Assessment of Personal Values for Data-Driven Human Resource Management

REVIEW

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ABSTRACT

Business organizations have introduced data analytics to human resource management (HRM) to predict employee behavior in recent years. This practice is called HR analytics, and uses the various properties of employees, including their personal values, as inputs. Personal values are conceptualized as stable personal traits that represent the relevant employee. Previous studies in the area have shown that the personal values of employees influence their attitudes and behaviors as well as the performance of their group. Assessing these values is thus important in HRM. Although most previous studies have measured personal values based on self-reported questionnaires, this method encounters many problems, such as the social desirability bias. Accordingly, more recent studies have proposed alternative methods that apply machine learning algorithms to linguistic or visual data. This study reviews research on personal values by focusing on the methods used to measure them, and discusses the usefulness of and the challenges to the measurement of personal values. We also discuss future directions of research on the assessment of personal values.

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KEYWORDS:

Personal values; HR analytics; Machine learning; Natural language processing; Large language model

TO CITE THIS ARTICLE:

Kimura, T. 2023. Assessment of Personal Values for Data-Driven Human Resource Management. *Data Science Journal*, 22: 22, pp. 1–13. DOI: https://doi.org/10.5334/dsj-2023-022

1. INTRODUCTION

With the rise in the strategic importance of business analytics in recent years, HR practitioners have been drawn to data-driven HRM to support rational and effective decision-making (Margherita 2021). Business analytics in the context of HRM is called HR analytics, people analytics, or workforce analytics (Marler & Boudreau 2017), and has been applied to a variety of HR activities, including recruitment and selection (Wang & Zhi 2021). For instance, some organizations use machine learning to assess the personality traits of candidates during recruitment to choose employees who match their requirements and corporate culture (Garg et al. 2022).

The importance of assessing personal values for personnel selection has also been recognized in previous studies in the area. Because personal values include one's desired goals, people are motivated to behave in ways that allow them to express their values and achieve their goals (Arieli, Sagiv, & Roccas 2020). Empirical research supports this view, and has shown that personal values can be used to predict work-related behavior (Sagiv & Roccas 2021). Accordingly, personal values can be regarded as a critical variable for predicting an employee's attitudes and behaviors, and thus constitute an essential input as well as a response variable in HR analytics.

Personal values and methods of measuring them have attracted considerable attention in psychology research. Self-report questionnaires are the most popular method to this end (Sagiv & Schwartz 2022). However, because personal values encapsulate people's beliefs as conditioned by socially desired ends, self-report measures are prone to the social desirability bias (Crowne & Marlowe 1960). Recent research has thus proposed new methods of measuring personal values that use machine learning algorithms to avoid such biases. The author of this study recognizes the importance of measuring and analyzing personal values in the context of data-driven HRM, and thus reviews research on the measurement of personal values and propose promising directions for future research in the area.

2. WHY ARE PERSONAL VALUES IMPORTANT?

Personal values are defined as 'broad, trans-situational, desirable goals that serve as guiding principles in people's lives' (Arieli, Sagiv, & Roccas 2020: 232). As suggested by this definition, personal values are 'broad' in that they influence all aspects of a person's life, rather than being associated with specific tasks and purposes. Moreover, personal values are 'trans-situational.' As noted by Rokeach (1973), personal values are enduring and stable across situations and over time. Moreover, they are desired goals that represent what a person believes to be personally or socially desirable. Although some scholars have used 'personal values' and 'personality' interchangeably—as revealed in the meta-analysis by Parks-Leduc, Feldman, and Bardi (2015)—they are distinct constructs. While personality is a descriptive construct, personal values are motivational constructs. Specifically, while personality represents what a person is like, which is not always desirable, personal values are what they believe they should be and, therefore, are essentially desirable (Sagiv & Roccas 2021).

A number of aspects of personal values are crucial in human resource management. First, because personal values represent a person's desired goals, people are motivated to behave in ways that enable them to express their values (Ponizovskiy et al. 2019). Accordingly, personal values predict work-related behavior, and determine the fit between people and their work roles (Mubako et al. 2021; Sagiv & Roccas 2021). Second, the congruence between the values of the employee and those of the organization influences the attitude and behavior of the employee as well as organizational outcomes (Hoffman & Woehr 2006). A meta-analysis by Verquer, Beehr, and Wagner (2003) as well as a recent review by Arieli, Sagiv, and Roccas (2020) showed that such a congruence of values is positively correlated with the employees' job satisfaction and organizational commitment, and is negatively correlated with their turnover intention. Third, research on workforce diversity has shown that while diversity in personal values reduces positive emergent states (e.g., team cohesion and identification) and increases intra-team conflict (Triana et al. 2021), it can promote team creativity and innovativeness (Wang et al. 2019).

The second and third of the above aspects seem at least partially conflicting. While the former emphasizes intra-organization homogeneity in personal values, the latter claims the utility of intra-organization heterogeneity. However, both indicate that personal values can be regarded as a critical variable for predicting organizational dynamics. Finally, personal values influence not only those harboring them, but also the people around them. Oreg and Berson (2011) have shown that a leader's values work as a behavioral guide for their followers, and thus influence how the followers behave. Therefore, when an employer hires a person for a leadership role, they should consider the influence of the candidate's values on followers.

Personal values are not entirely innate, but are combinations of inheritance and development through social factors (Sagiv et al. 2017). However, past research has revealed that personal values develop in the early stages of one's life and become stable in adulthood (Abramson, Daniel, & Knafo-Noam 2018; Milfont, Milojev, & Sibley 2016). From the perspective of human resource management, this fundamental nature of personal values suggests the importance of assessing them for personnel selection (Vanderstukken, Van den Broeck, & Proost 2016).

3. MEASUREMENT OF PERSONAL VALUES

Researchers have developed various methods for measuring personal values. The most popular ones rely on Schwartz's value theory (Schwartz 1992; 2012). While moral values have drawn growing attention in business and management, Schwartz's value theory and typology remain the most widely used. One of the reasons for this is that they predict significant work-related behavior, including moral behavior (Aquilar et al. 2018; Feldman et al. 2015; Pulfrey & Butera 2013; Sagiv & Roccas 2021). The theory regards personal values as continuous entities rather than discrete ones. According to it, personal values contain two higher-order dimensions, i.e., openness to change versus conservation, and self-enhancement versus self-transcendence. Each of these dimensions has several components, and a person's system of personal values consists of 10 types of values. They are organized in a circumplex structure in which neighboring types of values are compatible with each other, and those located on opposite sides are conflicting or incompatible. Furthermore, the theory proposes that individuals differ in their priorities related to these 10 types of values.

Previous studies have mainly used psychological measures based on the 10 types of values proposed by Schwartz's theory or a further segmented form of 19 types. The most popular ones are the Schwartz Value Survey (SVS; Schwartz 1992) and the Portrait Values Questionnaire (PVQ; Schwartz et al. 2001). Both are self-reported questionnaires. The SVS is a direct method in which respondents rate the importance of abstract goals. On the contrary, the PVQ is an indirect method in which respondents read a description of a person's portrait, and rate the similarity between the person and themselves.

Because the SVS measures the degree to which respondents agree with desirable goals, it is susceptible to the acquiescence bias, a problem whereby respondents rate all items as important such that this skews the distribution of the response (Bentler, Jackson, & Messick 1971). To solve this problem, Lee, Soutar, and Louviere (2008) developed the Best–Worst Schwarz Value Survey that applies a best–worst scaling (BWS; Finn & Louviere 1992) to the SVS. The BWS can alleviate the acquiescence bias and the central tendency by forcing respondents to choose the most distinct pairs of alternatives.

A problem common to both the SVS and the PVQ is that they contain a large number of items and are thus time consuming to complete. To solve this problem, Lindeman and Verkasalo (2005) developed the SSVS (Short Schwartz's Value Survey), a shortened version of the SVS that reduces the original 57 items to 10 items. Sandy et al. (2017) developed a brief version of the PVQ that contained 20 items as well as an ultra-brief version containing 10 items, compared to the original version with 40 items. All of these shortened versions reduce the burden on the respondents while maintaining their validity as a measure of personal values. Specifically, the scores on values obtained by using these short versions are highly correlated with those obtained from their corresponding original versions (on average, 0.61 and 0.93, respectively).

Despite the above-mentioned attempts to accurately measure personal values, the problem posed by the social desirability bias persists because the above measures are self-reported. The social desirability bias is the tendency of respondents to express opinions in their answers that are different from their actual ones to win the approval of others or avoid their disapproval (Crowne & Marlowe 1960). According to Paulhus (1984), the social desirability bias occurs through impression management or self-deceptive enhancement. While impression management is the intentional distortion of responses to project the desired impression, self-deceptive enhancement is an unintentional, positively biased response to project or protect a positive image.

The social desirability bias often occurs in self-reported surveys designed to measure a construct that contains social desirability. Because personal values represent end states that individuals believe are socially desirable (Rokeach 1973), self-reported surveys are prone to the social desirability bias (Fisher & Katz 2000). Indeed, past studies have shown that both the SVS and the PVQ are susceptible to the social desirability bias. Schwartz et al. (1997) claimed that the self-reported SVS is significantly correlated with scores on the Marlowe-Crowne Social Desirability measure (MCSD, developed by Crowne and Marlowe (1960)) in hypothesized directions. Danioni and Barni (2021) used a shortened version of the PVQ (PVQ-21; Schwartz 2003), and reported that some of the self-reported dimensions of the questionnaire were moderately but significantly correlated with the dimension of impression management of the shortened Paulhus Balanced Inventory of Desirable Responding (BIDR-6; Bobbio & Manganelli 2011). Although some scholars have argued that the social desirability bias is not a serious problem in anonymous surveys (Larson 2019), it can be detrimental to assessments for personnel selection in which the respondents must be identified.

Researchers have also proposed measurements based on one's evaluations of others to address the problem of distortions in self-reporting. Dobwalls et al. (2014) investigated the degree of self-other agreement in measuring personal values. The self-other agreement is the strength of the correlation between one's ratings of oneself and those of others, and represents the extent to which the observer and the target view the latter in the same way. Dobwalls et al. (2014) reported moderate correlations between ratings of the self and those of the other (median $r = 0.47$, range 0.43–0.50), suggesting that these ratings often differ. However, no evidence to date has shown that other-rated personal values predict behavior more accurately than self-reported values. Moreover, it is usually difficult to secure the cooperation of others who know the target well enough to provide accurate answers about the target's values. Therefore, using self-other agreement measures in personnel selection is unrealistic. Furthermore, one's evaluations of others cannot be free from the social desirability bias because others who have close relationships with the target are likely to intentionally or unintentionally evaluate the target positively (Allik et al. 2010).

Researchers have also proposed self-reported measures that are implicit rather than explicit. The Implicit Association Test (IAT) has attracted attention as a method to measure individual differences through implicit methods, and has been applied to measure personal values. Dentale et al. (2018) showed the construct validity and criterion validity of the Achievement-Benevolence IAT (AB-IAT), which measures two poles in Schwartz's model: achievement and benevolence. Their results of a correlation analysis of construct validity were consistent with the circumplex structure in Schwartz's model, and showed that each type of value had the highest correlation with a neighboring type of value. The IAT score was significantly correlated with the corresponding behavior in the context of criterion validity after controlling for social desirability (partial correlation coefficient = –0.23). Dentale et al. also showed that the AB-IAT is less susceptible to the social desirability bias than explicit self-reported measures. Danioni et al. (2020) also reported that the Values Implicit Association Test (VIAT), a version of the IAT for measuring personal values, is less affected by the social desirability bias than the PVQ. While PVQ scores were significantly correlated with the dimension of impression management of BIDR-6 in their study, VIAT scores were found to have no significant correlation with BIDR-6 (Danioni et al. 2020).

Schimmack (2021) has noted that because the IAT exhibits higher validity in attitude polarization than in attitude intensity, it may have a higher validity in measuring personal values with a polarized structure as proposed by Schwartz's model. However, some studies, although not focused on Schwartz's personal values, have reported the low test-retest reliability of the IAT. For instance, Bar-Anan and Nosek (2014) showed that the test-retest correlations of the IAT and its brief version (BIAT) are not high despite the short intervals (i.e., within one day) between the first and second sets of measurements (r = 0.41 for the IAT, r = 0.53 for the BIAT). Gawronski et al. (2017) reviewed past findings on the test-retest reliability of the IAT and reported a moderate level of test-retest correlation (mean r = 0.44 and median r = 0.45). These moderate correlations of the IAT suggest its low temporal stability, which is detrimental for measuring enduring states like personal values.

4. PERSONALITY ASSESSMENT BASED ON LINGUISTIC ANALYSIS

Due to the accumulation of vast amounts of text data through social networking services and websites, and given technological developments in big data analytics, various methods to measure personal values by using linguistic data have emerged in recent years. These methods are based on the insight from previous studies whereby people's cognitive processes are manifested in how they use natural language (Bardi, Calogero, & Mullen 2008). Using linguistic data can reduce the burden on the respondents of having to fill out long questionnaires. It can also reduce the effects of their impression management and self-enhancement. Moreover, using large amounts of text data can increase the accuracy of the measurements. Furthermore, because data from tweets and blogs may be time-series data, they are suitable for measuring personal values that are conceptualized as enduring beliefs.

The analysis of text data through natural language processing (NLP) is one of the most notable technology-enablers in HR analytics (Cho, Choi, & Choi 2023; Margherita 2021; Polzer 2022). Recent research has applied NLP to analyses of employee data, including employer branding (Karkhanis, Chandnani, & Chakraborti 2023), employee sentiment analysis (Hegde et al. 2022), predicting employee turnover (Choi & Choi 2021), and perceptions of leadership, (Bhatia et al. 2022).

NLP has been used for personality assessment in the context of personnel selection (Fyffe et al. 2023; Lee et al. 2023) and resume screening (Najjar, Amro, & Macedo 2021). Research on talent acquisition has proposed and examined the use of NLP for CV screening, skills' assessment, and analyses of video interviews (Fayoumi & Loucopoulos 2023; Mishra, Rodriguez, & Portillo 2020; Palshikar et al. 2019). For instance, Mishra, Rodriguez, and Portillo (2020) proposed a method to assess the cultural match between the organization and the applicant by calculating the cosine similarities between their use of terms.

With developments in the analysis of text data, the assessment of personal values based on them has drawn the attention of researchers and industry practitioners. As recently as a decade ago, researchers used to assess personal values based on text data by using simple text analysis. Bardi et al. (2008) used lexical co-occurrence to gauge the strength of associations between words based on the idea that 'a word is characterized by the company that it keeps' (Firth 1957: 11). Specifically, the idea is that the relative co-occurrence of words represents the degree to which they converge on a single construct. Bardi et al. created a dictionary of personal values from newspaper articles based on Schwartz's theory (Schwartz 1992) and analyzed the co-occurrence of words. Their results showed the same patterns of correlation between the lexical co-occurrence of the 10 values and self-reported values, suggesting the convergent validity of the value lexicon. Their results also showed the validity of predictions based on correlation analyses between the types of values and corresponding behaviors as proposed by Schwartz's theory. According to their results, the mean correlation coefficient between corresponding value-behavior pairs (r = 0.56) was much higher than that for the non-corresponding value-behavior pairs (r = 0.07).

Christen et al. (2016) used data from a thesaurus to identify personal values by relying on the tradition of psycho-lexical analysis, in which natural language is supposed to include predicates when a property is important in the spoken language. He generated value maps from the data by using expert evaluations and machine classification through a sequential superparamagnetic clustering algorithm (Ott et al. 2005). However, these studies did not investigate the association between an individual's personal values and their use of natural language.

Recent studies have used linguistic data obtained from personally used natural languages. Ponizovskiy et al. (2020) created a value dictionary based on linguistic data from blog posts, essays, and SNS updates, and by applying expert ratings and exploratory factor analysis (EFA). All value types in their dictionary showed a high internal consistency (Cronbach's alpha with the

Spearman-Brown adjustment: range 0.80–0.99, mean 0.94), suggesting convergent validity. They also showed that each type of value was more strongly correlated with the theoretically corresponding psychological construct than with the other constructs, suggesting discriminant validity. However, each value type in their dictionary showed only a weak to moderate correlation with the self-reported value and the corresponding psychological constructs in their analysis.

Rather than directly measuring personal values, Altuntas, Gloor, and Budner (2022) developed a machine learning model to predict personal values based on a concept called the Honest Signal (Pentland 2008)—small signs represented by an individual's body movement, short words, or manner of speaking that give away their true intent, personality, emotions, or personal values. Altuntas et al. used archived email data to train a model to predict personal values operationalized by Schwartz's theory. The class imbalance in the training data was adjusted by using SMOTE. They applied various classification models—i.e., logistic regression, support vector machines, stochastic gradient descent, and the XGBoost classifier—by using 10-fold cross-validation, and optimized them by using GridSearchCV. The XGBoost classifier delivered the best performance, and predicted some of the value types of Power, Achievement, and Transcendence in Schwartz's model, with accuracies of 0.858, 0.793, and 0.748, respectively.

Hassanein et al. (2021) used an API called IBM Watson's Personality Insights to extract features from Twitter data and classify the values in Schwartz's model. Their research was based on past findings on the relationship between personal values and personality (Parks-Leduc, Feldman & Bardi 2015: Roccas et al. 2002). Assuming that the extracted set of features represent personal values, they used logistic regression, random forest, normal linear regression, and linear regression with an elastic net regularizer to classify the Big Five personality traits (McCrae & Costa 1987). Logistic regression achieved the highest accuracy (mean 0.802), followed by linear regression with the elastic net regularizer (mean 0.784). However, Hickman, Tay, and Woo (2019) expressed doubts about the validity of the IBM Watson Personality Insights, and reported low correlations or those in opposite directions between the results of Watson and self-reported measures.

Some recent studies have used advanced machine learning algorithms to identify personal values. For instance, Kiesel et al. (2022) attempted to identify the personal values underlying argumentation. They classified the values based on the Bidirectional Encoder Representations from Transformers (BERT; Devlin et al. 2018), SVM, and the 1-baseline by using argumentation-related data from Africa, China, India, and the USA. The data were manually annotated by multiple human annotators, and the value of the average value-wise agreement alpha was 0.49 (Krippendorff 2004). The 1-baseline was designed to classify each argument as resorting to all values so that it always achieved a recall of one. In their analysis, BERT achieved the highest F-1 score in terms of identifying lower-order personal values (BERT: 0.25, SVM: 0.20, 1-baseline: 0.16), but performed worse than the baseline on higher-order values (BERT: 0.71, SVM: 0.67, 1-baseline: 0.75).

Qiu et al. (2022) built a large dataset of values called VALUENET to create a chatbot. VALUENET consisted of text scenarios representing human attitudes, and was used to create the chatbot by relying on the structure of the personal values proposed by Schwartz's model (2012). The data were annotated by 681 human annotators by using 10 values proposed by Schwartz et al. (2012). Their model of classification used fastText (Joulin et al. 2016), BERT, robustly optimized BERT (RoBERTa; Liu et al. 2019), the distilled version of BERT (DistilBERT; Sanh et al. 2019), and Bayesian additive regression trees (BART; Lewis et al. 2019). The accuracy of each model ranged from 0.55 to 0.67, and the BART model delivered the highest accuracy that was, however, only moderately high.

5. ETHICS OF THE ASSESSMENT OF PERSONAL VALUES FOR HR ANALYTICS

Due to the accumulation of evidence of their influence on an individual's work-related behavior and group functioning, personal values are worth considering for data-driven human resource management. In parallel with the increased attention to the assessment of personal values and technological developments in this area, several ethical issues have emerged that need to be addressed by employers.

First, employers must comply with local privacy laws and regulations in collecting and handling employee and applicant data. For instance, the General Data Protection Regulation (GDPR) in the European Union requires employers to obtain explicit consent from their employees before collecting and processing their data, and to ensure that the data are stored securely and used only for legitimate purposes. In Japan, the Act on the Protection of Personal Information (APPI) applies similar regulations to employers regarding the collection, processing, storage, and use of data. The laws and regulations regarding the collection and analysis of employee data vary widely across countries and regions. 'Cybervetting' (Berkelaar 2014) is not formally prohibited by law in many countries. However, from an ethical point of view, employers should ensure the privacy of their applicants and employees, and should use the collected data only for legitimate purposes. Employers should take appropriate measures to ensure the security and confidentiality of the data, including encryption, access controls, and other measures that can prevent the unauthorized access, modification, or disclosure of the data.

Second, employers need to remember that assessing personal values has the potential for bias and discrimination in selection and subsequent interactions. Stereotyping can occur, whereby an individual's behavior and attitude are almost always judged based on the results of assessments of their personal values. Such stereotyping can occur even though assessments of personal values cannot be perfectly accurate, and personal values explain only part of the variance in people's behaviors and attitudes. Discrimination is another issue. Moreover, employers must avoid mistreating applicants based on personal values relating to their religion or political beliefs. Indeed, empirical studies have revealed that personal values influence a person's political orientation and voting behavior (Baro 2022; Dennison, Davidov, & Sedding 2020). However, employers who use assessments of personal values to make hiring decisions should be able to explain why an applicant's values are adequate for the job based on their suitability according to the relevant requirements rather than their political beliefs. Furthermore, employers and organizational members need to have a mindset to promote diversity (Van Knippenberg, Van Ginkel, & Homan 2013) and use data on personal values only for legitimate business-related purposes.

Furthermore, any algorithm can make inaccurate assessments. Algorithms often make biased assessments because the training data are biased and unrepresentative. For instance, an algorithm can make a biased assessment based on the applicant's cultural background—for instance, people from countries characterized by individualism (Hofstede 2011) are likely to be assessed as individualistic. Moreover, individuals do not always express their values directly or explicitly in communication. The resulting inaccurate or biased assessment can result in well-qualified applicants being passed over or, even worse, it can lead to stereotyping and discrimination.

Measuring personal values based on the applicants' use of natural language—e.g., social networking updates, blog posts, and argumentation—is promising for HR analytics. However, using them for assessment without the applicant's consent is ethically problematic (Holland, Dowling, & Brewster 2022). On the contrary, obtaining consent from applicants and employees before data collection leads to another practical issue. Suppose that applicants are informed that employers will use their SNS and blogs to assess them. In this case, they are likely to engage in impression management on these platforms such that the assessment is distorted (Ponizovskiy et al. 2020). Satisfying the demands of both ethics and accuracy is thus a challenge in the assessment of personal values for HR analytics.

6. DIRECTIONS OF FUTURE RESEARCH

As reviewed above, personal values have traditionally been measured by self-reported questionnaires. Because self-reported measures are susceptible to the social desirability bias, measurements based on one's ratings of others have been introduced. However, these ratings can also be distorted by the social desirability bias. With the accumulation of vast amounts of text data and the development of natural language processing technologies, novel methods have been proposed to measure personal values by using linguistic data. Personal values as measured by traditional self-reported questionnaires and machine learning are moderately correlated, suggesting that machine learning methods can reduce or eliminate the social desirability bias. However, this does not guarantee that machine learning methods can measure and identify personal values more accurately than traditional methods. Therefore, future research should examine the extent to which personal values as measured by machine learning models accurately predict theoretically expected behaviors compared with values measured by using traditional methods.

The most promising avenue for future research in the area is to use the large language model (LLM) to assess personal values. The LLM is a language model that uses neural networks with billions of parameters that are trained on massive amounts of unlabeled text data through self-supervised learning techniques (Fan et al. 2023). Popular examples of the LLM include the Generative Pre-trained Transformer 4 (GPT-4) by OpenAI, Bard by Google, and the Large Language Model Meta AI (LLaMA) by Meta. LLMs can perform various language-related tasks with only a few prompts consisting of descriptions in human language. By using them as the input, LLMs can perform a wide range of language-related tasks, such as answering questions, generating text, and translating languages (Teubner et al. 2023; Vidgof, Bachhofner, & Mendling 2023).

LLMs can measure people's personal values by using their self-composed introductory statements as input data. However, applicants may engage in impression management if they are asked to write their own introductions in the context of personnel selection. One option that could be taken to address this problem is to exploit the characteristics of human cognitive ability. As suggested by research on cognitive overload (e.g., Collins 2020; Galant, Zawada, & Maciejewska 2020), reducing the applicants' cognitive resources for managing impressions during assessment prevents impression management. For instance, assessors can have applicants discuss thought-provoking topics with one another and use the content of their discussions as prompts for LLMs.

The validity of assessing personal values by using LLMs has not yet been established. Therefore, future research should investigate whether the assessment of personal values by using the LLM can be used to predict behavior in a way that is consistent with robust theories of personal values. LLMs can instantly produce value measurements by using such text data as the applicants' social networking posts and blog posts. However, this ease of measurement can make it easier to violate the applicants' privacy and confidentiality. Therefore, employers should pay greater attention to ethical considerations in the use of LLMs for assessing personal values.

The prediction of personal values based on facial expressions was recently proposed as well. Gloor et al. (2021) developed a model to measure an individual's personal values that included moral values and some of Schwartz's value types (Conservation and Transcendence). However, the model achieved only moderate levels of accuracy scores (0.733 for Conservation and 0.714 for Transcendence), possibly because facial expressions depend on one's emotions, which constitute a temporary and subjective psychological state that is more unstable than personal values, and is triggered by external stimuli. Moreover, emotion recognition by using facial expressions is challenging (Adyapady & Annappa 2023).

Related to the above issue are controversies regarding the work by Wang and Kosinski (2018), who developed a deep neural network model to detect people's sexual orientation based on facial images as input data. For instance, Agüera y Arcas (2018) criticized their work by claiming that their prediction might be based on factors other than facial expressions or facial structure, such as the subject's makeup, facial hair, and glasses. Future research should be cautious in extracting and generalizing important features because hasty conclusions can result in biased or stereotyped views of an individual's personal values, and may lead to discrimination.

7. CONCLUSIONS

Personal values are stable and difficult to change, and can be used to predict behavior. Hence, assessing personal values during personnel selection is useful for organizations from the perspective of human resource management. Although traditional methods based on self-reports from psychological research are still widely utilized to measure personal values, they are susceptible to the social desirability bias. Researchers have recently developed methods that apply natural language processing, including deep learning algorithms, to the assessment of personal values. However, they are also susceptible to the social desirability bias. A promising method involves using LLMs to this end. Future research can benefit from examining the convergent, discriminant, and predictive validity of the assessment of personal values based on LLMs by relying on the typology of these values proposed by Schwarz's theory. Finally, practitioners and researchers must ensure that the ethical considerations highlighted in this study are taken into account when assessing people's personal values.

ACKNOWLEDGEMENTS

I wish to thank the anonymous reviewers for insightful comments and suggestions on the earlier version of this paper.

COMPETING INTERESTS

The author has no competing interests to declare.

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TO CITE THIS ARTICLE:
Kimura, T. 2023. Assessment of Personal Values for Data-Driven Human Resource Management. *Data Science Journal*, 22: 22, pp. 1–13. DOI: https://doi.org/10.5334/dsj-2023-022

Submitted: 06 October 2022
Accepted: 19 June 2023
Published: 11 July 2023