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Honesty-Humility's effect on data sharing decisions in the context of HR-Analytics

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Contents

Abstract

With Human Resource Analytics showing a consistent trend of both rising popularity and implementation, employees are faced with the decision to share their data and weighing benefits and risks. In comparison to past research, this study presents a novel perspective by replacing BIG-5 with HEXACO's Honesty-Humility (HH) and experimentally manipulating the benefit instead of punishment. In an online experiment 496 participants are presented a vignette with either a collective or individual advantage to their choice. The proposed interaction effect, in which higher levels of HH are expected to be more likely to share data regardless of context, while lower levels of HH are predicted to be more selfish and thus more likely to share in the individual benefit manipulation, was not found. Privacy concern was measured and theorized to predict decreased likeliness to share yet showed a significant effect to increase it. Possible explanations are discussed. As the manipulation check was not significant, the expected, but also not significant interaction effect with HH on data sharing is explored and an additional interaction between HH and privacy concern found. Low levels of the personality trait interact with privacy concern in the decision to share data, while higher levels do not. At any level, HH predicts higher data sharing when including privacy concern in the model. Thus, the results align with past research showing that individuals with high levels of HH act prosocial regardless of the context. Lastly effects of demographic measures are explored.

Keywords: Honesty-Humility, privacy concern, data sharing, Human Resource Analytics

Introduction

In the past years workplaces around the world have continuously been transforming. During the COVID-19 pandemic this trend was especially visible, with remote work being made a necessity. Fuelled by globalization and digitization, daily lives of employees, including team structures, connectivity to and via digital devices as well as skill requirements are adapting to the evolving environment. Within this a major influence has emerged: *Big data* is not only the collection, but the creation and use of immense amounts of information (De Mauro et al., 2015). With it come challenges, like privacy and security, but also opportunities for more efficiency, faster feedback and many other uses. Its application is widespread for consumer analysis (Mariani & Fosso Wamba, 2020), in finance (Hasan et al., 2020), but also impacts the people working with it directly. This is the case for *Human Resource Analytics* (HRA), or often also referred to as people analytics.

HRA can be used by *Human Resource Management* (HRM) across all industries and all types of companies, dealing with a wide range of topics such as staffing, performance management, training and development and compensation. While in the past the duties of HRM were mainly administrative, since the 1980s a necessity for a more strategic and holistic role has arisen (Ulrich & Dulebohn, 2015). By using data about digital – (Singer et al., 2017; Zander & Zieglmeier, 2023) and analogue behaviour (DiClaudio, 2019; Waber, 2013) and information about education, training and demographics of employees, HRA has been found to be directly linked to the financial performance of firms, as well as several other beneficial key performance indicators (Aral et al., 2012; Levenson, 2011; López-Arceiz et al., 2018; Mondore et al., 2011). Logically this would suggest that it is widespread and commonly used. Yet in 2014, Falleta has found that HRA only actively plays a key role in 15% of firms, while Lawler and Boudreau (2015) have found that less than 30% use it for business impact applications. To put the slow integration into perspective, Deloitte’s Human Capital Trends survey from 2018 (Deloitte Insights, 2018) and 2023 (Deloitte Insights, 2023) can be compared. In the earlier version 84% of respondents acknowledged HRA as important or very important and it was the second most popular HR Trend. Nevertheless, even in 2023 only 19% felt that their organization was ready to leverage workers data to both the organizations and employees’ benefit. This was in stark contrast to the still high 83% of the same year, that saw it as important or very important to the company’s success.

Several possible reasons have been suggested to answer the conflicting realities. Many of the most repeated topics can be discussed along the work of Tambe, Cappelli, and Yakubovich (2019), who identified four challenges. Firstly, complexity of HR phenomena refers to statistics and IT skills by the user in order to analyse and execute. Secondly constraints imposed by small data sets can be expanded as a topic to include data selection, collection and management, which is often discussed. Thirdly fairness and ethical and legal constraints are named, with a fourth challenge being possible adverse employee reactions. Summarized, it is clear that humans play an extensive role in big data analytics and especially in HRA. Not only as knowledgeable users, but also as the source of the data. The current study aims to extend beyond typical ethical considerations and thoughts on privacy or safety and instead focus specifically on the underlying personal reasons for the decision to consent to the data creation and usage. In such decisions privacy calculus theory becomes an applicable tool, which suggests that s simple equation is used. Risks are weighted against possible benefits and result in the action. A major part of the threat of consenting stems from privacy concern, where employees have to consider potential misuse of their data, improper access and errors (DiClaudio, 2019; Southey, 2016; Teebken & Hess, 2021).

Nevertheless, the reasoning behind personal decisions of consent extends beyond the cost-benefit equation. The data every employee owns has another effect. From the data that every employee brings into, and creates at companies, if processed well, immense amounts of knowledge can be created. As Sir Francis Bacon (1597) famously stated “knowledge itself is power”. This power and consequently also economic success is locked directly behind the access to the data. Therefore, from a research perspective a parallel can be drawn between HRA consent decisions and *economic games*. The latter deal with redistribution of, mainly monetary, wealth and manipulate differences in power over it. In, for example, the dictator game (Forsythe et al., 1994; Kahneman et al., 1986) the distributor alone can decide how much the recipient will receive. Similarly in the context of HRA, data can be categorized as essential for business, therefore taking away the employee’s power. In other firms and situations, or in ultimatum games (Güth et al., 1982) as the economic game equivalent, workers might be able to decline the offer, leaving both sides without the possible benefits, such as improved recommendations for training or firm wide success. Even tough employees could gain potential advantages from sharing their data, adverse reactions are described in the literature. Jain & Jain (2020) call any large-scale automation a threat to jobs. Mirbabaie et al. (2021) discuss the fear of replacement by decision makers and Khan & Tang (2016) outright call it unlikely that employees would be enthusiastic about HRA. If privacy calculus theory could be applied to cover this topic fully, then the presentation of benefits should lead to more acceptance. Past research isn’t lacking proof of its usefulness, with Aral et al. (2020) having shown a correlation between HRA and financial performance of the firm and other's studying its significant positive relations to teams' efficiency, objective decision, immediate feedback on performance and the identification of possible career paths (Bersin, 2016; Tursunbayeva et al., 2018; Von Schenk et al., 2021). Even when actively presented with explanations and advantages, as one could argue employees just don't know what they gain, results are still ambiguous (Zander & Zieglmeier, 2023). Since a simple cost-use equation, privacy concern and situational factors aren't able to explain the outcome fully, then personality and more specifically social behaviour must also play a role, which is also the case in economic games. The link of personality traits and cooperation has played a significant role in many different of such studies (Thielmann et al., 2020). Each decision taken has an effect on another person. Sharing can generally be considered prosocial, in each context equally, while egoistical decisions might benefit the person in power and hurt other involved parties.

Historically *BIG-5* has been used in economic games to predict prosocial behaviour but has also been shown to lack explainability in several areas. On the contrary to the studies showing a correlation to cooperation, many alike have found opposing results (Brocklebank et al., 2011; Hirsh & Peterson, 2009; Kurzban & Houser, 2001; Lönnqvist et al., 2011). Consequently, a newer personality construct *HEXACO* has been proposed (Ashton & Lee, 2007) and it's added factor Honesty-Humility (HH) offers a significant improvement to most of the criticism (Hilbig et al., 2014). HH, compared to HEXACO agreeableness, explains active cooperation, meaning not exploiting others, while having the chance to do so. When participants with low levels of HH were presented with an opportunity to defect, that was both tempting and at the same time not linked to, or at least unlikely to lead to punishment, then they were more likely to do so compared to their counterparts with higher levels of HH (Zettler et al., 2013). In economic games, those higher in HH more consistently share their wealth across both dictator and ultimatum games (Thielmann & Hilbig, 2018b). On the other hand, especially when participants have more power, low levels of HH predict selfish behaviour.

While punishment and power have been researched, a gap emerges from the literature. In this study each participant is presented with the same fictive HRA scenario and asked whether they would share their data. The benefit is experimentally manipulated and presented as either collective or individual and thus differences of the personality trait are expected to influence the decision. Therefore, the research question of this study is:

"When the benefit is manipulated between a collective or individual advantage, how does HH influence the consent decision in the context of HRA?"

Present research

Human resource analytics

HRM are “all those activities associated with the management of employment relationships in the firm” (Boxall & Purcell, 2003:1). Among others it incorporates activities regarding health & safety, recruitment, employer branding, training and development of personnel, planning of staffing, team building, retention, benefits administration and also performance evaluation (Collins, 2013; Daily, 2013; Davenport et al., 2010; Harris et al., 2011; Kremer, 2018; Overby, 2013; Roberts, 2013). While the general topics have stayed similar, the aim and daily business has been steadily developing from a purely administrative to a more and more strategic role (Ulrich & Dulebohn, 2015). There are many reasons for this, with the war for talent being a well recognizable and trending example, and the newly found importance of the department, which is more frequently included in business and company decisions, another one. This change has led to a necessity for a link between the effect of business strategy, external outcomes and global benchmarks, which can be seen in definitions by van den Heuvel and Bondarouk (2017), who mention the identification and quantification of people drivers of business outcomes, as well as Fitz-enz (2009), Marler and Boudreau (2017) and Kryseynksi et al. (2017) who include business goals or outcomes.

Parallel to the evolution of the role, the business environment around it has been undergoing changes. Specifically digitalization (Strohmeier, 2020) and a steady increase in available and processed data, have changed decision making processes in HRM. Two of such expansions have been the incorporation of more data-driven decision-making processes as well as the automation of all activities.

The general digitization of HRM has been called e-HRM, showing links to overall performance in organization, but nevertheless never reaching the level of potential and hype that another major factor behind the transition has received (Baykal, 2019; Dahlbom et al., 2020; Zavyalova et al., 2022). This particular result of the adaptation to the ever-increasing amount of data and evolving role in businesses is called HRA. Over time it has been given many names like people analytics (Tursunbayeva et al., 2018), human resources analytics (Belizón et al., 2023; Kapoor & Kabra, 2014; T. H. Rasmussen et al., 2023), workforce analytics (Hota & Ghosh, 2013; Simón & Ferreiro, 2018), talent analytics and human capital analytics (Cappelli & Keller, 2014; Davenport, & Harris, 2010; Fitz-enz, 2010; Kutik, 2014)

Its definitions vary from simple statistical software to predictive modelling, including various tools and technologies, or include both, such as Bassi (2012). The most common contribution to the definitions lies in the approach for data-driven decision making. Levenson (2011) sees HRA as a general way to improve decisions, while Bassi (2010) and Davenport and Harris (2007) emphasize the fact-based approach, similar to Fitzenz (2009), who defines it as a "logical analysis … for reasoning, discussion and calculation". Authors like Jain and Jain (2020) have further included the use of technology, which can in practice include machine learning, artificial intelligence, and deep learning, with work by Kryseynski et al. (2017) defining it even wider as "data, metrics, statistics and scientific methods, with the help of technology…". In short it is the act of using, and making available, the data related to personnel in a company, in order to apply insights of effectiveness and necessity to decisions that have or will be taken.

The definition by Marler and Boudreau (2017), which describes a "practice enabled by IT that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making." is used for this study. This is for two reasons. Firstly, as participants will have a wide range of understanding of AI and related topics, the inclusion of such new technologies could lead to more variation in the effect of the vignette, which would be hard to interpret, and therefore will be excluded. Secondly, the definition should be both broad to include the variety of processes and outcomes, yet narrow enough so that participants, who have not had direct contact with the term, can understand it.

Even though HRA has also been called a managerial fad (Fiol & O'connor, 2003; T. Rasmussen & Ulrich, 2015), it's link to positive organizational outcomes has been well documented. The use of HRA correlates directly with financial performance of the firm (Aral et al., 2012; Jiang et al., 2012b; Mondore et al., 2011), indirectly via human capital and employee motivation, voluntary turnover and operational outcomes (Jiang et al., 2012a), greater commitment (Gong et al., 2009), enhanced safety performance (Zacharatos et al., 2005) and lower turnover (Batt, 2002) among various other organizational indicators (Combs et al., 2006). This is made possible by a variety of collected data, which can vary greatly in different firms and studies and are affected by the specific goals of its users. They can range from public to private information as well as behavioural analysis and the use of sensors. Bersin (2013), for example, names educational history, demographic and performance information, similar to Margherita (2022) with cognitive tests, curriculum vitaes, surveys and social network data. DiClaudio (2019) offers are more concrete case, with calendaring, travelling, time away from work, usage of time key cars, auto mileage tracking and conference call logs. Waber (2013) describes a similar direction with the use of sensors and digital devices to monitor employee mobility in order to analyse teams’ collaboration and individuals work patterns. What might feel most intrusive, as suggested in a study by Zander and Zieglmeier (2023), which found little consent for it, could be the collection of data from private messages or mails, or the collection of data on the frequency of meetings, which could point to a project being at risk (Singer et al., 2017). Such data collection has already been moving from scientific studies to practice and can be found in tools such as the HRA software by Jiva Software. Nevertheless, research on the implementation and especially on the acceptance in practical examples is scarce.

The data can in turn be used to predict training costs, attrition rates and employee contribution (Marler & Boudreau, 2017), help objectifying decisions and increase team efficiency (Tursunbayeva et al., 2018), identify career paths, onboarding, reporting, recruiting (Sousa et al., 2019) and offer feedback on performance (Tong et al., 2021), among many other use cases. A practical example would be to analyse correlations between training programs and improved performance or leadership actions and retention rate.

All of this also comes with challenges, where implementation and active usage are the first hurdle. HRA use has only been found to actively play a key role in 15% of firms (Falletta, 2014), has shown less than 30% usage for correlations between HR and business impact and yet 70% in regard to HR efficiency (Lawler and Boudreau, 2015). Clearly showing high perceived importance, both in 2018 and 2023, respondents of the Deloitte Human Capital Trend survey have acknowledged HRA as important or very important 83% and 84% respectively (Deloitte Insights, 2018; Deloitte Insights, 2023). In 2023, only 19% perceived their organisation to be ready to use their employee’s data to both their individual and collective advantage.

This leads to the conclusion that the role of HRM is still in the process of its evolution. To continue its current path, Tambe, Cappelli and Yakubovich (2019) name four areas to tackle. Firstly, the complexity of HR phenomena, where practitioners will have to understand and execute analysis. Secondly the constraints imposed by small data sets and the collection to increase these. Different angles can be discussed for this problem, with many leading the same direction, such as not fully accessible or integrated data (Douthitt & Mondore, 2013), not fully collected or inaccurate data (Angrave et al., 2016; Bassi, 2012; Patre, 2016). Thirdly fairness, ethical and legal constraints need to be taken into consideration. Fourthly employees might react in different ways, with not all being positive. Kahn & Tang (2016) have called it unlikely that employees will be enthusiastic about HRA. Jain and Jain (2020) argue that any large-scale automation could be seen as a threat to jobs and also show a decrease in morale in a case study for employees at

Coca Cola after being asked to submit information continuously. Closely related Bhave, Teo & Dalal (2020) argue that forcing employees to share data could lead to increased mental stress.

On the other hand, one could imagine that presenting employees with their many possible benefits, such as stated earlier, could lead to general consent and more data, but studies such as by Zander & Zieglmaier (2013), have shown reality to be more complex. Depending on the data collected, as well as the use case, participants showed varying levels of acceptance, even when presented with potential advantages.

Concluding, the further development of HRA relies on the perception of employees and user. With clear evidence of benefits for companies and its employees as well as interest by practitioners, widespread integration should be expected, while on the other hand many risks and reservations are provided by those who build the foundation and provide the data. With information and cyber security being their own well-established fields, psychology provides a perspective of human experience and focusses on individuals understanding of their gains and fears. Sharing your personal data for the collective gain can be considered prosocial behaviour and those involved must be willing to come together to put shared goals over individual ones. Naturally people are different in personality traits and values and will therefore not only perceive and judge HRA consent decisions differently, but also act appropriately to their self.

Honesty-Humility

Historically many different personality theories have been proposed. As such, one to seven factors have been described (Calabrese et al., 2012; Digman, 1997; Musek, 2007; Simms, 2007; Waller et al., 1991). One particular theory, BIG 5, has become popular and well established even into popular psychology. It includes five core dimensions: conscientiousness, agreeableness, neuroticism, openness to experience and extraversion (McCrae & Costa, 2008). The construct has also been used regularly for research on prosocial behaviour, showing significant correlations (Kline et al., 2019). Specifically, it's factor agreeableness has been found to predict cooperation in economic games (Ben-Ner et al., 2004; Koole et al., 2001; Pothos et al., 2011; Volk et al., 2011). In one variant, the dictator game, participants are given a certain amount of money and tasked with the decision on how much to keep, as well as how much to give to another participant. A meta study by Engel (2011) found that an average of 28% is given to the recipient, with results showing significant heterogeneity, which can partly be accounted to personality traits. On the other hand, other authors did not replicate a link between agreeableness and prosocial behaviour (Brocklebank et al., 2011; Hirsh & Peterson, 2009; Kurzban & Houser, 2001;

Lönnqvist et al., 2011), leaving further studies with a gap to fill. Hilbig (2013) proposes that agreeableness is relevant for cooperation, but only for some aspects of it. One particular aspect, that of active versus passive cooperation, might be the culprit of difference. Agreeableness seems to be insufficient at explaining fair and prosocial tendencies when there is a possibility of exploiting without consequences, while it is well fit for situations in which one forgives and is tolerant of others, even when exploited (Ashton & Lee, 2007; Hilbig, Zettler, Leist, et al., 2013). The latter being passive - and the first mentioned active cooperation. Certain situations, especially those with anonymity in consent decisions, could allow employees to benefit from the HRA outcomes, while not sharing, therefore exploiting the system by taking more than they are given. On the other hand, there are many risks associated with sharing data, which could necessitate the data sharer to be forgiving and tolerant.

Another area in which agreeableness lacks precision is "giving versus taking" (Zhao et al., 2018). The authors describe a stronger effect for taking in the context of wealth allocation, proposing those high in agreeableness being less interested in unfairly redistributing what isn't perceived as theirs. In the context of HRA the original owner of the data has not been as frequently manipulated as in economic games and leaves room for a discussion. Employees could perceive their work and personal data as their own or as part of the work they transfer to the company and get paid for. They could also distinguish between parts they have owned before entering the firm, such as their past education and the newly acquired training received at their employment. In past research, it is expected that employees perceive themselves as owners of data, without differentiation at the individual level of each specific information. This parallels legal frameworks such as the GDPR (European Parliament & Council, 2016), by which employees need to consent to the use of their data, and therefore has acted as a solid foundation for current research, yet also leaves the option for novel and in-depth studies.

The criticism of the conflicting results of BIG-5 research, has pathed a way for more research using a newer theory, which in turns paints a clearer picture (Hilbig et al, 2014). HEXACO is a six-factor model and was based on lexical studies across more than 10 European and Asian languages (Ashton & Lee, 2001). As such it is of similar nature as the BIG-5, consisting of Honesty-Humility (HH), emotionality (E), extraversion (X), agreeableness (A), conscientiousness (C) and openness to experience (O), with the standout difference being the addition of the new factor HH. The new factor HH plays a key role in the explanation of prosocial behaviour. It is defined as the "tendency to be fair and genuine in dealing with others, in the sense of cooperating with others even when one might exploit them without suffering retaliation" (Ashton & Lee, 2007, p. 156). High levels of HH are linked to sincerity, fairness, greed avoidance and modesty, compared to low levels of HH, which relate to dishonesty, unfairness, greed and entitlement. Past studies have shown small to medium correlations with Agreeableness of BIG-5 (Ashton et al., 2007; Hilbig, Zettler, Moshagen, et al., 2013; McAbee et al., 2019; Zettler et al., 2011). The new factor extends and improves its explanation power for several areas. For example, for egoism (De Vries et al., 2009), dark triad personality traits (Lee & Ashton, 2005), moral behaviours such as honesty (Zettler & Hilbig, 2015), fairness (Hilbig, Thielmann, et al., 2015) and trustworthiness (Thielmann & Hilbig, 2015). Furthermore, it is better equipped to deal with the earlier mentioned criticism. In the HEXACO model, A can only explain nonretaliation, meaning passive cooperation, like in BIG-5 agreeableness, while HH explains nonexploitation, or active cooperation. Therefore, prosocial behaviour described with BIG-5 is well-covered by HEXACO, but not in the opposite direction.

HH has also shown direct links to more real-world examples, such as larger contributions to public goods (Hilbig et al., 2011), refraining from stockpiling during the COVID-19 pandemic, which was not due to the belief that others wouldn't do so themselves (Columbus, 2021) and ecologically responsible behaviour (Soutter et al., 2020). Consistent positive links to prosocial behaviour in general (Klein et al., 2017; Mischkowski et al., 2018; Pfattheicher & Böhm, 2017) and willingness to exchange individual in favour of the maximum collective benefit (Hilbig et al., 2014).

Individuals low in HH kept more money for themselves in dictator games, where exploiting is possible without repercussions, yet in ultimatum games, where the recipient can reject the proposed split, started distributing more equally. In comparison, those with high levels of HH, made more fair decisions, regardless of the change in context (Thielmann & Hilbig, 2018a). Similarly, Zettler et al. (2013) have shown that participants high in HH cooperated consistently, while those low in HH, started to defect as soon as the involved risk was lowered, and the benefit raised. In opposition to BIG-5, only HEXACO was able to predict variance in prisoner dilemmas (Zettler et al., 2013). Overall high HH was linked to greater collaboration in windfall games. These economic games are different to dictator games as the initial wealth to allocate is explained as an unexpected gain and it is made clear that it has not been earned by either party (Zhao et al., 2018). A third type of economic game, explain where HRA lies. That is between the dictator and the ultimatum game, where the receiver can either accept or reject the offer. There are situations in which the firm has full control, such as core business data, and can collect data of their employees without including them in the process. On the other hand, some data can only be voluntarily provided by employees. Therefore, both sides share the pool of power. Nevertheless, it isn't wealth that is discussed, but data, individual and firm wide success.

One could always argue that those high in HH are just gullible and don't fully understand their actions, yet a study by (Zettler et al., 2013) tested exactly for sensitivity to situations and understanding of the strategy behind social dilemmas and disputed this very argument.

With many situational and initial factors influencing each consent decision, this study presents a vignette of a fictional HRA situation, in which participants are asked how likely they are to share their data. The experiment differentiates between 2 groups. One group is presented an individual benefit, meaning that they would share their data for themselves, while the second group is shown a collective benefit, in this case, for their team. Therefore, the expected gain of each participant is manipulated. The text explicitly mentions anonymity for the data sharing decision and therefore presents a situation without repercussions. In line with economic research, specifically dictator games, low levels of HH would be expected to predict more selfish behaviour. Those with higher levels of HH are predicted to share more, regardless of context. Following the privacy calculus theory, in an effort to present a clear picture for each participant, both groups read through the same statement for the use of their data. It was described as "strictly limited to", in general terms as not to interfere with the manipulation and broadly included several areas.

The main hypothesis is split between the two benefit manipulations and follows the presented research:

Hypothesis 1a:

In the collective benefit manipulation (CBM), participants with higher levels of Honesty-Humility will be more likely to share their data.

Hypothesis 1b:

In the individual benefit manipulation (IBM), participants with lower levels of Honesty-Humility will be more likely to share their data.

Privacy concern

A relevant part of employee reactions and a necessity in all large-scale data use discussion are privacy concern. In this case they refer primarily to information - and not physical privacy. Information privacy overall focusses on the control over the collection, the timing and place of it, as well as the use (Bélanger & Crossler, 2011). Comparingly, privacy concern is defined as how individuals perceive what might occur with their data after they have shared it

(Dinev & Hart, 2006) and their beliefs about the risks with sharing information (Cho et al., 2010; Zhou & Li, 2014). As an overarching theme, digitization itself is suggested to be a perceived threat to rights to privacy (Bhave et al., 2020). Employees have to take account of the potential misuse of their data, (DiClaudio, 2019; Shen et al., 2018; Son et al., 2020; Southey, 2016) like identifying their behaviour in aspects unrelated to the business (Vaníčková & Bílek, 2021) or the analysis of private data (Chatterjee, 2019; Dimitropoulos et al., 2020). Teebken & Hess (2021) also describe improper access, errors in collection and analysis, as well as lack of awareness as potential dangers. Overby (2013) specifically points to employees possibly raising such trust and privacy issues when data is collected for analytics in HRA. On the other hand, studies have shown that employees are willing to share their data if they don't perceive the risk of misuse to be high (Chatterjee et al., 2020; Chatterjee & Kar, 2018)

In contrast, the decision to share data can, to an extent, be taken away. For example, when data is deemed as required for core business. Adding to complexity of the ethical discussion are social pressure and one-time consent. In some cases, employees might feel forced to share their data, as anonymity will not always be given, leading to fear of worse performance reviews or peer pressure. If employees are asked for permission to collect or use their data, they will generally be informed about the applications of such. In the context of the fast-developing HRA, which needs to adopt to new business requirements quickly, the data will be used in different ways regularly. Informing and asking for consent every time might not always be feasible, and companies might then ask for general consent, only temporarily including employees in the process and without knowledge about the behind the scenes of HRA. As a logical consequence, employees will then have more difficulty accurately judging what and why they are sharing their data.

In privacy calculus theory (Laufer, Robert and Wolfe, 1977), perceived benefits are weighted against potential risks. Applying this theory researchers (Chatterjee et al., 2022) have found that privacy concern is directly related to the usage of HRA (r = -.43). On a broader scale a significant effect of privacy concern on sharing of data has also been found. A meta study by Baruh, Secinti, & Cemalcilar (2017) presented a correlation of r = -.22 for the intention to share data, and r = -.13 for behavioural outcomes.

Accordingly, this study proposes the following secondary hypothesis:

H2: Individuals who are more concerned about their data will be less likely to share their data.

Having established a link between HRA and privacy concern in literature, the question for a model with more explanatory power pertains. Personality traits are expected to play a significant role yet remain relatively understudied in this context. Results of work by Zander & Zieglmaier (2023) showcase this gap in practice. When asked to consent to HRA, according to privacy calculus theory, benefits and risks should explain the decisions, yet each individual reacted differently to situations beyond the presentation of advantages and disadvantages. 3 core explanations were categorized in their qualitative work. While sensitivity, which pertains to the data itself, and risks and concern, are both related to privacy concern, value reveals a different angle. It describes how participants rated the gained benefits, both individually, for themselves, and collectively, as a firm, and the risks involved with each of the presented HRA processes. Examining these interactions shows the nuance of the relationship of the decision to share data.

In sum, HH and its predictive attributes of social behaviour, privacy concern and situational factors of HRA come together to form a complex interplay of influences that lead to a, in practice, often binomial decision of yes or no. The outcome in turn affects not only the employee, but his or her team and the whole company. Both egoistical and prosocial choices come with risks and benefits alike. With research showing that HRA is here to stay, a better understanding of each individual’s perception could lead to better communication and execution by and for all stakeholders so risks can be minimized and collective benefit maximised.

Methods

The cross-sectional two group experiment was carried out in an online setting in English with two groups. Participants were not informed of their group, which differed in the manipulation, with one being presented an individual benefit and the other being presented a collective benefit to the decision to share data. The groups were randomised by using a random generator provided by sociosurvey.com. To reduce the potential effect of the order of the questionnaires for privacy concern and HH, further randomization resulted in a total of 4 groups.

This study did not include any interaction with research personnel that could influence the participants directly. The author who analysed the data was fully aware of the groups and hypotheses. As such it could the study can be categorized as single-blind.

Estimated sample size

The sample size was estimated with the help of G*Power (Erdfelder et al., 2009). Past research has shown a small to medium sized effect between HH and prosocial behaviour, such as Zhao & Smillie (2015) with r = .24. A linear multiple regression fixed model was calculated, with R^2 deviation from zero, using a power of .95 to detect a f^2 effect of .0611 at the standard .05 alpha error probability. It resulted in a sample size of 215 participants. For this study an estimated 15% (n = 32) were not expected to finish or to be excluded to other reasons, such as missing data. The result was to aim for a total sample size of 247.

Sample

Convenience sampling and professional survey participant recruitment services were combined for this study. Participants were directly recruited in Europe and the USA between 10.01.2024 and 23.01.2024. Due to the public availability of the study in groups on Facebook, Reddit, LinkedIn and on X (Twitter) anyone following the election criteria was able to take part without geographical restrictions, yet the active efforts by the author were limited to the beforementioned regions. Further participants were recruited via the survey portal SurveyCircle and via private instant messaging services such as WhatsApp and Discord. To increase the sample size, the service Make Opinion (https://makeopinion.com/) was intended to increase the total number by 150 complete surveys.

At the start of filtering a total of 951 clicks on the survey were registered. Due to technical limitations, it is impossible to differentiate between a search engine, or similar non-human access and a human starting the survey. Therefore, disregarding those who only looked at the first page, out of 596 experiments that were started, 513 completed it. The drop-out rate was 13.93% and low for such an online study.

The final sample consisted of 513 participants, of which 7 did not consent to participate in the study. By further excluding seven test completions by the author, two survey completions that have documented their age as 99 years and one participant whose data on education was missing, the filtered sample of 496 was reached. Participants were on average 43.75 years old (*SD* = 16.38). Their age ranged between 18 and 85. 61.09% (*n* = 303) were female, 38.1% (*n* = 189) were male and 0.81% (*n* = 4) described themselves as non-binary. For further demographics see Table 1.

Table 1

Sociodemographic Characteristics of Participants

Variable	*n*	%	CBM	IBM
Gender				
Female	303	61.09	163 (32.9%)	140 (28.2%)
Male	189	38.1	85 (17.1%)	104 (21.0%)
Non-binary	4	0.81	2 (0.4%)	2 (0.4%)
Education				
High School Diploma	199	40.12	83 (16.7%)	116 (23.4%)
College or university	179	36.09	110 (22.2%)	69 (13.9%)
Postgraduate degree	57	11.49	27 (5.4%)	30 (6.0%)
Compulsory school	16	3.23	7 (1.4%)	9 (1.8%)

Apprenticeship	42	8.47	22 (4.4%)	20 (4.0%)
Other	3	0.6	1 (0.2%)	2 (0.4%)
Occupation*				
Full-time	213	40.65	108 (21.8%)	105 (21.2%)
Part-time	53	10.11	30 (6.0%)	23 (4.6%)
Student	63	12.02	33 (6.7%)	30 (6.0%)
Retired	75	14.31	40 (8.1%)	35 (7.1%)
Unemployed	61	11.64	28 (5.6%)	33 (6.7%)
Self-employed	47	8.97	20 (4.0%)	27 (5.4%)
None of the above	12	2.29	5 (1.0%)	7 (1.4%)

Note. n = 496. Percentages are rounded. Participants were on average 43.75 years old (*SD* = 16.38). *28 (5.65%) participants picked two answers for occupation.

77.06% (n = 383) amount received monetary compensation to complete the study, while 23.94% (n = 114) did not. As those who were paid, were recruited via makeopinion.com, the exact amount of compensation is unknown to the author.

Procedure

Participants first read through an introduction page. There they were informed that their data would be processed anonymously, the requirements of the study and were given a decision to whether they want to consent and partake. If they did not consent, they were redirected to a page thanking them for their time. In that case no data beyond the consent decision was recorded.

Next, they were randomly assigned a group. They either completed the HEXACO Honesty-Humility (10 items) and then the privacy questionnaire (15 items) or vice versa. Afterwards the benefit manipulation was shown. One group was presented with individual benefits and the other with collective benefits. The groups text differed in 4 instances, where they were either shown your/you (individual) or your team (collective). At the end of the one-page vignette, they were asked to rate their likeliness to share their data on a Likert scale from 1-7. By presenting a definition that focusses on the key aspects of HRA, instead of a futuristic and open one, readers will have a good understanding of the concept, regardless of their previous knowledge.

Next, in order to assess the manipulation, they were asked to rate their benefit between individual and collective on a Likert scale from 1-7. Before moving onto the outro, demographic questions about age, gender, education and occupation were asked. On the last page participants were informed about the experiments hypotheses and offered an email address to reach out to, in case of feedback or questions. No communication was received until a month after the end of the study. At any point the participants were able to see their progress in percentages at the top right of the page.

Measurements

Honesty-Humility

For this study the short version of the HEXACO self-report (Ashton & Lee, 2009) was used. Out of the 60-items, 10 test for HH and thus were extracted to form the presented questionnaire. Participants answered on a scale from 1 (Strongly disagree) to 7 (Strongly agree). Examples include "If I knew that I could never get caught, I would be willing to steal a million dollars." Or "I want people to know that I am an important person of high status.". The scale has shown appropriate internal consistency in past research (Ashton & Lee, 2009) and is neither outstandingly susceptible to response styles (Hilbig, Moshagen, et al., 2015) nor socially desirable responses. While BIG-5 was evaluated to be a weaker predictor in the theoretical research and therefore not used, HEXACO as a measurement is also preferred to similar constructs such as the BIG-6. It's Honesty-Propriety is generally measured via the 30QB6 scale. Internal consistency for it was low (Thielmann et al., 2017). It is important to mention that this key difference together with how closely related the two constructs are (Thalmayer et al., 2011), clearly points to the use of the HEXACO personality inventory from a measurement perspective.

Responses were mean averaged after reversing 6 items (Cronbach's $\alpha = 0.72$).

Privacy concern

Privacy concern was measured with a scale by Smith, Milberg & Burke (1996). It has 15 items, none of which were reversed. Participants answered on a scale from 1 (strongly disagree) to 7 (strongly agree). The scale was chosen for its relevance to this studies context. Compared to newer adaptions, it stands out as the wording is using companies, rather than more recent and often used scales such as Malhotra et al. (2004) and Hong and Thong (2013), who broaden their focus to internet users. Examples include "It usually bothers me when companies ask me for personal information." Or "Companies should devote more time and effort to preventing unauthorized access to personal information."

Responses were mean averaged (Cronbach's α = .9).

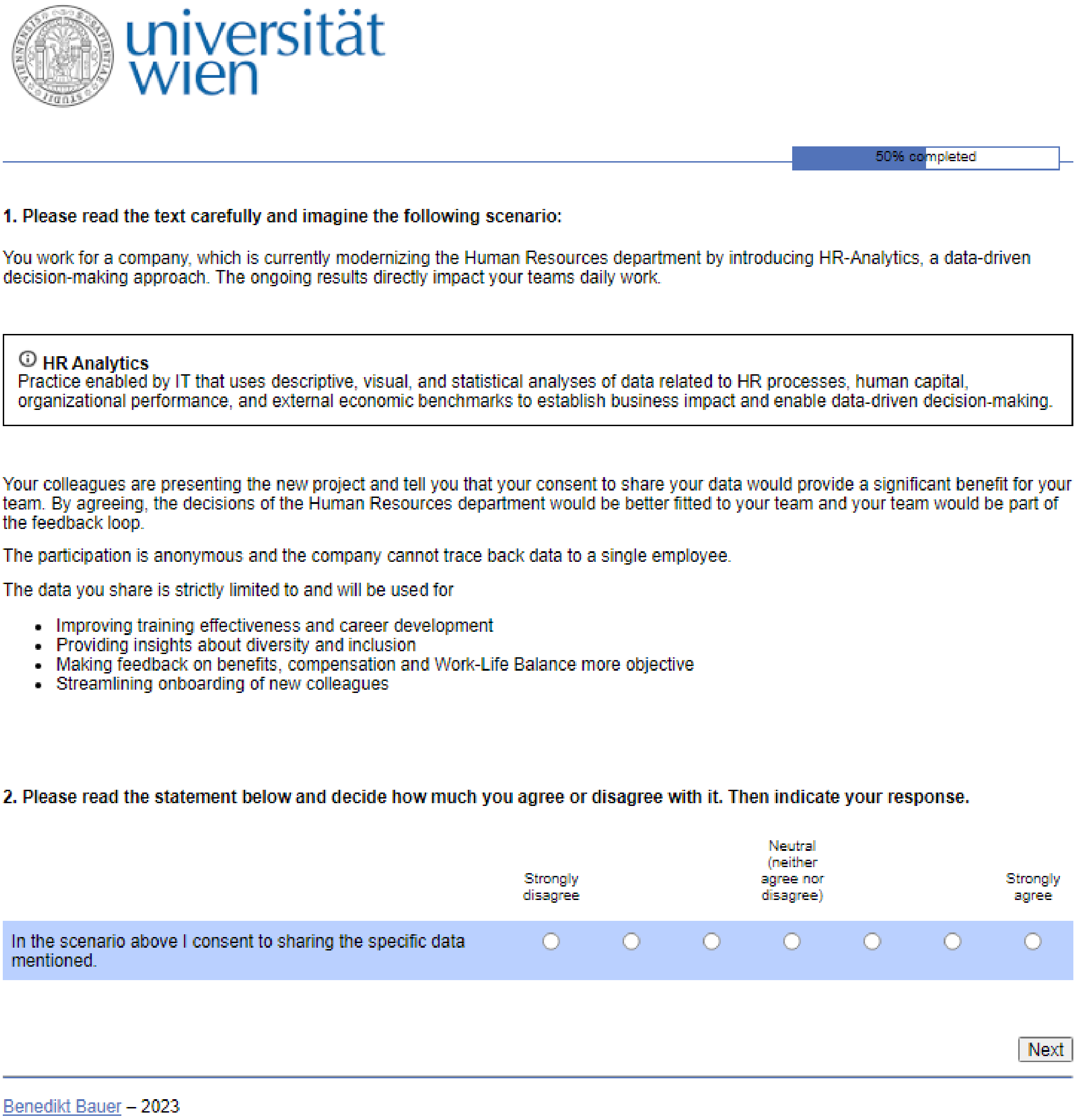
Benefit Manipulation

The benefit manipulation was created specifically for this experiment. At the point of the study the author was not aware of any research that is equal in its content and therefore the vignette is novel. Participants were asked to read the text carefully and imagine the described scenario. They were informed about HRA with the definition by Marler and Boudreau (2017), which was chosen so that it would be easier for participants to enclose and understand HRA, as it has been described both in non-specific or futuristic and very open terms. Even though today there are already AI programs that are used in this context, the understanding of what they are limited to and what they can do, would be too complicated and long for this study. Therefore, the vignette was designed with the idea in mind to limit the introduced variance to the research questions. Relatedly participants were informed that their decision would be anonymous, which relates to the earlier discussed topic of repercussions. It was expected that readers linked possible negative effects of their decision only to the loss of benefits and not punishment by the HR department. These benefits were described in detail and together with the collected data noted to be strictly limited. Whenever a positive outcome was targeted at someone, which was the case 4 times, for the IBM it was presented at the reader themselves, while in the other group, it was presented as a collective benefit.

On the same page, they were then asked to indicate on a Likert scale of 1-7, how much they agreed or disagreed with the following sentence: "In the scenario above I consent to sharing the specific data mentioned". One was "strongly disagree" and seven was "strongly agree". For a full overview see Figure 1.

Figure 1

Collective Benefit Manipulation



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50% completed

1. Please read the text carefully and imagine the following scenario:

You work for a company, which is currently modernizing the Human Resources department by introducing HR-Analytics, a data-driven decision-making approach. The ongoing results directly impact your teams daily work.

HR Analytics
Practice enabled by IT that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making.

Your colleagues are presenting the new project and tell you that your consent to share your data would provide a significant benefit for your team. By agreeing, the decisions of the Human Resources department would be better fitted to your team and your team would be part of the feedback loop.

The participation is anonymous and the company cannot trace back data to a single employee.

The data you share is strictly limited to and will be used for

- Improving training effectiveness and career development
- Providing insights about diversity and inclusion
- Making feedback on benefits, compensation and Work-Life Balance more objective
- Streamlining onboarding of new colleagues

2. Please read the statement below and decide how much you agree or disagree with it. Then indicate your response.

	Strongly disagree			Neutral (neither agree nor disagree)			Strongly agree
In the scenario above I consent to sharing the specific data mentioned.	○	○	○	○	○	○	○

Next

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Note. The picture depicts the full page of the manipulation for the collective benefit as seen by participants.

No time limit was enforced on this page or any part of the study, so that anyone could read at and decide at their own pace. Arguably this leaves a risk for inattentive and overly fast reading, which is statistically explored in the results.

Manipulation check

Participants were asked to rate the perceived benefit of the vignette on a Likert scale from 1 ("exclusively individual") to 7 ("exclusively collective"). 4 was labelled as "Neutral".

Demographics

Gender was asked for with three options. Female, male or non-binary were chosen as options, in order to align with the importance of acknowledging diverse gender identities. Age was recorded next, followed by several options for employment status, leading to better interpretation of the sample. As university theses often rely on student samples, which provide mixed results when generalisation to the public is attempted (Hanel & Vione, 2016), collection of employment is important to fully understand the results and their impact. It was the only demographic question with multiple choice, offering Full-time, part-time, student, retired, unemployed, self-employed or none of the above. Lastly participants were asked for their highest level of educational qualification. Options ranged from compulsory school, high school diploma, apprenticeship, college or university to postgraduate degrees. In case none would be fitting, participants had the option to choose other and use the text field to describe it.

Results

Method of analysis

For the analysis weighted-least-squares (WLS) regression was preregistered in the case of homoscedasticity. One of the biggest difficulties with this approach is the estimation of weights, as they have to be as exact as possible (NIST, 2009). If they aren't precise, then results can become unpredictable. This risk also applies specifically to this survey, as the manipulation is novel and therefore difficult to estimate. Furthermore, it is well suited for small data sets, such as this study was expected to be, yet the final sample size is well above the preregistered goal. The aim was 247 with the final sample of valid cases reaching 496. WLS can also be used to increase the importance of specific data sections. This is the case when data can be hard to come by, or costly to reproduce (Shalizi, 2015). Firstly, the current study has shown to be economically viable in duration, with the mean time spent being 5 minutes and 33 seconds (*SD* = 3 minutes and 1 second). Secondly the survey itself was performed online and automated. Thirdly requirements for participants were very few, thus the survey was open to many potential participants. Consequently, concerning this aspect of WLS, it does not fit very well for this experiment. Another advantage of WLS is varying data quality. As mentioned, the study was automated and online, therefore without human error during data collection. Established questionnaires were used, thus the data can be assumed to be of good quality. This is further extended by the exclusion of all participants with any missing data as well as exploratory analysis for participants who took too little time to finish the survey. Lastly the study used Likert scales of 5 or 7 and should consequently be expected to have similar precision between the different measurements. Concluding, the analysis in the final paper will be using ordinary-least-squares (OLS) regression and disregard the preregistered use of WLS.

Confirmatory analyses

For the main hypotheses a novel experimental manipulation was created. Participants were randomly assigned to either the CBM (n = 250) or the IBM (n = 246). Privacy concern was assessed first for one half (n = 248) and the other half answered the HH questionnaire first.

In the CBM, participants rated their agreement to share their data on average 5.43 (out of 7, *SD* = 1.56), with 7 being the strongest consent. In the IBM the mean was 5.08 (*SD* = 1.79).

Across both manipulations the mean level of HH was 3.56 (out of 5, *SD* = 0.65). Privacy concern overall was 5.77 on average (out of 7, *SD* = 0.98).

The main research question focussed on the effects of the experimental manipulation and HH. To test the effect of the vignette a manipulation check was performed and consequently analysed.

Manipulation check

In a singular question manipulation check the CBM participants rated the vignette slightly more collective with a mean of 4.94 (out of 7, *SD* = 1.33) compared to the IBM with a mean of 4.78 (*SD* = 1.39).

To test the effect of the experimental analysis, outliers were excluded and OLS regression was performed. First the cook distance with a cut off at 4 / *n* (496) was used, which resulted in a new sample size for the manipulation check of 466. To test for heteroscedasticity in the model, a studentized Breusch-Pagan test was conducted. It showed a non-significant result ($BP = 0.47$, $df = 1$, $p = .49$). Therefore, as the null hypothesis is not rejected, there is no significant indication of heteroscedasticity in the model. OLS regression indicated a non-significant result ($F(1,464) = 0.18$, $p < .68$) with an R^2 of < 0.01. For the benefit manipulation f^2 was < 0.01 and therefore well below a low effect (Cohen, 1988).

The 95% confidence interval further indicated a non-significant result as can be seen in Table 2 and the violin plots in Figure 2.

Table 2

Linear regression between manipulation check and data sharing decision

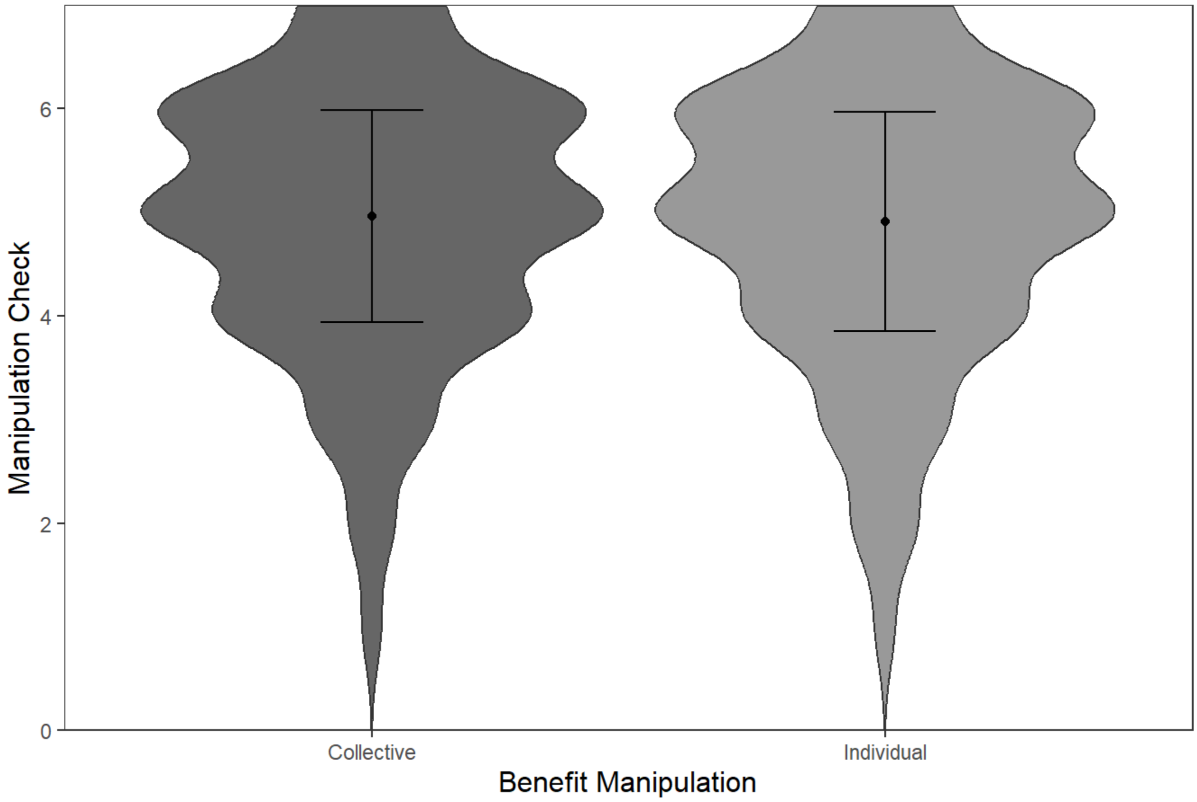
Variables	*B*	*SE*	*t*	*p*	95% *CI*
Intercept	5.00	0.08	59.00	<.01***	[4.80, 5.12]
Benefit manipulation	-0.05	0.12	-0.42	.68	[-0.29, 0.19]

Note. $n = 466$

*$p < .05$. **$p < .01$. ***$p < .001$.

Figure 2

Perception of the experimental manipulation between groups.



Note. $n = 466$*;* The center dots indicate the mean and lines the 95% confidence intervals. Grey areas show the number of observations in the respective areas, with narrower (wider) areas representing lower (higher) counts.

In exploratory analysis a Welch Two Sample t-test with data sharing decision as the outcome and the manipulation as the predictor was performed, which revealed a significant outcome (t = 2.30, df = 483.18, p-value = .02). Mean ratings for the IBM were 5,08 (SD = 1.79) and 5.43 (SD = 1.56) for the CBM. The 95% confidence interval for the means ranged from 0.05 to 0.64 in the direction of the collective group, thus indicating that there is a positive and significant difference between the groups.

Hypothesis 1a and 1b

It was proposed that in the CBM, participants with higher levels of HH would be more likely to share their data, while in the IBM, participants with lower levels of HH would be more likely to do so. In order to test these hypotheses first HH was centered on its mean. Then the cook distance with a cut off at 4 / n (496) was used, which resulted in a new sample size of 472. A studentized Breusch-Pagan test was conducted. The test yielded a statistic of BP = 6.60 with 3 degrees of freedom, resulting in a p-value of .09. The p-value suggests a statistically non-significant result, thus not indicating heteroscedasticity. Multicollinearity was assessed using the Variance Inflation Factor (*VIF*). For the predictor variable HH, the *VIF* was 1.87 and for benefit manipulation 1.00. Both variables did not exhibit substantial multicollinearity with other predictors.

OLS regression was performed for data sharing decision as the dependent variable with HH and benefit manipulation as independent variables together with their interaction. As presented in Table 3, the effect of HH and the interaction were not significant, while the effect of the benefit manipulation showed a significant result. Figure 3 visually represents the relationship.

The model overall showed a significant fit (F(3,468) = 2.6, p = .05, with R^2 of 0.02, yet the benefit manipulation was the only predictor showing individual significance (p = .02) indicating lower data sharing in the IBM compared to the CBM. For HH f^2 was < 0.01, 0.01 for the benefit manipulation and < 0.01 for the interaction between the two predictors.

Table 3

OLS Regression with data sharing as the independent variable and HH and benefit manipulation as dependent variables

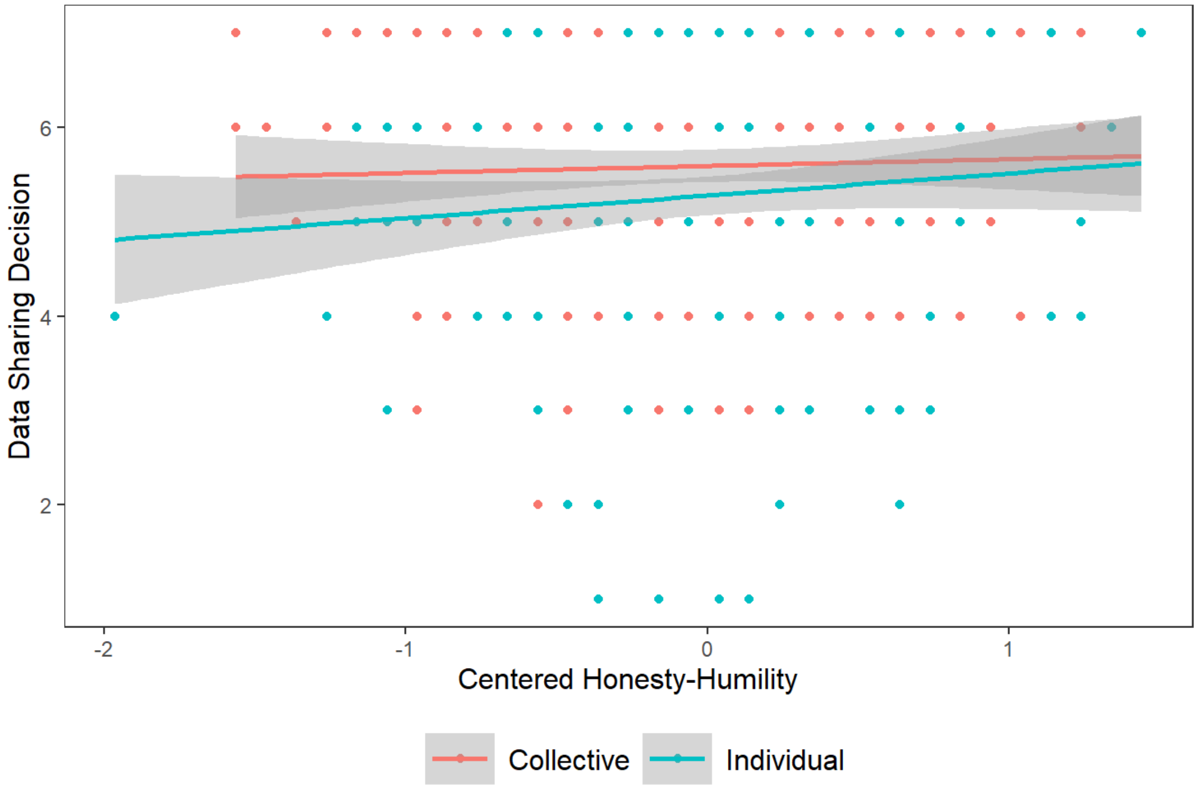
Variables	Estimate	Std. Error	*t*	*p*
Intercept	5.59	0.09	59.32	< .001 ***
Honesty-Humility (HH)	0.07	0.15	0.50	.62
Benefit (B)	-0.31	0.13	-2.33	.02 *
Interaction HH-B	0.16	0.21	0.77	.44

Note. $n = 472$

$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Figure 3

OLS Regression for benefit manipulation and HH as predictors of data sharing



Note. $n = 472$. Descriptively, the two lines ascend slightly with higher HH scores, whereas the CBM has a higher tendency to share data at any level of HH. Nevertheless, no significant effect was found.

In exploratory analysis the order of the two questionnaires, privacy concern and HH, were added to the model. The predictors individually as well the model overall were not significant (F(7,464) = 1.31, p = .24, R^2 = 0.02).

Hypothesis 2

Privacy concern was expected to play a significant role in the decision to share data and thus measured for hypothesis 2. To test it, first HH was centered on its mean. Then the cook distance with a cut off at 4 / n (496) was used, which resulted in a new sample size of 466. A studentized Breusch-Pagan test was conducted to assess heteroscedasticity in the regression model. The test yielded a test statistic (BP) of 1.30 with 1 degree of freedom, resulting in a non-significant p-value of 0.25. Therefore, there is insufficient evidence to reject the null hypothesis of homoscedasticity, indicating that the assumption of constant variance in the residuals is not violated. In the OLS regression results showed a significant result (F(1,464) = 10.59, p = < .01) indicating that individuals privacy concern significantly predicted their data sharing decision. Higher levels of privacy concern were related to increased likelihood to share data (f^2 = 0.02). The model explained a small amount of variance (R^2 = .02). Table 4 shows detailed results, which are visually presented in Figure 4.

Table 4

OLS Regression with data sharing as the independent and privacy concern as the dependent variable

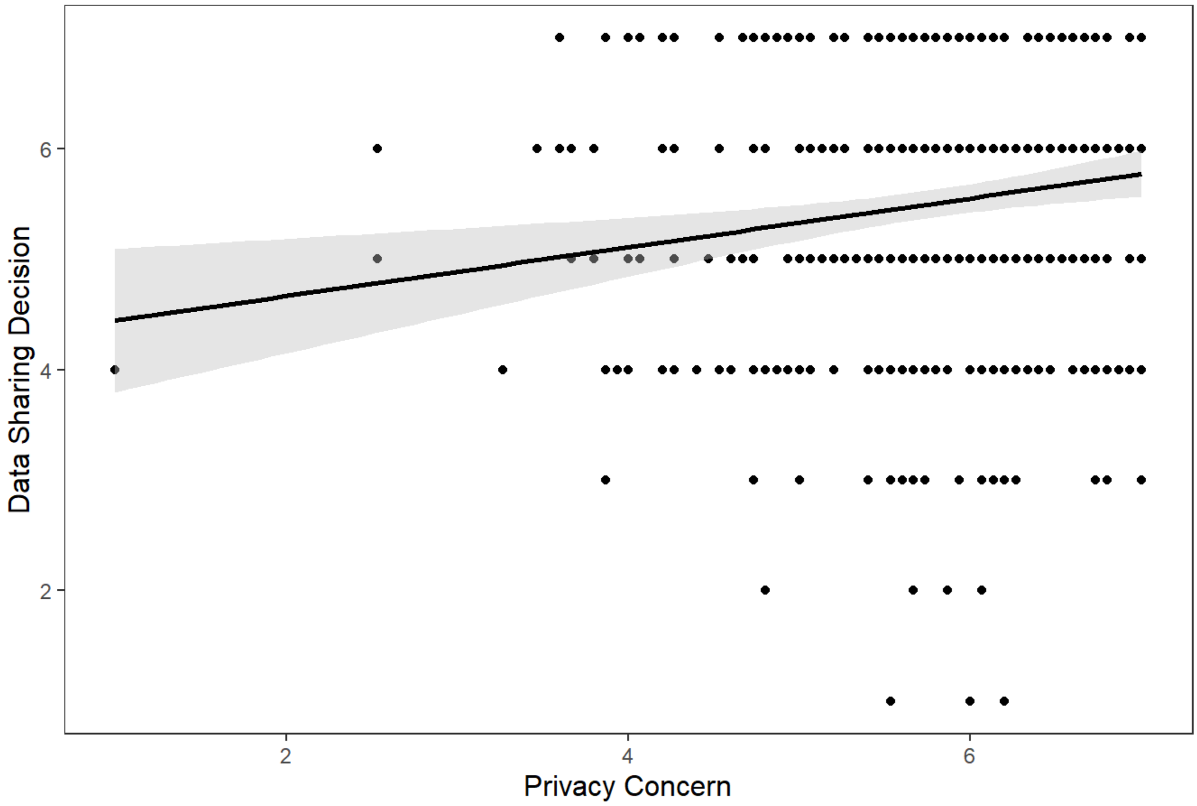
Variables	Estimate	Std. Error	*t*	*p*
Intercept	4.22	0.40	10.64	<.001 ***
Privacy concern	0.22	0.07	3.25	.001 ***

Note. n = 466

*p < .05. **p < .01. ***p < .001.

Figure 4

OLS regression for privacy concern and data sharing decision



Note. n = 466

Exploratory

In further exploratory analysis privacy concern was introduced to the model of hypothesis 1.

The same procedure was performed. HH was centered and a cook distance of 4 / n (496) lead to a new sample size of 465. A studentized Breusch-Pagan test was conducted. The test yielded a statistic of BP = 8.27 with 7 degrees of freedom, resulting in a p-value of .31. Therefore, there is insufficient evidence to reject the null hypothesis of homoscedasticity, indicating that the assumption of constant variance in the residuals is not violated.

The overall model can be considered significant (F(7,457) = 2.35, p = .02), with R^2 = 0.03, yet the individual predictors did not show significance as can be seen in Table 5.

Table 5

OLS Regression with data sharing as the independent variable and HH and benefit manipulation as dependent variables

Variables	Estimate	Std. Error	*t*	*p*
Intercept	4.80	0.65	7.36	< .001***
Honesty-Humility (HH)	1.69	1.05	1.61	.11
Benefit (B)	-0.16	0.95	-0.17	.87
Privacy concern (PC)	0.14	0.11	1.32	.19
Interaction HH-B	-0.05	1.53	-0.04	.97
Interaction HH-PC	-0.30	0.18	-1.68	.09
Interaction B-PC	-0.02	0.16	-0.13	.90
Interaction HH-B-PC	0.03	0.26	0.12	.91

Note. n = 465

*p < .05. **p < .01. ***p < .001.

For HH f^2 was 0.01, < 0,01 for benefit manipulation, < 0.01 for privacy concern, < 0.01, 0.01, < 0.01 for the interactions of HH and benefit manipulation, HH and privacy concern, benefit manipulation and privacy concern respectively and < 0.01 for the interaction between all three predictors.

Considering the insignificant result of the manipulation check the last analysis was also performed without the benefit manipulation.

After centering HH, the cook distance with a cut off of 4 / n (496) was used to create a sample of 465. OLS regression showed a significant overall model (F(3,461) = 3.95, p = .01), with R^2 = 0.02 and significant effects of predictors as shown in Table 6. Both HH and the interaction are significant with p < .05, while privacy concern is p < .1 and thus not significant. The results suggest that higher levels of HH are linked to a higher chance to share data. The interaction effect between HH and privacy concern further indicates a significant influence on data sharing, which is visually depicted in Figure 5 and further explored with simple slopes analysis.

For HH f^2 was 0.01, 0.01 for PC and < 0.01 for the interaction, thus indicating very small effects. A studentized Breusch-Pagan test was conducted. The test yielded a statistic of $BP = 3.26$ with 3 degrees of freedom, resulting in a p-value of .35. Thus, there is no evidence for heteroscedasticity.

Table 6

OLS Regression with data sharing as the independent variable and HH and benefit manipulation as dependent variables

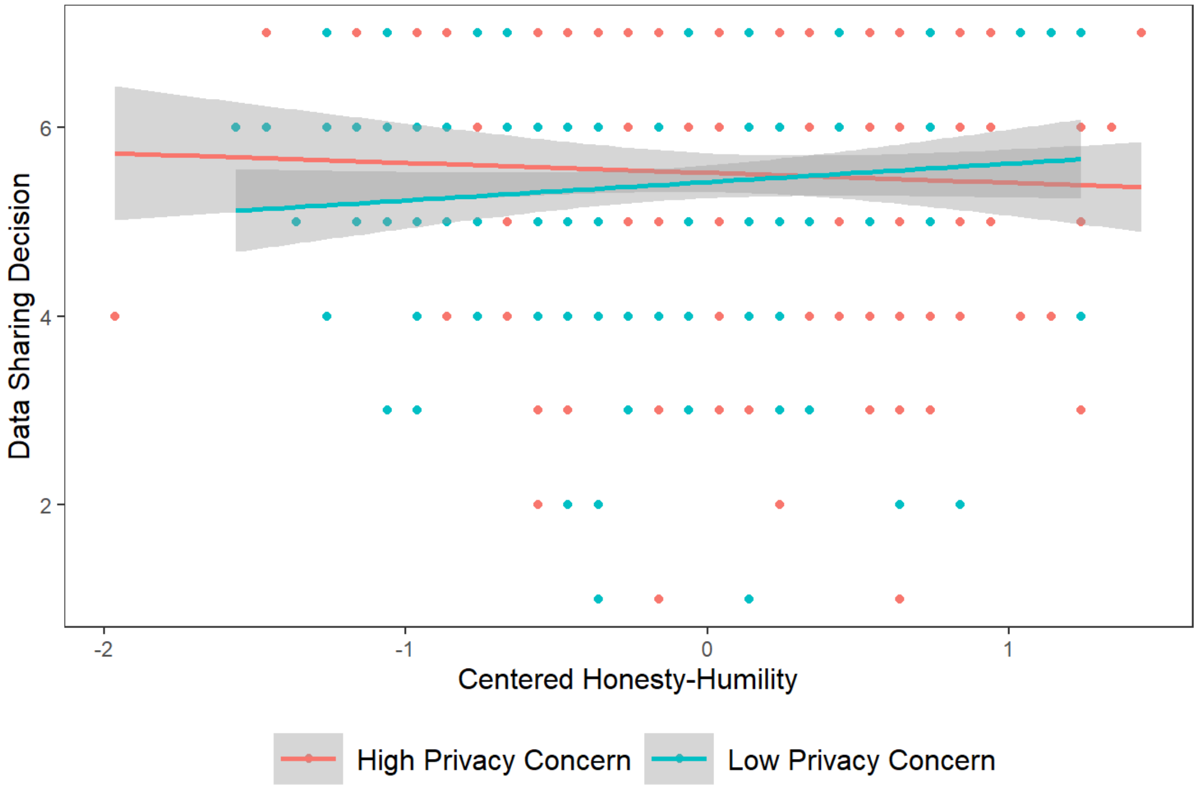
Variables	Estimate	Std. Error	*t*	*p*
Intercept	4.72	0.47	10.00	< .001***
Honesty-Humility (HH)	1.59	0.76	2.09	.04*
Privacy concern (PC)	0.13	0.08	1.68	.09
Interaction HH-PC	-0.27	0.13	-2.14	.03*

Note. $n = 465$

$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Figure 5

OLS regression with privacy concern and HH as predictors of data sharing decision



Note. n = 465. Descriptively participants with low privacy concern show lower consent to share data at lower levels of HH, which rises with higher levels of HH. For high privacy concern the effect is reversed. It is important to note that only low levels of HH were significant in simple slopes analysis.

Simple slopes analysis, presented in detail in Table 7, suggests a significant effect only for low privacy concern. At mean and high HH effects were not significant. Thus, analysis suggests that privacy concern positively influences the data sharing decision particularly among participants with low levels of HH, diminishing as they increase.

Table 7

Simple slopes analysis for privacy concern and HH as predictors of data sharing decision

Dependent Variable	Predictor (+/-1 *SD*)	*df*	*b*	*t*	*p*	sr^2	95% *CI*
Data sharing decision	PC (Low HH)	461	0.20	3.37	.001***	.02	[0.00, 0.05]
	PC (Mean HH)	461	0.09	1.74	.083	.01	[0.00, 0.02]
	PC (High HH)	461	-0.02	-0.26	.793	.00	[0.00, 0.00]

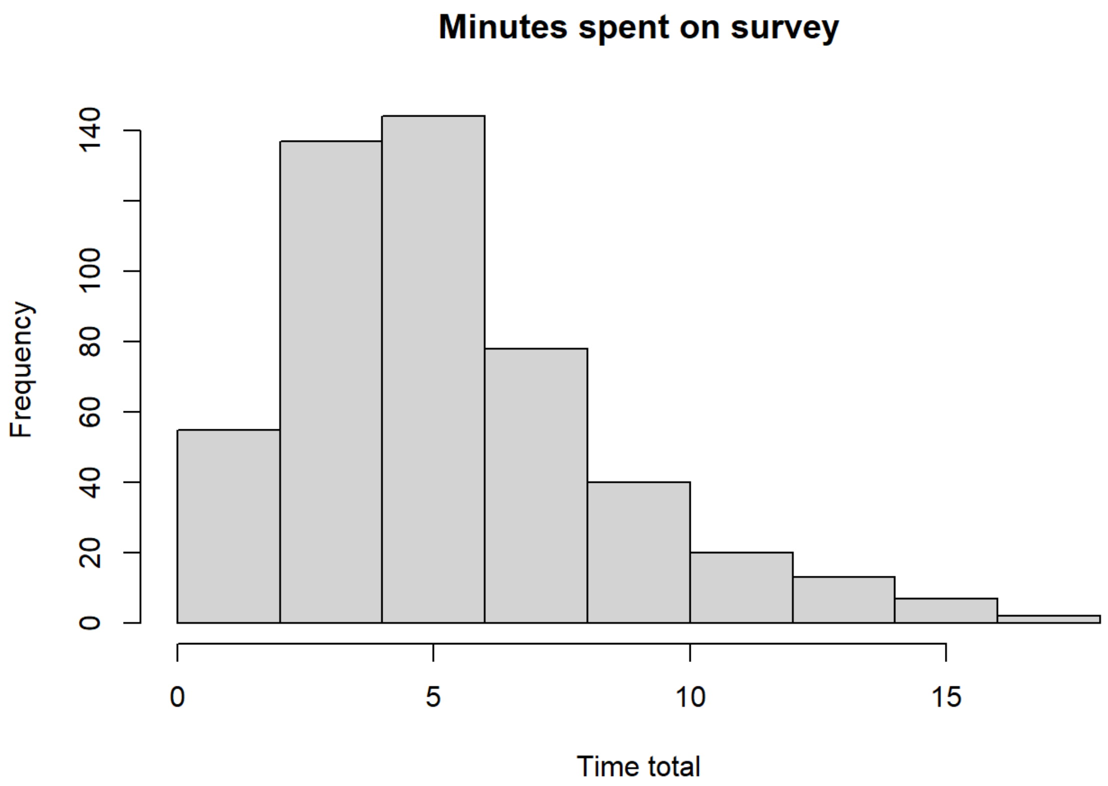
Note. $n = 465$

*$p < .05$. **$p < .01$. ***$p < .001$.

Furthermore, the possibility of participants skipping through and decreasing data quality was tested for. For each participant total time for the survey was measured by adding the individual time for each page. Survey completion took on average 5 minutes and 33 seconds (*SD* = 3 minutes and 1 second) and is visually presented in Figure 6.

Figure 6

Histogram for total time to finish

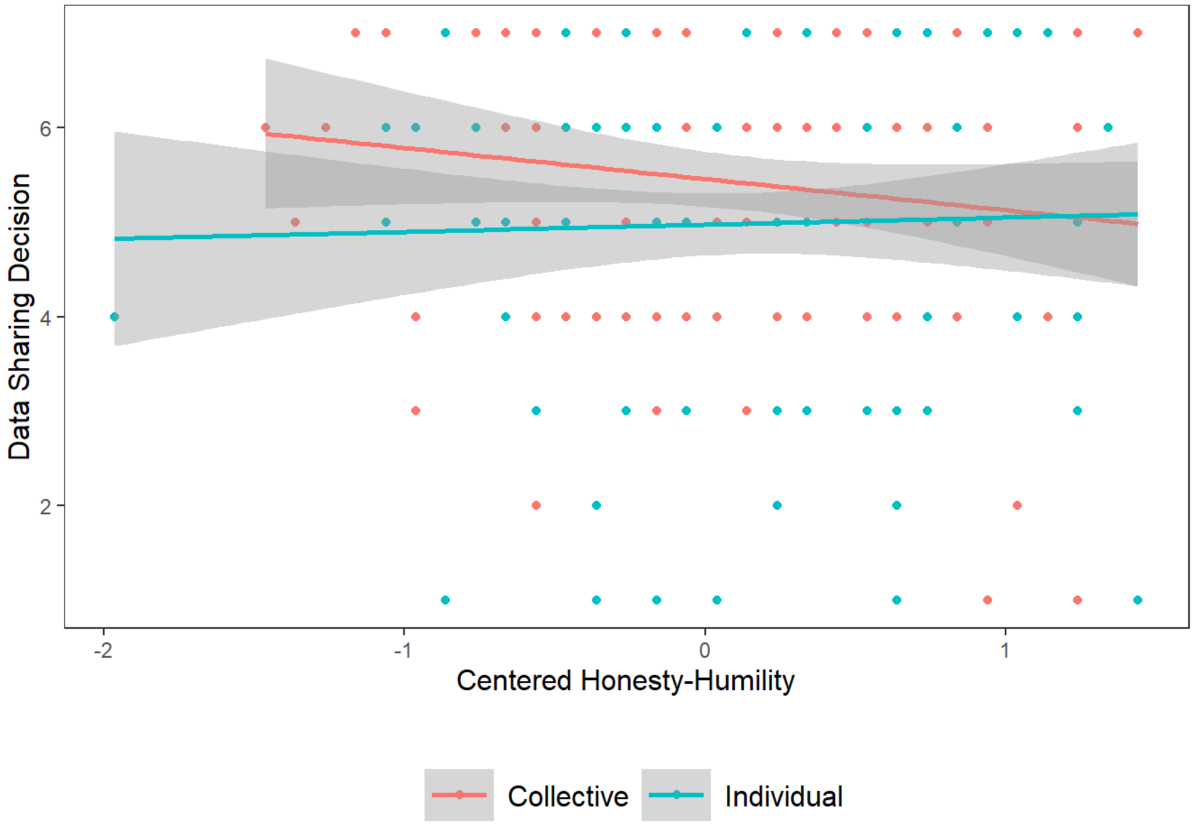


Note. $n = 496$

For the analysis, a cutoff of < 2 on the provided measure by sociosurvey was chosen. This conservative measure, as suggested by Leiner (2019) excluded only 2 participants. Using a cook distance cutoff of 4 / n (494), the number of included surveys was reduced to 421. Next the manipulation check was analysed using OLS. The results showed a non-significant outcome ($F(1,419) = 1.03$, $p = .31$), with R^2 of < 0.01 (f^2 = < 0.01). Hypothesis 1 was also tested with OLS after the same cook distance procedure reduced the sample to 441 and yielded similar results to the original model ($F(3,437) = 2.56$, $p = .05$). Statistical findings are visually presented in Figure 7 and offered in detail in Table 8. For HH f^2 was < 0.01, 0.02 for the benefit manipulation and < 0.01 for the interaction.

Figure 7

OLS regression for HH and benefit manipulation as predictors of data sharing decision



Note. n = 441

Table 8

OLS Regression with data sharing as the independent variable and HH and benefit manipulation as dependent variables

Variables	Estimate	Std. Error	*t*	*p*
Intercept	5.46	0.11	48.98	< .001***
Honesty-Humility (HH)	-0.03	0.17	-0.17	.87
Benefit (B)	-0.43	0.16	-2.69	.01*
Interaction HH-B	0.15	0.24	0.61	.54

Note. n = 441

$*p < .05$. $**p < .01$. $***p < .001$.

Another possible influence on the outcome was compensation, which differed between the matter of recruitment of participants. 113 (22.78%) were not paid any money, while 383 (77.22%) were paid by using the services of makeopinion.com. An OSL regression with data sharing as the independent variable, HH and benefit manipulation as predictors as well as their interaction yielded non-significant results ($F(7,488) = 0.95$, $p = .47$), with $R^2 = 0.01$. After including privacy concern the model still showed an insignificant outcome ($F(15,480) = 1.58$, $p = .08$), with $R^2 = 0.05$. Equally compensation did not have a significant influence on the manipulation check ($F(3,492) = 0.62$, $p = .60$), with $R^2 = < 0.01$.

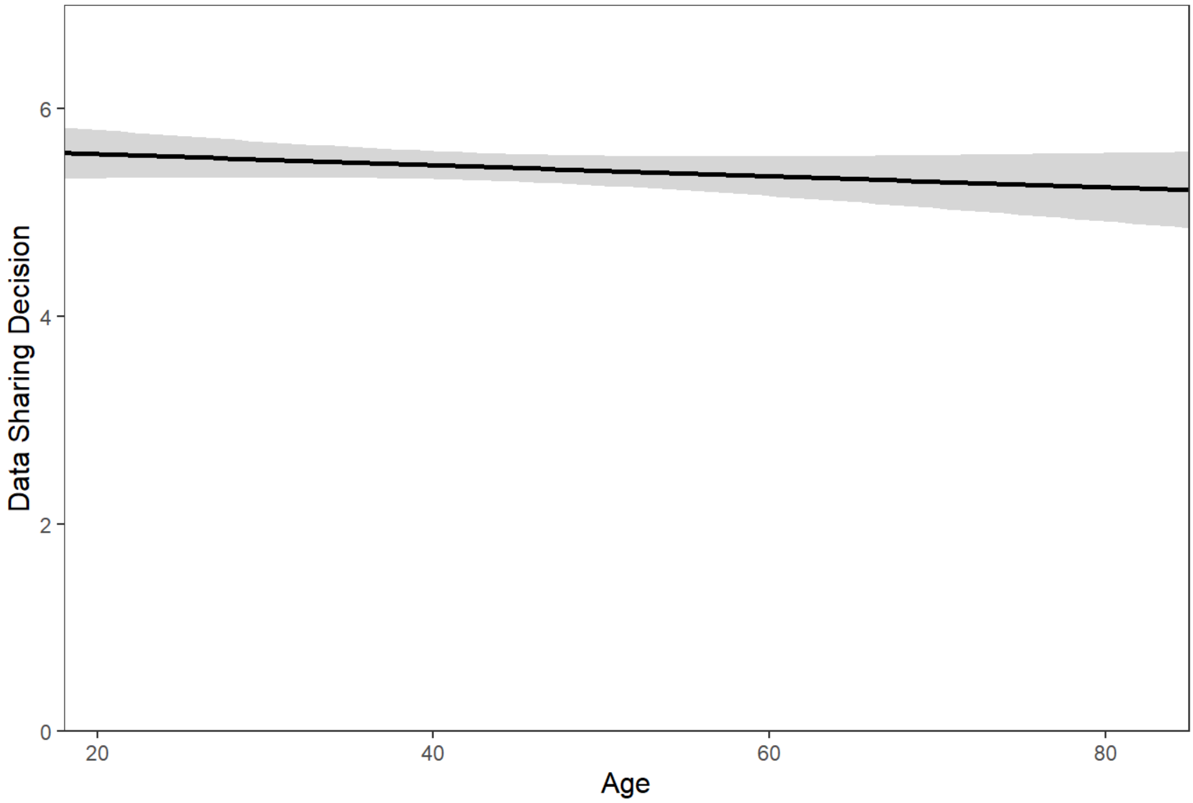
Demographics

In exploratory analysis demographics were included in the main hypotheses and yielded non-significant individual predictor results.

For data sharing decision as the independent variable, OLS regression was conducted by including all measured demographics as a predictor. Age was the only significant factor of the model ($F(1, 494) = 4.59$, $p = .03$, $R^2 = 0.01$) with f^2 of 0.01. OLS regression with data sharing as the independent variable and age as the dependent variable showed a significant result ($F(1,494) = 4.59$, $p = .03$), with $R^2 = 0.01$, visually depicted in Figure 8. For age f^2 was 0.01.

Figure 8

OLS regression for age and data sharing decision

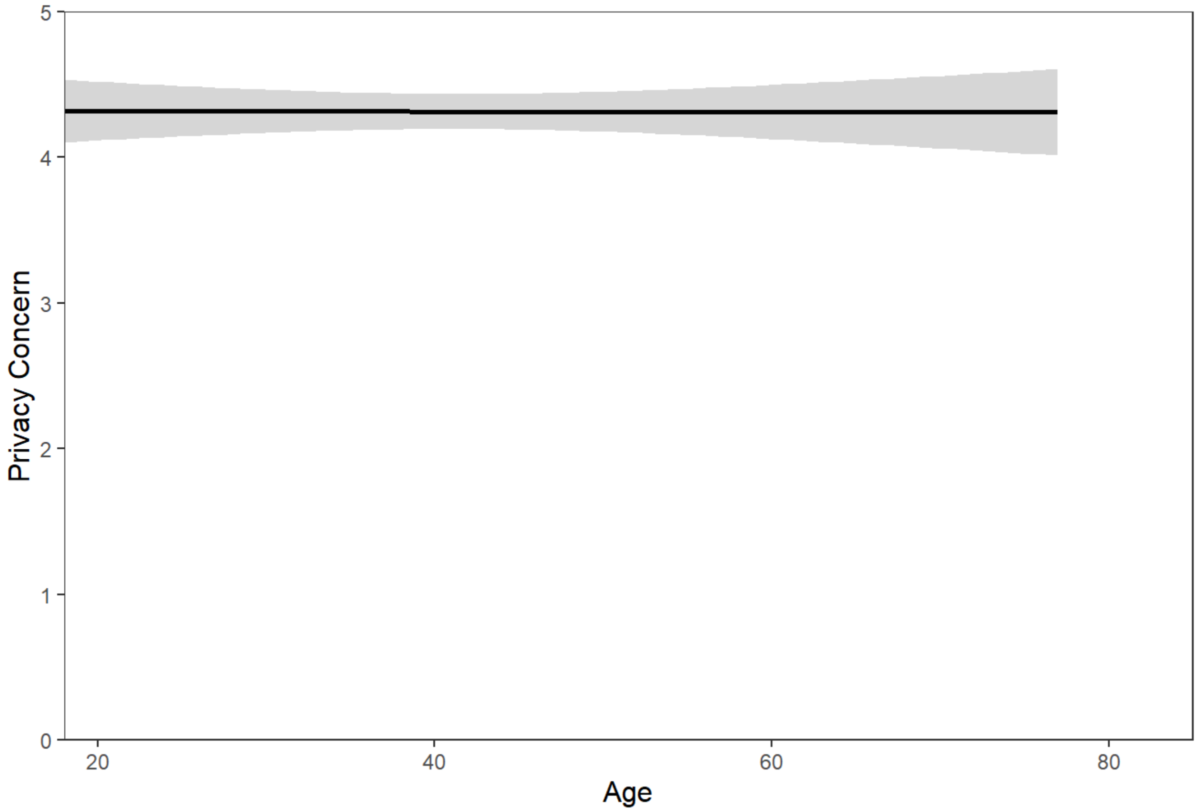


Note. n = 494

Further exploratory analyses focussed on privacy concern and demographics. OLS regression with age as the dependent variable, as can be seen in Figure 9, was again significant, with R^2 = 0,01 (F(1,494) = 13.81, p = < .001). For age f^2 was 0.02.

Figure 9

OLS regression for privacy concern and age



Note. n = 494

Education as the dependent variable in OLS regression (F(5,490) = 1.61, p = .16, R^2 = 0.02) also showed significant results, which are presented in Table 9.

For occupation the categories were not significant except for "None of the above", which only 12 participants picked (F(7,488) = 1.45, p = .18, R^2 = 0,02). Gender was a significant predictor of privacy concern as shown in Table 10 (F(2,493) = 3.48, p = .03, R^2 = 0.01). Female participants had higher privacy concern, compared to males. Non-binary participants did not show a significant relation in analysis.

Table 9

OLS Regression with privacy concern as the independent variable and education as the dependent variable

Variables	Estimate	Std. Error	*t*	*p*
Intercept	5.25	0.24	21.57	< .001***
High School	0.52	0.25	2.07	.04*
Apprenticeship	0.33	0.29	1.15	.25
College or University	0.62	0.25	2.42	.02*
Postgraduate degree	0.55	0.28	2.00	.05*
Other	0.38	0.61	0.62	.54

Note. $n = 496$

*$p < .05$. **$p < .01$. ***$p < .001$.

Table 10

OLS Regression with privacy concern as the independent variable and gender as the dependent variable

Variables	Estimate	Std. Error	*t*	*p*
Intercept	5.86	0.06	105.02	< .001***
Male	-0.23	0.09	-2.55	.01*
Non-binary	0.24	0.49	0.50	.62

Note. $n = 496$

*$p < .05$. **$p < .01$. ***$p < .001$.

Discussion

The aim of this study was to analyse the effect of the personality trait HH in a context-specific scenario of HRA on the willingness to share personal data. Those lower in HH were expected to share more when the benefit is individual, as is the nature of the trait (Ashton & Lee, 2007). On the other hand, those high in HH were expected to share more when the benefit is collective. The findings were ambiguous as the manipulation check revealed a non-significant result, which affects the interpretation of the non-significant effect of HH on data sharing decision as well as the non-significant effect of the interaction between HH and benefit manipulation.

This outcome suggests that there may not be a significant difference between the two benefit conditions. However, the Two Sample Welch Test for differences between means was significant thus implying the manipulation had a measurable effect. In the CBM the mean was 5.43 compared to the lower mean of the IBM of 5.08, suggesting that a benefit that extends beyond oneself might be more attractive. Another possible explanation of the effect is unequal randomization of the sample between the two groups, differentiating the conditions even before they had come in contact with the experimental manipulation. Nevertheless, the distribution described in Table 1 shows a sample, that was consistently close to equal across various demographic measures, which implies effective randomization. Alternatively, the benefit condition might have also been interpreted differently by the participants. While the targeted distinguishment is in the benefactor, IBM could have also been interpreted as for oneself and the CBM for oneself and one’s team, therefore always including the decision taker. Another possible underlying mechanism is the influence of the perceived recipient benefit. As such sharing behaviour is not only positively affected by personal gains, but also those of the recipient (Cyr & Choo, 2010), meaning that if the described benefits were attractive enough, there might be little difference in who receives them. In such scenarios, the difference would have been reduced and the manipulation’s effect changed. Thus, this study’s check would have been ineffective. In addition, the benefit could have been manipulated as intended, yet only to such a degree that the measurement was not precise enough, or the sample too small. Future studies should consider a more nuanced approach to the manipulation check with multiple questions. Taking into account a meta study (Gerber et al., 2018), which showed that possible benefits of data sharing are one of the best predictors of not only intention but actual behaviour, it is likely that the propositions were too interesting or not interesting enough, the differentiation too similar or the one question manipulation check too insensitive.

Furthermore, in the context of the vignette, exploration for a relation to the lack of punishment and relatively low power of readers need to be considered. In past economic games that focussed on HH, changes in decisions have often been due to an in- or decrease in punishment (Fehr & Gächter, 2000; Zettler et al., 2013). The perception of the participants power of the situation, which has been a big influencing factor in research on prosocial behaviour (Van Dijk et al., 2020) can also not be ruled out as a covariable. For example, Zander & Zieglmeier (2023) have found that employees experience potential peer pressure and a feeling of being watched or pressured by the analysis and HR department, hinting at a perceived power difference. The current manipulation only stated that the data cannot be tracked back to employees and did not explicitly state the interaction the HR staff had with the decision of the participant, therefore leaving room for interpretation. Summarizing, the manipulation results offer various perspectives for further studies, whereas as bigger distinction between the two groups, combined with a more sensitive check, emerges as the most important change.

The main model and first hypotheses are to be interpreted carefully. While the model overall was significant (p = .05) and explained 2% of the variance, neither the interaction nor HH suggested a correlation with the data sharing decision. The only individually significant predictor, with a p-value of .2, was the benefit manipulation in which the IBM, compared to the CBM, predicts lower likeliness to share data. Figure 2 shows the OLS regression visually. This contrasts the expectation as high levels of HH should not significantly differ, while those participants in the IBM with lower levels of HH would have been expected to show more egoism (de Vries, de Vries, De Hoogh, & Feji, 2009) and thus be more likely to share data when they individually benefit. To sum up, analysis did not provide evidence to prove neither hypothesis 1a, nor hypothesis 1b.

The second proposed hypothesis, which stated a negative effect of privacy concern on data sharing was also not supported. The analysis showed significant results, yet into the opposite direction. The higher the privacy concern, the higher the likeliness to share data. This is in stark contrast to many past findings, where more concern leads to less sharing (Özkan, 2018). Even if at first a counterintuitive outcome, several possible reasons can be discussed.

HRA information is very personal and, while in this case not being able to be traced back, offers a unique insight into the work lives of employees. In comparison to the focus on online interactions or commerce of a lot of research on privacy concern, this study offers more salient and arguably more complex dis- and advantages of data sharing. Hearth, et al. (2015) have reported a moderation model for sharing of genetic information, in which they find that increased awareness of risks and benefits are linked to higher privacy concern, but unexpectedly also to increased intention to share. The present research has not tested for awareness yet finds a similar outcome. Additionally, increased privacy concern, which does not negatively affect data sharing can be seen in the work of Boise et al. (2013). They report that concern increased for the elderly after a year of participation in-home sensor technology to detect health problems. Nevertheless, willingness to share this data stayed stable over time. Therefore, a closer distinction of the situational context of the benefits and risks should be accounted for. This study leaves the possibility open that higher concern could be related to more knowledge, which includes both up- and downsides, therefore not necessarily decreasing willingness to share.

The scale used to measure privacy concern (Smith et al., 1996) had good internal consistency, even to the point where the number of questions could arguably be reduced with similar results ($\alpha = 0.9$). It was partly chosen for this study as the wording matches the scenario in question and focusses on companies. Out of the 15 questions, 11 mentioned something that should be done, while only four focussed on the data sharer. The present experiment did not account for the possibility that participants might have answered the questionnaire as the standard they would expect from companies. If that was the case, then simply put, the higher the privacy standards the higher the willingness to share data. At this point, this assumption is no more than an appeal to study this relation further by asking specifically for the company mentioned in the vignette or experimentally manipulating the privacy standards of the firm. The current research lacks attention checks and specifically in this questionnaire also reversed items. Combined with the high internal consistency and a motivation of both those recruited via survey sharing platforms as well as those getting compensated for their time by makeopinion.com to finish quickly, inattentive answers offer a realistic alternative explanation.

Accordingly exploratory analysis was performed for possible changes for both the manipulation check and hypothesis 1 when excluding those who finished the experiment faster than a specific time. The average time was 5 minutes and 33 seconds, with a considerably high standard deviation of 3 minutes and 1 second. By using a conservative measure only two data sets were excluded, which, after applying a cook's distance of $4 / n$ for outliers, effectively reduced the sample size for hypothesis 1 from 471 of the original analysis to 441 and for the manipulation check from 466 to 421. However, it did not significantly change the results of either analysis. Hence the data suggests that participants who finished the study too quickly or inattentively did not skew the outcome in a meaningful way.

Additionally, different exploratory analysis based on the previous interpretation was conducted. Firstly, due to different methods of recruitment the participants differed in their compensation, which added an extra layer of complexity to explore. Hertwig & Ortmann (2001) argue that studies without monetary incentive typically create more variability, while Lönnqvist el al. (2011) have reported better predictions in prisoner dilemma games (Rapoport & Chammah, 1965) without them. Considering further work by Murphy et al. (2011), having shown individual preferences in economic games to be consistent over time and Epstein, Peysakhovich & Rand (2016), who effectively used machine learning to predict cooperative decisions, a difference by recruitment method was not expected, yet cannot be ruled out. 77.22% of participants were paid, while the rest completed the survey without monetary reward. By following the same steps of the OLS regressions performed for the confirmatory analysis of hypothesis as well as the addition of privacy concern to the model, while adding the compensation as a predictor, no model was able to reach significance. These results can be interpreted as evidence that the experiment was not significantly influenced by the different recruitment methods.

Secondly, privacy concern was added to the main model as a predictor. It added to the explained variance ($R^2 = 0.03$) and resulted in a significant model ($p = .02$). No individual predictor showed a *p*-value of lower than .09, while all the models' possible interactions were considered. Eminent is a notable change for the benefit manipulation, which loses its significance compared to the model without privacy concern. This, in combination with the failed manipulation check, could suggest that the group does in fact not have any significant influence on the data sharing decision, even while significant in the study's main model. Additional research is necessary to provide clear evidence.

To further explore these results and as a consequence of the ambiguous results of the manipulation, the model was repeated without it, thus including HH and privacy concern as interacting predictors of the data sharing decision. The model showed a significant outcome for both privacy concern, the interaction, as well as overall. Higher levels of HH predicted higher likeliness to share data, which falls in line with plenty of past research presented in this paper. Simple slopes analysis further suggested that the interaction between privacy concern and HH varies between the level of the latter. The effect of privacy concern is strongest, and only significant at low levels of HH ($B = 0.09$) The data therefore indicates that privacy concern only gains relevance once the prosocial personality factor is below a certain threshold. When one's levels are high, then the person is not influenced as much by outside matters and will pursue actions that benefits not only oneself, but also others. Similar effects have been found in a different context by Kleinlogel et al. (2018), when using HH to predict cheating behaviour. While high levels of HH always cheated less, low levels of HH were significantly affected by immoral primes. Interactions have also been reported for other factors, where again, those low in HH reduced their prosocial behaviour in the absence of a reward when their intuition was low, compared to no effect for individuals high in

HH (Laila & Pfattheicher, 2021). Altogether past research and the present study align in its results, where HEXACO’s new addition beyond BIG-5, HH, demonstrates the personality factor as a gatekeeper to selfish behaviour.

Thirdly and lastly the effects of demographics were analysed. They were not found to significantly influence the confirmatory analysis of this study. Nevertheless, and in line with past research age and gender influenced privacy concern significantly. Age showed a small effect (f^2 = 0.028), in which younger participants worried less. Women were generally more concerned about their data compared to men, with analysis of non-binary participants resulting in a non-significant outcome. For the latter outcome it must be noted that the category was only picked four times. Additionally, education was found to be a significant predictor of privacy concern. The highest significant effects on privacy concern were “College or University” followed by “Postgraduate degree” and “High School Diploma”. High School and College were picked significantly more than postgraduate degree (n = 199, 179, 57, respectively). The remaining three categories only amounted to 61 participants in total, making meaningful analysis and interpretation difficult. Thus, it can be assumed that higher levels of education correlate positively with privacy concern. Nevertheless, as discussed earlier, it might, in this case, not directly reflect hesitancy to make information available and instead be more accurately linked to interest, knowledge and reflection about data privacy and its risks and benefits.

Similarly, effects of demographics were explored for data sharing. The results suggested that older age was associated with lower data sharing. All other variables were not significant. Partly in line with these outcomes, research by Beierle et al. (2020) showed an effect of age and gender, but not education, where younger and female users were more willing to share. Considering the minimal effect size (Cohen, 1988) of f^2 = 0,0093 of age in this study the practical influence is nevertheless, negligible.

Limitations

Due to time and budget limitations, this study created an imaginative scenario and relied solely on self-reported information. Comparingly studies like by Zander & Zieglmeier (2023) have more closely mirrored real work scenarios. As such, especially considering the privacy paradox (Gerber et al., 2018), which states attitude to often mismatch behaviour, implications should not be generalised without careful consideration. Even though the sample was diverse and well established in the work life, it is unknown how many participants have had direct contact to HRA and thus can accurately imagine the scenario and self-report on their fictive actions.

Future research should consider adding attention checks as well as a minimum timer for the vignette. While the time measure of this study only considered two participants as too fast, nevertheless data quality would undeniably increase by adding both. Attention checks could act both as a way to test the understanding of the language, as with the public availability of the study, the general understanding of English was expected, but not tested for, as well as filter out those who only click through without proper focus. Contrary to the positive effect of the multicultural sample, non-response bias (Berg, 2005) could especially be relevant due to the nature of recruitment, where most participants chose to participate by picking from a study library. Therefore, the likeliness to share data for this context across groups should only carefully be generalised.

This novel design has provided several different possible moderators and directions for future research. Adding to those that have already mentioned, such as analysis of power dynamics in HRA consent situations and perception of benefits, are property rights. Oxoby and Spraggon (2005) found significant differences in results of economic games by informing participants that either givers or receivers have earned the wealth that is to be redistributed. The owner then valued their possessions higher. Dictators allocated 20% in the baseline, 50% when receivers earned wealth and made zero offers to the receiver when they earned it themselves. Building on the difference of "giving versus taking" (Zhao et al., 2018), it could be argued that every participant of the present study interpreted the ownership and source of their data differently. This would add a potentially significant covariable and further shows the complexity of data sharing in a complex and still relatively new context of HRA. Even if this study lacks evidence to accurately estimate the necessity of specific covariables, it would be advisable to increase the number of measurements and further narrow the focus of future studies.

Implementations

Studies like Beierle et al. (2020), which documented no effect between data sharing decisions and personality factors, should be expanded on the basis of the present experiment. The complex dynamic, where privacy concern and HH interact only at low levels of the personality, has shown significant results and thus warrants the examination of both the interaction and possible other factors that interplay with personality and data sharing consent.

For companies implementing or continuing their work with HRA, this study provides a valuable insight into consent decisions. Not only will employees behave differently overall, but especially those with lower levels of HH will react according to the information they are given. Whereas a direct tendency of participants with low levels of HH towards selfish decisions was expected, the data suggests consent is a more complex interplay between risks and benefits. Even when the opportunity to defect was explicitly mentioned as an anonymous choice, privacy concern played a significant role. Subsequently firms can expect a significant positive effect on consent decisions when they increase internal communication about HRA processes, information security and use. At the same it has to be noted, that the content must address concerns and be transparent. According to the presented results, the benefit should also be formulated as collective, meaning for the whole team or organisation, as comparatively individual advantages predicted a lower likeliness of data sharing. If a company holds itself to high privacy safety standards, then low levels of HH might not become sceptics, but knowledgeable data sharers.

The data has also indicated that higher levels of privacy concern are not linked to lower, but higher likeliness to share data, offering a unique perspective. Employees might feel the need to be informed, to understand and to make better decisions. *Inverse privacy* (Zieglmeier & Pretschner, 2023) is an idea is that fits well to these findings. In it the default stance is to communicate everything about what and why data is collected and how it will be used, compared to limiting it or waiting for employees to ask. It puts the obligation to deliver information on the data receiver, rather than the data provider. Considering all that has been reported in this study, a fearful approach to the topic should be exchanged for open communication and proactive information exchange.

Lastly it is worth mentioning that high levels of HH continue to predict prosocial behaviour, even when other results are ambiguous and therefore reflect a promising personality trait for employees and team members of any kind alike.

Ethics and open science statement

The study was preregistered at the Center for Open Science (https://osf.io/qwzh2) and approved by the Departmental Review Board of the Department of Occupational, Economic, and Social Psychology at the University of Vienna (Study protocol number: 2024/W/001). The analysis code is available at the Open Science Framework (https://osf.io/2qng3)

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Appendices

List of Figures

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List of Abbreviations

CBM Collective benefit manipulation
HH Honesty Humility
HRA Human Resource Analytics
HRM Human Resource Management
IBM Individual benefit manipulation
OLS Ordinary least squares
WLS Weighted least squares

Study materials

Introduction and consent

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0% completed

1. Welcome and thank you for participating!

This study is part of a master thesis at the University of Vienna and focusses on the decision to share data within different scenarios. It will cover some socio-demographic data, a privacy and personality questionnaire and a fictive scenario.

It will take approximately 5 minutes to complete. In order to participate you have to be 18 years or older.

The study exclusively serves scientific purposes. The survey is conducted at the Faculty of Psychology at the University of Vienna for a master thesis. Your survey results will be treated in strict confidence. The study data will be completely anonymised at all times. The results and data of this study may be published. This is done in anonymised form, i.e. without the data being able to be attributed to a specific person. Anonymous and anonymised data are not subject to data protection.

Participation in the study is voluntary and does not involve any known risks. You can cancel your participation in this study at any time without giving reasons. This will not result in any disadvantages for you. It is not possible to delete your answers at a later date.

It is important that you read the questions carefully and follow the instructions exactly. Please do not refresh the page or use the back button of your browser during the study.

If you have any questions about the study, you can contact me at the following e-mail address: a01447362@unet.univie.ac.at

Thank you for taking part in this survey!
Benedikt Bauer

2. I have read and understood the above information and agree to the conditions of participation.

- ○ Yes
- ○ No

Next

Benedikt Bauer – 2023

Privacy concern questionnaire (Smith et al., 1996)

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13% completed

Below, you will find a series of statements about personal information.

From the standpoint of personal privacy, please indicate the extent to which you, as an individual, agree or disagree with each statement.

	Strongly disagree			Neutral (neither agree nor disagree)			Strongly agree
It usually bothers me when companies ask me for personal information.	○	○	○	○	○	○	○
All the personal information in computer databases should be double-checked for accuracy-no matter how much this costs.	○	○	○	○	○	○	○
Companies should not use personal information for any purpose unless it has been authorized by the individuals who provided the information.	○	○	○	○	○	○	○
Companies should devote more time and effort to preventing unauthorized access to personal information.	○	○	○	○	○	○	○
When companies ask me for personal information, I sometimes think twice before providing it.	○	○	○	○	○	○	○
Companies should take more steps to make sure that the personal information in their files is accurate.	○	○	○	○	○	○	○
When people give personal information to a company for some reason, the company should never use the information for any other reason.	○	○	○	○	○	○	○
Companies should have better procedures to correct errors in personal information.	○	○	○	○	○	○	○
Computer databases that contain personal information should be protected from unauthorized access-no matter how much it costs.	○	○	○	○	○	○	○
It bothers me to give personal information to so many companies.	○	○	○	○	○	○	○
Companies should never sell the personal information in their computer databases to other companies.	○	○	○	○	○	○	○
Companies should devote more time and effort to verifying the accuracy of the personal information in their databases.	○	○	○	○	○	○	○
Companies should never share personal information with other companies unless it has been authorized by the individuals who provided the information.	○	○	○	○	○	○	○
Companies should take more steps to make sure that unauthorized people cannot access personal information in their computers.	○	○	○	○	○	○	○
I'm concerned that companies are collecting too much personal information about me.	○	○	○	○	○	○	○

Next

Benedikt Bauer – 2023

HEXACO self-report questionnaire – Honesty-Humility items of the short version (Ashton & Lee, 2009)

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25% completed

Below, you will find a series of statements about you. Please read each statement and decide how much you agree or disagree with that statement. Then indicate your response.

Please answer every statement, even if you are not completely sure of your response.

	Strongly disagree	Disagree	Neutral (neither agree nor disagree)	Agree	Strongly agree
I wouldn’t use flattery to get a raise or promotion at work, even if I thought it would succeed.	○	○	○	○	○
If I knew that I could never get caught, I would be willing to steal a million dollars.	○	○	○	○	○
Having a lot of money is not especially important to me.	○	○	○	○	○
I think that I am entitled to more respect than the average person is.	○	○	○	○	○
If I want something from someone, I will laugh at that person’s worst jokes.	○	○	○	○	○
I would never accept a bribe, even if it were very large.	○	○	○	○	○
I would get a lot of pleasure from owning expensive luxury goods.	○	○	○	○	○
I want people to know that I am an important person of high status.	○	○	○	○	○
I wouldn’t pretend to like someone just to get that person to do favors for me.	○	○	○	○	○
I’d be tempted to use counterfeit money, if I were sure I could get away with it.	○	○	○	○	○

Next

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Individual Benefit Manipulation

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38% completed

1. Please read the text carefully and imagine the following scenario:

You work for a company, which is currently modernizing the Human Resources department by introducing HR-Analytics, a data-driven decision-making approach. The ongoing results directly impact your daily work.

HR Analytics
Practice enabled by IT that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making.

Your colleagues are presenting the new project and tell you that your consent to share your data would provide a significant benefit for you. By agreeing, the decisions of the Human Resources department would be better fitted to you and you would be part of the feedback loop.

The participation is anonymous and the company cannot trace back data to a single employee.

The data you share is strictly limited to and will be used for

- Improving training effectiveness and career development
- Providing insights about diversity and inclusion
- Making feedback on benefits, compensation and Work-Life Balance more objective
- Streamlining onboarding of new colleagues

2. Please read the statement below and decide how much you agree or disagree with it. Then indicate your response.

	Strongly disagree			Neutral (neither agree nor disagree)			Strongly agree
In the scenario above I consent to sharing the specific data mentioned.	○	○	○	○	○	○	○

Next

Benedikt Bauer – 2023

Collective Benefit Manipulation

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50% completed

1. Please read the text carefully and imagine the following scenario:

You work for a company, which is currently modernizing the Human Resources department by introducing HR-Analytics, a data-driven decision-making approach. The ongoing results directly impact your teams daily work.

> **HR Analytics**
> Practice enabled by IT that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making.

Your colleagues are presenting the new project and tell you that your consent to share your data would provide a significant benefit for your team. By agreeing, the decisions of the Human Resources department would be better fitted to your team and your team would be part of the feedback loop.

The participation is anonymous and the company cannot trace back data to a single employee.

The data you share is strictly limited to and will be used for

- Improving training effectiveness and career development
- Providing insights about diversity and inclusion
- Making feedback on benefits, compensation and Work-Life Balance more objective
- Streamlining onboarding of new colleagues

2. Please read the statement below and decide how much you agree or disagree with it. Then indicate your response.

	Strongly disagree			Neutral (neither agree nor disagree)			Strongly agree
In the scenario above I consent to sharing the specific data mentioned.	○	○	○	○	○	○	○

Next

Benedikt Bauer – 2023

Manipulation check

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63% completed

1. Please indicate on the following scale of 1-7 whether you perceived the benefit of sharing data in this experiment as more individual or collective.

	Exclusively individual	Strongly individual	Slightly more individual	Neutral	Slightly more collective	Strongly collective	Exclusively collective
I perceived the benefit of the scenario that I just read as	○	○	○	○	○	○	○

Next

Benedikt Bauer – 2023

Demographic questions

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75% completed

1. What is your gender?

- ○ female
- ○ male
- ○ Non binary

2. How old are you?

I am [ ] years old

3. What is your employment status?

- ☐ Full-time
- ☐ Part-time
- ☐ Student
- ☐ Retired
- ☐ Unemployed
- ☐ Self-employed
- ☐ None of the above

4. What is your highest educational achievement?

Please select the highest level of qualification you have obtained.

- ○ Compulsory school
- ○ High School diploma
- ○ Apprenticeship
- ○ College or University
- ○ Postgraduate degree
- ○ Other: [ ]

Next

Benedikt Bauer – 2023

Post-experiment debriefing

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You have reached the end of the study. Thank you for your participation!

The aim of this study is to investigate the relationship between higher or lower levels of Honesty-Humility and two scenarios with differently described benefits for the reader.

Not all participants received the same information as you. While one scenario described individual benefits (for you), the other described collective benefits (for your team).

My hypothesis was that in the individual benefit group, participants with lower levels of Honesty-Humility would be more likely to share their data, while in the collective benefit group, participants with higher levels of Honesty-Humility would be more likely to do so.

Thank you for your participation in this study. By taking part, you have made an important contribution to my research. If you have any further questions or comments, you can contact me at a01447362@unet.univie.ac.at. I would also like to ask you to maintain confidentiality about the contents of this study.

I also would like to invite you to share this survey link with all who would be interested in participating:
https://sosci.univie.ac.at/HR-Analytics

For Survey Circle users: Redeem code: https://www.surveycircle.com/7JRN-L1AZ-GVWC-BG54/

If you are using Makeopinion, please follow this link:
https://redirects.makeopinion.com/?s=c&pr=8b8502b408743206b2b6e92415b8ad6f&buyer_subid_1=&buyer_subid_2=&session_id=

Benedikt Bauer – 2023

Abstract English

With Human Resource Analytics showing a consistent trend of both rising popularity and implementation, employees are faced with the decision to share their data and weighing benefits and risks. In comparison to past research, this study presents a novel perspective by replacing BIG-5 with HEXACO's Honesty-Humility (HH) and experimentally manipulating the benefit instead of punishment. In an online experiment 496 participants are presented a vignette with either a collective or individual advantage to their choice. The proposed interaction effect, in which higher levels of HH are expected to be more likely to share data regardless of context, while lower levels of HH are predicted to be more selfish and thus more likely to share in the individual benefit manipulation, was not found. Privacy concern was measured and theorized to predict decreased likeliness to share yet showed a significant effect to increase it. Possible explanations are discussed. As the manipulation check was not significant, the expected, but also not significant interaction effect with HH on data sharing is explored and an additional interaction between HH and privacy concern found. Low levels of the personality trait interact with privacy concern in the decision to share data, while higher levels do not. At any level, HH predicts higher data sharing when including privacy concern in the model. Thus, the results align with past research showing that individuals with high levels of HH act prosocial regardless of the context. Lastly effects of demographic measures are explored.

Keywords: Honesty-Humility, privacy concern, data sharing, Human Resource Analytics

Abstract German

Mit der steigenden Popularität und Implementierung von Human Resource Analytics (HRA) stehen immer mehr Mitarbeiter vor der Entscheidung, ob sie ihre Daten teilen und wägen Vorteile und Risiken ab. Im Kontrast zu bisheriger Forschung des Gebiets bietet diese Studie anhand des Wechsels von BIG-5 zu HEXACOs Honesty-Humility (HH) und der Manipulation des Nutzens anstelle der Bestrafung, einen neuen Blickwinkel. In einem Online-Experiment werden 496 Proband:innen eine Vignette zu HRA, welche entweder einen kollektiven oder individuellen Vorteil beschreibt, gefragt ob sie ihre Daten teilen möchten. In der Gruppe des individuellen Nutzens wird erwartet, dass Teilnehmer:innen mit niedrigeren HH Werten eher bereit sind Daten zu teilen, während Personen mit hohen HH Werten kontextungebunden teilbereiter sind. Darüber hinaus wurden Datenschutzbedenken gemessen und erwartet, dass diese einen negativen Zusammenhang zur Wahrscheinlichkeit des Teilens der Daten aufweisen. Die Ergebnisse zeigen eine signifikante Korrelation in die entgegengesetzte Richtung und werden diskutiert. Da die Manipulationsprüfung nicht signifikant war, wurde der erwartete, ebenfalls nicht signifikante Interaktionseffekt der Manipulation mit HH auf das Teilen der Daten untersucht und eine zusätzliche Interaktion zwischen HH und Datenschutzbedenken exploriert. Niedrige, aber nicht mittlere und hohe Werte der Persönlichkeitseigenschaft interagieren mit der Sorge um Datenschutz bei der Entscheidung diese zu teilen. Auf jedem Niveau sagen sie das Teilen der Daten voraus, sofern Datenschutzbedenken im Modell aufgenommen wurden. Die Ergebnisse stehen im Einklang mit vergangener Forschung, welche zeigt, dass Personen mit einer hohen Ausprägung von HH unabhängig vom Kontext prosozial handeln. Abschließend werden die Effekte der demografischen Faktoren dargestellt.

Schlüsselwörter: Honesty-Humility, Human Resource Analytics, Datenschutz, Daten teilen