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An Intelligent Advisory System to Support Managerial Decisions for A Social Safety Net

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A B S T R A C T

Social investment programs are designed to provide opportunities to the less privileged so that they can contribute to the socioeconomic development of society. Stakeholders in social safety net programs (SSNPs) target vulnerable groups, such as the urban poor, women, the unemployed, and the elderly, with initiatives that have a transformative impact. Inadequate policy awareness remains a challenge, resulting in low participation rates in SSNPs. To achieve all-inclusive development, deliberate policies and programs that target this population have to be initiated by government, corporate bodies, and public-minded individuals. Artificial intelligence (AI) techniques could play an important role in improving the managerial decision support and policy-making process of SSNPs and increasing the social resilience of urban populations. To enhance managerial decision-making in social investment programs, we used a Bayesian network to develop an intelligent decision support system called the Social Safety Net Expert System (SSNES). Using the SSNES, we provide an advisory system to stakeholders who make management decisions, which clearly demonstrates the efficacy of SSNPs and inclusive development.

A R T I C L E I N F O

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1. INTRODUCTION

In any society, poor, vulnerable, and disabled people exist. They often form the bottom of the socioeconomic pyramid and require deliberate socioeconomic intervention to harness their potential and move them into mainstream socioeconomic and political spheres (Mohantyet al.2014). A large number of people are restricted or excluded from the socioeconomic development process due toethnicity, gender, sexual orientation, age, poverty, or disability (Hernández and Pérez2016). As a result, inequality across the globe is increasing. Of total global assets, 85% is owned by the richest 10%of people, while a paltry 1% is owned by the poorest 50% (United Nations2017). The e ffects of such exclusion are staggering, deepening inequality across the globe.

The process of integrating these vulnerable groups into the sustainable development drive of society is called inclusive development (Grover2014;United Nations2017). Evidence has shown that successfully implemented social programs correlate well with sustainable development goals to eliminate poverty and provide peace and prosperity for all (GiribabuDandabathula et al.2018). However, the aims of inclusive development cannot be achieved without addressing the needs of disadvantaged people (Noga and Wollbring2013). Social instability, injustice, and social hazards canundermine sustainable development aiming to achieve a balance of economic, environmental, and social values and goals (Bibri and Krogstie2017). The explosive growth of urbanization and population in developing countries such as Nigeria has introduced new burdens on the development of modern infrastructures (Silva et al.2018). Deliberate targeting of the economically disadvantaged segment of society often involves policies, programs, and projects that are poverty-related, which are collectively referred to as social safety net programs (SSNPs) (Amornsiriphong and Piemyat2012), a metaphor for alleviating the challenges of the target group.

Inclusive development incorporates human rights standards and principles, such as nondiscrimination, participation,and accountability (Grover2014).To accomplish inclusive development, nations must consider factors such as creating gainful and productive employment. This should be accompanied by robust SSNPs to shield those who earn little or cannot work. Specifically, developing countries need to increase public services in social sectors such as health, education, water, transportation, and power. This requires prudent public expenditure and well-designed and-implemented fiscal policies that stimulate growth and mitigate poverty. Based on global experiences, valuable policy advisories can be offered in areas such as SSNPs, employment strategies, and job creation. In addition, such collaboration will reduce poverty, stimulate poverty-related growth, and achieve sustainable development goals. These efforts will also enhance the ability of governments to formulate fiscal policies and strategies. Vital public services must be made accessible to everyone. In this regard, governments must improve economic governance and public investment (Mohantyet al.2014).

As part of efforts to reach all segments of the less privileged and isolated for their integrated development into society, research studies have intensified in various socioeconomic spheres where perceived or existential threats of alienation exist. Different types of inclusive development have emerged, such as inclusive education (Kricke and Neubert2017), smart classrooms (Woguet al.2019), inclusive innovation (Amaro-Rosales and Gortari-Rabiela2016), inclusive growth (Raheem et al.2018), inclusive transformation (Liu et al.2018), inclusive industrial robotics (Wogu et al.2018), inclusive conflict prevention (Okewu et al.2019), and all-inclusiveness (Klaufus et al.2017). However, drawing the attention of stakeholders, such as governments, corporate bodies, and public-minded individuals, to the quest of harnessing the potential of these underprivileged groups is required for meaningful and productive economic activities. Efforts to promote SSNPs and inclusive development have included vocational education and training for the unemployed in India (Ahmed2016); promoting innovationfor inclusive development (Hernández and Pérez2016); a big data analytics framework to enhance and support decision-making in organizations (Elgendy and Elragal2016); the use of geographicinformation systems, demographic data, and data analytics techniques to calculate potential food insecurity and to assess food assistance distribution locations (Bacon and Baker2017); and a sustainable development capacity measurement model based on information entropy that identifies changes in sustainable development levels (Liang et al.2017). In summary, none of the above studies focused on using data analytics to design a framework for tackling problems associated with SSNPs to promote inclusive development. To achieve all-inclusive development, governments and public institutions must enhance their processes of decision-making and optimize social benefits schemes.

We assert that artificial intelligence (AI) and data analytics can contribute to the improvement of SSNP schemes. Poverty-related data can be used to understand the behavior and activities of the less privileged to guide the formulation of a robust response system using data analytics techniques such as statistics, data mining, knowledge discovery in databases, data warehouses, and machine learning (Wu et al.2016). The ability to elicit patterns in data is useful for e fficient and effective decision-making (Martin-Sanchez and Aguiar-Pulido2017). Learning patterns in data provide knowledge or information, offering stakeholders support for optimal decision-making. Decisions based on mere conjecture or boardroom politics can lead to suboptimal applications of scarce resources, and social investment programs would be no less affected. Only an unbiased and nonprejudiced data-driven decision process can address this issue (Kowalczyk and Buxman2015).

In this paper, we describe the development and use of an intelligent decision support system (DSS) called the Social Safety Net Expert System (SSNES) that uses poverty-related data and a learning algorithm to produce knowledge for assisting SSNP stakeholders with decisions and initiatives. The information provided includes the identification of genuine beneficiaries of social welfare packages and advice on the social investment intervention measures that would best serve the community and prevent the misuse of funds by political elites, which in some cases (e.g., in Bangladesh (Kundo2018)) have made SSNPs ineffective in reducing the poverty level. The paper is oriented toward researchers and practitioners in management sciences interested in the applications of AI.

2. RELATED WORK

2.1. Social Safety NetPrograms

SSNPs are a set of services offered by the state, corporate bodies, or public-minded individuals to assist the poor and vulnerable to prevent them from falling further into poverty or disadvantage (Ahmed2016) . Services include unemployment benefits (Das2016), welfare (Stranz et al.2017), basic healthcare (Oberlin and Pizmony-Levy2016), conditional cash transfers (Tovar and Urrutia2017) , social investment microcredit (Rahman2014), food and nutrition security (Porter and Goyal2016), child protection (Peterman et al.2017), support in case of debt insolvency (Spooner2017), shelters for the homeless (Bender et al.2018), support for aging populations (Mutchler et al.2018), and widow empowerment programs (Pradhan and Afrin2015), among others. SSNPs are carefully designed with the aim of empowering the less privileged so that their abilities can be harnessed for socioeconomic growth and development (United Nations2017). Hence, initiatives such as conditional cash transfers from the government, universal healthcare offers, and free education could assist the economically challenged in being more successful members of society, while the level of poverty is reduced in the process. In developed countries, SSNPs have been institutionalized. The USA and Canada are good examples of countries with structured SSNPs (Spross2015; Hoynes and Stabile2019). Advocates of SSNPs believe that these programs lower crime rates and reduce poverty levels. However, critics argue that economic growth is inhibited by the taxes committed to the support of SSNPs (Conning and Kevane2002) . They are also of the view that these initiatives are a barrier to socioeconomic advancement because SSNPs encourage people to be unproductive and poor (Spross2015) . Conversely, many individuals who have lost their sources of income and livelihood in times of economic troubles are often unwilling to use available SSNPs because of the fear of social stigmatization (Sherman2013). Regardless, in any society, a segment of the population is outside the mainstream of development and needs help being integrated. Deliberate social intervention policies and programs should be targeted at these population groups (Amornsiriphong and Piemyat2012).

Developing nations have started taking action toward the creation of SSNPs. In South Africa,people who are unable to support themselves can obtain grants, with the majority of grants administered by social services targeting children (Government of South Africa2017). In Nigeria, social investment programs include conditional cash transfers to the elderly and weak, a home-grown school feeding program, soft loans for small businesses, and monthly stipends for the unemployed (Umukoro 2013). In Niger, assistance through SSNPs has increased household resilience against unpredictable climate events (GamboBoukaryet al.2016). In Ethiopia, the Productive Safety Net Program provides cash transfers to improve child nutrition (Porter and Goyal2016). In Zambia, Kenya, Ghana, and Lesotho, social cash transfers lead toward and facilitate graduation from poverty (Daidone et al. 2015). Providing opportunities for everyone to contribute to development can broaden the global economic base and reduce poverty (Mohantyet al.2014). Hence, all groups of people should have a platform for receiving developmental benefits, creating opportunities, and taking part in decision-making. The importance of supporting decision-making in managerial decisions has been emphasized in many areas, such as infrastructure asset management (Chen and Bai2019), business process information management (Zavadskas et al.2019), environmentally sustainable and ecofriendlyautomotive production (IugaButnariu) , and corporate philanthropy (Wu et al.2018). Moreover, improved social service management contributes to reducing income inequality and achieving social justice (Dearing2017).

2.2. *Applications of DataAnalytics*

Data analytics could be used to understand the behavior and activities of the poor so that SSNP programs are not hijacked by fake beneficiaries. Data analytics refers to data-assisted problem-solving and decision-making that is used to unveil patterns in data, which are invaluable for knowledge and information generation for the purpose of rational and informed decision-making (Li et al.2016), leading to optimal resource allocation. Decision support systems (DSSes) can be used for trade-off and uncertainty analyses for the improved planning and management of cities and society (Chichernea2014). Data mined and knowledge extracted from social support networks can be used to enable a mechanism for the protection and promotion of resilience among poor populations of cities in developing countries (Juliano and Yunes2014). The resilience of individuals, families, and communities as a whole can be increased with patterns uncovered from SSNP data and knowledge that is learned and used effectively. Maintaining the resilience of urban systems requires interaction between social, psychological, physical, structural, and environmental factors, while monitoring systems such as the one presented in this paper are crucial for high awareness and shared decision-making for resilient people in a resilient city (Pitre˙naite˙-Žile˙niene˙ and Torresi2014). Data analytics draws techniques from a number of communities (Cooper2012), including statistics, business intelligence, web analytics, operations research, AI, social network analysis (Beheraet al.2017), and information visualization. Here, data mining and AI were used to design an intelligent DSS to serve as an advisory framework for stakeholders in the SSNP sector, confirming the social role and importance of software systems for communities (Damaševicˇius2009). The systematic use of AI methods could lead to the development of new social welfare institutions that are more responsive to the needs of people and more development-oriented (Patel2018).

3. METHODOLOGY

3.1. *Context*

We used Nigeria as a case study given ongoing deliberate government innovations and public policies targeted at enhancing and unleashing the potential of its vulnerable population through inclusive development. The increase in the population of those less privileged in Nigeria has caused insecurity challenges. Insurgency and ethnoreligious crises are the main humanitarian issues that have increased the proportion of those who are impoverished, resulting in large numbers of internally displaced persons (IDPs). IDPs are particularly found in Northeast Nigeria, where the Boko Haram insurgency has continued for years (Hamid and Baba2014), resulting in a serious humanitarian crisis. Included in IDPs are children, orphans, poor women, the disabled, and jobless youths and men. In addition to IDPs, the elderly, the rural and urban poor, unemployed and underemployed youths, and persons with disabilities exist country-wide. These are all people who need one or more forms of an SSNP. However, Nigeria has abundant human and material resources. Since gaining independence in 1960, insecurity and corruption have led to an impoverished population (Nwagboso2012 ; Tom and Attai2014). Nigeria‘s economic indicators are weak: massive unemployment, a harsh business environment, low productivity, a highly import-dependent economy, an unstable exchange rate, high susceptibility of the economy to external dynamics, low GDP, a high crime rate, a monolithic economy, and a double-digit interest rate. Given these factors, it is no surprise that a large portion of the population is unemployed, poor, disabled, and vulnerable.

For the effective targeting and identifying of SSNP beneficiaries in Nigeria, the following criteria were formulated: an elderly person 65 years old or above, a widow without any visible means of livelihood, a person with a disability, or an unemployed youth. However, the decision to offer social welfare packages involved a combination of these factors. In most cases, the decision was basedon evidence that had multivariate and multiconditional requirements. A compelling need exists to direct the attention of governments, corporate bodies, and public-minded individuals to the plight of this vulnerable segment of society. The aim is to empower those within these groups through social investment program (SIP) initiatives to unleash their potential for sustainable development (Okewu et al.2017 ;Okewu et al.2018). Ongoing SIP initiatives in Nigeria targeted at the economic empowerment and emancipation of economically challenged segments of the population are analyzed in Table1.

Table 1. Sample ongoing social investment programs in Nigeria.

WelfareScheme	TargetAudience	Details
The N-PowerVolunteer Corp	Unemployed youths (15–24years of age)	Empowering unemployed youths, including graduates and nongraduates, with skills to engage in productive ventures such as teaching, farming, and community services. Monthly stipend paid.
Conditional Cash Transfers	Poorest of the poor(elderly, disabled, widows, etc.)	Monthly stipend paid to the elderly, disabled, widows, etc. considered to be the poorest of the poor. Community-based approach is used to identify them through traditional and religious leaders.
Government Enterprise and Empowerment Program (GEEMP)	Small-holding farmers, cooperatives, market women, enterprising youths, and other small-scale businesses, particularly in rural areas	Soft loans ranging from 10,000 to 100,000 Nigerian naira given as start-up support to enhance entrepreneurial activities among the poor (farmers, artisans, traders, etc.).
Home-Grown School Feeding Program	Students in public primaryschools	A minimum of one meal served per day to students in public primary schools.
Rapid ResponseInitiative(RRI)	Poor with healthchallenges	A free medical service for urban and rural poor with health challenges with a particular focus on surgery operations.

3.2. Instruments

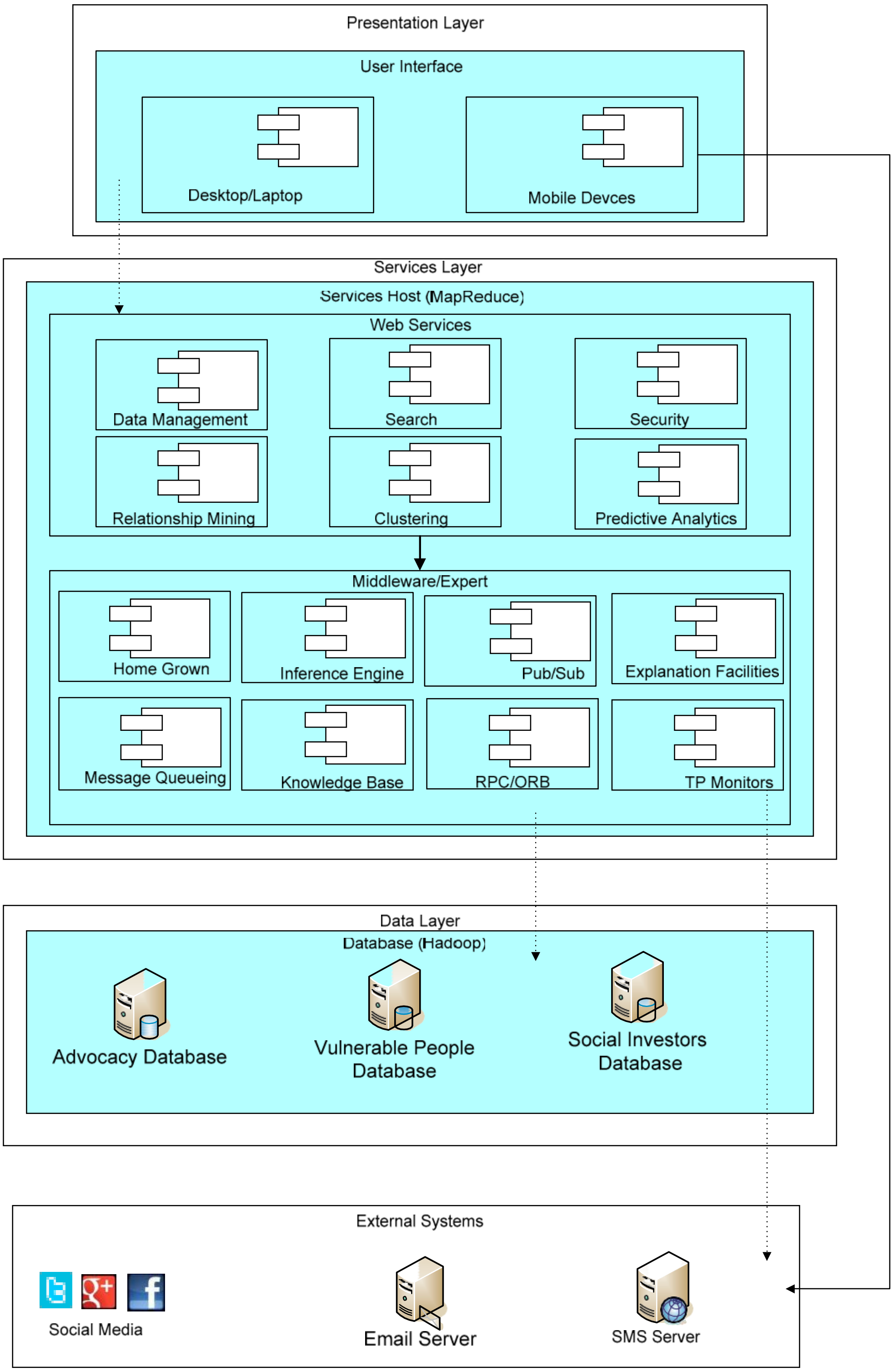
The criteria specified by social investment and communications art experts provide the stage for multicriteria decision modeling. We developed the Social Safety Net Expert System (SSNES), which uses a learning algorithm to understand patterns in poverty-related data to generate unbiased information that serves as the input in decision-making for the implementation of SIPs.

The layered architecture of SSNES is shown in Figure1, with four layers: presentation, services, data, and external systems. At the presentation layer, the user interfaces include fixed and mobile devices such as desktops, laptops, tablets, and phones, and users include social welfare beneficiaries and social investors.

The services and data layers use the HadoopMapReduce framework (Dean and Ghemawat2004) , a NoSQL technology known for handling big data, including both structured and unstructured data. It uses parallel and distributed processing so that the SSNES can respond quickly. The volume of national poverty-related social data is huge, complex, and sometimes unstructured: as a result, traditional data handling technologies, including statistical packages and SQL databases, would be inadequate. To create a properly functioning hybrid intelligent system for enhanced social investments decisions, components such as data management, predictive analytics, security, a knowledge base, an inference engine, explanation facilities, and relationship mining are integrated and have the ability to interoperate with external systems such as social media, SMS applications, and emailing systems.

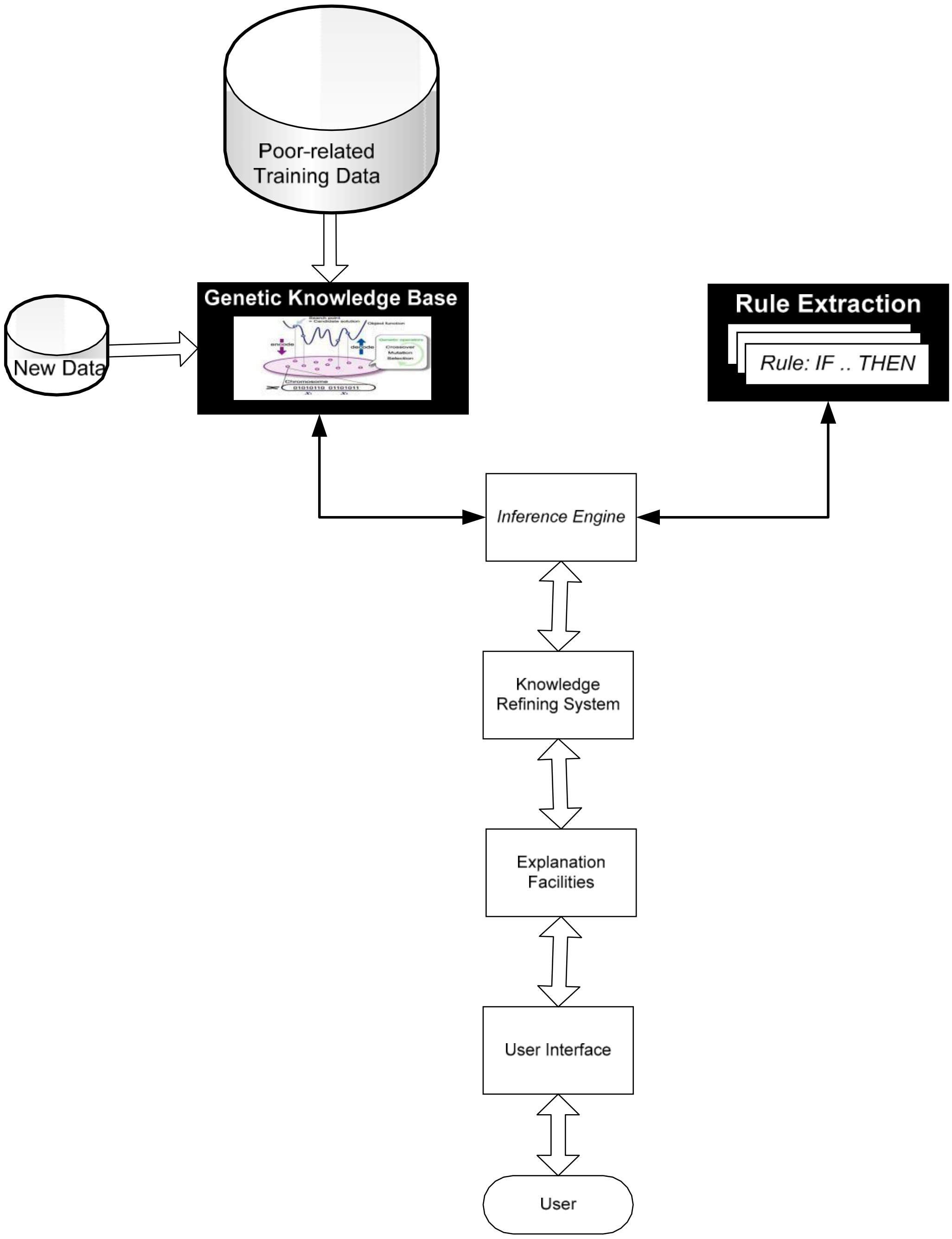
To ensure that the SSNES could reason and learn in a social investment environment characterized by uncertainty and imprecision and to include selective perception and divergent and contradicting opinions on what should constitute SSNP initiatives, intelligent technologies such as probabilistic reasoning and an evolutionary algorithm were integrated. Specifically, naïve Bayes and a decision treelearning algorithm were applied to the poverty-related data to generate knowledge that could guide optimal decision-making and problem-solving in the social welfare subsector.

Figure 1. The component-based layered architecture of the Social Safety Net Expert System (SSNES).



Naïve Bayes was used to determine the effectiveness of an SSNP advocacy strategy as a part of inclusive development. A decision tree learning algorithm was applied to predict if a person would qualify as a beneficiary of an SSNP. Decision tree learning relies on the mapping of observations foran item to draw conclusions about the target value of the item using the decision tree as a predictive model (Song and Kim2010). The Bayesian network (Heckerman1996) is a schematic diagram of a set of random variables and their conditional independence using a directed acyclic graph. For instance, probabilistic relationships between income levels and poverty levels could be illustrated using a Bayesian network such that when poverty levels are specified, the network computes the probabilities of income levels. A high-level overview of the SSNES intelligent decision system is shown in Figure2.

Figure 2. The Social Safety Net Expert System (SSNES).



3.3. *Procedure*

To provide a hybrid intelligent platform for problem-solving and decision-making in the social investment space, 17 SSNP advocacy campaign strategies and 11 examples of pastrecipients/nonrecipients of SSNP packages were analyzed. To start, examples of multivariate observations of the SSNP advocacy campaign strategies, which were past methods of creating awareness and raising the consciousness of social investors on the need to harness the potential of the less privileged for inclusive development, were compiled. As outlined in Table2, the training data were extracted from an SSNP advocacy database (only selected variables and records are shown). The data were anonymized to ensure privacy protection and adhere to ethical standards in handling information concerning vulnerable groups.

Table 2. A sample of poverty-related advocacy data.

Case	AdvocacyStrategy	Attention-Catching	Message Retention	Class: Impact_Rating
1.	Outdoor	Yes	High	Effective
2.	Outdoor	Yes	Low	Not Effective
3.	Outdoor	Yes	Fair	Effective
4.	Outdoor	No	High	Not Effective
5.	Outdoor	No	Fair	Not Effective
6.	Outdoor	No	Low	Not Effective
7.	Indoor	Yes	High	Effective
8.	Indoor	Yes	Fair	Effective
9.	Indoor	Yes	Low	Not Effective
10.	Indoor	No	High	Not Effective
11.	Indoor	No	Fair	Not Effective
12.	Indoor	No	Low	Not Effective
13.	Mixed	Yes	High	Effective
14.	Mixed	Yes	Low	Not Effective
15.	Mixed	No	High	Not Effective
16.	Mixed	No	Fair	Not Effective
17.	Mixed	No	Low	Not Effective

Expert opinions on the appropriateness of the variables or attributes (Advocacy Strategy, Attention-Catching, and Message Retention) and their values, including Advocacy Strategy (Outdoor, Indoor, or Mixed), Attention-Catching (Yes or No), and Message Retention (High, Fair, or Low), were sought from visual communications artists (as domain experts). The possible impact of these advocacy multivariate observations on social investment stakeholders was investigated to determine their effectiveness. The perceived advocacy campaign impact was expressed as a class attribute or variable (Impact_Rating) and its values (Effective, Not Effective), along with classification and soft computing standards.

A sample of the data used and elicited from a database of vulnerable people is presented in Table3(only selected variables and records are shown).These are examples of the less privileged that were classified as beneficiaries or otherwise in previous poverty-related socioeconomic empowerment initiatives.

Table 3. A sample of the data of vulnerable people.

Person	MaritalStatus	PhysicalState	Age	Employment Status	Class: Genuine_Beneficiary
1.	Widow	Not Disabled	Below 65	Unemployed	Yes
2.	Widow	Not Disabled	Below 65	Employed	No
3.	Widower	Disabled	65 and Above	Unemployed	Yes
4.	Widower	Not Disabled	Below 65	Unemployed	No
5.	Married	Not Disabled	65 and Above	Employed	Yes
6.	Married	Disabled	65 and Above	Unemployed	Yes
7.	Married	Disabled	Below 65	Unemployed	Yes
8.	Widow	Disabled	Below 65	Unemployed	Yes
9.	Widow	Not Disabled	65 and Above	Unemployed	Yes
10.	Widower	Disabled	Below 65	Employed	No
11.	Widower	Not Disabled	65 and Above	Employed	Yes

4. RESULTS

Using the training data (see sample in Table1; Advocacy Strategy, Attention-Catching, and Message Retention are attributes; Impact_Rating is the class label attribute), naïve Bayesian probability was applied to determine if an instance of a proposed advocacy campaign strategy would be effective at drawing attention to the situation of the underprivileged. Such a prediction can guide SSNP investors about the potential return on an advocacy investment.

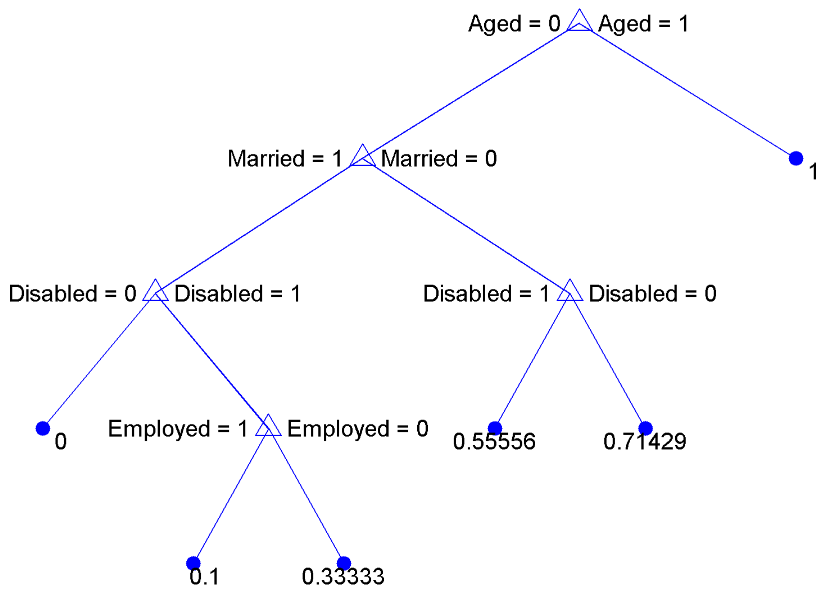
Given the above training data, the aim was to predict the class of the tuple X to determine if an advocacy campaign strategy would effectively draw the attention of critical stakeholders to the economic empowerment of the vulnerable segments of society. The information gain of each attribute is tabulated in Table4.

Table 4. Information gain of each attribute.

Attribute	Information Gain
Age	0.548
Marital Status	0.315
Physical State	0.186
Employment Status	0.105

Since age had the highest information gain among the attributes, it was selected as the splitting attribute. Node N was labeled with age, and branches were grown from each of the attribute‘s values. The tuples were then partitioned accordingly. The attribute with the highest information gain among the remaining attributes was then selected, and the process continued until a complete decision tree was obtained. The final decision tree returned by the algorithm is shown in Figure3.

Figure 3. Decision tree for determining a genuine social safety net program (SSNP) beneficiary: here, –Aged = 0| means Age is below 65, –Aged = 1| means Age is 65 and above, –Married = 0| means widow/widower, –Married = 1| means married, –Employed = 0| means unemployed, –Employed = 1| means employed, and the end leaves show the probability of genuine beneficiary status.



Based on the above tree, only two rules were generated, as follows: Rule 1: (Age = ―65 and Above‖) → (Genuine_Beneficiary = ―Yes‖); Rule 2: (Age = ―Below 65‖ ˆ Physical State = ―Not Disabled‖ ˆ Marital Status = ―Married‖) → (Genuine_Beneficiary = ―No‖).

5. EVALUATION

We evaluated the social effectiveness of the SSNES system using the methodology suggested by the World Bank (IEGIndependent Evaluation Group) for impact evaluations of SSNPs. We used the difference-in-differences method, which performs a before/after comparison with a comparison of means. The differences in the growth rates of outcomes between the beneficiaries who were selected using the SSNES system and nonbeneficiaries were interpreted as impacts attributable to the system. The SSNP interventions applied were unconditional cash transfers of 5000 naira per month to a bank account set up specifically to receive the assistance payments. The aim was to lift poor and vulnerable households out of poverty or protect them from falling into poverty. The intervention was applied in the poor informal neighborhood of Ota, Ogun State, Nigeria. The city itself has an estimated 163,783 residents and has the third largest concentration of industry in Nigeria. The intervention was applied to 314 households selected by the SSNES program and was funded by the World Bank program. The control population included the same number of households, who did not receive the SSNP intervention.

The monitored indicators of the intervention included healthcare usage (number of preventive healthcare procedures, such as parasite treatments, attended childbirths, and health check-ups), school attendance (ratio of children attending school classes), consumption (household expenditures), poverty headcount (ratio of households with their income or expenditure falling under the poverty line), and child labor (hours of work among children). The SSNP intervention resulted in an increase in school enrollment by 13%, an increase in health checks by 15%, an increase in consumption by 7%, a reduction in extreme poverty (headcount ratio) by 11%, and a decrease in child labor by 6%. The results demonstrate the effectiveness of the developed decision support system for reducing poverty and increasing the social resilience of the population.

6. DISCUSSION

The best methods for creating awareness and sensitivity and educating communities about integrating the less fortunate into inclusive development can be learned from data patterns. Both data mining and machine learning techniques were used to design the proposed system, including a Naive Bayes and a decision tree classifier.

The rules defined in Section3essentially form the initial knowledge base of the DSS and were designed and proposed to enhance SSNP initiatives and support inclusive development. The SSNES performs ―data-to-information-to-decision‖ conversion using a learning algorithm to understand multivariate and multicriteria rules to generate further rules or knowledge. The SSNES was built to enable the identification of patterns in poverty-related data to generate knowledge or information that will guide critical stakeholders to implement social welfare schemes that economically empower vulnerable populations. As such, the SSNES offers support to governments, corporate bodies, and public-minded individuals committed to social investment.

The knowledge base component of the SSNES applies metaheuristics to poverty-related training data to find patterns in data and elicit the best rules. This component also contains expert-generated rules obtained from applying data mining techniques such as the decision tree algorithm, which is a classification algorithm. The component called inference engine handles reasoning and is based on the rules in the knowledge base. To enhance machine reasoning, it interprets the rules. As the name suggests, the knowledge refining system component streamlines the rules generated for rational and informed decision-making. The explanation facilities component clarifies the actions taken by the SSNES. The user refers to persons that rely on the system for the purposes of decision-making, and software actions are communicated via the user interface.

The integration of the naïve Bayesian probability and decision tree algorithm data mining techniques allows SSNES to be an intelligent expert system that can learn and reason in imprecise and uncertain environments characterized by selective perception, sentiment analysis, and divergent opinions of stakeholders in the SSNP ecosystem. The SSNES uses a metaheuristic search and a multilayered approach to learn and generate the best rules from SSNP data for the purposes of problem-solving and informed and rational decision-making.

Our outcomes indicate that a hybrid intelligent expert system can be designed using the limited amount of data available on the beneficiaries of SSNPs. Since the core objective was to demonstrate if data analytics could be used to build a DSS for SSNPs and inclusive development, the result is considered to be positive. Hence, despite the constraints of using a limited number of training data, sufficient grounds exist to infer that the expert system could predict the efficacy of an advocacy campaign strategy for drawing the attention of stakeholders toward the poor.

Note that here we did not evaluate the success of the SSNP itself, as there are mixed opinions on whether SSNPs contribute to reducing poverty levels (Gilligan et al.2009), but rather we evaluated the eligibility of candidates to receive transfers. The SSNES had the capability to determine if a person qualified as a beneficiary for the SSNP packages. Data analytics can be used to resolve problems, enhance decision-making (Elgendy and Elragal2016), and increase e fficacy in the SSNP subsector and promote inclusive and socially responsible development through informed decision-making (Li et al.2016) . The lack of sample size (17 SSNP advocacy campaign strategies and 11 examples of past recipients/nonrecipients of the SSNP packages) could have constrained the statistical significance of the outcome (Turner et al.2006), as the larger the training dataset, the more representative it would be of an SSNP database.

7. CONCLUSIONS

This study addressed the dual issues of advocacy and identification of genuine beneficiaries of social welfare schemes. The poor and vulnerable in society can be empowered to broaden the national economic base through inclusive and sustainable development. To achieve the aims of all-inclusive sustainable development, deliberate policies and programs that target this population have to be initiated by government, corporate bodies, and public-minded individuals. To address problems associated with social safety net program (SSNP) advocacy and to enhance managerial decision-making in social investment programs, intelligent technologies (Bayesian network, decision tree learning) were used to develop a hybrid intelligent decision support system called the Social Safety Net Expert System (SSNES).

The SSNES has the ability to reason and learn patterns in poverty-related social data by generating a set of rules (knowledge base). Generated knowledge guides managerial decision-making for the social welfare of vulnerable populations, including the rural and urban poor, widows, the disabled, the unemployed, and the elderly, among others. The SSNES produces knowledge that could guide stakeholders and SSNP managers when making decisions to introduce economic empowerment programs for the less privileged to increase their social resilience. Using the SSNES system, we provide an advisory system for stakeholders and managers that clearly demonstrates the efficacy of SSNPs in inclusive development.

Conflicts of Interest:

The authors declare no conflicts of interest.

References:

1. Ahmed, Tutan. 2016. Labour market outcome for formal vocational education and training in India: Safety net and beyond. IIMB Management Review 28: 98–110.
2. Amaro-Rosales, Marcela, and RebecadeGortari-Rabiela. 2016. Inclusive innovation in the Mexican agricultural sector: coffee producers in Veracruz. EconomíaInforma 400: 86–104.
3. Amornsiriphong, Somsak, and S. Piemyat. 2012. Social Capital: Means of Social Safety Net and Social Protection in Thai Communities. Procedia Engineering 32: 1152–56.
4. Bacon, Christopher M., and Gregory A. Baker. 2017. The rise of food banks and the challenge of matching food assistance with potential need: towards a spatially specific, rapid assessment approach. Agriculture and Human Values 34: 899–919.
5. Behera, Ranjan Kumar, Santanu Kumar Rath, Sanjay Misra, RobertasDamaševicˇius, and RytisMaskeliu¯ nas. 2017.Large Scale Community Detection Using a Small World Model. Applied Science 7: 1173.
6. Bender, Kimberly, Stephanie Begun, Kaite Dunn, Emily Mackay, and Jonah DeChants. 2018. Homeless Youths‘ Interests in Social Action via Photovoice. Journal of Community Practice 26: 107–20.
7. Bibri, Simon Elias, and John Krogstie. 2017. Smart sustainable cities of the future: An extensive interdisciplinary literature review. Sustainable Cities and Society 31: 183–12.
8. Chen, Lin, and QiangBai. 2019. Optimization in Decision Making in Infrastructure Asset Management: A Review.Applied Sciences 9: 1380.

9. Chichernea, Virgil. 2014. The Use of Decision Support Systems (Dss) in Smart City Planning and Management.Romanian Economic Business Review, Romanian-American University8: 238–51.

10. Conning, Jonathan, and Michael Kevane. 2002. Community-based targeting mechanisms for social safety nets: A critical review. World Development 30: 375–94.

11. Cooper, Adams. 2012. A Brief History of Analytics A Briefing Paper. JISC CETIS Analytics Series 1: 1–21.

12. Daidone, Silvio, Luca Pellerano, SudhanshuHanda, and Benjamin Davis. 2015. Is graduation from social safety nets possible? Evidence from sub-saharan Africa. IDS Bulletin 46: 93–102.

13. Damaševicˇius, Robertas. 2009. On the human, organizational, and technical aspects of software development and analysis. Information Systems Development: Towards a Service Provision Society, 11–19.

14. Das, TusharKanti. 2016. Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) as Social Safety Net: Analysis of Public Works in Odisha, India. Review of Economic Perspectives 16: 337–60.

15. Dean, Jeffrey, and Sanjay Ghemawat. 2004. MapReduce: Simplified data processing on large clusters. Paper presented at 6th Conference on Symposium on Operating Systems Design & Implementation (OSDI'04),Berkeley, CA, USA, December 6–8; Volume 6.

16. Dearing, Tiziana C. 2017. Social Services, Social Justice, and Social Innovations: Lessons for Addressing Income Inequality. Religions 8: 89.

17. Elgendy, Nada, and Ahmed Elragal. 2016. Big Data Analytics in Support of the Decision Making Process. Procedia Computer Science 100: 1071–84.

18. GamboBoukary, Aboubakr, AdamaDiaw, and Tobias Wünscher. 2016. Factors Affecting Rural Households' Resilience to Food Insecurity in Niger. Sustainability 8: 181.

19. Gilligan, Daniel O., John Hoddinott, and AlemayehuSeyoumTaffesse. 2009. The Impact of Ethiopia's Productive Safety Net Programme and its Linkages. Journal of Development Studies 45: 1684–1706

20. GiribabuDandabathula, ChandrikaMohapatra, Sudhakar Reddy C., and P. V. V. PrasadaRao. 2018. Holistic correlation of world's largest social safety net and its outcomes with sustainable development goals. International Journal of Sustainable Development and World Ecology 26: 113–28.

21. Government of South Africa. 2017. Services: Social Relief of Distress Programme; Cape Town: Government of South Africa.

22. Grover, Adit. 2014. Importance of CSR in Inclusive Development. In International Relations Conference on India and Development Partnerships in Asia and Africa: Towards a New Paradigm (IRC-2013). Procedia—Social and Behavioral Sciences 157: 103–8.

23. Hamid, Adamu Muhammad, and Ibrahim M. Baba. 2014. Resolving Nigeria's _Boko Haram' Insurgence: What Role for the Media? Procedia—Social and Behavioral Sciences 155: 14–20.

24. Heckerman, David. 1996. A tutorial on Learning with Bayesian Network. Redmond: Microsoft Research.

25. Hernández, José Luis Sampedro, and Claudia Díaz Pérez. 2016. Innovation for Inclusive Development: A proposal for analysis. EconomíaInforma 396: 34–48.

26. Hoynes, Hilary, and Mark Stabile. 2019. How do the US and Canadian social safety nets compare for women and children? Journal of Labor Economics 37: S253–S288.

27. IEG (Independent Evaluation Group). 2011. Evidence and Lessons Learned from Impact Evaluations on Social Safety Nets. Washington: World Bank.

28. Iuga (Butnariu), Anca N., Vasile N. Popa, and Luminita I. Popa. 2019. Comparative Analysis of Automotive Products Regarding the Influence of Eco-Friendly Methods to Emissions' Reduction. Energies 12: 6.

29. Juliano, Maria Cristina Carvalho, and Maria Angela MattarYunes. 2014. Reflections on the social support network as a mechanism for the protection and promotion of resilience. Ambiente&Sociedade 17: 135–54.

30. Klaufus, Christien, Paulus van Lindert, Femke van Noorloos, and Griet Steel. 2017. All-Inclusiveness versusExclusion: Urban Project Development in Latin America and Africa. Sustainability 9: 2038.

31. Kowalczyk, Martin, and Peter Buxman. 2015. An ambidextrous perspective on business intelligence and analytics support in decision processes: Insights from a multiple case study. Decision Support Systems 80: 1–13.

32. Kricke, Meike, and Stefan Neubert. 2017. Inclusive Education as a Democratic Challenge—Ambivalences of Communities in Contexts of Power. Education Science 7: 12.

33. Kundo, Hare Krisna. 2018. Micro politics of social safety net programmes: The case of the food-for-workprogramme in Bangladesh. Development Policy Review 36: O815–O830.

34. Li, Yan, Manoj A. Thomas, and Kweku-MuataOsei-Bryson. 2016. A snail shell process model for knowledge discovery via data analytics. Decision Support Systems 91: 1–12.

35. Liang, Xuedong, Dongyang Si, and Xinli Zhang. 2017. Regional Sustainable Development Analysis Based on Information Entropy—Sichuan Province as an Example. International Journal of Environmental Research and Public Health 14: 1219.

36. Liu, Ying, Yanliu Lin, Na Fu, Stan Geertman, and Frank van Oort. 2018. Towards inclusive and sustainable transformation in shenzhen: Urban redevelopment, displacement patterns of migrants and policy implications. Journal of Cleaner Production 173: 24–38.

37. Martin-Sanchez, F., and V. Aguiar-Pulido. 2017. Analytics and Decision Support Systems in Global Health Informatics. Global Health Informatics 2017: 195–217.

38. Mohanty, Aparajita, ShashikalaGurpur, and Chaitra R. Beerannavar. 2014. Rethinking Inclusive Development: A Human Rights Critique of South Asia. Procedia—Social and Behavioral Sciences 157: 128–36.

39. Mutchler, Jan E., Yang Li, and Ping Xu. 2018. How strong is the social security safety net? using the elder index to assess gaps in economic security. Journal of Aging and Social Policy 31: 1–15.

40. Noga, Jacqueline, and GregorWollbring. 2013. An Analysis of the United Nations Conference on Sustainable Development (Rio +20) Discourse Using an Ability Expectation Lens. Sustainability 5: 3615–39.

41. Nwagboso, Chris. 2012. Security Challenges and Economy of the Nigerian State (2007–2011). American InternationalJournal of Contemporary Research 2: 244–58.

42. Oberlin, Kathleen C., and Oren Pizmony-Levy. 2016. Beyond Access: Social Safety Nets and the Use of Free Health Care Services. Sociological Perspectives 59: 640–67.

43. Okewu, Emmanuel, Sanjay Misra, RytisMaskeliu¯ nas, RobertasDamaševicˇius, and Luis Fernandez-Sanz. 2017. Optimizing Green Computing Awareness for Environmental Sustainability and Economic Security as a Stochastic Optimization Problem. Sustainability 9: 1857.

44. Okewu, Emmanuel, Sanjay Misra, Luis Fernandez-Sanz, RytisMaskeliu¯ nas, and RobertasDamaševicˇius. 2018. An e-environment system for socio-economic sustainability and national security. ProblemyEkorozwoju 13: 121–32.

45. Okewu, Emmanuel, Sanjay Misra, Luis Fernandez-Sanz, FolusoAyeni, Victor Mbarika, and RobertasDamasevicˇius. 2019. Deep Neural Networks for Curbing Climate Change-Induced FarmersHerdsmen Clashes in a Sustainable Social Inclusion Initiative. ProblemyEkorozwoju—Problems of Sustainable Development 14: 143–55.

46. Patel, Leila. 2018. Social Protection in Africa: Beyond Safety Nets? The Journal of Sociology & Social Welfare 45: 4. Peterman, Amber, Anastasia (Naomi) Neijhoft, Sarah Cook, and Tia M. Palermo. 2017. Understanding the linkages between social safety nets and childhood violence: A review of the evidence from low-and middle-incomecountries. Health Policy and Planning 32: 1049–71.

47. Pitre˙naite˙-Žile˙niene˙, Birute, and FabrizioTorresi. 2014. Integrated Approach to a Resilient City: Associating Social, Environmental and Infrastructure Resilience in its Whole. European Journal of Interdisciplinary Studies, Bucharest Economic Academy 6: 1.

48. Porter, Catherine, and RadhikaGoyal. 2016. Social protection for all ages? Impacts of Ethiopia‘s Productive Safety Net Program on child nutrition. Social Science and Medicine 159: 92–99.

49. Pradhan, Mohammad Abdul Hannan, and Sabiha Afrin. 2015. A Review of Social Safety Nets Programs for Women in Bangladesh: Issue and Challenges. Advances in Economics and Business 3: 149–56.

50. Raheem, Ibrahim D., Kazeem O. Isah, and Abdulfatai A. Adedeji. 2018. Inclusive growth, human capital development and natural resource rent in SSA. Economic Change and Restructuring 51: 29–48.

51. Rahman, Mohammad Mahbubur. 2014. Estimating the Average Treatment Effect of Social Safety Net Programmes in Bangladesh. Journal of Development Studies 50: 1550–69.

52. Sherman, Jennifer. 2013. Surviving the Great Recession: Growing Need and the Stigmatized Safety Net. Social Problems 60: 409–32.

53. Silva, BhagyaNathali, Murad Khan, and Kijun Han. 2018. Towards sustainable smart cities: A review of trends, architectures, components, and open challenges in smart cities. Sustainable Cities and Society 38: 697–713.

54. Song, Jin Yu, and Hui Kang Kim. 2010. A Study of Decision Tree in Detecting Intrusions. Journal of the Korean Data Analysis Society 12: 983–96.

55. Spooner, Joseph. 2017. Seeking shelter in personal insolvency law: Recession, eviction, and bankruptcy‘s social safety net. Journal of Law and Society 44: 374–405.

56. Spross, Jeff. 2015. America‘s social safety net is way too skimpy—And horribly designed. The Week, May 8.

57. Stranz, Hugo, PatrikKarlsson, and Stefan Wiklund. 2017. The wide-meshed safety net. decision-making on social assistance eligibility in Sweden. European Journal of Social Work 20: 711–23.

58. Tom, Edet J., and Amadu J. Attai. 2014. The Legislature and National Development: The Nigerian Experience.Global Journal of Arts Humanities and Social Sciences 2: 63–78.

59. Tovar, Jorge, and Miguel Urrutia. 2017. The Impact of Social Safety Net Programs on Household Savings in Colombia. Developing Economies 55: 23–37.

60. Turner, Carl W., James R. Lewis, and Jakob Nielsen. 2006. Determining usability test sample size. In International Encyclopedia of Ergonomics and Human Factors. Edited by WaldemarKarwowski. Boca Raton: CRC Press, pp. 3084–88.

61. Umukoro, Nathaniel. 2013. Poverty and Social Protection in Nigeria. Journal of Developing Societies 29: 305–22.

62. United Nations. 2017. United Nations Development Programme. Inclusive Development.

63. Wogu, IkedinachiAyodele, Sanjay Misra, Patrick Assibong, AdewoleAdewumi, RobertasDamasevicius, and RytisMaskeliunas. 2018. A Critical Review of the Politics of Artificial Intelligent Machines, Alienation and the Existential Risk Threat to America‘s Labour Force. In Computational Science and Its Applications—ICCSA 2018. Basel: Springer International Publishing, pp. 217–32.

64. Wogu, IkedinachiAyodele P., Sanjay Misra, Patrick A. Assibong, Esther FadekeOlu-Owolabi, RytisMaskeliu¯nas, and RobertasDamasevicius. 2019. Artificial intelligence, smart classrooms and online education in the 21st century: Implications for human development. Journal of Cases on Information Technology 21: 66–79.

65. Wu, Caesar, RajkumarBuyya, and KotagiriRamamohanarao. 2016. Big Data Analytics = Machine Learning +Cloud Computing. Big Data 2016: 3–38.

66. Wu, Wenqing, Kexin Yu, Chien-Chi Chu, Jie Zhou, Hong Xu, and Sang-Bing Tsai. 2018. Diffusion of Corporate Philanthropy in Social and Political Network Environments: Evidence from China. Sustainability 10: 1897.

67. Zavadskas, KazimierasEdmundas, JurgitaAntucheviciene, and PrasenjitChatterjee. 2019. Multiple-Criteria Decision-Making (MCDM) Techniques for Business Processes Information Management. Information 10: 4.