Moral Disengagement in Social Media Generated Big Data

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Abstract. Big data raises manifold ethical questions. While there is a certain consensus on general principles for addressing these issues, little is known about when and why decision-makers display such ethical conduct or opt for unethical behavior with regard to collecting, storing, analyzing, or using big data. To address this research gap, we draw on the concept of moral disengagement. Moral disengagement describes psychological mechanisms by which individuals rationalize and thus disengage themselves from unethical conduct. We develop a theoretical model in which the motivation for monetary benefits as well as the motivation for hedonic benefits is set into relation to moral disengagement and the tendency to make unethical decisions in the context of social media generated big data. Our model spells out four sets of testable propositions that invite further research.

Keywords: Moral disengagement, big data, intrinsic motives, extrinsic motives, unethical behavior

1 Introduction

The past years witnessed an increasingly rapid digitization of not only business processes but of basically all fields of society and human life. This development goes hand in hand with the exponential growth of digital data. In fact, “big data” has emerged as a phenomenon characterized as a multifold shift in how data becomes available and potentially relevant in our society [1]. First, in terms of volume, big data refers to data sets that include huge amounts of data thanks to both digital storing technologies and the diffusion of data-creating devices such as smart phones. Second, in terms of variety, big data reflects that the type and nature of data is changing thanks to new sensors and the ability to store text, sound, images, etc. Third, in terms of velocity, big data is linked to the potential real-time availability of data. Due to the volume and complexity of such data sets, big data challenges conventional methods of capturing, storing, analyzing, and using data. At the same time, it opens up new possibilities for data analysis as well as ethical issues such as data privacy, data security, and data property rights [1].

Within the past years, practitioners and researchers have focused their attention especially on areas where ethical issues occur and have suggested possibilities to avoid the unethical use of big data from the beginning [e.g. 1, 2, 3, 4]. Simultaneously, misuse of big data can be observed frequently. In order to understand why big data is used in an unethical way, it is important to examine the psychological and cognitive processes of decision-makers with respect to moral reasoning and ethical decision making.

For that reason, we develop a conceptual framework, linking extrinsic and intrinsic motives with moral disengagement, and the tendency to make unethical decisions in the use of big data.

2 Theoretical Background

2.1 Big Data and Unethical Behavior

Discussions about challenges and ethical issues in big data become more and more pronounced both through the increasing number of principles and guidelines as well as increasing research. The following section aims to highlight the most prominent concern and challenges as they relate to an ethical use of big data. To be precise, this section does not refer to any technical issues within big data but focusses on normative challenges in regard to its use. In particular, it emphasizes issues that can arise from intended as well as unintended use of big data.

Discrimination: Big Data analysis can lead to positive and negative discrimination of certain individuals or groups of individuals [2, 5, 6]. Such discrimination can range from customized pricing strategies based on previous purchases, personal likes and dislikes as well as socioeconomic status [cf. 7] to decisions as to which kind of healthcare receives investment in low and middle income countries [8]. To overcome this, most ethics codes call for considering the benefits and harms of each analysis [6, 9].

Privacy: Privacy is defined as the "state of being free from public attention" [10]. While the extent to which privacy is considered important differs across cultures [11], there is nonetheless a call for strict privacy guidelines [5, 12]. The collection and storage of big data increases the possibility of breaching an individual's privacy. Many public debates on this often reference the idea of the 'right to be forgotten'. Some core ethical issue here is the question of how long data can be stored and what kind of data should be stored and who should control the data [2] or own the data [13, 14]. To further protect individuals, anonymizing data is a called for practice [6, 12, 14, 15, 16] to avoid compromising personal identities [3, 17].

Surveillance: Surveillance or dataveillance is another ethical challenge for big data users [2, 18]. Take the example of smart cities [1]. While big data can help optimize traffic flow or the general flow of movement during peak hours to avoid severe traffic jams or overcrowded public transport, it can also be used to track the movements of individuals and survey their movements throughout the day. Similarly, the mass surveillance of social media activities can lead to suppressed speech [7].

Limited knowledge of users: This issue is particularly tricky. Here, the question is less what analysist or owners of big data are using it for, but rather if and to what extent users are aware of how their data is used. This aspect is challenging as 1) most people do not read any terms and conditions supplied by companies before they provide their data and 2) often do not understand potential harm that could come to them. To least overcome parts of this problem, guidelines call for a transparent communication about how the data is used [3, 5, 6, 16] so as to provide data providers with the necessary information to make an informed decision.

Data use outside of context: On top of new laws in some countries which prohibit companies to use any data collected from individuals outside the explicit use these individuals have agreed to, it is a commonly agreed upon ethical rule that data should not be used for any purpose except for which they were provided initially [5, ,12, 13, 16, 19, 20]. Moreover, it is important to understand the data in its wider context so as not to misinterpret findings [14].

On top of the publications on ethical behavior in regards to big data, there is a discussion on knowing when to break rules [12] – e.g., in situations of natural disaster, emergencies or potential threats to security. This discussion substantiates that the issues above are inherently ambivalent issues. That is to say that they are neither black nor white. The potential of negative consequences very much depends on conscious and unconscious decisions by those in charge of collecting, processing, analyzing and using big data. However, these decisions are not made by an individual but often by many different individuals who might not always be aware of potentially negative consequences of their respective decisions [4, 21] – which in turn further complicates the ethical use of big data.

2.2 Moral Disengagement

Based on social cognitive theory [22], Bandura [23] developed the notion of moral disengagement. Social cognitive theory takes an agentic perspective where people exercise control over their own thoughts and actions [22, 24]. This regulatory system operates through the three self-monitoring, judgmental, and self-reactive functions [25]. Hence people monitor constantly their behavior which is then evaluated against their own (moral) standards and situation-related characteristics [25]. Depending on the moral judgement, positive self-reactions or negative self-sanctioning anticipate behavior and motivate individuals to behave in accordance to their moral standards [23]. This self-regulatory system is, however, not immutable as self-influences operate solely if they are activated. There are, however, numerous psychological mechanisms by which individuals can disengage themselves from unethical conduct and therewith from self-sanctioning [25]. Attribution of blame, dehumanization, disregarding or distorting the consequences, diffusion of responsibility, displacement of responsibility, advantageous comparison, euphemistic language, and moral justification illustrate key mechanisms through which individuals can disengage themselves from harmful behavior and do not activate self-influences [22]. Attribution of blame and dehumanization can enable individuals to morally disengage from detrimental actions by making the victim herself/himself personally responsible for such behavior. In case of attribution of blame, it is argued that the victim has provoked harmful outcomes on herself or himself by own doings [23]. When victims are dehumanized, individuals feel no longer obliged to evaluate their actions against their moral values as their victim does not belong to the same group [23]. Disregarding or distorting consequences, diffusion of responsibility, as well as displacement of responsibility enable individuals to neglect or ignore own harmful actions. With disregarding or distorting the consequences, harm for others is ignored. This is especially given, when consequences for others are not visible to the individual or occur with a temporally delay [23]. When individuals question or deny personal accountability, diffusion of responsibility is given. Personal accountability can be reduced in cases where group decisions are taken or when division of labor is given and such collective behavior causes harm [23]. Displacement of responsibility diffuses personal accountability as individuals reject their personal role for causing harm. Displacement of responsibility especially occurs where individuals feel obliged to follow orders from legitimate, authorized people. Advantageous comparison, euphemistic language, and moral justification help individuals to misinterpret harmful behavior as morally acceptable or even as completely benevolent. Advantageous comparison allows to downplay own wrongdoing, by comparing it with even more harmful actions. The more malign the contrasting behaviors, the easier it gets to see one's own conduct as acceptable [23]. With euphemistic language, individuals reduce or neglect detrimental conduct by using neutral language or by verbally sanitizing these kinds of actions [23]. Moral justification describes the mechanism by which individuals excuse harmful conduct with a moral imperative. Detrimental conduct is therefore serving moral purposes or is at least personally and socially justifiable from a moral standpoint [23].

3 Propositions and Framework Development

This paper develops a theoretical framework where the motivation for monetary benefits as well as the motivation for hedonic benefits is set into relation to moral disengagement and the tendency to make unethical decisions in the context of big data generated by social media. In limiting the underlying motivational basis on two contrasting types of motivation, we follow previous research [26, 27].

Following Amabile [28], individuals are "extrinsically motivated when they engage in the work in order to obtain some goal that is apart from the work itself" (p. 188). Motivation for monetary benefits illustrates therewith a generic expression for extrinsic motivation.

In the work place, monetary benefits occur manifold from regular wages to variable forms of compensations, financial rewards or pecuniary advantages and have been found to potentially evoke in general unethical behavior [e.g. 29].

The linkage of monetary benefits and moral disengagement has also attracted the attention of researchers and has been object of scientific research [e.g. 26, 30, 31]. Baron et al. [26] found for instance that financial gains and moral disengagement are positively related among entrepreneurs. Moore [30] connected organizational corruption with moral disengagement and argued that moral disengagement can be a crucial factor for organizational corruption as it affects the initiation, facilitation, and perpetuation of corruption in the workplace. Monetary benefits can especially be found in the perpetuation of organizational corruption, as individuals who are more likely to make unethical decisions in the interest of the organization have a higher probability of organizational advancement and in turn higher monetary benefits. Shepherd and Baron [31] examined the assessment of business founders with respect to the attractiveness of business opportunities which cause harm to the natural environment. They found that moral disengagement enabled entrepreneurs to perceive opportunities as highly attractive even if they would harm the environment.

Given these previous findings, it can be assumed that motivation for monetary benefits can cause deviant behavior in all work-related facets. For that reason, we propose that also in the context of big data motivation for monetary benefits is positively related to moral disengagement.

Proposition 1a: Employees' motivation for monetary benefits is positively related to moral disengagement.

In contrast to motivation for monetary benefits, motivation for hedonic benefits illustrates a generic intrinsic motivation as behavior is not triggered by an externally offered incentive but is conducted out of interest for the activity itself [32]. Intrinsically motivated individuals "seek [subsequently] enjoyment, interest, satisfaction of curiosity, self-expression, or personal challenge in the work" [32, p. 188].

Intrinsic motivation has been found to generally impact positively different work-related activities [e.g. 33, 34], the selection of specific career paths [35], and has proven to affect performance on some tasks more positively than conditions related to extrinsic motivation [32].

Despite the general notion that intrinsic motivation can influence individuals to morally disengage, recent research examined the relationship of moral disengagement and intrinsic motivation and came to contradicting conclusions [26, 27]. In their study on entrepreneurs, Baron et al. [26] found a negative relationship between intrinsic motivation for self-realization and moral disengagement. Scheiner et al. [27] examined the motivation for hedonic benefits and moral disengagement in the context of an idea competition and found also partial support for the negative relationship.

In light of previous findings, individuals with a high intrinsic motivation seem to be less likely to morally disengage. For that reason, we propose that motivation for hedonic benefits is negatively related moral disengagement in the context of big data.

Proposition 1b: Employees' motivation for hedonic benefits is negatively related to moral disengagement.

One key aspect of big data in the context of social media is that there are novel ways to collect data, both with regard to new data sources (such as browsers, smartphones, health trackers etc.) and with regard to different types of data (such as text, sound, pictures, and other metrics generated in online search behavior, login personal or financial information, or motion and health data). This new volume and variety of data that can be collected certainly creates opportunities for innovations that benefit not only companies but also consumers, citizens, and society at large. As already reviewed above, these novel options for data collection also give rise to ethical questions such as privacy concerns and with regard to the property rights of the data collected from individuals.

Against this background, numerous industry and policy guidelines have formulated standards for the ethical conduct of big data collection [36, 37, 38]. Two principles are particularly important in this regard. First, the principle of *voluntary consent* highlights that personal data should only be collected from people with their explicit and voluntary agreement [36]. Second, the principle of *transparency* requires that the people whose data is collected are informed about how, what kind of data is actually gathered (and treated later on) [36]. Given these two principles, unethical conduct in the data collection phase can fall into several categories: Data could be collected without the consent (or even against the will) of individuals. Data collection could occur without individuals having full knowledge of what kind of data is actually collected. Finally, data collectors could fail to display transparency or could legally live up to the transparency principle in ways that themselves fail to be transparent, e.g. when the terms of agreement or the data privacy statement are hard to find, in extra small print or difficult to read/understand because of its technical wording, or the sheer length of the text.

From a business perspective, it is tempting to have as few restraints in the data collection as possible and therefore to violate the aforementioned ethical principles. Moral disengagement could increase the tendency towards such unethical conduct through several of its underlying mechanisms. Attribution of blame [22] would occur if data collectors shifted the blame onto individuals who do not protect or even freely share their data, e.g. by claiming that people can and should decide for themselves how to protect their data or that individuals are responsible in the first place [23] if they download a social media app that collects motion data via a smartphone. Another moral disengagement mechanism that could favor unethical behavior in big data would be advantageous comparison. As there are drastic examples of how personal and sensitive data was collected against the will of individuals in other areas of digital life – e.g. the alleged spying through web-cams –, decision-makers could always euphemistically downplay their own wrongdoing [23].

In short, as the collection of big data in the context of social media creates various options for unethical behavior and as several moral disengagement mechanisms could rationalize such actions, we propose:

Proposition 2a: Employees' moral disengagement is positively related to their tendency for unethical conduct with regard to the collection of big data.

In addition to the issues of data collection, the volume and velocity of big data also raise questions of data storage in the context of social media. Ever bigger amounts of data need to be stored at reasonable cost, should often be available in real-time and accessible irrespective of where the data was collected or is needed. As a consequence, new data storage architectures, often cloud-based, emerge.

As new storage solutions create opportunities, they also create risks that call for a responsible data storage management to address potential concerns of data privacy, data sovereignty, and data security. Similarly to the data collection, various ethical principles have emerged to govern these issues. With regard to data privacy, respecting the privacy of individuals requires that personal information that reveal someone's identity should either be blinded or only be stored if absolutely necessary, with the respective individuals giving their consent to the storage of personalized data [38]. With regard to data sovereignty, individuals should know what kind of data is stored about them, should be able to check this data record and have the ability to call for correction if the data is faulty [39]. In fact, if faulty data is stored and people cannot check and correct it, they might be unjustly blocked, for example, from attaining credit or health insurance

[40]. Finally, with regard to data security, sensitive data – ranging from passwords to private conversations and health data – needs to be protected not only against being lost but also against being stolen or manipulated by third parties. Otherwise, issues of identity theft, credit card fraud, privacy infringements etc. could significantly harm the individuals who cannot protect themselves against such risks once their data is stored.

While guidelines for the ethical conduct of storing big data thus exist, keeping such standards can be costly, require effort, or limit a company's options, thus creating the temptation to violate them. Unethical conduct with regard to data storage then spans various practices: Decision-makers could store personal, sensitive information of individuals without their knowledge or even against their will; they could leave opaque which information is stored and difficult to check and correct it; and they could fail to invest in necessary IT security, thus tolerating poor IT architectures with known security weaknesses.

Given the nature of these issues, moral disengagement mechanisms could enhance the likelihood for unethical conduct with regard to data storage in several ways. To start with, attribution of blame [22] could mean that individuals whose data is stored are attributed responsibility because their own behavior allowed the data collection and storage in the first place. Diffusion of responsibility could occur when decision-makers such as managers in big data enterprises refer to technological system constraints that allegedly make a different conduct unfeasible, with the responsibility diffused to ICT engineers, software developers etc. Advantageous comparison could, again, refer to bigger scandals, e.g to Yahoo's infamous 2016 data breach [41] where the sensitive information of 500 million users was hacked– thus effectively downplaying one's own wrongdoing [23] if data security does not live up to the desired standards.

In short, as the storage of big data creates specific options for unethical behavior and as moral disengagement mechanisms can be argued to rationalize such actions, we propose:

Proposition 2b: Employees' moral disengagement is positively related to their tendency for unethical conduct with regard to the storage of big data.

The sheer variety and volume of big data leads to various challenges when analyzing big data. To this end, new tools have been developed and are still being developed to navigate the volume of data.

These new tools can be highly effective in analyzing patterns and supporting the identification of idea solutions. At the same time, big data analysis entails many potential ethical challenges. Some of those challenges relate to the actual tools used in the analysis and tackle challenges known from statistical analysis such the outlier problem. Moreover, while guarding anonymity is a principle already readily used in statistical analysis, this challenge's magnitude increases significantly in the context of big data in social media. This is because by pulling data from various social media sources, it would be possible to reconstruct an individual's life quite accurately. Therefore, to safeguard the identity of individuals, many principles in big data analysis call for anonymization of the data prior to running any analysis [6, 12, 14, 15] and to implement measures that disallow re-identification of individuals [12]. Indeed, recently guidelines for research and analysis of data from specific social media platforms have started to emerge [e.g. 16].

Furthermore, the volume, variety and velocity of big data makes its analysis very complex. As such, there is a danger that analytics used fully or partly ignore the context in which the data was collected. This effect is made more complicated by the variety of not only data types but by also of data sources. These complexities notwithstanding, many principles in big data analysis very clearly point to the importance of the context of data [15, 16, 42] in order to fully understand its meaning.

The process of data anonymization and especially the avoidance of re-identification can be very complex and therefore costly. Moreover, companies might have a vested interest in being able to identify individuals in order to target them with specific products or service offerings. Similarly, implementing mechanisms that robustly ensure that the context of the data is respected increases the complexity of big data analysis and might even impede certain types of analyses.

Against the backdrop of these challenges, moral disengagement mechanisms could increase the likelihood for unethical conduct during data analysis. First, disregarding or distorting consequences [22] might lead individuals who are in charge of big data analysis to ignore the context of the data analyzed. Here, individuals might simply choose to ignore potential consequence of not respecting data context in order to simplify their work or to be able to use a greater volume or variety of data in their analysis. Similar to data storage, big data analysis might not follow anonymization and re-identification avoidance principles by displacing responsibility to individuals who provided the information in the first place. Moreover, big data analysis is rarely done by one individual [4]. Indeed, most companies use pre-build software to analyze their data. Thus, the programmer of the software and the user might have no link to each other. Therefore, both sites – software programmer and software user – might make use of diffusion of responsibility due to the potentially large number of people involved in a single analysis.

In sum, as the analysis of big data creates specific options for unethical behavior and as moral disengagement mechanisms can be used to rationalize such actions, we propose:

Proposition 2c: Employees' moral disengagement is positively related to their tendency for unethical conduct with regard to the analysis of big data.

The use case for big data is enormous. Big data use can range from applications for public safety [43] to smart cities by optimizing traffic flows based on movement profiles of commuters and targeted advertisement and investment decisions. Especially in the area of development [44], big data has led to reduced costs in decision-making and has been applied in areas such as underwater animal tracking [45] or providing information on where best to build schools to protect them from droughts [46].

To ensure that big data is used ethically, various principles have emerged. For instance, The Ten Commandments of Computer Ethics by the Computer Ethics Institute call for using big data in way that is respectful to people [20]. Similar guidance can also be found in publications by Accenture [5], Zook and colleagues [12], the ICO [6], Davies and Patterson [13] and Narayanan and colleagues [9]. The discussion of potential negative consequences of big data uses is very prominent in the field of big data research [e.g.16, 47].

Despite these guidelines and calls for a respectful use of big data that keeps in mind potential negative effects to both data providers and the general public, there are many reasons why such ethical approaches might not be fully implemented. One such use is surveillance of citizens or customers. Such techniques allow big data users to profile individuals [2, 14] and use it to, for example, predict behaviors and movement patterns. Furthermore, big data can be used to positively or negatively discriminate individuals or groups of people [2, 5, 6, 42]. Potential consequences of discrimination include customized pricing strategies based on previous purchases, personal likes and dislikes and socioeconomic status [48] as well as decisions which impact healthcare investment in low and middle income countries [8]. In higher education, big data is used more and more frequently to develop performance prediction tools for individual students [49]. While such information can help an education institution to better support students, as in the case of Arizona State University, it can also be used to predict students who intend to transfer to another university [50].

As the decision on how to use big data clearly lies with individual decision-makers, misuse might be rooted in mechanisms of moral disengagement. For instance, in the case of higher education institutions using big data to preempt student transfer and its consequent loss of income, the decision-makers might engage in advantageous comparison by pointing to other institutions that engage in similar activities or who might use data to preemptively expel them. Dehumanization may occur where consequences of big data use impact many people or people who are far away and therefore might seem less "real" to decision-makers. If we consider a scenario where a smaller group of individuals that are identified as being more likely to have a costly disease are excluded from healthcare services, moral justification could be used to argue that it is in the interest of everyone else to keep their healthcare costs down.

In sum, we thus propose:

Proposition 2d: Employees' moral disengagement is positively related to their tendency for unethical conduct with regard to the usage of big data.

Consistent with our line of argumentation, we propose that the relationship between motivation for monetary benefits and the tendency to make unethical decisions in the context of data collection, data storage, data analysis, and data usage can be explained, in part, through moral disengagement. In cases where individuals are motivated by monetary benefits, they are less likely to evaluate their doing from a moral standpoint. For that reason, decision-makers are more likely to actively morally disengage from self-regulation and self-sanctioning, which could lead to a higher tendency to make unethical decisions. We thus posit:

Propositions 3a: Moral disengagement mediates the positive relationship between employees' motivation for monetary benefits and the tendency for unethical conduct with regard to the collection of big data.

Propositions 3b: Moral disengagement mediates the positive relationship between employees' motivation for monetary benefits and the tendency for unethical conduct with regard to the storage of big data.

Propositions 3c: Moral disengagement mediates the positive relationship between employees' motivation for monetary benefits and the tendency for unethical conduct with regard to the analysis of big data.

Propositions 3d: Moral disengagement mediates the positive relationship between employees' motivation for monetary benefits and the tendency for unethical conduct with regard to the usage of big data.

Given our previous propositions, we suggest that the relationship between motivation for hedonic benefits and the tendency to make unethical decisions in the contexts of data collection, data storage, data analysis, and data usage can be explained, in part, through moral disengagement processes. Individuals motivated by hedonic benefits are more likely to evaluate their behavior from a moral perspective. Thus, they are less likely to disengage from self-regulation and self-sanctioning. This should result in a lower likelihood to make unethical decisions. Consequently, we propose:

Propositions 4a: Moral disengagement mediates the negative relationship between employees' motivation for hedonic benefits and the tendency for unethical conduct with regard to the collection of big data.

Propositions 4b: Moral disengagement mediates the negative relationship between employees' motivation for hedonic benefits and the tendency for unethical conduct with regard to the storage of big data.

Propositions 4c: Moral disengagement mediates the negative relationship between employees' motivation for hedonic benefits and the tendency for unethical conduct with regard to the analysis of big data.

Propositions 4d: Moral disengagement mediates the negative relationship between employees' motivation for hedonic benefits and the tendency for unethical conduct with regard to the usage of big data.

Based on these propositions, our overarching theoretical framework is represented graphically in Figure 1. While our model starts with the assumption that different types of motivation are relevant for ethical (mis)conduct in the context of big data, our framework puts the concept of moral disengagement at its core. We posit that moral disengagement is not only related to employees' tendency for ethical misconduct with regard to the collection, storage, analysis, and usage of big data. We also propose that moral disengagement mediates the relationship between extrinsic/intrinsic motives and ethical conduct.

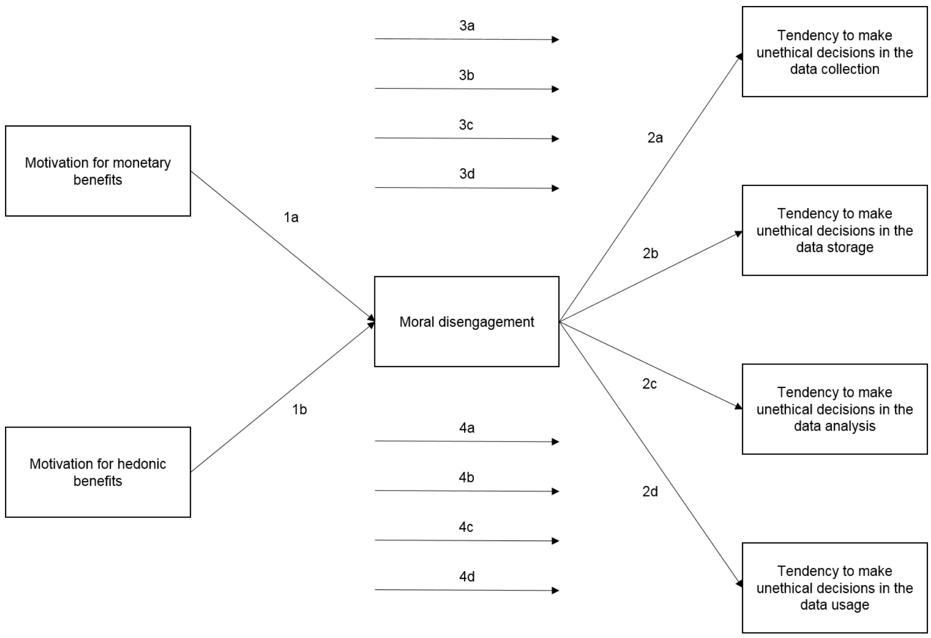

Figure 1: Theoretical Framework

4 Conclusions

As one facet of the mega trend of digitization, "big data" has received increasing attention by practitioners and academics alike. Early on, this debate acknowledged that big data does not only raise technological issues and questions about business use cases. Big data also invokes ethical questions. In fact, numerous guidelines, principles, and standards have emerged that seek to canonize an emerging consensus on how to ethically deal with big data.

While there is thus ample research on the normative implications of big data and on rules for ethical conduct, so far little is known about when and why decision-makers abide by these rules or opt for unethical behavior instead. The purpose of this paper was to address this research gap. To this end, we identified and discussed relevant factors that influence decision-makers' tendency for unethical conduct in the context of big data generated by social media. At the center of our theoretical framework stands the concept of moral disengagement. Moral disengagement occurs when decision-makers who perceive a certain behavior as unethical find ways to rationalize such behavior, thus disengaging themselves from unethical conduct and therewith from processes of self-sanctioning that would otherwise inhibit the unethical behavior.

To elaborate the role of moral disengagement, our framework derived four groups of propositions. First, we theorized that different types of motivation relate differently to moral disengagement. While extrinsic motives tend to be positively related to moral disengagement, we proposed a negative relationship for intrinsic motives. Second, we differentiated decision-making in the context of big data to fall into the four domains of big data collection, big data storage, big data analysis, and big data usage. We then proposed that moral disengagement is positively related to unethical conduct in each of these domains. For our third and fourth proposition sets, we propose that moral disengagement works as a mediator for the relationship between motives and ethical (mis)conduct.

Needless to say, our study is not without limitations. While we hold that motivations and moral disengagement play an essential critical role for ethical (mis)conduct), there are certainly other situational and personality factors that we have not explored despite their potential relevance. Further research is thus needed to expand our conceptual framework. We hope that our contribution may serve as a useful starting point in this regard. In terms of future empirical research, our framework builds upon testable propositions that can be used in further studies. As big data continues to play an ever bigger role in our lives, so will the question of when and why decision-makers choose to respect or violate principles for its ethical use. Moral disengagement research can help to illuminate this question.

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