, erroneous data, a change of research focus, weaknesses in the study design, and a lack of informative value as obstacles for data publication (Kletke et al., 2024). Researchers might experience these evaluations to a varying degree, but it is likely that they are aware of these evaluations at the same time. This awareness reflects in the overlap between evaluation contents and aspects of social norms and behavioral control.

Moreover, the likelihood and value of an expected consequence influences the impact of evaluations. People are more highly motivated to show a certain behavior (e.g., sharing data) when the expected outcome is considered likely and of high value (Wigfield & Eccles, 2000). The problem with RDM and data sharing in particular may be, that the advantages are not visible directly but rather become evident in the long term, and when many people participate. However, the disadvantages, such as being resource-intensive and time consuming, are evident immediately. Concerning RDM, the perceived value of data sharing has been linked to the intention to share research data (Stieglitz et al., 2020). Here, possible advantages (e.g., reputation and network possibilities) and disadvantages (e.g., career disadvantages) correlated with the perceived value, while the intention to share research data was additionally associated with the fear of data misuse and the fear of losing one's unique value in research. While the authors did not analyze attitudinal conflict directly, it seems evident, that positive and negative evaluations were prevalent at the same time, potentially causing attitudinal ambivalence.

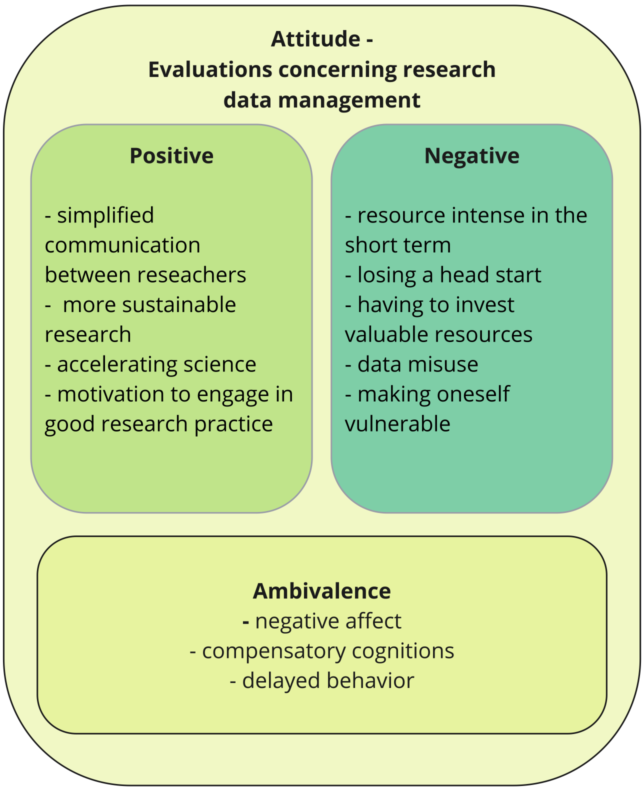

Figure 2: Positive and negative evaluations concerning RDM constitute RDM-related attitudes and may cause aversive attitudinal ambivalence.

Ambivalence refers to the notion of strong, opposing evaluations at the same time (Priester & Petty, 1996). Ambivalence is experienced as a state of conflict including a

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feeling of being torn between the two sides of an evaluation. This attitudinal conflict leads to choice delay and negative affect (van Harreveld et al., 2015). A conflicting attitude about data sharing may lead to postponing the decision on whether to share one's data and to a negative feeling about the topic altogether. Ambivalence has been investigated concerning topics ranging from the social domain, such as relationships or politics, to more technological domains, such as artificial intelligence and robots (For an overview see: Stapels 2021; van Harreveld et al., 2015). Technology seems to evoke especially high levels of ambivalence due to its apparent advantages and intransparent risks at the same time, leading to a feeling of conflict and to avoidance. Concretely, feeling ambivalent towards the topic of RDM may lead to feeling negatively about RDM and postponing engaging with it (See Figure 2). As a result, researchers may be prone to avoiding the topic altogether, despite being convinced of the advantages. In mixed-methods survey among over 300 members of the German Psychological Society researchers indicated hopes as well as fears towards data sharing, which were uncorrelated – that is, more positive attitudes did not go with less negative attitudes and vice versa (Abele-Brehm et al., 2019). Hopes and fears exist at the same time, which is an indicator of ambivalence.

Empirical Analysis of Ambivalence in Attitudes towards Data Sharing

To investigate ambivalence towards RDM, specifically data sharing, empirically, we had the opportunity to re-use a large data set created by the BMBF funded UNEKE project that is publicly available (Stieglitz et al., 2020; Wilms et al., 2020). The reused data set contains data of N = 2190 members of German universities and assessed researchers practices and attitudes towards data sharing. Data were collected via an online survey that was distributed by the administration of the respective university. The survey included items regarding RDM practice as well as evaluations concerning RDM assessed with adapted and self-developed questionnaires. Further information on the measures and a codebook is provided with the original data set.

We hypothesized that positive and negative evaluations concerning data sharing would be present at the same time, operationalized as objective ambivalence (Thompson et al., 1995). We utilize the "Griffin" formula of ambivalence $(P+N)/2 - |P - N|$ which combines positive evaluations (P) and negative evaluations (N) to a score of ambivalence. Low values indicate the absence of ambivalence while high values indicate the presence of ambivalence. Due to the secondary nature of analyses, no control group could be tested against. That is why we investigated ambivalence on an absolute level. We hypothesized that using this formula, ambivalence would be evident, while using the aggregated positive evaluations as P and the aggregated negative evaluations as N. All variables concerning positive evaluations (e.g., "Sharing my primary research data is valuable for me") towards data sharing were aggregated to a positivity mean and all variables concerning negative evaluations (e.g., "It would take me a lot of time to share my primary research data") were aggregated to a negativity mean of 23 items, respectively. The preregistration was uploaded before the analyses were performed and can be found here (https://osf.io/ur5vf) and the reproducible analysis code can be found in the TUDO Data Repository (https://doi.org/10.4232/1.13327).

As in previous work concerning ambivalence, high levels of ambivalence are determined by testing against the lower tercile of the scale (see also Stapels and Eyssel (2022)). In the current data set, all items were answered on a scale from 1 to 5, so when employing the above mentioned formula: (P+N)/2 - |P – N|, values between -1 and 5 are possible, with the lower tercile being 1. We tested whether the ambivalence score is higher than 1 with a one sample t-test and a significance level of $p < .05$.

Results were in line with the hypothesis that attitudes towards data sharing are ambivalent. While people showed moderate positive ($M = 3.13$, $SD = 0.83$, empirical range = 1 – 5) as well as moderate negative evaluations ($M = 2.84$, $SD = 0.84$, empirical range = 1 – 5) a calculation of ambivalence scores revealed that attitudes were indeed ambivalent, $M = 2.00$, $SD = 1.00$, empirical range = -0.87 – 4.93; $t(1180) = 34.33$, $p < .001$ (see Figure 3), with a large effect size ($d = 1.0$).

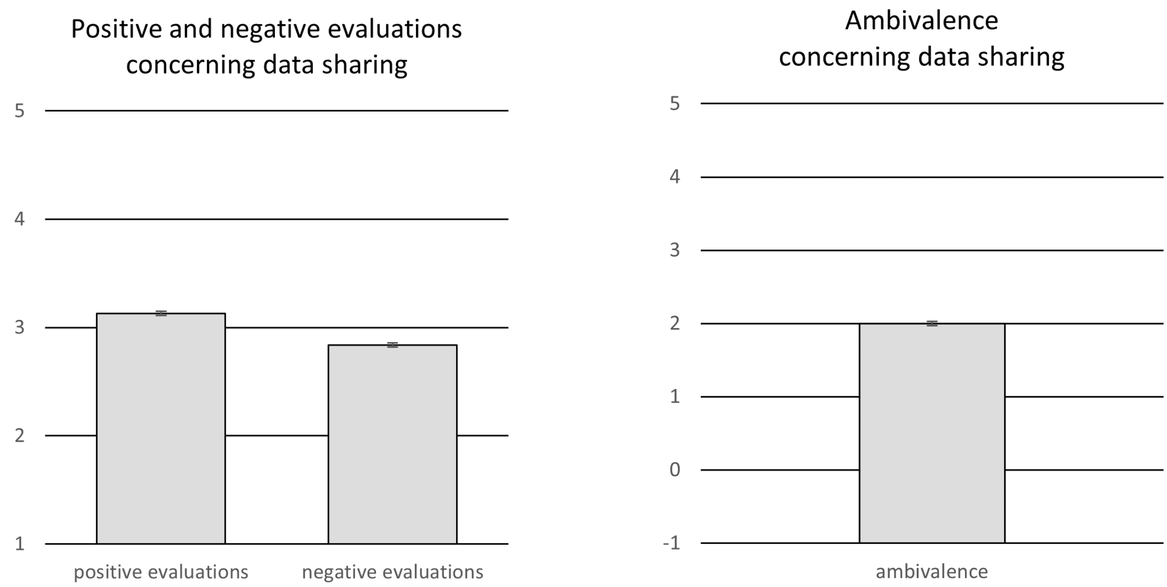

Figure 3: Left: Mean positive and negative evaluations concerning data sharing. Right: Ambivalence concerning data sharing derived from positive and negative evaluations (N = 2190). Error bars show standard errors.

Figure 3 illustrates, that positive and negative evaluations were present at the same time, resulting in ambivalent attitudes. This underlines the contrast to a neutral or ambiguous attitude, which would consist of low levels of positive and low levels of negative evaluations and, in turn, low ambivalence. Furthermore, if people had either positive OR negative attitudes, the positive and negative evaluations may have looked the same, however, the ambivalence score would have been much lower since is calculated on the individual level. This analysis may be taken as a first empirical indicator of conflicting attitudes and ambivalence towards data sharing. That is, positive and negative attitudes towards data sharing do not exclude each other, but people seem to have them at the same time.

Implications concerning attitudes

In order to address researchers' attitudes towards engaging in RDM, their experienced attitudinal conflict needs to be acknowledged – if researchers are informed, that a potential negative feeling towards RDM may stem from an attitudinal conflict and not from a negative attitude altogether, this might ameliorate their attitude. Oftentimes, people use their emotions to derive information about their attitude, and by clearly investigating such attitude, the emotion might be revealed as a byproduct of the process of attitude formation (van Harreveld et al., 2015). When supporting the resolution of ambivalent attitudes, it might prove efficient for RDM support staff to provide information on the negative sides of evaluations, e.g., the costs and dangers of RDM and data sharing, since negative information tends to be more impactful than positive information (for an overview see Rozin and Royzman (2001)).

As elaborated above, the value of a certain behavior is directly linked to people's motivation to engage in it. E.g., understanding the value of RDM practices and clearly stating the likelihood of the expected outcome might give researchers a better understanding of whether their investment in RDM practices will pay off. Valuable information for researchers might be: What is the impact of organized data or publicly shared data? How likely is it, that people will re-use my data and that I will be cited? What if they find mistakes in my analysis? How likely is it, that putting data publications on my resume will give me an advantage in an application process? Of course, one could also increase the perceived value of a certain behavior with universally efficient incentives, such as money. Recent research has shown that already relatively small amounts increase the likelihood of certain behaviors significantly (in this case: the intention to get vaccinated) – even independently from previous knowledge or social status (Campos-Mercade et al., 2021). E.g., the Berlin Institute of Health at Charité provides financial incentives for open data publications (e.g., providing 300.000€ in 2022), supported by an algorithm, that detects eligible publications (Kip et al., 2022). However, a more cost-effective approach might be to include social incentives such as badges[1], as is already the case with some journals or the Open Science Framework. Data availability also plays an increasing role in conferences, e.g., in computer science (Hermann et al., 2020). Such incentives have been shown to increase trust in scientists and might also be implemented university-wide in order to make good RDM visible (Schneider et al., 2022). There are also approaches to integrate monetary with social incentives

[1]For an overview by the Center for Open Science see: https://www.cos.io/initiatives/badges

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via data publication competitions, e.g., the FAIR4Chem Award in chemistry[2]. Here, a monetary incentive is combined with visibility through an interview and further information about the respective research on the NFDI4Chem Website, which may provide a good visibility on a national level. Such incentives are closely related to and overlap with subjective norms.

2.2 Subjective Norm

In addition to attitudes, subjective norms influence behavioral intentions. Our perception of the way that a certain behavior is handled in our peer group, in our team, in our institution, or in our society influences the likelihood of engaging in such behavior. These norms can be implicit or explicit, e.g., a "culture" of how certain things are handled that is passed on between colleagues versus explicit norms, policies, and guidelines. Examples for implicit norms are how research data management is handled at the institution or in the subject area, whether colleagues usually publish their data sets, or whether colleagues' shared files follow a file naming convention. Examples for explicit norms are the "Guidelines for Safeguarding Good Research Practice"[3] by the DFG, but also many universities have their own policies that researchers are required to follow, such as the "Principles of research data management at TU Dortmund University"[4]. In addition to direct colleagues at their university, data publication practices differ largely between subject areas (Tedersoo et al., 2021) and thus, conventions in the respective subject area may play a role in the formation of the subjective norm. Furthermore, (Fecher and colleagues (2015)) conclude from a meta-analysis on data sharing, that research policies are needed to incentivize data publications and to improve the quality of research results.

Implications concerning Subjective Norms

There are already many good explicit norms in place concerning RDM in the form of policies and guidelines, although not all researchers might be yet committed to them. RDM practitioners could draw attention to policies and remind researchers of their obligations, not as a duty, but rather as an opportunity to lead a value based work-life. Furthermore, institutions that do not yet have committed to a policy might establish one with the support of research data service staff. However, publishing a policy on the universities website might not be enough – people need to be aware of the policy and of the personal relevance to their research.

[2] Due to a lack of persistent identifiers for the mentioned awards and guidelines, the webpages are indicated here: https://www.nfdi4chem.de/fair4chem-award/ (retrieved on March 10th, 2025)

[3] https://www.dfg.de/resource/blob/174052/1a235cb138c77e353789263b8730b1df/kodex-gwp-en-data.pdf (retrieved on March 10th, 2025)

[4] https://www.tu-dortmund.de/en/research/research-data-management/principles-of-rdm/ (retrieved on March 10th, 2025)

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Psychological research on persuasion has shown that people are more likely to engage in a behavior, when it is visible that many others also engage in it (Cialdini & Goldstein, 2004) – people tend to orient strongly on their peers concerning their behavior. Therefore, people may be more inclined to engage in RDM-related behavior if they see their peers doing the same. This could be further encouraged by making good RDM visible. One example for making RDM visible by RDM service staff is the nomination of Data Champions. E.g., at TU Dortmund University, researchers that already employ exemplary data management are appointed as data champions and an interview with them is published on the universities landing pages' news feed and on the research data services page[5]. That way, best practices were shared throughout the university and beyond. Another example for making RDM visible is a Regular's Table. E.g., at TU Dortmund University, researchers interested or engaged in the National Research Data Infrastructure (NFDI) meet quarterly for lunch and talk about recent RDM developments within the NFDIs consortia. Further possibilities for visible RDM may include putting data publications on CVs or showing statistics of published data sets and materials on the university websites. Of course, the highly competitive university environment makes it very difficult to engage in activities that do not immediately benefit one's career, but could be advantageous to set oneself apart from competitors. One example for an institutional display is the FAIR Dashboard by the Berlin Institute of Health which gives an overview over open research at Charité[6]. Overall, it is strongly advisable, that changes on the institutional or political level are to increase the visibility of open data and good RDM practices in order to make a shift in social norms concerning RDM even possible.

2.3 Perceived Behavioral Control

The third main factor influencing behavioral intentions is Perceived Behavioral Control. That is, the likelihood of doing something depends on whether the person believes that they are *able* to carry out the respective behavior. This perceived behavioral control consists of people's personal abilities as well as the resources available to them. Concerning RDM, researchers must perceive their personal as well as institutional resources to be sufficient to engage in RDM (e.g., time, personnel, and financial resources) as well as perceive their abilities to be sufficient to carry out RDM-related tasks. In a quick changing environment, that frequently develops new standards and practices, this might be especially challenging.

[5] https://fdm.tu-dortmund.de/en/rdm-at-tu-dortmund/data-champions/ (retrieved on March 10th, 2025)

[6] BIH QUEST Center for Responsible Research. (n. d.). Charité Dashboard on Responsible Research. Retrieved March 10th, 2025, from https://quest-dashboard.charite.de/

Implications concerning Perceived Behavioral Control

Increasing researchers' perceived behavioral control over RDM-related behaviors might be the part where RDM staff may contribute best. For once, researchers' RDM needs may be identified by RDM staff and realistic and suitable solutions may be recommended – since RDM staff are the ones keeping an overview over the quickly changing RDM landscape. That way, RDM staff may advise in navigating the many options, e.g., concerning data organization and annotation, choosing a repository or a way of publishing data. In that context, Data Stewards play a crucial role in guiding researchers concerning their daily RDM activities especially in enriching research data for future publication. Furthermore, RDM services may provide accessible information e.g., through their websites. Moreover, hands-on workshops are suitable to educate on various RDM topics. Since there is a wide variety of topics that might be covered, it could be fruitful to accumulate resources and provide materials and workshops to broader audiences, e.g., as in the RDM Curriculum of the UA Ruhr Universities (Dortmund, Bochum, and Essen)[7]. Here, researchers and staff from all universities may participate in workshops by all three partners and the workshops are continuously updated and adjusted to the audiences needs. Many universities and institutions also provide self-learning formats so that competences may be acquired asynchronously. High-quality education programs concerning RDM are of essence to ensure that perceived behavioral control concerning RDM is ensured. Furthermore, if resources for RDM are lacking, RDM staff may also provide information on funding opportunities for RDM or communicate researchers' resource-related needs to the organizational level. However, simply providing information does not necessarily increase perceived behavioral control. Rather, it is necessary to ensure people's self-efficacy and perceived controllability of the respective behavior (Ajzen, 2002). That is, they need to feel that they can perform the behavior relatively easily and that they have control over it. In terms of data management, this can be achieved, for example, by collaborating with RDM service staff on data publications and data management plans, rather than simply consuming information, and deciding independently, when, how, and what data to share.

Perceived behavioral control is an especially important factor for subsequent behavior because it strengthens the influence of attitudes and weakens influence of subjective norms (La Barbera & Ajzen, 2020). That is, if people feel competent, they are more likely to form an intention and act according to their attitude instead of according to social norms. This way, providing information and education about RDM may enable researchers to engage in RDM, even if the social norms are not yet in favor of RDM. Figure 4 presents an overview of RDM-related attitudes, norms, and aspects concerning perceived behavioral control.

[7] https://www.uni-due.de/rds/en/rdmcurriculum.php (retrieved on March 10th, 2025)

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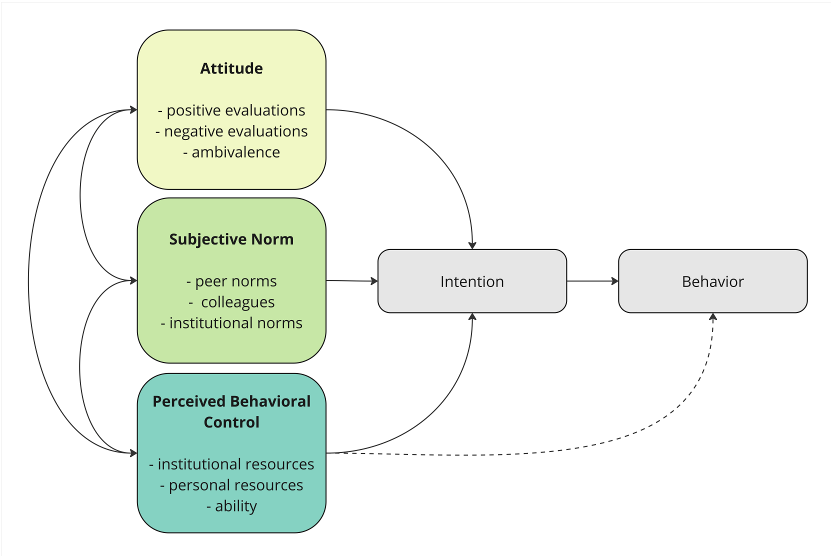

Figure 4: Theory of Planned Behavior: Attitude, Subjective Norm and Perceived Behavioral Control applied to RDM.

2.4 Other psychological Factors in RDM

In addition to the propositions made by the Theory of Planned Behavior, some additional empirical findings may be helpful in understanding the formation of intention and behavior. Importantly, due to self-regulatory problems, even a strong intention is not always followed the intended behavior. However, an intention is more likely to be followed by the respective behavior, if it is formulated as specific as possible (Gollwitzer & Brandstätter, 1997). For example, formulating specific if - then plans can help in goal achievement (e.g., “If I see the reminder on my phone every second Friday at 10 a.m., then I will clean up all unnecessary files and rename all files in accordance with the naming convention [. . .]). Ideally, sticking to these if - then plans will lead to the formation of habits, making data management less effortful (Canova & Manganelli, 2020). If researchers intend to engage in RDM, service staff may assist them in developing specific plans on how and when to pursue RDM-related tasks, e.g., help in developing file naming conventions, finding repositories, developing backup strategies, ensuring with their expertise that those plans are attainable and purposeful.

These suggestions all rely on voluntary participation – research on reactance has shown that people show more unwanted behavior when they feel controlled (Brehm & Brehm, 1981). It is likely that trying to persuade researchers to engage in proper RDM is not efficient. Rather, RDM staff may help getting internal and external hurdles out of the way and provide the prerequisites for good RDM.

Furthermore, psychotherapy research has shown, that orienting on values (e.g., practicing good research) rather than avoiding negative experiences (e.g., more work in the short term) can increase overall wellbeing (Fries & Grawe, 2006; Linehan, 1999).

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That is, the active pursuit of individual and positive values leads to a greater wellbeing that the mere avoidance of behaviors that may be experienced as negative in the short term. This is supported by research derived from the World Values Survey, which examined values and life satisfaction in large samples on all inhabited continents and found an association between feelings of agency and wellbeing (Welzel & Inglehart, 2010). Therefore, people may even profit psychologically from being encouraged to engage in value-oriented behavior. This approach enables the recognition of individual needs and attitudes while simultaneously pursuing value-oriented objectives. Altogether, these findings suggest, that a transparent communication about RDM at an eye-level that is supportive and not prescriptive is the most promising to encourage proper RDM strategies. However, it should be noted that anecdotal evidence suggests, that different groups of reserachers (e.g., students, professors) might differ systematically in their attitudes and malleability of attitudes concerning data publication, their referenced subjective norms and peer groups, as well as in their compliance concerning measures increasing perceived behavioral control, as workshops and recommendations. Interventions should be designed to suit the respective target group. Figure 5 presents a summary of recommendations concerning attitudes, subjective norms, perceived behavioral control, and further psychological factors where research data services can support researchers in the formation of behavioral intentions and subsequent behavior.

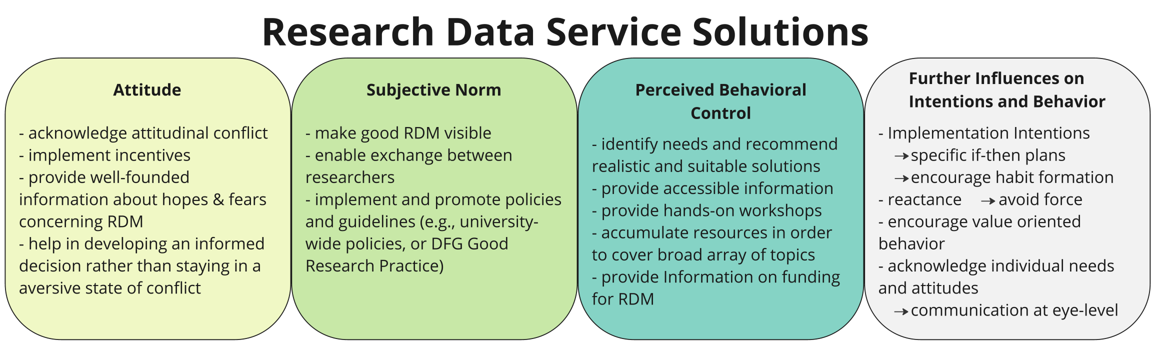

Figure 5: Suggestions for Research Data Support Staff.

3 Suggestions for RDM Services

In retrospect, the measures taken at TU Dortmund University are well in line with the theory of planned behavior and the above described measures for founding and developing data services. To get started with RDM, TU Dortmund University was engaged in a third-party funded BMBF project. This project increased the awareness concerning the necessity of RDM services on the administrative side, as well as the awareness concerning good RDM practices on the researcher's side. During interviews with

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professors, the central RDM personnel got directly in touch with the researchers and thus had the opportunity to get to know the demands and the attitudes in the different research areas represented at the University (Kletke et al., 2024). Based on the findings the RDM personnel guided the development of an RDM policy that was written by a working group of researchers. Early participation of the researchers increased the acceptance of this institutional norm and resulted in a rapid approval by the senate, setting the foundation for the policy to become a subjective norm. Within this policy, the University ensured that all necessary RDM infrastructure, in terms of hard-, software and personnel, would be established. The existence of this norm was the foundation for the Research Data Service. Based on the growing demand to address RDM within third-party funding applications, the Research Data Service was scaled to its current extent. Data Stewards and Data Curators are guiding researchers to establish sustainable RDM concepts and to describe them properly in third-party funding proposals. Thus, we are addressing the perceived behavioral control of the researchers as a vehicle for implementing best RDM practices that spill over to day-to-day handling of research data.

In order to pave the way for good RDM behavior, we have established TUDOdata, a data repository based on the common Dataverse platform running on the secure infrastructure of TU Dortmund University, capable of storing data and accompanying them with descriptive metadata. The system and related materials, such as FAQ and publication process flow diagrams, guide researchers through the task of data publication and archiving. Data curators ensure the quality of published data by subjecting data and metadata to a curation process. Archived data can be easily be published with one click starting the curation and publication process, with minimal effort for the researchers. This minimizes the addressed negative evaluations raised, such as time-consuming data publication processes and the trustworthiness of the data storage systems. In addition, the system is easy to use and provides self-guidance, so that researchers' control over the data publication process is high, hopefully resulting in a high perceived behavioral control.

The presence of Data Stewards and Data Curators on campus enables a short service route and the dissemination of best research data practices that positively influence researchers' data management. Outstanding data management strategies and novelties are portrayed on the website by Data Champions interviews and researchers are encouraged to network concerning topics like the NFDI. For the future of the TU Dortmund Universities Research Data Service, we will ensure that new measures are double checked with the Theory of Planned Behavior. We aim to balance the identified psychological factors to maintain a stable and homogeneous support service that adresses the needs, norms, and the perceptions of the researchers and guides them towards good research data management practices.

The Research Data Service with all measures described above grew organically one after the other based on the current knowledge of RDM at that time. We did not use the Theory of Planned Behavior as a strategic template to foster RDM at TU Dortmund

University. In retrospect, however, it has become clear that many measures align well. The approach taken by TU Dortmund University can be used as a blueprint for setting up a central RDM service. The above described measures are applicable to the Theory of Planned Behavior, which may have supported their success. It should be noted, that, while these measures are structured among psychological factors in the current work, they address a psychological as well as structural level. Without support on an institutional level that enables good RDM psychological and societal changes may be much harder to achieve. Whether the measures actually improve RDM and data sharing at TU Dortmund University could be investigated in future research.

4 Limitations and Outlook

The practical applicability of the proposed concepts should be tested experimentally. However, with the Theory of Planned Behavior, we build on a broad empirical basis and may be confident concerning the underlying factors. In a first analysis of attitudes concerning data sharing, we found empirical evidence of ambivalent attitudes towards data sharing. This might be investigated in more detail in the future, e.g., what the most important conflicting evaluations are and how such attitudinal conflict may be resolved. Future research might provide empricial evidence of the applicability of the other factors in the model to RDM in general and especially data sharing. Many of the additional psychological effects mentioned followed a subjective selection based on the author's background in psychology. There may be more important factors that were not considered here, due to the short nature of the work.

Nevertheless, tackling psychological hurdles concerning RDM is only fruitful if the needed infrastructures and resources are provided by universities, funders and other institutions, such as the National Research Data Infrastructure (Kraft et al., 2021), which is still under development and consolidation. The support of data publications on structural level, e.g., by removing technological and organizational barriers, is a prerequisite for the impact of measures addressing psychological factors concerning data publication.

5 Conclusion

In conclusion, intentions to pursue RDM-related behavioral intentions and behaviors may depend on researchers' attitudes, subjective norms, and perceived behavioral control concerning those behaviors. Due to many important advantages and disadvantages concerning data sharing, these evaluations evoke attitudinal conflict, namely ambivalence, that should be taken into account. RDM support staff can facilitate

RDM-related behaviors, such as data sharing, by acknowledging researchers' attitudes and attitudinal conflict and providing well-founded and individually curated information materials, supporting implicit and explicit norms concerning RDM, and, most importantly, enabling researchers to control their RDM concerning knowledge and resources. Further strategies, such as implementing specific plans for RDM and acknowledging the individual values associated with RDM may support the formation of actual behavior from the respective intentions. If researchers are convinced of the value of RDM and have the resources and skills to carry it out, most psychological barriers can be overcome.

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