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Original Article

Alternative Risk Scoring Data for Small-Scale Farmers

Benjamin Otieno[1], Franklin Wabwoba[2], George Musumba[3]

[1,2]*Department of Information Technology, Kibabii University, Bungoma, Kenya.*
[3]*Department of Computer Science, Dedan Kimathi University of Technology, Nyeri, Kenya.*

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Abstract *- Small-scale farmers suffer unfairness during credit risk scoring. This arises from the fact that scoring done using computer machine-learning algorithms has an inherent bias, otherwise called algorithm bias. The data that the small-scale farmers present is another source of bias. This paper explores these data types to bring out the specific challenges with the data and how the same can be remedied. The research findings show that of the possible 23 data types lenders ask from farmers, 14 are regarded as important. Out of these 14, 7 are commonly unavailable while the remaining 7 are not, introducing missing data records. The findings also show that other than the personal/behavioral data that the loan-seeker provides, where the lender asks for historical or environmental data, there is room for the loan-seeker to provide misleading information. This paper proposes 14 data types that can improve the quality of credit risk scoring. The study further proposes using the Internet of things and blockchain to source the environmental and historical data to improve the availability of the missing and outlier challenge in data.*

Keywords *- Credit risk scoring, Fairness, Missing data, Outliers, Algorithm bias.*

1. Introduction

Probabilistic decisions are always subject to bias. The same can be said of decisions made from statistical inference. Credit risk scoring (CRS) is an exercise that ends up with a decision either to lend or not to lend based on some statistical data or some probability. CRS, therefore, becomes an exercise with inherent unfairness. The unfairness can be even more pronounced when the decision is strictly left to the computer, and no human intervention (to attempt to correct the bias) is introduced.

The source of the unfairness can be the algorithm or the data used. Where machine learning (ML) algorithms are used, different algorithms treat the data differently. There are various contributors to the data bias. Such issues as label bias [1, 2], missing values [3] and outliers [4] are common contributors to bias. Some data labels, such as race and gender, can easily result in bias. Different algorithms treat missing data differently, and the different treatments can introduce bias. Outliers also introduce bias in the decision arrived at. Where the ML algorithm learns certain rules and then the entity is classified as an outlier, the result could be unfair.

CRS data presented by small-scale farmers to lenders usually is in the form of behavioral and personal data as provided by the loan seeker. It is common to have outliers and missing values in this data, as provided by the loan-seekers [5]. The outliers could result from misunderstanding the question by the loan-seeker or intentional manipulation of the data by the loan-seeker. On the other hand, the missing values can result from partial completion, missing by design and item non-response. In either case, the resultant decision is bound to be an unfair decision. This research gap necessitated the proposal of alternative data and data sources to address the two challenges.

Access to credit contributes greatly to the productivity of small-scale farmers [6]. Besides farming experience, education, herd size, and the number of cultivation practices, access to farming finance has been determined to impact farming efficiency for small-scale farmers [7] significantly. Access to finance, however, is still a challenge, with only 40% of the small-scale farmers having access to loans from formal credit, with the rest resorting to informal credit [6].

Traditionally, lenders ask loan-seekers for some specific data to aid in CRS. The credit risk scores are, in turn, used to decide whether to lend or not. If the lender is more sophisticated, the scores can further be used to price the loan where the decision to lend has arrived. Data used in CRS can be broadly classified as personal/behavioral, historical, and environmental data [8, 9, 10].

In the course of CRS, some borrowers suffer bias. Bias can broadly result from any combination of any of the six sources – data bias, measurement bias, survey bias, observer bias, human bias or algorithm bias [11]. In CRS, the data and the algorithm are two major contributors to unfairness. This paper discusses some common biases arising from the data used in CRS for small-scale farmers and proposes some ways to address them. On data, there are two common sources of unfairness – missing values and outliers.

The rest of the paper is organized as follows. Section 2 has the related works, section 3 details how the experiment was carried out, section 4 has the results and the discussion of these results, and section 5 provides a conclusion of the research.

2. Related Works

One noted limitation with farmers is that they do not routinely maintain the information lenders require, thus complicating the risk-scoring task [12]. Another factor that complicates risk scoring for small-scale farmers is the influence of external factors on the risk scores. External factors such as climate conditions affect a client's creditworthiness [13]. Other factors such as farm typology, commodity, and geographical location also affect the farmer's risk score [14]. These contribute to the missingness of data, and where the farmers try to avail the data, there are possibilities of outliers. Using quantitative data alone for CRS can be disadvantageous to low-income populations, for example, where borrowers with fewer assets are deemed more at risk of default [15]. For micro-lending, qualitative analysis is of great importance in arriving at a borrower's credit score [16]. Some banks use pure judgmental methods, like Teba Bank in South Africa, Unibanka in Latvia, and United Bulgarian Bank in Bulgaria, whereas others use a combination of statistical methods and judgmental methods, such as CAC Leasing in Slovakia and Credit Indemnity in South Africa [17]. For micro borrowers, the more complicated the risk scoring method, the costlier the credit appraisal gets [15]. It presents a strong case for alternative source data for CRS for the small-holder farmers who fall under micro-borrowers to reduce the bias posed by conventional data used in CRS.

3. Materials and Methods

The experiment was carried out in Kakamega County in Kenya, one of the forty-seven counties in Kenya. Kakamega County is typically an agricultural economy, with over 70% of the population being small-scale farmers.

Through focus group meetings with farmers, the researchers asked the 49 participants spread over the whole county which data the lenders sought from them as a condition to advance the loan. The researchers assumed that the reason why the lenders asked for the data was to use the data for credit scoring.

Three different research assistants led the focus group meetings. The assistants took the research groups through the goals of the research and got various sets of information from the various groups. The focus of data collection was on twenty-one different considerations. These considerations were: the age of the borrower, gender, literacy level, primary bank, average bank transaction per month, marital status, number of dependents, number of children, crop(s), land title, car log book, guarantor, financial records, farming history records, bank statements, Inputs required per acre (Kenya Shillings), produce markets (direct, middleman, processor), land acreage, average rainfall (mm), average atmospheric temperature (degrees Celsius), source of income, annual expenditure (Kenya Shillings) and insurance. The questions posed to the respondents included which of the various data mentioned were asked of them by the lenders when they sought to borrow for the purpose of their agricultural ventures. The farmers were also asked how readily the information was available. The farmers were also asked to state whether they were awarded the loans or not and, for the ones that were denied, whether they felt it was an act of unfairness. Other information obtained was the individual small-scale rating (based on perception) of the importance of the various data asked for by the lenders towards risk scoring. The reasons for the loan decline were obtained for the small-scale farmers who had been denied credit at one point. Common reasons for loan default from the small-scale farmers' experience and the specific contributors to the success of small-scale farming were also obtained.

The researchers interviewed various lenders drawn from saving cooperatives, microfinance institutions and banks. The interviews were followed up with the request to the respondents to fill out an online questionnaire[i]. It was aimed at correlating the perceptions of the borrowers to the positions taken by the lenders. The same twenty-one data items discussed with the small-scale farmers were posed to the lenders, and the question of their importance in CRS was asked. The lenders were also asked about the availability of the data whenever they asked for the same from the borrowers. The small-scale farmers' responses were nominal, varying from extremely important, very important, important, somewhat important and not important at all. These were converted to numeric values ranging from 1 to 5, with 1 representing not important and 5 representing extremely important.

There was a total of 14 lenders (respondents) reached in the data collection. 6 were commercial banks, 2 were microfinance institutions, 3 were savings and credit societies, 2 were affirmative funds, 1 was a development financial institution, and 1 was a manufacturing entity that lends to farmers. Again, the response was in the same nominal form for this set of respondents, converting to numeric values.

4. Results and Discussion

The outcomes of the focus group discussions with the farmers were a combination of qualitative (perceptions) data and quantitative data (based on individual farmer experience with the lenders). Some information extracted from the focus group meetings included whether the small-scale farmer had borrowed or not and what the experience had been for those who had borrowed.

Table 1. Data lenders ask borrowers for CRS

Data label	Percentage of respondents who confirm having been asked for this data
Age	93%
Gender	90%
Literacy Level	74%
Primary Bank	34%
Average bank transaction per month	46%
Marital Status	87%
No of dependents	66%
No of children	42%
Crop(s)	39%
Land title	40%
Car log book	25%
Guarantor	80%
Financial records	53%
Farming history records	58%
Bank statements	38%
Inputs required per acre (Kenya Shillings)	49%
Produce markets (direct, middleman, processor)	76%
Land acreage	44%
Average rainfall (mm)	92%
Average Temperature (degrees Celsius)	89%
Source of income	83%
Annual Expenditure (Kenya Shillings)	37%
Insurance	59%

The focus group discussions also established the kind of data commonly asked by the lenders and whether the information is usually readily available[ii].

The data obtained from the borrowers (Table 1) shows that almost every lender asked for the age of the borrower (94% of the participants in the focus group meetings), the gender of the borrower (90% of the participants), literacy level (74%), marital status (87%), number of dependants (66%), guarantor (80%), farming history records (57%), markets for the produce (76%) source of income (83%), other financial services the farmer uses (such as mobile banking, insurance among others) (59%), the average atmospheric temperature which affects the farming process(89%)

4.1. Second-Order Heading

The lender's response on the importance they place on the specific information they ask from borrowers for the purpose of CRS[iii] was analysed. The overall importance of any one factor was taken as an average of the importance attached to a factor by the various lenders. For example, when asked what importance the lenders attached to farming history records, the 14 respondents had the following scores: 4, 3, 5, 5, 5, 5, 5, 5, 3, 3, 3, 3, 4 and 2 making an average of 3.9286. The lenders considered age, availability of bank account, availability of bank transaction history, detail on the crops, land title, guarantor, financial records, farming history records, bank statements, detail on the farm inputs, availability of markets, land acreage, rainfall data, source of income, annual expense of the farmer and other financial services the farmer uses as very important detail that can be used in CRS (Table 2). The lenders opined that the availability of gender, literacy level, marital status, number of dependents, car log book and data on atmospheric temperature are important to CRS. The lenders did not identify any particular data as unimportant to the CRS process. The consensus on the importance of the various factors across the lenders was determined using the standard deviation given by the formula $\sigma = \sqrt{\frac{\sum x_i - \mu}{N}}$ Where σ is the standard deviation, xi is the individual scores given by the lenders, μ is the class mean, and N is the total number of respondents (14 in this case). The lower the σ, the more there is consensus amongst the respondents, with figures above 1 being regarded as in disagreement. The lenders were consistent in their agreement on the importance of the data apart from when it came to the importance of gender, availability of bank account, average transaction per month and a car log book. In these four (gender, availability of bank account, average transaction per month and car log book), the standard deviation was greater than 1 (Table 2), showing that some lenders regarded the data as extremely important, whereas some regarded the data as not so important.

This is not unusual given the difference in structures of the lenders sampled. The lending philosophies of the different types of lenders may have contributed to this high standard deviation.

From the farmer's perspective, a question on the importance of the various data asked for by the financial institutions was asked. The response showed that the farmers opine that the data that would have given the financial institutions information most useful towards CRS include the type of crops, farming history records, guarantor, land acreage, average rainfall, average temperature, source of income and annual expenditure. All these had an average score above 3.0.

Other factors such as the age of the farmer, literacy level, whether the farmer is banked or not, a record of bank transactions per month, land title, financial records, bank statements, the market for the farm produce, insurance and other services the farmer uses and availability of collateral were also ranked as important (with a range above 2 but below 3).

Table 2. Importance of CRS data – lenders' perspective

Data label	Importance (Mean)	Importance (Std Dev)
Age	3.3571	0.9035
Gender	2.7143	1.1952
Literacy Level	2.7143	0.6389
Primary Bank	3	1.0498
Average bank transaction per month	3.5	1.1606
Marital Status	2.6429	0.4949
No of dependents	2	0.3499
No of children	1.9286	0.4518
Crop(s)	3.6429	0.8806
Land title	3.3571	0.9897
Car log book	2.7143	1.1249
Guarantor	3.5	0.9897
Financial records	3.5714	0.833
Farming history records	3.9286	0.833
Bank statements	3.5714	0.9897
Inputs required per acre (Kenya Shillings)	3.7143	0.3499
Produce markets (direct, middleman, processor)	3.7857	0.8806
Land acreage	3.7857	0.6999
Average rainfall (mm)	3.1429	0.6999
Average Temperature (degrees Celsius)	2.7143	0.6999
Source of income	3.1429	0.833
Annual Expenditure (Kenya Shillings)	3.3571	0.8806
Other financial services farmer uses (mobile banking, insurance, table banking, savings and credit etc.)	3.5714	0.4518

The rest of the factors were not regarded by the small-scale farmers as being very valuable to the financial institutions in assessing the credit risk of the small-scale farmers.

Used in isolation, the input from the farmers could potentially reduce type I error without reducing type II error. This necessitated a comparison of the borrower's and the lender's perception of the importance of the various data. The importance of a factor was taken as an average of the respondents' responses. For example, when the loan-seekers were asked what importance age was to the CRS, all 49 respondents responded with the scores 4, 5, 4, 4, 2, 1, 5, 1, 3, 1, 4, 3, 4, 5, 1, 4, 1, 4, 3, 1, 2, 2, 1, 3, 4, 4, 4, 5, 2, 4, 5, 2, 1, 4, 4, 4, 2, 1, 3, 3, 3, 3, 3, 3, 3, 3, 2, 2 and 4 averaging to 2.9796. When asked what importance would be attached to the amount of rainfall in CRS, 48 respondents responded with scores averaging 3.8958. The same was applied to all the other factors (both from the lender's and the borrower's perspective.

There was some convergence in agreement on what data was deemed important by both the lender and the loan seekers. Taking figures above the mean of 2.5 as an agreement between the lender and the borrower, there is agreement on the fact that some data, whether available or not, are important towards CRS. These were age, type of crops, guarantor, financial records, farming history records, bank statements, farm inputs, the market for the produce, land acreage, average rainfall, average temperature, source of income, annual expenditure and insurance. These were thus regarded to be of considerable importance towards CRS for small-scale farmers (indicated by the bars above the blue line in Fig 1). It reduces the data usually asked for by financial institutions from 23 to 14.

4.2. Missing Data

Of the 14 data regarded as important, not all is easily available at all times. Some of the data that is viewed as important yet not very easily available amongst the small-scale farmers include financial records (27%), farming history records (27%), the guarantee of the markets for the produce (32%), rainfall data (16%) and temperature (20%) (Fig 2). From the data obtained both from the small-scale farmers and the lenders, it is evident that the conventional data lenders ask from the small-scale farmers when they apply for loans is not always available. Taking anything above 50% as easily available, it is evident that of the 14 remaining data to be used in CRS, seven (7) were regarded as not easily available, or small-scale farmers had difficulties availing to the lenders. It, therefore, became important to get alternative avenues through which this data can be availed.

Data could be missing due to partial completion, by design or non-response [11]. When loan-seekers provide data for CRS, there are possibilities that they can skip some sections of the form, having not clearly understood the parts. Partial completion or break-off in filling CRS data can result in missing data. Given small-scale farmers' literacy levels, it would be expected that partial completion resulting from ignorance could be common. Where loan seekers intentionally decide not to provide certain information or where they respond with N/A, the data is considered to be missing by design. Where loan-seekers intentionally miss providing information, a new challenge arises; the challenge of trust for those who opt to provide the data. More tamper-proof data sources ought to be devised to beat this challenge. As opposed to where the data is not provided as a result of not understanding or intentionally masking the data, loan seekers can also find themselves in a situation where they understand what data the lender is asking for, they are willing to provide the data, but they do not have the data. It can be classified as item non-response. It has been established that many small-scale farmers do not routinely maintain the information required by lenders [12]. It is, therefore, not uncommon to have item non-response in the CRS data provided by small-scale farmers.

4.3. Fairness

There are several possible causes of unfairness in decision-making. These include sample selection bias, measurement bias, survey bias, observer bias, prejudice bias and algorithm bias [11]. There are ways in which algorithm bias can be reduced to achieve fairness in CRS for small-scale farmers [18]. This paper looks at the bias caused by the data. These can fall under measurement bias, observer bias and prejudice bias. The bias can result from missing data [19] or outliers [20].

4.4. Missingness and Unfairness

This missing data can greatly cause unfair decisions in CRS [11]. The information the clients provide for risk appraisal is, at times, either incomplete or not entirely accurate [21]. It is, therefore, imperative to treat the three sources of data missingness (partial completion, missing by design and item non-response) if fairness has to be achieved.

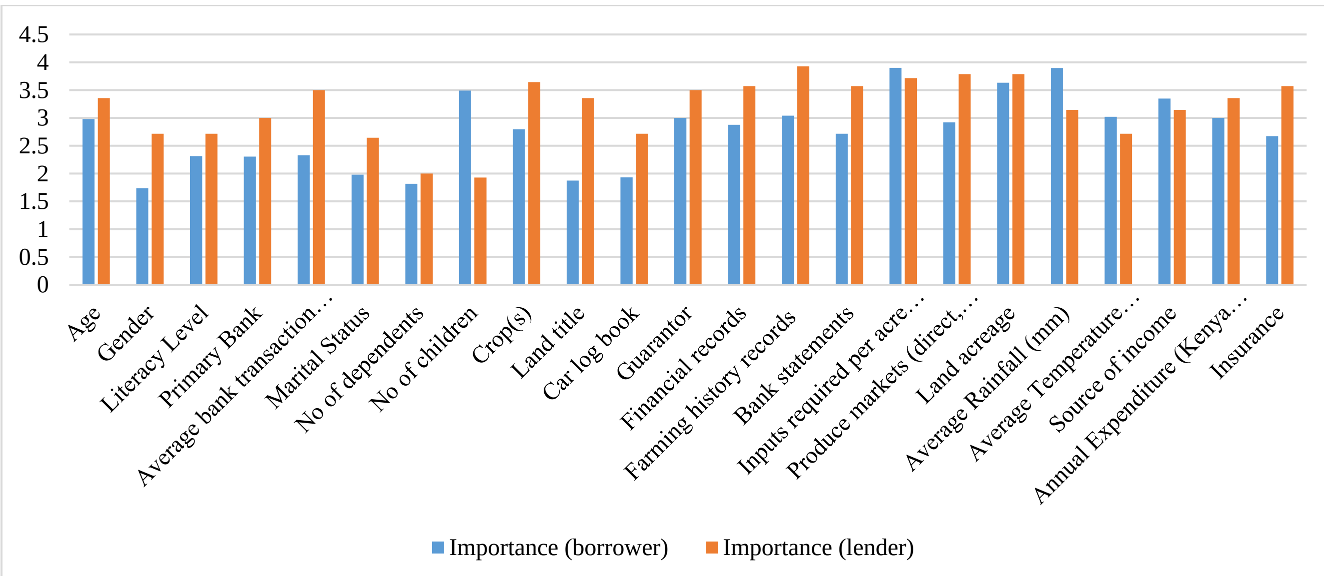

Fig. 1 Comparison of the importance of CRS data – lenders' and borrowers' perspective

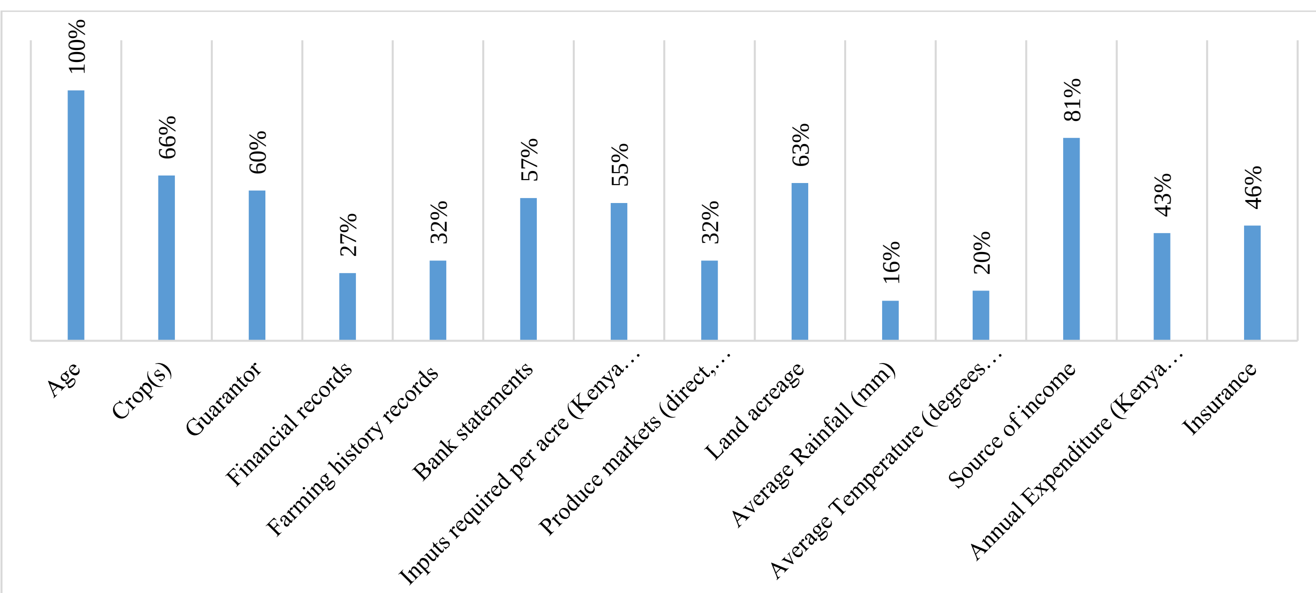

Fig. 2 Availability of data regarded as important in CRS for small-scale farmers

4.5. Alternative Data Sources

The Internet of things (IoT) has been touted to have desirable results when used by small-scale farmers [22]. Some of the benefits include Improvement in the use efficiency of inputs (soil, water, fertilizers, pesticides, etc.), reduced cost of production, increased profits, sustainability, food safety, protection of the environment and connection to markets. This IoT can be a source of reliable unadulterated data that can, in turn, be used in CRS. Data such as farm inputs, temperature and rainfall can be sourced and modelled in the CRS algorithm. In the past, this particular data never formed CRS for small-scale farmers. Due to the importance both the borrowers and the lenders put into it, this modelling of the IoT data into the CRS algorithm is very important. A combination of internet and wireless communications, a Remote Monitoring System (RMS) can be used to collect these data from farmers in real-time [23]. In the use of IoT, the goal is to have low-cost, easy-to-use technology [24].

Limited experimentations have been done using smart contracts in small-scale farming. Farm records digitization using smart contracts [25] and maintaining supply chain contracts [26] are some ways smart contracts have been used. The researchers propose the usage of permissions hyperledger for the implementation of data coming from smart contracts. Permissioned hyperledger allows membership-based blockchain implementation where only members are allowed to add to the blocks in the blockchain, and access is by proof of membership. It is a deviation from the cryptocurrency implementation of hypeledgers, where proof of works is required [27]. In modelling CRS data, the data sourced through permissioned hyperledger include bank transactions, average bank transactions per month, guarantor, financial records, farming history records, bank statements, produce markets (direct, middleman, processor) and insurance. The researchers propose a hyperledger fabric that can be used to generate accurate data and be trusted by the various players in the chain.

This paper searches through twenty-three different data commonly asked for by financial institutions and proposed fourteen (14) as being important towards CRS for small-scale farmers. From the 14, 7 are confirmed to be not commonly used because they are not available. The research further proposes, other than the conventional source of data (being the personal/behavioural data sourced from the borrower), two other sources of data that can address the challenge of missing data and outliers (resulting from incorrect responses) be used. These are permissioned hyperledger and IoT. (Fig 3). In the proposal, the bank transactions, average bank transactions per month, guarantor, financial records, farming history records, bank statements, produce markets (direct, middleman, processor), and insurance records can be maintained in the permissioned hypeledgers. In contrast, farm inputs, average rainfall (mm), and average atmospheric temperature (degrees Celsius) can be sourced directly from the farm through the use of IoT.

5. Conclusion

Borrowers suffer various biases during CRS, with the lenders attempting to reduce the bad loan book. The bias comes about from either the algorithm or the data being used. There are specific challenges with the data used for CRS for small-scale farmers. Opting for alternative data and alternative sources has the potential to increase the accuracy of the scores. This research proposes that the 14 different data be sourced through blockchain and IoT and be used in CRS.

Further research on implementing this should be done, and the efficacy of the resulting CRS should be confirmed. The researchers theorize that this has the potential of increasing the accuracy of the data (hence reducing outliers) while reducing the missing values challenge at the same time, a key component in fairness in CRS. Due to the subjectivity of the responses obtained, there may be internal inconsistency in the responses, introducing further bias in the research outcomes. This is a noted weakness in this paper, and the researchers propose using Analytic Hierarchy Process (AHP) Consistency Index (CI) to manage this weakness. Further works in this area with a target of AHP-CI of less than 10% should indicate the data's good internal consistency, further reducing the bias.

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