THE INTERNATIONAL JOURNAL OF HUMAN RESOURCE MANAGEMENT
2023, VOL. 34, NO. 13, 2582–2594
https://doi.org/10.1080/09585192.2023.2225282

Routledge
Taylor & Francis Group

COMMENT

The theoretical value of understanding HRM's financial value

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ABSTRACT
Although the paper by Joo et al. (2022) purports to demonstrate the value of acquiring star performers, we argue that the value of their paper lies more in the demonstration of the use of utility analysis as strong theory, implemented with computational modeling. We articulate why we see the Joo et al. (2022) paper contributing to a strong theory about employee value and how its efforts represent more of a theoretical contribution to the star performers, employee value, employee performance, and utility analysis literatures than one simply about the specific returns on investment related to acquiring star employees. Our commentary explains our view of their contribution and develops new questions and directions for future research that this perspective implies.

KEYWORDS
Employee value; utility analysis; strong theory; computational modeling

Introduction

The intent of the paper by Joo et al. (2022) is to provide a better understanding of the financial value of star performers. To accomplish their goal, they use various processes for computing the value of employee performance (SD_y), which are then incorporated into utility analyses. The authors offer a number of conclusions from their paper, including that their 'overall empirical finding was that HRM creates greater financial value by obtaining more stars' (p. 29), that their 'results highlight the need to use utility analysis procedures that more fully consider the presence of stars' (p. 27), and that 'extant procedures often significantly underestimated the value brought by obtaining more stars' (p. 27). We do not dispute the analytical approach or mathematical findings from

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Joo et al. (2022); in fact, we applaud them. We argue, however, that the empirical findings from Joo et al. (2022) are unsuited for making claims about the validity of the proposed methods. That said, what we see instead is a larger contribution: one that speaks to how research can develop more precise theory about the nature of employee performance.

The Joo et al. (2022) paper provides a series of approaches that estimate the extent to which differences in performance have financial implications for organizations. In the set of techniques known as utility analysis, the key parameter SD_y is defined as the dollar value of a one standard deviation difference in the criterion (Boudreau, 1991; Cascio et al., 2019). As originally defined, this parameter assumes that the organizational value contributed by employees is normally distributed. As Joo et al. (2022) appropriately criticize, this assumption conflicts with key advances in the study of job performance: there exist star performers who produce disproportionally larger amounts of output compared to their peers (e.g. Asgari et al., 2021; Kehoe et al., 2018; Morris et al., 2021; O'Boyle & Aguinis, 2012; Taylor & Bendickson, 2021) thus making the distribution of job performance non-normal (Aguinis et al., 2016; O'Boyle & Kroska, 2017). Consequently, Joo et al. (2022) employ various methods of computing SD_y to represent the idea that the value from employee performance is non-normal and in particular is influenced by the substantial contributions of star employees. The methods they use, in order of their presentation, give greater heed to this non-normality.

Through a large number of demonstrations of utility analysis calculations, varying a number of parameters and contrasting the results from the different methods for estimating SD_y, the authors conclude that stars do contribute greater value because the method of SD_y that best incorporates the non-normality of actual performance scores—the method they call the 'observed distribution procedure'—produces notably higher estimates of workforce utility. We argue that this conclusion is not supported; at the same time, we do not say it is falsified nor do we claim that it is incorrect. Rather, we argue that there is simply no way to validate the financial predictions made by these utility analyses. This is a limitation of the utility analysis technique (Sturman, 2012) and not a particular fault of the Joo et al. (2022) paper. On the other hand, the contribution we feel that is truly made here is that the authors provide a critical step to develop and refine a strong theory of employee performance value that is indeed a major contribution to research on star employees, employee value, employee performance, and utility analysis. Their work provides a more specified theoretical structure that informs a computational model (cf., Ballard et al., 2021; Harrison et al., 2007), demonstrating the implications of non-normality in performance ratings at the organizational level. In other words, we argue that Joo et al. (2022)

make an interesting and highly valuable contribution because they refine theory of the value of employee performance and use that information through an application of computational modeling to enhance the field's understanding of the implications of that theory.

Refinement of a strong theory of job performance

The idea that employee performance has value and that this value varies across employees is a fundamental assumption of the driving paradigm of human resource research. This idea speaks to why it is important to study employee performance and performance measurement; it also explains why there is potential value in investments in the workforce in general and in some valued employees in particular. Although this assumption is rarely explicitly stated, it must be accepted if one is seeking to understand how firms create and capture value from employee job performance (Barney & Clark, 2007; Bowman & Ambrosini, 2000; Call & Ployhart, 2021; Lepak et al., 2007; Sundaram & Inkpen, 2004).

The explicit modeling of employee value, though, is far less common. Examples include calculating differences in value from 'good' versus 'poor' employees (Tiffin, 1942) or otherwise providing a linear function to convert employee performance or productivity into a dollar value (Brogden & Taylor, 1950, Schmidt & Kaplan, 1971). These means of converting information about employee job performance to a specific metric of value (e.g. dollars, euros, yuan), however, have gone untested (Sturman, 2012). In the spirit of the long-articulated (e.g. Meehl, 1967, 1978) and often reiterated (e.g. Edwards & Berry, 2010; Meehl, 1990) view that management theory should increase its precision, Sturman (2012) called for greater attention to making explicit the idea of employee value, using theory to improve such estimates, refining methodological tools to examine such estimates, and ultimately using these estimates to develop theoretical models of employee outcomes. A key contribution of Joo et al. (2022) is that it actually provides a refined estimate of employee value creation, driven by the theoretical and empirical contributions of research on 'star performers' (e.g. Joo et al., 2017; Kehoe et al., 2018). Joo et al. (2022) then use this improved model of employee value creation to inform and specify the implications of the human resource effort of acquiring more star performers.

As Joo et al. (2022) well note, the 'classic' utility analysis formula (Brogden, 1949; Cronbach & Gleser, 1965) includes a linear transformation of employee performance scores into financial terms. This is accomplished using the metric known as SD_y, which represents the financial value of an employee who performs one standard deviation above average (Boudreau, 1991; Cascio et al., 2019).

$$U = N_S SD_y r \frac{\varnothing}{p} - N_A C_A \tag{1}$$

This equation provides the utility formula for evaluating a selection context. In the formula, U = financial value of using the selection device; N_S = number of applicants selected; r = validity coefficient for the selection device; p = proportion of applicants acquired (i.e. the selection ratio) while assuming top-down acquisition; $\varnothing$ = ordinate (i.e. height) of a normal curve associated with the selection ratio; N_A = number of applicants; and C_A = cost per applicant. The ratio ($\frac{\phi}{p}$) provides the average value, expressed in standardized units, of those selected, which is based on the assumption that the quality of applicants on the selection test follows a normal distribution. Then, the product of r and ($\frac{\phi}{p}$) provides the predicted average job performance of those hired, expressed in standardized units. Thus, multiplying this product by SD_y (which is the value of employee performance expressed in standardized units) provides the value gained, on average, from each selected individual. Although Joo et al. (2022) demonstrate the implications of non-normally distributed performance value due to the presence of stars for a selection context, the implications of their approach are applicable to utility analytic evaluations of any sort of human resource practice, such as in compensation (e.g. Sturman et al., 2003) or for training and development (e.g. Avolio et al., 2010; Carretero-Gómez & Cabrera, 2012).

As this basic description of the mathematics shows, there are assumptions made about the nature of the utility analysis parameters. By its definition and how it is employed in the above formula, SD_y assumes both a linear transformation between performance and value and normality of the related distributions: the distribution of scores on the selective device, the distribution of performance scores, and therefore the resulting distribution of employee value. While many have noted this issue as a criticism of utility analysis (e.g. Boudreau, 1991; Boudreau et al., 1994; Cascio et al., 1992; Cronbach & Gleser, 1965; Macan & Highhouse, 1994; Schmidt et al., 1979), Joo et al. (2022) actually take steps to address this limitation.

Originally, utility analysis was proposed as a tool to help make human resource investment decisions. While this specific purpose has met with limited success as a practitioner decision aid (cf., Latham & Whyte, 1994; Sturman, 2000; Whyte & Latham, 1997), Sturman (2012) proposed that utility analysis may better serve as a theoretical tool because it provides an explicit way to model employee value yielding specific predictions.

Joo et al. (2022) have done just this. They have refined theory of employee value by providing a new function in place of SD_y where this function is based on the advancement in the human resource literature that star employees exist and employee performance does not follow a normal distribution.

Viewed in this way, Joo et al. (2022) provide a theory-based refinement that better expresses the value associated with employee performance given the performance distribution of a particular job. Although not explicitly stated in such terms, the Joo et al. (2022) paper provides a seemingly slight but ultimately impactful change to the utility formula, replacing the constant parameter SD_y with a value function. Representing that value function as v(p), the formula changes incrementally but importantly to

$$U = N_S v(p) r\left(\frac{\varnothing}{p}\right) - N_A C_A \tag{2}$$

The Joo et al. (2022) paper walks the reader through a series of value functions that increasingly account for non-normally distributed performance scores. Specifically, they provide four methods of computing SD_y—what we now label as v(p)—that begin to incorporate the potential for non-normality in the performance-to-value conversion. We wish to highlight this particular effort, as we argue it constitutes an effort to refine the theory of employee value. So, in contrast to the simplest depiction of employee value—where SD_y equals a constant of 0.4 times the average annual wage of a position—their proposed estimate is that v(p) equals the observed standard deviation of employee performance divided by the estimated standard deviation of performance (based on estimates of performance at the 85^{th}, 50^{th}, 15^{th}, and minimum distribution), times 1.1 times the average salary.[1]

Why this value function matters

The reason we highlight the introduction of a value function to the utility analysis formula is because it provides a refinement to the theory of human resource value. A theory-driven refinement of the estimation of employee utility shows that consideration of the non-normality of employee performance yields substantially different estimates of workforce value by an average factor of 9.08 (nearly a single order of magnitude). Showing that utility analysis estimates can be bigger is itself not a major contribution, considering that a key criticism of the basic utility analysis formula is it yields estimates that are likely far too large anyway

(Sturman, 2000). The contribution here comes from the new research questions that can be considered with a revised, more precise estimate of the employee value function.

With this new value function, Joo et al. (2022) examine the value associated with obtaining more star performers. More notably, they delve into the pattern of the value function associated with different proportions of stars based on distinct distributional assumptions. By comparing differences in value obtained by the implementation of the various value functions, Joo et al. (2022) show that productive stars add great financial value to the organization and there exist diminishing returns for focusing on obtaining the most productive stars. It is only by contrasting these different value functions that they are able to reach this conclusion, thus showing that having a more precise theory of employee value informs new research possibilities.

Utility analysis as computational modeling rather than decision aid

We have argued that the Joo et al. (2022) paper, by presenting a formal model based on theoretical reasoning, provides a demonstration on how utility analysis can serve a theoretical purpose for articulating how human resource practices influence individual performance thereby having an influence on organizational value. Utility models, by their nature, describe an emergence process: how individual-level employee performance emerges as organizational-level value. The value function is the parameter that lies at the core of how individual-level behaviors translate to organizational-level outcomes. Furthermore, although not specifically part of Joo et al.'s (2022) application, the longitudinal application of utility analysis has long been considered (Boudreau & Berger, 1985). As such, utility analysis models can be seen as the basis for computational modeling (Ballard et al., 2021; Davis et al., 2007; Harrison et al., 2007).

Computational modeling 'is the practice of articulating theory in the form of mathematical equations…and evaluating… theory by simulating the model' (Ballard et al., 2021, p. 252). In this light, refining the utility model is refining the functions upon which a computational model can be based. The utility models run by Joo et al. (2022) are thus actually computational models, describing the effects of selection systems given various parameters (the various characteristics of the selection system as described by Joo et al. (2022) in addition to the key parameter of the value function). For example, in the value functions—labeled as v(p) in Equation 2 above—Joo et al. (2022) incorporate the effects caused by non-normality in employee performance. They also demonstrate the consistency of their implications by varying a set of other parameters in their modeling. The computational modeling Joo et al. (2022) employ allows them to reveal the overall trend of their findings; it also allows further investigation into how sensitive their results are to other parameters in their model (Sturman, 2000). While the computational model they employ is fairly simple—it is static, based on fairly straight-forward arithmetic operations, and does not consider performance or utility over time—it is still an instance of how the utility analysis tool can be applied to computational modeling, and thus how computational models can provide particular conclusions.

Going forward, utility analysis can be used to create more complex—and thus hopefully more theoretically interesting and accurate—computational models. Again, we recognize that it was not Joo et al.'s (2022) purpose to demonstrate such an application; rather, we see that what they have done has great potential in this area and presents perhaps the first effort to make such a demonstration, purposefully or not. Taking into account all of the utility analysis enhancements for future efforts would certainly reach a level of complexity that would be made easier with computer modeling (Sturman, 2000, 2003). Computational modeling is increasingly advocated as a method for developing and testing complex theories (e.g. Ballard et al., 2021; Ballard et al., 2016; Harrison et al., 2007; Vancouver et al., 2020), and there have certainly been many complex developments that have been proposed to the basic utility model (e.g. Boudreau, 1983a; Boudreau, 1983b; Boudreau & Berger, 1985; De Corte, 1994; Murphy, 1986). Joo et al. (2022) present a new complex component—the value function—to the utility model, yet one that is driven by theoretical developments related to job performance rather than contextual aspects of the human resource intervention being examined. Including a more complex value function with the host of other utility analysis refinements would provide an improved theoretical model rather than a better practitioner-oriented decision aid.

Other contributions and new research directions

Beyond its potential contributions to computational modeling, when one considers Joo et al. (2022) through the lens of a paper contributing to our understanding of the performance value function, the paper's implications for future research increase. While a key contribution of the Joo et al. (2022) study is that it takes one set of key findings from human resource management research (i.e. the literature on star performers) and uses that literature to refine the estimate of employee value, there are many other findings in human resource management research that could similarly be examined to consider their implications for employee value. This includes work on teams, dynamic performance, performance and turnover, citizenship and counterproductive work behaviors, and likely many others. Despite the long-held pervasive but implicit assumption of the existence of employee value and some sort of employee value function, there have been essentially no efforts to articulate the specific process. As argued by Sturman (2012), 'it is time to be explicit about employee value' (p. 782). Certainly, this can provide value for utility analyses' application to computational modeling, and it has value for understanding the role of job performance as well. Although it may not have been their original intent, we applaud the Joo et al. (2022) paper's contributions in this area. There are also several ways in which the estimates from Joo et al. (2022) could be further refined.

While the focus of Joo et al.'s (2022) effort was understandably on the specification of SD_y, the rest of the utility function remained in its simplest form. Utility analysis work, however, has provided a large array of refinements to the basic utility analysis formula that influence its estimations (Sturman, 2000). The refinement of SD_y is a critical step, but the implementation of a fully complex utility model could potentially provide more accurate insights into the value associated with human resource practices given the presence of star employees.

Joo et al. (2022) also show the value in questioning distributional assumptions. A key point made in Joo et al. (2022) is that, evidenced by the literature on star performers as well as the data they used in this paper and elsewhere (Joo et al., 2017; O'Boyle & Aguinis, 2012), performance does not follow a normal distribution; thus, the fundamental assumption of SD_y is flawed. That said, there is reason to delve further into this issue. First, most notably, SD_y actually does not assume that the performance distribution of those hired follows a normal distribution; rather, it assumes that the distribution of performance if all applicants were hired (or if people are hired randomly) follows a normal distribution. The data upon which Joo et al. (2017, 2022) question the normality assumption is the performance of people already in a specific profession. Take for example the number of publications (a metric used in a large number of their samples). The individuals in the specific professions that actually seek to publish in their top five field-specific journals are not a random sampling of the workforce. Rather it is quite a small subset. According to the U.S. Census Bureau (2021), only 2% of the U.S. population aged 18 and over have a Ph.D. (U.S. Census Bureau, 2021). If only looking at the top 2% of a normal distribution, summary statistics of that subset would have substantial skewness (skew = 1.52) and kurtosis (kurtosis = 2.86). Having a more restricted sample would only lead to more skew and kurtosis. Thus, one should expect to find even greater skew in samples that are even more restricted, such as when looking at outcomes like home runs from major league ball players (which represents 1,026 individuals total from the applicable workforce, a ratio far less than 1%).

Second, as acknowledged by Joo et al. (2022), they use objective measures of job performance (e.g. number of some performance metrics like publications, chapters, presentations, patents, etc.). As such, the nature of these metrics typically creates a lower bound (i.e. 0). Objective measures of job performance are also more subject to influences of shocks and events outside of the individual's control and thus are more affected by transient error than are subjective ratings (Sturman et al., 2005). It is clear from the Joo et al. (2017, 2022) data that the performance measures, particularly when looking at objective measures from highly selective occupations, are not normally distributed. Because the nature of the performance distribution has critical implications for developing a more precise value function, Joo et al. (2022) highlight the need for more work considering the implications of the performance distribution on the functionality of utility analysis equations to further enhance the accuracy of utility models.

Another key direction for future research revealed by our perspective of the Joo et al. (2022) article is that the need exists to develop ways to test the validity of utility models. As we noted earlier, the estimates provided by Joo et al. (2022) are purely hypothetical, albeit theoretically driven by implications of research on performance stars. The conclusions drawn in the paper, although not validated, speak to the theoretical implications of skewed performance outcomes. This certainly is not a flaw, as indeed our field has journals specifically devoted to theoretical papers. Nonetheless, the most useful theories are ones that can be tested and further refined (cf., Meehl, 1967, 1978, 1990). Utility analysis provides a mechanism to create strong theory, with very specific predictions about the consequences of organizational human resource policies and practices (Sturman, 2012). Enhancing utility analysis based on findings from other areas of human resource management research—like Joo et al. (2022) do with research on star performers—provides a specific articulation of the impact that human resource practices are predicted to have. While we advocate one line of research further develops and refines that theoretical model, another line of research considering how to test, validate, and improve that model could prove exceptionally valuable as well.

Conclusion

Joo et al. (2022) provide a valuable, first-of-its-kind demonstration of a theoretically driven utility-based model, yielding specific predictions and implications about human resource policy. Although there certainly have been prior examples of utility analysis demonstrations (e.g. Boudreau, 1991; De Corte, 1994; Schmidt et al., 1979; Sturman et al., 2003), Joo et al. (2022) is the first demonstration of which we are aware that refines utility analysis based on theory to estimate implications through a computational model. If we have one criticism of the Joo et al. (2022) paper, it is only that it does not go far enough. We therefore hope others will see Joo et al. (2022) as an example to follow to consider how refined, research-based value functions can alter our predictions about human resource policy. Certainly, this is truly a muted criticism; no research can do all things, and the Joo et al. (2022) paper thus leaves the reader with several promising paths for a type of research that has been called for (Sturman, 2012) but heretofore been undelivered. A key point of our commentary is that the Joo et al. (2022) paper is really the first to delve into this process of altering an explicit employee value function, and thus their work is a valuable starting point for hopefully much future research in this area.

Note

1. In Joo et al.'s (2022) procedures, their approach (referred to as the "global procedure") is based on differences between the 85th, 50th, 15th, and minimum percentiles, and then further simplified based on the overall average finding reported in Burke and Frederick (1986) that the ratio of SD_y to SD_O is an average of 2.75. They then multiply this by the estimate of SD_y using the 40% rule (where SD_y = 0.4 * mean salary), and thus their estimate from the global procedure ultimately equals (2.75 * 0.4 * mean salary =) 1.1 * mean salary.

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