


Employee Classification in Reward Allocation Using ML Algorithms

Parakramaweera Sunil Dharmapala

 <https://orcid.org/0000-0003-4050-6754>

Lone Star College, Cypress, USA

INTRODUCTION

Authors were primarily motivated by a research study reported by Olsen (2015), where he presented a theoretical model based on arguments of prior research. Prior research suggested that cultural values affect individuals' preferences in work rewards (i.e., pay and benefits) and are allocated according to rules based on 'equity', 'equality', or 'need'. Drawing on equity and social exchange theories, Olsen (2015) presented a theoretical model with nine propositions that incorporated both individual and societal values as determinants of the reward allocation preferences. He proposed that societal values and individual values had main and interactive effects on reward allocation preferences and that the effects of societal values are partially mediated by individual values. He opined that prior research on reward allocation preferences focused mostly on the effects of societal or individual values and claimed that his theoretical model attempted to clarify and distinguish values at these two levels and to better understand their main and interactive effects on individual reward allocation rule preferences. Prior research included the publications listed under Literature Review. Olsen's model considered only three categories; 'equity', 'equality', and 'need', whereas in this study the authors expand it to four and include 'seniority' as well, and they analyze reward allocation preferences from a different perspective using machine learning algorithms (MLAs).

An advantage of using MLAs in our study is that the string variable 'employee category' is multinomial with values 'performer', 'starter', 'needy' and 'senior', and it does not have to be coded with numerical values as it is done in statistical methods and then use 'dummy' variables to run in Regression Analysis. Same advantage applies to other string variables that are categorical input features.

LITERATURE REVIEW

This work reports the research studies conducted in the past relevant to 'reward allocation' in various groups and organizations with a wide spectrum of backgrounds.

Datta (2012) addressed the issue of, "How can managers optimally distribute rewards among individuals in a job group? His research introduced an innovative portfolio management scheme for employee rewards distribution and created a process that exemplifies rewards distribution using four different rewards allocation scenarios based on varying managerial prerogatives. Markovsky and Eriksson (2012) offered a comparison between direct and indirect methods for measuring perceptions of 'distributive justice' in reward allocations. The direct method simply asks respondents what they would consider to be a fair salary for a particular person in a given set of circumstances. In contrast, the indirect method infers fair salaries from respondents' judgments about the relative unfairness of hypothetical salaries.

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They concluded that the two methods yielded incompatible results and that neither was immune to bias, and they suggested new directions for research to gain a better understanding of these problems and to circumvent them. Fischer (2007) presented a six-nation study where they showed associations between (i) organizational performance and equity, (ii) unemployment and need, and (iii) income inequality and need. While focusing on ‘Rewarding Seniority’, Fischer (2008) explored cultural and organizational predictors of seniority allocations. And earlier, Fischer (2004) highlighted cross-cultural differences in reward allocation while presenting two studies that investigated the use of reward allocation principles based on equity, equality, need and seniority by work organizations in Germany and the UK. He also suggested that more research focusing on real-life allocations was needed to develop a better understanding of cross-cultural differences. He et al. (2004) studied the reward allocation preferences of Chinese employees where they reported the effects of ownership reform, collectivism and goal priority. In order to test their hypotheses, they conducted hierarchical multiple regression analyses on differential and equalitarian allocation preferences. Tajima (1997) investigated people’s expectation of others’ ingroup favoritism, and the effect of expecting others to take part in reward allocation decision on ingroup favoritism in reward allocation. His findings suggested that ingroup favoritism was not a result of quasi-strategy of self-interest in an attempt to maximize own gains, but of psychological group formation. Younies et al. (2008) studied how medical sector employees in the private and public health sector view the Reward and Recognition (RR) systems in the UAE, where outstanding employees expect their effort to be acknowledged by the organization. However, they claimed that the variety of rewards and recognitions systems used by organizations may be perceived differently by different employees. Hu et al. (2004) investigated the relationships between employee categorization criteria and Chinese managers’ allocation behaviors. They examined, using a vignette approach and a four-factor within-subjects design, the effects of relationship (guanxi), loyalty, and competence, as well as their interactions with allocation context (private vs public). Their results showed that subordinates who had a close relationship with the allocator, high loyalty, or high competence were rewarded more. Ng (2011) conducted an experiment that examined the effect of personal status on bias, and how such an effect might vary with group status. When asked to allocate money rewards directly to ingroup and outgroup members who had done equal works, subjects allocated equally regardless of status manipulations, indicating that personal status could lead to bias either by itself or jointly with group status. Islam and Ismail (2003) presented a research study that intended to find out the specific reward and recognition ways preferred by the employees working in various Malaysian organizations. They opine those employees who perform exceptionally well expected their contributions to be recognized or to be appreciated by the top management. Bamberger and Levi (2009) examined the effects of two key team-based pay characteristics – (i) reward allocation procedures (i.e., reward based on norms of equity, equality or some combination of the two) and (ii) incentive intensity – on both the amount and type of help given to one another among members of outcome-interdependent teams. They used a (2 x 3) experimental design with ANOVA and hierarchical regression analyses to test their hypotheses. Tower et al. (2011) conducted a study to examine the extent to which individualist–collectivist values were endorsed by Russian and British participants and the relationship between these values and allocation of rewards to self and co-worker in a hypothetical scenario. In addition, qualitative data from group discussions were used to explain reward allocation decisions and to explore the specific ways in which Russian collectivism differed from British individualism. Krishnan (2000) re-examined the consistently reported strong ‘need’ and weak ‘merit’ preference in reward allocation under collectivism, including allocator-recipient relationship, the nature of the resource, and resource scarcity as independent variables. Responses by 76 female college students in India to allocation scenarios indicated both significant merit and need preference depending largely

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